Single, Multiple and Simultaneous Current Sensors
FDI based on an Adaptive Observer for PMSM Drives

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Abstract—This paper deals with a new method single, multiple and simultaneous current sensors faults detection isolation (FDI) and identification for permanent magnet synchronous motor (PMSM) drives. A new state variable is introduced so that an augmented system can be constructed to treat PMSM sensor faults as actuator faults. This method uses the PMSM model and a bank of adaptive observers to generate residuals. The resulting residuals are used for sensor fault detection. A logic algorithm is built in such a way to isolate and identify the faulty sensor for a stator phase current fault after detecting the fault occurrence. The validity of the proposed method is verified by simulation tests.

Keywords—PMSM, adaptive observers, current sensors, fault detection, isolation and identification.

I. NOMENCLATURE

PMSM  Permanent Magnet Synchronous Motor.
\( d-q \)  Synchronous axis reference frame quantities.
\( \alpha-\beta \)  Stationary axis reference frame quantities.
\( i_d, i_q \)  Stator \( d \) and \( q \) axis currents.
\( i_{\alpha}, i_{\beta} \)  Stator \( \alpha \) and \( \beta \) axis currents.
\( u_{\alpha}, u_{\beta} \)  Stator \( \alpha \) and \( \beta \) axis voltages.
\( \lambda_{\alpha}, \lambda_{\beta} \)  Stator \( \alpha \) and \( \beta \) axis flux linkages.
\( L_{d}, L_{q} \)  Stator \( d \) and \( q \) axis inductances.
\( \Phi_{e} \)  Permanent magnet flux linkage.
\( R \)  Stator resistance.
\( J \)  Total rotor inertia.
\( f \)  Viscous friction coefficient.
\( p \)  Number of the pole pairs.
\( \theta_r \)  Electrical rotor angular position.
\( \omega_r \)  Electrical rotor speed.
\( T_{em} \)  Electromagnetic torque.
\( T_{L} \)  Load torque.
\( ^{\hat{}} \)  Estimated and reference value

II. INTRODUCTION

Nowadays, due to their high efficiency, high ratio of torque to weight, high power factor, faster response and rugged construction, PMSMs are the most widely used for high performance variable speed in many industry applications [1]. They have increasingly been used in electrical vehicles, aircraft, nuclear power stations, submarines, robotic applications, medical and industrial servo drives. In some of these applications, continuous operation is necessary and thus a break down of the PMSM drive is unacceptable [2].

Early detection of abnormalities in the PMSM will help to avoid expensive failures. Indeed, the detection, location, and analysis of faults play a very important role in good operation of the electrical machines and they are essentials for major concerns such as the efficiency and the performance of applications involving PMSM [2].

Sensor failure is one of several faults occurring in the drive system. Sensors are of great importance in the installation of monitoring and control system, the detection of sensor faults is of a high priority level in FDI system. Some work in the field of sensor fault tolerance for other than PMSMs is found. In [3], [4], the authors have studied current and speed sensors faults for an induction machine. Good simulation results are reported. But, not many details are given on fault detection. Current sensors, position sensor, and the dc-voltage sensor for induction machine control are treated in [5] and good simulation and experimental results are reported. In [6]–[10], current faults are considered for doubly fed induction generator. Two Luenberger observers are simultaneously used to generate residuals for the current sensors. Fault identification logic is designed to isolate current sensor faults in stator or in rotor. As soon as the fault is identified, the control loops are reconfigured using observer outputs. Good simulation and experimental results are presented. In [11], the authors have used a new, easy and fast sensor FDI algorithm based on redundancies in temporal window, using the PS approach for a doubly fed induction generator based VSWS and a hysteresis current-controlled induction machine drive. The ac-currents, dc and ac-voltage sensors are treated. Good simulation and experimental results are reported.

All cited approaches focus on doubly fed induction generator or induction machines. Hardly any work on sensor-fault-tolerant control of PMSM can be found. Work on sensor fault tolerant control of PMSM has been only presented in [12], [13], [14]. Current, position, and the dc-link voltage sensors fault detection are studied for a PMSM drives in [12]. Good experimental results are reported. But, the exact way of isolating a fault is not presented. In [13], two-stage extended Kalman filter and a back-electromotive-force adaptive observer) and a maximum-likelihood voting algorithm are combined with the actual sensor to build a fault-tolerant controller (FTC). Only position sensor is studied for PMSM drive and good simulation and experimental results are reported. In [14], the author has used a nonlinear parity relation method for detection of additive faults for virtual sensors for \( d-q \) axis currents and speed sensor. But, abnormal changes in \( d-q \) axis currents may
indicate a fault appearing in the phase current sensors or the rotor position encoder, but this design will not provide more specific information. Furthermore, detection of multiple virtual d-q axis current sensors faults is beyond the ability of the proposed algorithm.

This paper proposes a new FDI algorithm of current sensors faults detection problem. Before dealing with the problem, we reformulated the model by using a transformation filter, which increases the system's state. This algorithm is based on the construction of nonlinear adaptive bank observers to generate residuals. The resulting residuals are used for sensor fault detection. A logic algorithm is used in such a way to isolate and identify the faulty sensor for a stator current faults after detecting the fault occurrence. The advantages of the innovative FDI algorithm proposed here, is the capability of single, multiple and simultaneous current sensors faults detection and isolation. Simulation work demonstrates the effectiveness of this algorithm.

III. PMSM MODEL

The voltage and flux equations for the PMSM in the stationary reference α-β frame can be expressed as:

\[
\begin{bmatrix}
\dot{\lambda}_a \\
\dot{\lambda}_b \\
\end{bmatrix} =
\begin{bmatrix}
R & 0 \\
0 & R \\
\end{bmatrix}
\begin{bmatrix}
\lambda_a \\
\lambda_b \\
\end{bmatrix} +
\begin{bmatrix}
d \theta/ \lambda_a \\
\end{bmatrix}
\begin{bmatrix}
i_a \\
\end{bmatrix}
\]

(1)

\[
\begin{bmatrix}
\lambda_a \\
\lambda_b \\
\end{bmatrix} =
\begin{bmatrix}
L_{\alpha\alpha} & L_{\alpha\beta} \\
L_{\beta\alpha} & L_{\beta\beta} \\
\end{bmatrix}
\begin{bmatrix}
i_a \\
i_b \\
\end{bmatrix} +
\begin{bmatrix}
\Phi_{a} \cos(\theta) \\
\Phi_{b} \sin(\theta) \\
\end{bmatrix}
\]

(2)

With:

\[ L_{\alpha\alpha} = L_{\alpha} + L_{\alpha} \cos(2\theta); \quad L_{\beta\beta} = L_{\beta} - L_{\beta} \cos(2\theta); \]
\[ L_{\alpha\beta} = L_{\alpha} \sin(2\theta); \]
\[ L_{\alpha} = \frac{L_{\theta} + L_{\theta}}{2}; \quad L_{\beta} = \frac{L_{\theta} - L_{\theta}}{2}. \]

The electromagnetic torque equation can be described as:

\[ T_{em} = \frac{3p}{2}(\lambda_a i_b - \lambda_b i_a) \]

(3)

The PMSM dynamic equation can be expressed as:

\[ T_{em} - T_L = J \frac{d\omega}{dt} + f \omega_r \]

(4)

Where; the electrical rotor angular position is related to the electrical rotor speed as follows:

\[ \frac{d\theta_e}{dt} = p \omega_r \]

(5)

IV. SENSOR FAULTS DETECTION AND ISOLATION

A. Current Sensor faults detection structure

The PMSM sensor FDI subsystem performs the tasks of failure detection and identification by continuously monitoring the outputs of the sensors. Under nominal conditions, these measurements follow predictable patterns, within a tolerance determined by the amount of uncertainties introduced by random system disturbances and measurement noise in the sensors. Usually, sensor FDI tasks are accomplished by observer when the output of a failed sensor deviates from its predicted pattern [15].

For PMSM current sensor fault detection, the α-β axis currents \( i_a \) and \( i_b \) are assumed to be measured directly through sensors: sensor \( i; i = 1 \) to 2 [see Fig.1]. But, the two currents \( i_a \) and \( i_b \) are not practically measurable. These two virtual sensing signals are calculated from the measured phase currents \( i_{av} \) by applying a linear Clarke's transformation. Considering that \( i_a \) and \( i_b \) exist in control memory, they present less computational complexity. Therefore, \( \dot{i}_a \) and \( \dot{i}_b \) signals, are selected in this fault detection design for simplicity. Instead of using a detected change in \( i_a \) and \( i_b \) signals as real fault symptoms in the two virtual current sensors (sensors 1 and 2), it can be used as an indication of possible faults in the really sensors for phase currents measurement.

For detection of α-β axis current sensors faults, a bank of output adaptive observers has been implemented as shown in fig. 1. The number of these adaptive observers is equal to the number of PMSM current sensor outputs. Thus, each observer is driven by a one sensor output, all the inputs of the system and the actual state vector. In this case, a fault on the \( i \)th output sensor affects only the residual function of the output observer by the \( i \)th output [15].

![Fig. 1. Bank of estimators for output residual generation](image)

The residual is generated for each sensor, comparing the observer output with the sensor output. Each residual is not affected by the other sensors. Therefore, α-β axis current sensors fault identification is straightforward: each residual is only sensitive to a single sensor \( i \). If the \( i \)th residual goes above the threshold level, a fault has been detected in the \( i \)th sensor [15]. As mentioned previously, a detected fault on one of the α-β axis current sensor (sensor 1 or 2) indicate a fault appearing in the phase current sensors, but this design will not provide more specific information whether the faulty sensor is in phase “a” or “b”. Therefore, the really phase current sensors fault isolation and identification tasks become not straightforward. To overcome this problem, this FDI system with the above structure needs an additional computing block for isolation and identification of faulty phase current sensors. The details of this FDI algorithm associated with the additional current sensors fault isolation and identification algorithm are given in the following sections.

B. Extended PMSM model and proposed method

To formulate the current sensor fault detection problem, the dynamic model of PMSM is extended in this section.

According to equations (1) and (2), the state space model of the synchronous motor can be rewritten as the following nonlinear system:

\[
\begin{aligned}
\dot{x}(t) &= f(x) + g(x)u(t) \\
y(t) &= Cx(t)
\end{aligned}
\]

(6)

where \( x(t) \) is the state vector defined as \( x(t) = [i_a, i_b]^T \), \( u(t) \) is the input vector defined as \( u(t) = [u_a, u_b]^T \), \( y(t) \) is the output vector defined as \( y(t) = [y_1, y_2]^T \).
The state vector is defined as:

\[
\begin{bmatrix}
\frac{\dot{z}}{x} + \frac{\dot{f}(x, \xi) + g(x)}{\mu}
\end{bmatrix}
\]

Therefore, as mentioned previously the system is extended and the initial sensor fault problem has become, after this transformation, an actuator fault problem. Based on the approach developed in [17], it is easy to build the corresponding extended faulty model:

\[
\begin{bmatrix}
\frac{\dot{z}}{x} + \sum_{j=1}^{4} g_j(x) \mu_j + g_3(x) \mu_3
\end{bmatrix}
\]

This paper focuses only on sensors faults. The transformation used here allows us to treat the FDI sensor problem as an actuator one. It should be noted that the faulty inputs of the new vector \( \mu \) which is defined as:

\[
\begin{bmatrix}
\mu_1 & \mu_2 & \mu_3 & \mu_4
\end{bmatrix} = \begin{bmatrix}
u_1 & u_2 & y_1 & y_2
\end{bmatrix}
\]

Up on the adaptation technique, a bank of nonlinear observers is designed covering all possible faulty models below [18], [19]:

\[
\begin{bmatrix}
\frac{\dot{z}}{x} + \sum_{j=1}^{4} g_j(x) \mu_j + g_3(x) \mu_3 + H_i(\hat{z}_i - z)
\end{bmatrix}
\]

Each observer isolates the fault associated with each sensor. We have mentioned that in the case of multiple and simultaneous faults, while the second fault occurs, the first fault still acts in the system. The banks of adaptive observers run simultaneously with the system.

C. Residual generation

Independent residuals are constructed for each different sensor failure. Residuals are designed enhance fault isolation for an individual failure and not to the others. In general, residuals \( r_i \) are functions of the difference between real \( \theta_i \), and estimated \( \hat{\theta}_i \) sensor outputs, which can be defined as:

\[
r_i = \theta_i - \hat{\theta}_i; \quad i \in \{1, 2\}
\]

With; \( \hat{\theta}_i = \text{c}_i x \)

Infact, for PMSM current sensor fault detection and isolation, the following residuals are constructed:
\[ \begin{align*}
    r_1 &= i_a - i_a \\
    r_2 &= i_b - i_b 
\end{align*} \]  \hspace{1cm} (13)

**D. Current Sensor fault detection**

For stator current fault detection, the residuals (14) are used. A fault is detected and the flag CURRENT FAULT DETECT (\(\text{flag } \hat{i}\)) is set if the any of the residuals \(r_1^{\text{abs}}, r_2^{\text{abs}}\) exceeds a fixed constant threshold [8].

\[ \begin{align*}
    r_1^{\text{abs}} &= |r_1| \\
    r_2^{\text{abs}} &= |r_2| 
\end{align*} \]  \hspace{1cm} (14)

**E. Isolation and identifying the faulty current sensor**

In order to isolate and identify the stator current sensor fault whether the faulty sensor is in phase ‘a’ or ‘b’, the residuals \(r_1^{\text{abs}}\) and \(r_2^{\text{abs}}\) defined in the previous sections are used.

In fact, due to the character of the Clarke's transformation (15), a fault in stator phase ‘a’ will influence \(\alpha\) and \(\beta\) stator current components. A fault in phase ‘b’ will only affect the stator \(\beta\) current component. Therefore, a fault in stator phase ‘b’ can be detected by an increase of the \(\beta\)-residual (\(r_2^{\text{abs}}\)). A fault in phase ‘a’ will lead to a change in both the \(\alpha\) and \(\beta\) residuals (\(r_1^{\text{abs}}\) and \(r_2^{\text{abs}}\)), where the change in the residual \(r_2^{\text{abs}}\) will be smaller than the change resulting from a fault of phase ‘b’. A fault of both current sensors in phases ‘a’ and ‘b’ will also lead to an increase of both residuals \(r_1^{\text{abs}}\) and \(r_2^{\text{abs}}\) [6]. This is a multiple fault scenario.

\[ \begin{align*}
    i_a &= \dot{i}_a \\
    i_b &= \frac{i_b - i_b}{\sqrt{3}} = \frac{2i_b + i_b}{\sqrt{3}} 
\end{align*} \]  \hspace{1cm} (15)

This is difficult to distinguish from a single fault in phase ‘a’, since the magnitude of the residuals is only slightly different. To solve this problem, detection of a current sensor fault in phase ‘b’ may be realized by a new residual \(r_b^{\text{abs}}\), which is only affected by the fault in phase ‘b’.

\[ r_b^{\text{abs}} = r_2^{\text{abs}} - \frac{1}{\sqrt{3}} r_1^{\text{abs}} \]  \hspace{1cm} (16)

The logic presented in fig. 2 can identify the single, multiple and simultaneous faulty sensors for a stator current fault. It is necessary to use residuals in stator fixed reference frame. Besides, the thresholds are fixed constants.

![Identification of the faulty current sensor location.](image)

**V. SIMULATION RESULTS**

In this section, simulation results are given based on the developed method for sensor FDI. General structure of the simulation setup is illustrated in Fig.3. In this diagram, the PMSM is controlled by a PWM Voltage Source Inverter (VSI) using vector control strategy [20]. The used PMSM parameters are listed in Table I.

During simulation tests, the reference rotor speed is changed from 0 to 500 rpm at \(t=0.1\)s with a step load torque \(T_l = 0.7\) Nm applied to the system at the same time. Besides, the current sensor faults are built by adding offsets currents of amplitude \(f_a = f_b = -0.6A\) to the actual signals.

![Simulation results of electromagnetic torque and rotor speed.](image)
b) Zooms of simulation electromagnetic torque and speed responses.

c) Simulation results of currents in phases ‘a’ and ‘b’ for the faulty motor current sensors.

d) Zooms of simulation currents in phases ‘a’ and ‘b’ for the faulty motor current sensors.

B. Evaluation of FDI unit with faulty currents sensors

Fig. 5 shows, the two residuals associated to the observers \( r_i^{ab} \), \( i = 1, 2 \) and the residual \( r_i^{abs} \), where they stay approximately at zero until \( t = t_1 \). At \( t = t_1 \), a fault is injected on phase ‘b’ current sensor. As shown in Fig. 6, an abrupt change in observed stator \( \beta \) current component at \( t = t_1 \) reveals a deviation of the residual \( r_i^{ab} \) from zero. If one of the residuals \( r_i^{ab} \) and \( r_i^{abs} \) exceeds a preset threshold, the flag \( i \) is set as shown in Fig. 7. So, the current sensor fault is detected. By using the logic presented in Fig. 3, the faulty phase ‘b’ sensor is identified since the corresponding flag is set as it is shown in Fig. 7. A single fault in phase ‘b’ affects the residuals \( r_2^{ab} \) and \( r_2^{abs} \). The fault in phase ‘b’ current sensor is removed at \( t = t_2 \), when the fault in phase ‘a’ current sensor has been introduced. As shown in Fig. 8, a change in stator currents at \( t = t_2 \) reveals a deviation of the residuals \( r_1^{ab} \) and \( r_2^{ab} \) associated respectively to the first and second observers, from their actual values, where the change in \( r_2^{ab} \) is smaller than the change resulting from a fault of phase ‘b’. But, the residual \( r_2^{ab} \) has not been affected by this single fault. Besides, the faulty phase ‘a’ sensor is identified since the corresponding flag \( i_a \) is set as illustrated in Fig. 7. At \( t = t_3 \), the flags reset to zero after the injected fault is removed. A single fault in stator phase ‘a’ affects the residuals \( r_1^{ab} \) and \( r_1^{abs} \). At \( t = t_4 \), when the simultaneous current sensors faults in phases ‘a’ and ‘b’ are imposed, the current sensor fault is detected since the current fault flag \( i \) is set. As shown in Fig. 7, the simultaneous faults in phases ‘a’ and ‘b’ are identified since the flags flag \( i_a \) and flag \( i_b \) are set. Besides, these simultaneous faults affect the residuals \( r_1^{ab} \), \( r_2^{ab} \) and \( r_0^{abs} \).
An approach utilizing a bank of adaptive observers with an augmented state vector was developed for detection, isolation and identification of PMSM current sensors faults. These observers are used to generate residuals for the stator current sensors. In order to identify for stator current sensor fault whether the faulty sensor is in phase ‘a’ or ‘b’, a fault logic bloc is presented and used. Simulation results show that the proposed algorithm can successfully detect, isolate and identify single, multiple and simultaneous current sensors faults related to the above signals.

In a future follow up research work, the FDI algorithm developed in this work will be followed by the design of a Fault Tolerant Control. Hence, this is achieved by the design of a reconfiguring unit which, is built up on the basis of the information provided by the FDI unit. This adjusts the structure and the tuning of the controller in order to preserve its performances also for a faulty PMSM.

VII. APPENDIX

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>PERMANENT MAGNET SYNCHRONOUS MOTOR SPECIFICATIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
<td>Rated characteristics</td>
</tr>
<tr>
<td>$R$</td>
<td>6.2 Ω</td>
</tr>
<tr>
<td>$L_{di}$</td>
<td>25.025 mH</td>
</tr>
<tr>
<td>$L_{dq}$</td>
<td>40.17 mH</td>
</tr>
<tr>
<td>$\Phi_m$</td>
<td>0.305 Wb</td>
</tr>
<tr>
<td>$J$</td>
<td>0.0036 Kg.m²</td>
</tr>
<tr>
<td>$f$</td>
<td>0.0011 Nms.rad¹</td>
</tr>
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</table>

VI. CONCLUSION


