Intelligent fault monitoring and diagnosis in electrical machines

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**Abstract**

The aim of this paper is to develop an intelligent diagnosis method for fault detection and isolation in induction motors. We consider failures in three components of induction motor: bearing, stator winding and rotor winding. Firstly, a model-based nonlinear observer in the proposed method is designed based on available information. The fault detection decision is carried out by comparing the model-based observer speed with their signatures. Secondly, multiple state observers are constructed based on possible fault function set. The fault isolation decision is made by checking each residual generated by observer state estimation. Finally, simulation tests are given to verify the effectiveness of the proposed fault diagnosis scheme.

**1. Introduction**

The induction motor is indispensable because of its ruggedness and low cost. Advances in power electronics and the field orientation design methodology promise that induction motor will replace dc motor. An important problem in industrial servo system is to continually monitor induction motor and detect changes whenever they occur. This paper will focus on this area.

Various approaches to fault detection have been reported during the last two decades. It has been shown that the use of adequate process models can allow early fault detection with normal measurable variables [1]. In [2], an expert system model is developed for fault detection. In [3], the authors develop a frequency monitoring method for detecting fault in induction motors. In [4], a chip thickness and cutting force model is built for predicting process faults. In [5], a robust fusion approach based on fuzzy logic is developed for reliable machinery health assessment. In [6], an adaptive observer technique is proposed for a fault diagnosis of actuators. In [7], a dynamical model is presented to detect incipient faults. In [8], a technique to improve the fault detection is presented by using the classical multiple signal classification (MUSIC) method. In [9], we develop a linear state observer for detecting the cutting tool wear. In [10], a robust observer is proposed for fault diagnosis of robotic systems without speed information. In [11], a generic neurofuzzy model-based approach is presented for detecting faults in induction motors. In [12], analytic-wavelet-ridge-based technique is used for detecting fault in brushless direct current motors. In [13], adaptive neural fuzzy inference system is proposed for detecting inter-turn insulation and bearing wear faults in induction motor. In [14], vision-based signal processing is used for finding alignment errors.

This paper intends to develop an intelligent method for checking failures which may happen in induction motors. The basic idea of the proposed method is to use the information provided by the model-based observer to undertake fault detection and isolation scheme in induction motors. The main advantage of the proposed algorithms is that it is not necessary to use flux sensors which need to be inserted in the air gap and involve a redesign of the machine which reduces reliability and implies both additional costs and technological difficulties. We first design a nonlinear observer based on an available induction motor model. The fault detection decision is carried out by comparing the observer speed with their signatures. In the next design, multiple state observers are constructed based on possible fault functions set. The fault isolation
decision is made by checking each residual generated by observer state estimation. Finally, the fault diagnosis scheme developed is tested and the results show that the proposed scheme can effectively diagnose a bearing fault (a typical fault example in induction motor).

2. Model of induction motor

Induction motors are, in general, supplied from three phase a.c. power grids and thus contained three phase coiled windings. An equivalent two-phase machine was introduced in literature [16] with two rotor windings and two stator windings. Their voltage equations in machine variables are expressed as

\[
\begin{align*}
(\psi_{sa}) &= (u_{sa}) + \begin{bmatrix} -R_s & 0 \\ 0 & -R_s \end{bmatrix} (i_{sa}) \\
(\psi_{sb}) &= (u_{sb}) + \begin{bmatrix} 0 & -R_s \\ -R_s & 0 \end{bmatrix} (i_{sb})
\end{align*}
\]  

(1)

\[
\begin{align*}
(\psi_{rd}) &= (R_r 0) (i_{rd}) \\
(\psi_{rq}) &= (0 R_r) (i_{rq}) = 0
\end{align*}
\]  

(2)

where \( R, i, \psi, u \) denote resistance, current, flux linkage, and stator voltage to the machine; the subscripts \( s \) and \( r \) represent stator and rotor of the machine, \((a, b)\) denote the components of a vector with respect to a fixed stator reference frame, \((d', q')\) denote the components of a vector with respect to a frame rotating at speed \( n_w \omega \); and \( n_w \) represents the number of pole pairs of the induction machine and \( \omega \) represents the rotor speed.

By introducing an angle \( \delta \) with \( \delta = n_w \omega T \), \( \delta(0) = 0 \), we transform the vectors \((i_{rd}, i_{rq}, \psi_{rd}, \psi_{rq})\) into vectors \((i_a, i_b, \psi_a, \psi_b)\) in the stationary frame \((a, b)\)

\[
\begin{align*}
(i_a) &= \begin{bmatrix} \cos \delta & -\sin \delta \\ \sin \delta & \cos \delta \end{bmatrix} (i_{rd}) \\
(i_b) &= \begin{bmatrix} \cos \delta & \sin \delta \\ -\sin \delta & \cos \delta \end{bmatrix} (i_{rq})
\end{align*}
\]  

(3)

\[
\begin{align*}
(\psi_a) &= \begin{bmatrix} \cos \delta & -\sin \delta \\ \sin \delta & \cos \delta \end{bmatrix} (\psi_{rd}) \\
(\psi_b) &= \begin{bmatrix} \cos \delta & \sin \delta \\ -\sin \delta & \cos \delta \end{bmatrix} (\psi_{rq})
\end{align*}
\]  

(4)

For a magnetically linear system, the flux linkages are expressed as

\[
\begin{align*}
(\psi_{sa}) &= \begin{bmatrix} L_s & 0 \\ 0 & L_s \end{bmatrix} (i_a) + \begin{bmatrix} M & 0 \\ 0 & M \end{bmatrix} (i_b) \\
(\psi_{sb}) &= \begin{bmatrix} M & 0 \\ 0 & M \end{bmatrix} (i_a) + \begin{bmatrix} L_s & 0 \\ 0 & L_s \end{bmatrix} (i_b)
\end{align*}
\]  

(5)

\[
\begin{align*}
(\psi_a) &= \begin{bmatrix} M & 0 \\ 0 & M \end{bmatrix} (i_a) + \begin{bmatrix} L_r & 0 \\ 0 & L_r \end{bmatrix} (i_b) \\
(\psi_b) &= \begin{bmatrix} L_r & 0 \\ 0 & L_r \end{bmatrix} (i_a) + \begin{bmatrix} M & 0 \\ 0 & M \end{bmatrix} (i_b)
\end{align*}
\]  

(6)

where \((L_s, L_r)\) are the inductances and \(M\) is the mutual inductance.

The mechanical equation of motion is as follows:

\[
\frac{T_l}{J} + k_0 \omega + \dot{\omega} = \mu (\psi_a_i_b - \psi_b_i_a)
\]  

(7)

where \( T_l, J \) are the load torque and rotor inertia; \( k_0 \) is the damping coefficient of the motor; and \( \mu = M/L_r \).

Now the following dynamics of an induction motor described by the fifth-order model (see [17] for its detailed derivation) is obtained

\[
\begin{align*}
\dot{\psi}_a &= -2\psi_a - \omega\psi_b + 2M\dot{i}_a \\
\dot{\psi}_b &= -2\psi_b + \omega\psi_a + 2M\dot{i}_b \\
\dot{\psi}_a &= -2\psi_a - \omega\psi_b + 2M\dot{i}_a \\
\dot{\psi}_b &= -2\psi_b + \omega\psi_a + 2M\dot{i}_b \\
\dot{i}_a &= -\frac{R_s}{L_s} i_a + \frac{1}{L_s} u_a + \beta \omega \psi_a + \beta \omega \psi_b - 2M \dot{i}_a \\
\dot{i}_b &= -\frac{R_s}{L_s} i_b + \frac{1}{L_s} u_b + \beta \omega \psi_a - 2M \dot{i}_b \\
\end{align*}
\]  

(8)

where \((\psi_a, \psi_b, (i_a, i_b), (u_a, u_b))\) are the rotor flux linkage, stator currents and voltage inputs; \((R_r, R_s, (L_s, L_r))\) are the resistance and inductance; the number of pole pairs is equal to one; and \( \sigma = L_c(1 - M^2/(\tau L_s)) \). The measured variables are \((\omega, i_a, i_b)\), while the state variables \((\psi_a, \psi_b)\) are not measured.

The present paper has the following task: fault detection and isolation indicate that something is going wrong in the monitored system and faults are to be detected in different sectors of the induction motor. Our monitoring scheme will concentrate on sensing specific failures modes in one of three induction motor components [18]: the stator winding, the rotor winding, or the bearings.

When the bearing starts to deteriorate, the bearing friction will increase and it is directly reflected in the speed of the motor; the speed of the motor reduces and the torque rises [13]. This can be expressed by the following equation

\[
\dot{\psi} = \mu (\psi_a_i_b - \psi_b_i_a) - k_0 \omega - \frac{T_l}{J} + D(t - T) \zeta_1(\omega)
\]  

(9)

where the term \( D(t - T) \zeta_1(\omega) \) denotes the changes in the system dynamics due to the occurrence of a bearing fault. The function \( \zeta_1(\omega) = \sum_{k=0}^{N} k \omega^k \) represents the bias due to a bearing fault, and the function \( D(t - T) \) characterizes the time profile of the fault, where \( T \) is the fault occurrence time. In this paper, we consider the case of abrupt fault; therefore, \( D(\cdot) \) takes on the form of a step function, i.e.,

\[
D(t - T) = \begin{cases} 0, & \text{if } t < T \\ 1, & \text{if } t \geq T \end{cases}
\]  

(10)

**Remark 2.1.** In the case of incipient (i.e., slowly developing) failure, the time profile function \( D(\cdot) \) may take the form of a ramp, that is

\[
D(t - T) = \begin{cases} 0, & \text{if } t < T \\ 1 - e^{-\theta(t - T)} & \text{if } t \geq T \end{cases}
\]  

(11)

where \( \theta > 0 \) is an unknown constant that represents the rate at which the fault in states and actuators evolves. Small value of \( \theta \) characterizes slowly developing fault.

When the rotor failure occurs, the rotor resistance will change [19]. This can be expressed by the following equations

\[
\begin{align*}
\dot{\psi}_a &= -2\psi_a - \omega\psi_b + 2M\dot{i}_a + D(t - T) \zeta_2(\psi_a, i_a) \\
\dot{\psi}_b &= -2\psi_b + \omega\psi_a + 2M\dot{i}_b + D(t - T) \zeta_3(\psi_b, i_b)
\end{align*}
\]  

(12)

(13)

where

\[
\begin{align*}
\zeta_2(\psi_a, i_a) &= -2\psi_a + 2M\dot{i}_a \\
\zeta_3(\psi_b, i_b) &= -2\psi_b + 2M\dot{i}_b
\end{align*}
\]  

(14)

(15)
and $\bar{z}$ is the rotor resistance variations due to the rotor failure. Similarly, for the stator, if the stator failure occurs due to mechanics, the stator resistance will change. This together with the rotor failure can be expressed by the following equations

$$
\dot{\beta}_a = -\frac{R_s}{\sigma} \beta_a + \frac{1}{\sigma} \psi_a + \beta \psi_b + \beta \omega \psi_a - 2M \beta_a \beta_b + D(t-T) \zeta_4 (\beta_a, \psi_a) 
$$

(16)

$$
\dot{\beta}_b = -\frac{R_s}{\sigma} \beta_b + \frac{1}{\sigma} \psi_b + \beta \psi_a - 2M \beta_a \beta_b + D(t-T) \zeta_5 (\beta_b, \psi_b) 
$$

(17)

where

$$
\zeta_4 (\beta_a, \psi_a) = -\frac{R_s}{\sigma} \beta_a + \beta \psi_a - \bar{z} M \beta_a, 
$$

(18)

$$
\zeta_5 (\beta_b, \psi_b) = -\frac{R_s}{\sigma} \beta_b + \beta \psi_b - \bar{z} M \beta_b, 
$$

(19)

and $\bar{z}$ is the stator resistance variations due to the stator failure.

3. Intelligent fault monitoring scheme

In this section, we use the model-based estimator to generate the residuals allowing to study out a decision in a stage of monitoring the induction motor during the fault occurrence.

Our estimation model is an observer since the variables $\psi_{ia}, \psi_{ib}$ are not measured. The proposed observer model is given by

$$
\begin{align*}
\dot{\psi}_a &= \mu (\psi_{ia} \beta_a - \psi_{ib} \beta_b) - k_0 \dot{\psi}_a - \frac{\psi_a}{T} \\
\dot{\psi}_b &= -\zeta \psi_a - \omega \psi_a + z M \tilde{\psi}_a \tilde{\psi}_b + \psi_{ia} \tilde{\psi}_b + \beta \psi_a - \beta \omega \psi_b - \beta \psi_a \\
\dot{\beta}_a &= -\frac{R_s}{\sigma} \beta_a + \frac{1}{\sigma} \psi_a + \beta \psi_b + \beta \omega \psi_a - 2M \beta_a \beta_b + c_1 \beta_a \\
\dot{\beta}_b &= -\frac{R_s}{\sigma} \beta_b + \frac{1}{\sigma} \psi_b + \beta \psi_a - 2M \beta_a \beta_b + c_2 \beta_b
\end{align*}
$$

(20)

where $\mu, \psi_{ia}, \psi_{ib}, \beta_a, \beta_b$ are the estimates of $\mu, \psi_{ia}, \psi_{ib}, \beta_a, \beta_b$; $c_1, c_2$ are the design parameters; and $\tilde{w}_a = w - w$. $\delta_a = \delta_a - \delta_b, \delta_b = \delta_b - \delta_b$. Notice that the proposed observer (20) is the design of an output feedback algorithm, on the basis of $\zeta, \delta_a, \delta_b$ measurements only.

We start by computing the error equation from the measured vector and its estimate. Using (8) and (20), the following error dynamics is obtained

$$
\begin{align*}
\dot{\hat{\psi}}_a &= \mu (\psi_{ia} \beta_a - \psi_{ib} \beta_b) - k_0 \hat{\psi}_a \\
\dot{\hat{\psi}}_b &= -\zeta \hat{\psi}_a - \omega \hat{\psi}_a + z M \hat{\psi}_a \hat{\psi}_b + \hat{\psi}_{ia} \hat{\psi}_b + \beta \hat{\psi}_a - \beta \omega \hat{\psi}_b - \beta \hat{\psi}_a \\
\dot{\hat{\beta}}_a &= -\frac{R_s}{\sigma} \hat{\beta}_a + \frac{1}{\sigma} \hat{\psi}_a + \beta \hat{\psi}_b + \beta \omega \hat{\psi}_a - 2M \hat{\beta}_a \hat{\beta}_b + c_1 \hat{\beta}_a \\
\dot{\hat{\beta}}_b &= -\frac{R_s}{\sigma} \hat{\beta}_b + \frac{1}{\sigma} \hat{\psi}_b + \beta \hat{\psi}_a - 2M \hat{\beta}_a \hat{\beta}_b + c_2 \hat{\beta}_b
\end{align*}
$$

(21)

where the output of the fault is zero when $t < T$. Now, we will derive an upper bound for $|\hat{\psi}|$ during the time interval $[0,T]$.

Define the Lyapunov function

$$
V = \frac{1}{2} (\hat{\psi}_a^2 + \hat{\psi}_b^2 + \hat{\beta}_a^2 + \hat{\beta}_b^2).
$$

(22)

Its time derivative is given by

$$
\dot{V} = -k_0 \hat{\psi}_a^2 + \mu (\psi_{ia} \beta_a - \psi_{ib} \beta_b) \hat{\psi}_a - \zeta \hat{\psi}_a^2 - (\omega \hat{\psi}_a + \mu \beta \hat{\psi}_b \hat{w} + \beta \hat{\psi}_a - \beta \omega \hat{\psi}_b - \beta \hat{\psi}_a)
$$

$$
\dot{\beta}_a \hat{\psi}_a + \beta \hat{\psi}_b + \beta \omega \hat{\psi}_a - 2 M \hat{\beta}_a \hat{\beta}_b + c_1 \hat{\beta}_a
$$

$$
\dot{\beta}_b \hat{\psi}_a + \beta \hat{\psi}_b - \beta \omega \hat{\psi}_b - \beta \hat{\psi}_a
$$

$$
\dot{\hat{\beta}}_a = -\frac{R_s}{\sigma} \hat{\beta}_a + \frac{1}{\sigma} \hat{\psi}_a + \beta \hat{\psi}_b + \beta \omega \hat{\psi}_a - 2 M \hat{\beta}_a \hat{\beta}_b + c_1 \hat{\beta}_a
$$

$$
\dot{\hat{\beta}}_b = -\frac{R_s}{\sigma} \hat{\beta}_b + \frac{1}{\sigma} \hat{\psi}_b + \beta \hat{\psi}_a - 2 M \hat{\beta}_a \hat{\beta}_b + c_2 \hat{\beta}_b
$$

where $\hat{\beta}_a, \hat{\beta}_b$ are the design parameters; and $\beta_a, \beta_b$ is the stator resistance variations due to the stator failure.

Let $\hat{\chi} = \min(\chi, \zeta, c_1, c_2)$. Therefore, we have

$$
\dot{V} \leq -2 \hat{\chi} \dot{\chi} V
$$

(24)

This results in

$$
V \leq e^{-2 \hat{\chi} (t-t_0)} V(t_0),
$$

(25)

where $t_0$ is the initial time. Since $\frac{1}{2} \dot{\chi} \dot{\chi} \leq V$, we have

$$
\dot{\chi} \dot{\chi} \leq 2 e^{-2 \hat{\chi} (t-t_0)} V(t_0)
$$

$$
= e^{-2 \hat{\chi} (t-t_0)} \times \left[ \chi^2 (t_0) + 2 \frac{\chi^2 (t_0)}{2} + \frac{\chi^2 (t_0)}{3} + \frac{\chi^2 (t_0)}{4} \right].
$$

(26)

Notice that the variables $(\psi_{ia}, \psi_{ib})$ are not measured and thus the initial values $\psi_{ia}(t_0), \psi_{ib}(t_0)$ are not available. However, we may replace the initial value $\psi_{ia}(t_0)$ by a conservative estimate $\psi_{ia}(t_0)$, where $|\psi_{ia}(t_0)| \leq \psi_{ia}(t_0)$. Similarly, we apply the estimate $\psi_{ib}(t_0)$ to $\psi_{ib}(t_0)$, where $|\psi_{ib}(t_0)| \leq \psi_{ib}(t_0)$. Since the first term contains an exponential function $e^{-2 \hat{\chi} (t-t_0)}$, the replacements will not affect the threshold seriously.

The time-varying threshold bound $\hat{\chi}_M(t)$ is chosen as follows, for $t < T$,

$$
\hat{\chi}_M(t) = e^{-\hat{\chi} (t-t_0)} \times \sqrt{\chi^2 (t_0) + \frac{\chi^2 (t_0)}{2} + \frac{\chi^2 (t_0)}{3} + \frac{\chi^2 (t_0)}{4}}.
$$

(27)

The detailed fault monitoring scheme can be seen from Fig. 1. The intelligent decision scheme for fault detection is as follows.

Fault monitoring scheme: The decision for detecting a fault is made when the estimate error component $|\hat{\chi}(t)|$ exceeds its corresponding threshold bound $\hat{\chi}_M$. The fault detection decision time $T_0 \geq T$ is obtained while $|\hat{\chi}(t)| > \hat{\chi}_M$.
4. Intelligent fault isolation scheme

In a practical problem, it is quite difficult to determine what kind of faults occurs a priori, even we have detected the occurrence of a fault. Hence, it is necessary to isolate the faulty element.

As the fault is unknown, the fault isolation task may require all possible fault functions for finding a fault type (or fault pattern). Let us see a fault set $O_F$.

$$
O_F = \begin{cases} 
\begin{bmatrix}
\zeta_1(o) \\
\zeta_2(p_a, i_b) \\
\zeta_3(p_a, i_b) \\
\zeta_4(i_e, i_a) \\
\zeta_5(i_b, i_b) 
\end{bmatrix}
= \begin{bmatrix}
\left( \sum_{i=1}^{N} k_{iW} \right) & 0 & 0 \\
-\gamma^2 x_a + \gamma^2 M_i a & 0 & 0 \\
0 & -\gamma^2 x_a + \gamma^2 M_i b & 0 \\
0 & 0 & -\gamma^2 x_b + \gamma^2 M_i b \\
0 & 0 & 0 
\end{bmatrix}
\end{cases}
$$

The idea of the isolation algorithm is to use the multiple observer method as suggested in [15], called the Generalized Observer Scheme (GOS). Assume that a fault is detected at time $T_0$; accordingly, at this moment the fault isolation scheme is activated.

Denoting by $(o_a, p_a, i_a, i_b, i_b)$ the state variables estimates and by $(\hat{o}_a, \hat{p}_a, \hat{i}_a, \hat{i}_b, \hat{i}_b)$ the corresponding estimation errors, we introduce the following 3 isolation observers

$$
\dot{\hat{o}}_a = \mu(\hat{p}_a i_a + \hat{i}_b i_b) - k_0 \hat{o}_a + \hat{c}_h
$$

$$
\dot{\hat{p}}_a = -2 \hat{p}_a + \mu \hat{i}_a + \mu \hat{w}_a + \mu \hat{m}_a - \beta o_1 \hat{i}_b + \hat{c}_h
$$

$$
\dot{\hat{i}}_a = -\frac{k_1}{l_a} i_a + \frac{1}{l_a} u_a + 2 \hat{p}_a \hat{h}_b + \hat{w}_a \hat{h}_a - 2 M_i a + c_{1h} \hat{i}_b + \hat{c}_h
$$

$$
\dot{\hat{i}}_b = -\frac{k_1}{l_b} i_b + \frac{1}{l_b} u_a + 2 \hat{p}_a \hat{h}_b + \hat{w}_a \hat{h}_a - 2 M_i b + c_{2h} \hat{i}_b + \hat{c}_h
$$

$$
\begin{align*}
\hat{o}_1 &= \mu \left( \hat{p}_a i_a + \hat{i}_b i_b \right) - k_0 \hat{o}_1 - \frac{N}{N-1} \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \\
\hat{p}_1 &= -2 \hat{p}_1 + \mu \hat{i}_a + \mu \hat{w}_a + \mu \hat{m}_a - \beta o_1 \hat{i}_b - \hat{c}_{1h} \\
\hat{i}_1 &= -\frac{k_1}{l_a} i_a + \frac{1}{l_a} u_a + 2 \hat{p}_a \hat{h}_b + \hat{w}_a \hat{h}_a - 2 M_i a + c_{1h} \hat{i}_b - \hat{c}_{1h} \\
\hat{i}_2 &= -\frac{k_1}{l_b} i_b + \frac{1}{l_b} u_a + 2 \hat{p}_a \hat{h}_b + \hat{w}_a \hat{h}_a - 2 M_i b + c_{2h} \hat{i}_b - \hat{c}_{2h}
\end{align*}
$$

$h = 1, 2, 3$ (28)

where the subscript $h$ represents the variable of the $h$th isolation observer; the function $\hat{c}_h$ is the $h$ th estimated fault element of the $h$ th isolation observer; and the parameters $c_{1h}$, $c_{2h}$ are the designed observer gains.

We now investigate the thresholds for the intelligent fault isolation scheme. Let us suppose that a fault occurs at time $T$, i.e., $T = T_0$ when $t = T$, and that it is detected at time $t = T_0$ by the proposed fault detection scheme, i.e., the first time constant such that $|\hat{o}(t)| > \hat{c}_m$.

To derive threshold values for the proposed observers, without loss of generality, we consider the case in the presence of the 1 th fault

$$
\begin{bmatrix}
\sum_{i=1}^{N} k_i^{(1)} \hat{o}_i \\
0 \\
0 \\
0
\end{bmatrix}
$$

where the estimates $k_i^{(1)}$ are known. With (8) and (28), the error dynamical equations are given by

$$
\begin{align*}
\dot{\hat{o}}_1 &= \mu \left( \hat{p}_a i_a + \hat{i}_b i_b \right) - k_0 \hat{o}_1 - \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \\
\dot{\hat{p}}_1 &= -2 \hat{p}_1 + \mu \hat{i}_a + \mu \hat{w}_a + \mu \hat{m}_a - \beta o_1 \hat{i}_b - \hat{c}_{1h} \\
\dot{\hat{i}}_1 &= -\frac{k_1}{l_a} i_a + \frac{1}{l_a} u_a + 2 \hat{p}_a \hat{h}_b + \hat{w}_a \hat{h}_a - 2 M_i a + c_{1h} \hat{i}_b - \hat{c}_{1h} \\
\dot{\hat{i}}_2 &= -\frac{k_1}{l_b} i_b + \frac{1}{l_b} u_a + 2 \hat{p}_a \hat{h}_b + \hat{w}_a \hat{h}_a - 2 M_i b + c_{2h} \hat{i}_b - \hat{c}_{2h}
\end{align*}
$$

Note that $2ab \leq \eta^{-1} a^2 + b^2$. Thus, we have

$$
\begin{align*}
V_1 &= -k_0 \hat{o}_1^2 - \hat{p}_1^2 - \hat{i}_{1h}^2 - \hat{c}_{1h}^2 - \hat{c}_{2h}^2 + \frac{1}{2} \eta \hat{c}_m^2 \\
&= -k_0 \hat{o}_1^2 - \hat{p}_1^2 - \hat{i}_{1h}^2 - \hat{c}_{1h}^2 - \hat{c}_{2h}^2 + \frac{1}{2} \eta \hat{c}_m^2 \\
&= -k_0 \hat{o}_1^2 - \hat{p}_1^2 - \hat{i}_{1h}^2 - \hat{c}_{1h}^2 - \hat{c}_{2h}^2 + \frac{1}{2} \eta \hat{c}_m^2
\end{align*}
$$

where the parameter $\eta$ should be chosen such that $k_0 - \frac{1}{2} \eta > 0$. Let $\hat{x}_m = \min(k_0 - \frac{1}{2} \eta, \mu, \alpha, c_{1h}, c_{2h})$. Eq. (30) becomes

$$
\begin{align*}
V_1 &\leq -2 \hat{x}_m V_1 + \frac{1}{2} \eta \left\langle \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \right\rangle^2 \\
&\leq -2 \hat{x}_m V_1 + \frac{1}{2} \eta \left\langle \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \right\rangle^2 \\
&= -2 \hat{x}_m V_1 + \frac{1}{2} \eta \left\langle \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \right\rangle^2
\end{align*}
$$

This produces the following inequality

$$
\begin{align*}
V_1 &\leq e^{-2\hat{x}_m(t-T_0)} V_1 (T_0) + \int_{T_0}^{t} e^{-2\hat{x}_m(t-\tau)} \\
&\times \frac{1}{2} \eta \left\langle \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \right\rangle^2 d\tau \\
&\leq e^{-2\hat{x}_m(t-T_0)} V_1 (T_0) + \int_{T_0}^{t} e^{-2\hat{x}_m(t-\tau)} \\
&\times \frac{1}{2} \eta \left\langle \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \right\rangle^2 d\tau
\end{align*}
$$

Since $\frac{1}{2} \eta \hat{c}_m^2 \leq V_1$, we have

$$
\left\langle \hat{o}_1 \right\rangle \leq e^{-\hat{x}_m(t-T_0)} \\
\times \sqrt{\hat{c}_m^2(T_0) + \hat{c}_m^2(T_0) + \hat{c}_m^2(T_0) + \hat{c}_m^2(T_0) + \hat{c}_m^2(T_0)} + \int_{T_0}^{t} e^{-2\hat{x}_m(t-\tau)} \eta \left\langle \sum_{i=1}^{N} (k_i - k_i^{(1)}) \hat{o}_i \right\rangle^2 d\tau
$$

This bound cannot be used for the threshold, since the value of $k_i$ is unknown. It is reasonable to assume that we know the range of $k_i$ whose element lies in a known bounded set such that $k_{mi} \leq k_i \leq k_{Mi}, i = 1, 2, \ldots, N$.

Thus, the following threshold function for fault isolation decision is obtained
where we have used the following facts:

\[
|k_l - k_l^{(1)}| \leq \frac{k_{Mi} - k_{mi}}{2} + |k_l - k_{mi} + k_{Mi}| \frac{1}{2}
\]  

(34)

Taking a similar procedure, we can obtain the threshold functions \(\hat{e}_{2m}\) and \(\hat{e}_{3m}\) for \(|\hat{\omega}_2|\) and \(|\hat{\omega}_3|\) respectively.

Intelligent fault isolation scheme: The decision on the occurrence of the \(h\)-th fault is made when the estimate error component \(|\hat{\omega}_h(t)| \leq \hat{e}_{hM}\) and the remaining errors \(|\hat{\omega}_l(t)| > \hat{e}_{hM}(l = 1, 2, 3; l \neq h)\) for some time \(t > T_1\), where \(T_1\) is the fault isolation decision time \(T_1 \geq T_0 \geq T\).

It should be noticed that our diagnosis system is first to use the estimator detecting fault. After a fault has been detected, the fault isolation observers are activated. Each observer corresponds to a particular type of fault. A diagram of the overall fault diagnosis scheme is shown in Fig. 2.

Remark 4.1. It is possible that the \(h\)-th fault may lead the following error estimation set at the same time

\[
|\hat{\omega}_h(t)| \leq \hat{e}_{hM} \quad \text{and} \quad |\hat{\omega}_l(t)| \leq \hat{e}_{hM} \quad (l = 2, 1, 3; \ l \neq h)
\]  

(35)

In this case, the \(l\)th fault must lead a different error estimation set from the \(h\)th fault; otherwise, the fault isolation cannot be made.

Remark 4.2. The proposed fault isolation scheme can also be extended to the case of the incipient fault. The key point is to design the threshold function in this scheme. Utilizing the inequality \(e^{-\lambda(T - \tau)} \leq e^{-\lambda(T - |\hat{\omega}|)}\) where \(\lambda_m\) is the conservative estimate of \(\hat{\omega}\) and \(T_0\) is the fault detection time given in Section 3, it is not difficult to obtain the threshold function by taking a similar procedure derived above.

5. Simulation test

We tested the proposed intelligent fault monitoring and diagnosis (isolation) schemes in a three-phase single pole pair 0.6-kW induction motor (OE-MER 7-80/C) (see [20]), whose parameters are listed in the following:

- Rated power: 600 W
- Rated speed: 1000 rev/min
- Rated torque: 5.8 Nm.
- Rated frequency: 16.7 Hz
- Excitation current: 2 A
- Rated current: 2 A
- Stator resistance: \(R_s = 5.3\ \Omega\).
- Rotor resistance: \(R_p = 3.3\ \Omega\).
- Mutual inductance: \(M = 0.34\ \text{H}\).
- Rotor inductance: \(L = 0.375\ \text{H}\).
- Stator inductance: \(L_s = 0.365\ \text{H}\).
- Motor-load inertia: \(J = 0.0075\ \text{kg} \cdot \text{m}^2\).

We consider possible faults being given by (27). In the test, we consider the first fault which takes the form of \(k_1\omega + k_2\omega^2\) with \(N = 2\). The ranges of \(k_1, k_2, \omega, R_s\) are \(5 \times 10^{-5} \leq k_1 \leq 2 \times 10^{-4}\), \(1.5 \times 10^{-5} \leq k_2 \leq 4 \times 10^{-5}\), \(15 \leq \omega \leq 20\), \(7.5 \leq R_s \leq 9.5\) respectively.

For generating the residual signal, the observer (20) was first designed

\[
\begin{align*}
\hat{\omega} &= 120(\hat{\psi}_b - \hat{\psi}_a) - \omega - \frac{5.8}{R_s} \omega \\
\hat{\psi}_a &= -8.8\hat{\psi}_a + 0.002\hat{\psi}_a + 2.992\hat{\psi}_b + 120u_a \hat{\psi}_a + 3.397\hat{\psi}_a - 0.3861\omega \hat{\psi}_a \\
\hat{\psi}_b &= -8.8\hat{\psi}_b + 0.002\hat{\psi}_a + 2.992\hat{\psi}_b - 120u_a \hat{\psi}_b + 0.3861\hat{\psi}_b + 3.397\hat{\psi}_b \\
\hat{i}_a &= -2.257\hat{i}_a + 0.425\hat{i}_b + 3.397\hat{\psi}_a - 0.3861\omega \hat{\psi}_a - 1.1552\hat{i}_a + \hat{i}_a \\
\hat{i}_b &= -2.257\hat{i}_b + 0.425\hat{i}_b + 3.397\hat{\psi}_b - 0.3861\omega \hat{\psi}_b - 1.1552\hat{i}_b + \hat{i}_b
\end{align*}
\]

This observer was tested to show how an induction motor is tracked and the role of the speed estimate is used. The observer gains are designed as \(c_1 = c_2 = 1\). The initial conditions of the motor and of the observer are set to

\[
\begin{align*}
\omega(0) &= 1, \quad \psi_a(0) = 0, \quad \psi_b(0) = 1, \quad \hat{i}_a(0) = 0, \quad \hat{i}_b(0) = 0, \\
\hat{\omega}(0) &= 1, \quad \hat{\psi}_a(0) = 0, \quad \hat{\psi}_b(0) = 0, \quad \hat{i}_a(0) = 0, \quad \hat{i}_b(0) = 0.
\end{align*}
\]

Fig. 3 shows the time histories of flux modulus, stator currents and their estimates whose estimates. Fig. 4 shows the time profiles of rotor speed. Note that all the estimated variables converge within 0.5 s to the true variables. The estimated speed tracks tightly the true speed.

Since the observer can work well, we now design the threshold of the fault detection. According to the values of \(k_0, 2, c_1, c_2\), we obtain that \(\lambda_m = 1\). The threshold is given by

\[
\hat{\varepsilon}_m(t) = e^{-\lambda_m(t - \tau)} \times \sqrt{\hat{\omega}^2(0) + \hat{\psi}_a^2(0) + \hat{\psi}_b^2(0) + \hat{i}_a^2(0) + \hat{i}_b^2(0)}
\]

Notice that the variables \(\omega, i_a, i_b\) are measurable, while the variables \(\psi_a, \psi_b\) are not measured. Thus, the initial values of \(\omega(0), i_a(0), i_b(0)\) are set to zero, while \(\psi_a(0)\) and
\[ \omega - \omega_0 \leq C_0 \sqrt{t} \]

Therefore, the threshold is \( e^{-\frac{1}{2}} \sqrt{2} \) which has been shown in Fig. 4.

When a fault occurs due to bearing factor, the error performance of the rotor speed will be degraded and the fault can be detected by using this signal. The failure is triggered at \( T = 1 \) s. Fig. 5 shows the time profiles of the fault when the fault \( 0.0001\omega + 0.00002\omega^2 \) occurs. In the simulation, the fault is assumed to be unknown and the designed observer is used for monitoring the fault occurrence. It is observed from Fig. 6 that the speed error is degraded seriously after the fault occurrence. Note that from the figure the error \( \omega \) between the state and the estimation exceeds the threshold bound \( \tilde{C}_M(t) \) after some time; the fault is detected at time \( T_0 = 1.1341 \) s. Although we can make sure that a fault has occurred, the fault type is not known. At this moment, the fault isolation scheme (28) is activated.

As proposed in Section 4, the following fault set is used for the fault isolation observer

\[
\begin{bmatrix}
0.00009\omega + 0.000025\omega^2 \\
0 \\
0 \\
0 \\
0 \\
17\beta\dot{\psi}_a - 17M\beta_1 \\
17\beta\dot{\psi}_b - 17M\beta_2 \\
0 \\
-17\dot{\psi}_a + 17M\dot{\beta}_a \\
-17\dot{\psi}_b + 17M\dot{\beta}_b \\
-\frac{\delta}{2}\dot{\beta}_2 \\
-\frac{\delta}{2}\dot{\beta}_1
\end{bmatrix}
\]

The estimated errors in the speed components \( \dot{\omega}_1, \dot{\omega}_2, \dot{\omega}_3 \) associated with the fault isolation scheme are shown in Fig. 7. It is observed that the speed error of the first isolation observer always remains below its threshold after some time; the speed error of the second isolation observer exceeds its thresholds for some time \( t > 1.7496 \) s; the speed error of the third isolation observer exceeds its...
thresholds for some time \( t > 1.8111 \) s. This indicates that the fault belongs to the first fault set, i.e., the bearing fault. The fault isolation time is confirmed at \( T_1 = 1.8111 \) s. From the test, this verifies that the proposed algorithms not only monitor the system, but also diagnose the fault occurrence effectively in the motor components.

6. Conclusions and future work

In this paper, fault monitoring and diagnosis algorithms have been proposed for induction motors. Using an observer model, the monitoring technique is applied to send out a warning signal when a fault is detected. Thereafter, utilizing fault function set, multiple observer models are used to identify the fault type. The detailed test has been given to show the effectiveness of the proposed method.

Although we have presented a complete simulation on a computer in Section 5, it is still necessary to conduct an experiment in a real world. In future research, we will set up an experimental system for an induction motor where we may change the resistor of the phase which represents the fault of rotor or stator, and measure the results. The proposed fault monitoring and diagnosis algorithms will be used to diagnose the fault in such a system.

References