Current Sensors Faults Detection, Isolation and Control Reconfiguration for PMSM Drives

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***Abstract*—This paper deals with a new method current sensors faults detection isolation (FDI) and reconfiguration of the control loops of a permanent magnet synchronous motor (PMSM) drives. The stator currents are measured as well as observed. During fault free operation, the measured signals are used for the PMSM control. In the case of current sensors faults, the faulty measurements are detected and isolated using the new FDI algorithm. This algorithm uses an augmented 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. After sensor fault detection and isolation, the control is reconfigured using the healthy observer's outputs. The validity of the proposed method is verified by simulation tests.**

Keywords—PMSM, adaptive observers, current sensors, fault detection and isolation, reconfiguration of control loops.

I. NOMENCLATURE

PMSM	Permanent Magnet Synchronous Motor.
d-q	Synchronous axis reference frame quantities.
α-β	Stationary axis reference frame quantities.
i_d , i_q	Stator *d* and *q* axis currents.
i_α , i_β	Stator α and β axis currents.
u_α , u_β	Stator α and β axis voltages.
λ_α , λ_β	Stator α and β axis flux linkages.
L_d , L_q	Stator *d* and *q* axis inductances.
Φ_v	Permanent magnet flux linkage.
R	Stator resistance.
J	Total rotor inertia.
f	Viscous friction coefficient.
p	Number of the pole pairs.
θ_r	Electrical rotor angular position.
ω_r	Electrical rotor speed.
T_{em}	Electromagnetic torque.
T_L	Load torque.
$\hat{}$, *	Estimated and reference value

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II. INTRODUCTION

Permanent magnet synchronous machines (PMSMs) are widely used in industry thanks to their high efficiency, high ratio of torque to weight, high power factor, faster response and rugged construction [1], [2]. For these applications high reliability, survivability and availability are required. Therefore, fault tolerant control (FTC) has become an increasingly interesting topic in the last decade [3]. The FTC objective is to ensure the continuous system functionality, even after faults occurrence [4]. This is helpful for improving the system availability and reliability. Besides, this allows to reduce the down time costs and avoid expensive repairs [2], [4].

There are numerous study results about fault detection, isolation and FTC [1]–[17], but most of them focused on of inverter faults [1], [2], [5], [6] or physical damage of the electrical machine [7]. In [8], [9], 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 [10] and good simulation and experimental results are reported. In [11]–[15], 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. But, the most cited sensor FTC approaches focus on doubly fed induction generator or induction machines. Work on sensor fault detection and FTC of PMSM has been presented in [3], [16], [17]. In [3], two-stage extended Kalman filter and a back-electromotive-force (BEMF) adaptive observer and a maximum-likelihood voting algorithm are combined with the actual sensor to build a FTC. Only position sensor is studied for PMSM drive where simulation and experimental results are reported. Current, position, and the dc-link voltage sensors fault detection are studied for a PMSM drives in [16]. Good experimental results are reported. But, the exact way of isolating a fault is not presented. In [18], 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 PMSM current sensors faults detection, isolation and a reconfiguration of the current control loops. Before dealing with the FDI algorithm, we reformulated the model by using a transformation filter, which increases the system's state. This FDI algorithm is based on this augmented system and 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. After current sensor fault detection and isolation, the control is reconfigured using the healthy observer's outputs. 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:

$$\begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} = \begin{bmatrix} R & 0 \\ 0 & R \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \lambda_\alpha \\ \lambda_\beta \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} \lambda_\alpha \\ \lambda_\beta \end{bmatrix} = \begin{bmatrix} L_\alpha & L_{\alpha\beta} \\ L_{\alpha\beta} & L_\beta \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + \begin{bmatrix} \Phi_v \cos(\theta_r) \\ \Phi_v \sin(\theta_r) \end{bmatrix} \tag{2}$$

With:

$L_\alpha = L_0 + L_1 \cos(2\theta_r)$; $L_\beta = L_0 - L_1 \cos(2\theta_r)$;

$L_{\alpha\beta} = L_1 \sin(2\theta_r)$; $L_0 = \frac{L_d + L_q}{2}$; $L_1 = \frac{L_d - L_q}{2}$.

The electromagnetic torque equation can be described as:

$$T_{em} = \frac{3p}{2}\left(\lambda_\alpha i_\beta - \lambda_\beta i_\alpha\right) \tag{3}$$

The PMSM dynamic equation can be expressed as:

$$T_{em} - T_L = J\frac{d\omega_r}{dt} + f\omega_r \tag{4}$$

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

$$\frac{d\theta_r}{dt} = p\omega_r \tag{5}$$

IV. SENSOR FAULTS DETECTION, ISOLATION AND CONTROL RECONFIGURATION

A. Proposed schemes for FDI and reconfiguration

The fault-tolerant control scheme is realized in three steps: fault detection, fault isolation and identification, and reconfiguration. A bank of observers is used for three purposes: to provide residuals for the fault detection, to provide information for the fault isolation, and to provide replacements to the sensor readings for the reconfiguration. Fig.1 shows the whole process. Therein, Fault Detection means that it is known that any fault has occurred but not what fault it is. Fault Isolation means that the location of the fault has been determined. Reconfiguration means that the control is switched to substitute signals that replace the faulty sensors [13].

The FDI unit 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 [18].

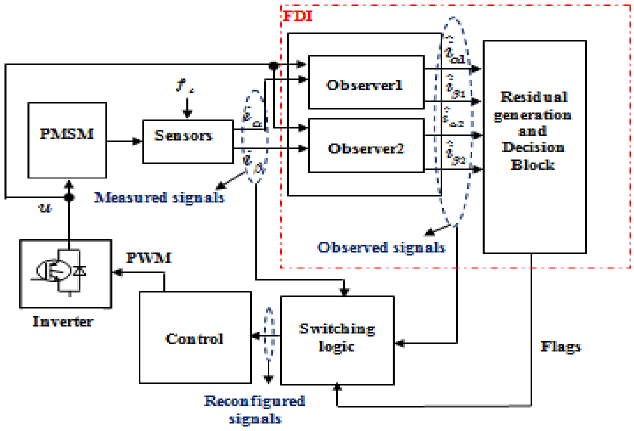

Fig. 1. Bank of observers, FDI unit, and control reconfiguration.

For detection of PMSM sensors fault, 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 [18]. Two adaptive observers are used.

Thus, each observer is driven by a one sensor output and all the inputs of the system. 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 [18].

A residual is generated for each sensor, comparing the observer output with the sensor output. Each residual is not affected by the other sensors, and therefore fault identification is straightforward: each residual is only sensitive to a single PMSM sensor. If the *i*th residual goes above the threshold level, a fault has been detected in the *i*th sensor [18].

In the following sections, it is explained how the residuals are generated using the bank of adaptive observers, how Fault Detection is realized using these residuals, and how Fault Isolation determines which phase the faulty current sensor is located, although this information is not needed for successful reconfiguration.

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. The phase currents i_{abc} are measured through sensors. Note that i_α and i_β are not practically measurable. These two values are calculated from the measured phase currents i_{abc} by applying the Clarke's transformation.

Considering that i_α and i_β exist in control memory, they present less computational complexity. Therefore, i_α and i_β signals are selected in this fault detection design for simplicity. Instead of using a detected change in i_α and i_β signals as real fault symptoms in the two virtual sensors, it can be used as an indication of possible faults in the sensors for phase currents measurement.

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

$$\begin{cases} \dot{x}(t) = f(x) + g(x)u(t) \\ y(t) = Cx(t) \end{cases} \tag{6}$$

where $x(t)$ is the state vector defined as $x(t)=\begin{bmatrix} i_\alpha & i_\beta \end{bmatrix}^T$, $u(t)$ is the system input defined as $u(t)=\begin{bmatrix} u_\alpha & u_\beta \end{bmatrix}^T$, $y(t)$ is the output vector defined as $y(t)=\begin{bmatrix} y_1 & y_2 \end{bmatrix}^T$, $f(x)=\begin{bmatrix} f_1(x) & f_2(x) \end{bmatrix}^T$ is a nonlinear vector function with nonlinear elements defined as :

$$f_1(x)=(-\frac{RL_\beta}{D}+\frac{2L_1 p\omega_r L_a}{D})i_\alpha+(\frac{RL_{\alpha\beta}}{D}-\frac{2L_1 p\omega_r L_b}{D})i_\beta+\frac{p\omega_r\Phi_v(L_0+L_1)}{D}\sin(\theta_r);$$

$$f_2(x)=(-\frac{RL_\alpha}{D}-\frac{2L_1 p\omega_r L_a}{D})i_\beta+(\frac{RL_{\alpha\beta}}{D}-\frac{2L_1 p\omega_r L_b}{D})i_\alpha-\frac{p\omega_r\Phi_v(L_0+L_1)}{D}\cos(\theta_r);$$

$L_a=L_0\sin(2\theta_r)$; $L_b=L_1+L_0\cos(2\theta_r)$; $D=L_\alpha L_\beta-L_{\alpha\beta}{}^2$,

$g(x)$ is a matrix function $g(x)=\begin{bmatrix} \frac{L_\beta}{D} & -\frac{L_{\alpha\beta}}{D} \\ -\frac{L_{\alpha\beta}}{D} & \frac{L_\alpha}{D} \end{bmatrix}$ and

C is the matrix of c_i elements (i=1to2)

$C=\begin{bmatrix} c_1 \\ c_2 \end{bmatrix}=\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

In this paper, is assumed that only offset current sensor faults can occur $y_j^f=y_j+f_j=\theta_{cj}$ for $t\geq t_f$, $j=1,2$, and $\lim_{t\to\infty}\left|y_j(t)-\theta_{cj}\right|\neq 0$, where f_1 and f_2 represent respectively the stator *α-β* axis current sensors faults effect. The means y_j^f is the actual output of the *j*th sensor when it is faulty, while y_j is the expected output when it is healthy.

As mentioned previously, the currents i_α and i_β are practically calculated from phase currents i_{abc}. So, the effects of the stator *α-β* axis currents f_1 and f_2 are related to the errors in phase 'a' and 'b' current sensors outputs f_a and f_b as follows [10]:

$$\begin{cases} f_1=f_a \\ f_2=\frac{2}{\sqrt{3}}f_b+\frac{1}{\sqrt{3}}f_a \end{cases} \tag{7}$$

Abnormal changes in i_α and i_β may indicate a fault occurring in the phase current sensors. Furthermore, as the calculation of i_α and i_β are coupled, if a fault occurring in the measurement current devices for i_{abc}, faults in i_α and i_β will appear simultaneously. This is a multiple or simultaneous fault scenario.

To detect, isolate and identify multiple and simultaneous sensor faults, the authors in [19] introduced a transformation which increases system's state. In this part, a sensor fault detection algorithm based on an augmented system's state for the single, multiple and simultaneous sensors faults is proposed.

Before dealing with the problem, a filter is applied to the output vector y :

$$\dot{\xi}=A_f\xi+B_f y \tag{8}$$

Where; the state vector is $\xi^T=\begin{bmatrix} \xi_1 & \xi_2 \end{bmatrix}$, $A_f\in\Re^{2\times2}$ is selected as a Hurwitz matrix and $B_f\in\Re^{2\times2}$ is chosen as an invertible matrix. The new input is formed as $\mu^T=\begin{bmatrix} u & y \end{bmatrix}$ and the extended system form is defined as:

$$\begin{cases} \dot{z}=\underline{f}(x,\xi)+\underline{g}(x)\mu \\ Y=\begin{bmatrix} C & 0_{2\times2} \end{bmatrix}z \end{cases} \tag{9}$$

Where; z denotes the new vector state, $z=\begin{bmatrix} x & \xi \end{bmatrix}^T$, $\underline{f}(x,\xi)$ is a vector with nonlinear and linear elements $\underline{f}(x,\xi)=\begin{bmatrix} f(x) & A_f\xi \end{bmatrix}^T$, $\underline{g}(x)$ is a matrix with nonlinear and linear elements $\underline{g}(x)=\begin{bmatrix} g(x) & 0_{2\times2} \\ 0_{2\times2} & B_f \end{bmatrix}$ and the vector μ is the new input one $\mu^T=\begin{bmatrix} u_\alpha & u_\beta & c_1x & c_2x \end{bmatrix}$.

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 [20], it is easy to build the corresponding extended faulty model:

$$\begin{cases} \dot{z}=\underline{f}(z)+\sum_{j\neq l}\underline{g}_j(x)\mu_j+\underline{g}_l(x)\mu^f{}_l \\ Y=\begin{bmatrix} C & 0_{2\times2} \end{bmatrix}z \end{cases} \tag{10}$$

When; the fault is in the *l*th actuator with $\underline{g}(x)=\begin{bmatrix} \underline{g}_1(x)....\underline{g}_4(x) \end{bmatrix}$.

The new system input as already mentioned is the vector μ which is defined as:

$\mu^T=\begin{bmatrix} \mu_1 & \mu_2 & \mu_3 & \mu_4 \end{bmatrix}=\begin{bmatrix} u_1 & u_2 & y_1 & y_2 \end{bmatrix}$.

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 μ are μ_3 to μ_4.

Up on the adaptation technique, a bank of nonlinear observers is designed covering all possible faulty models below [21], [22]:

$$\begin{cases} \dot{\hat{z}}_l=\underline{f}(z)+\sum_{j\neq l}\underline{g}_j(x)\mu_j+\underline{g}_l(x)\hat{\theta}_l+H_l(\hat{z}_l-z) \\ \dot{\hat{\theta}}_{cl}=-2\gamma(\hat{z}_l-z)^T P_l g_l(x) \\ \hat{Y}_l=\begin{bmatrix} C & 0_{2\times2} \end{bmatrix}\hat{z}_l \qquad l=\{3,4\} \end{cases} \tag{11}$$

With:

$\hat{Y}_k=\begin{bmatrix} \hat{i}_{\alpha k} & \hat{i}_{\beta k} \end{bmatrix}^T$; $k=l-2$

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 θ_{ci} and estimated $\hat{\theta}_{ci}$ sensor outputs, which can be defined as:

$$r_i = \theta_{ci} - \hat{\theta}_{ci}\ ;\ i \in \{1,2\} \tag{12}$$

With; $\theta_{ci} = c_i x$

Infact, for PMSM current sensor fault detection and isolation, the following residuals are constructed:

$$\begin{cases} r_1 = \left| i_\alpha - \hat{i}_{\alpha 1} \right| \\ r_2 = \left| i_\beta - \hat{i}_{\beta 2} \right| \end{cases} \tag{13}$$

D. Current Sensor fault detection

For stator current fault detection, the residuals (13) are used. A fault is detected and the flag CURRENT FAULT DETECT (flag *i*) is set if the any of the residuals r_1, r_2 exceeds a fixed constant threshold [13].

E. Isolation and identifying the faulty current sensor

It is easy to isolate and identify the stator current sensor fault whether the faulty sensor is in phase 'a' or 'b'. In order to achieve this, the residuals r_1 and r_2 defined in the previous section are used.

Due to the character of the Clarke's transformation (14), a fault in stator phase 'a' will influence α and β stator current components. Both residuals are going to be different from zero in case it is faulty. This is a multiple fault scenario. A fault in phase 'b' will only affect the stator β current component. This is a single fault scenario.

$$\begin{cases} i_\alpha = i_a \\ i_\beta = \dfrac{i_b - i_c}{\sqrt{3}} = \dfrac{2i_b + i_a}{\sqrt{3}} \end{cases} \tag{14}$$

The logic presented in Fig. 2 [13] can identify the faulty sensor for a stator current fault. It is necessary to use residuals in stator fixed reference frame. Besides, the thesholds are fixed constants.

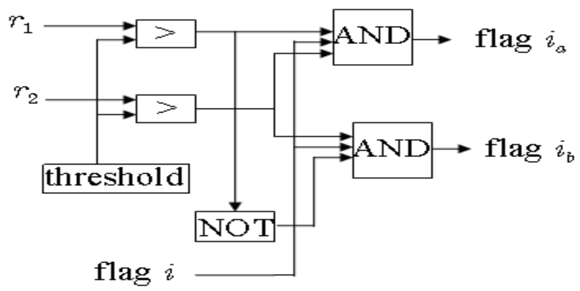

Fig. 2. Identification of the faulty current sensor location.

F. Reconfiguration

After sensor fault detection and isolation, the control scheme is reconfigured using observer replacement for the faulty sensor. In the case of a current sensor fault, the healthy observed currents $\hat{i}_{\alpha 2}$ of observer 2 and of $\hat{i}_{\beta 1}$ observer 1(See Fig.1 and Fig.3) are used for current control. In this case, the normal control loop is switched to reconfigured loop operation by the fault detection signal flag *i*. Since only flag *i* is used for reconfiguration control, the identification of the faulty sensor location is not essential for the fault-tolerant control of the drive.

V. Simulation Results

In this section, simulation results are given based on the developed method for current sensor FDI and control reconfiguration. General structure of the simulation setup is illustrated in Fig.3. In this diagram, a simplified *α-β* axis electrical model of a three-phase PMSM drives is simulated under Matlab-Simulink environment. The *d-q* axis currents and flux are calculated from the *α-β* axis currents and flux by applying the Park's transformation. Besides, the PMSM is controlled by a PWM Voltage Source Inverter (VSI) using vector control strategy [23]. The used PMSM parameters are listed in Table I.

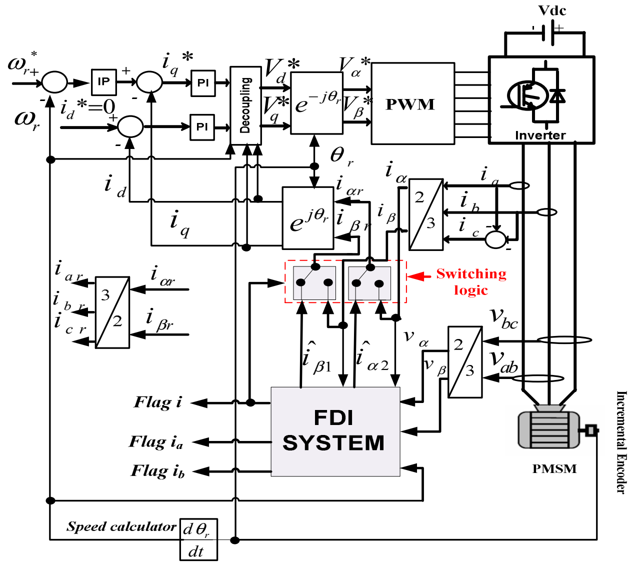

Fig. 3. FDI unit and PMSM reconfiguration of current control in *d-q* reference frame.

To investigate the performance of the previously FDI algorithm for current sensor PMSM faults and control reconfiguration, during simulation tests, the current sensor faults are built by adding offsets currents of amplitude $f_a = f_b = 0{,}6A$ to the actual signals.

At the beginning of the simulation run, the reference rotor speed is set at 500 rpm with a step load torque T_l = 2 Nm applied to the system at t = 0.7 s. A fault is injected on phase 'b' current sensor at t=1.59s and is later removed at t=3.59s, when the fault in phase 'a' current sensor has been introduced.

The impact of faults amplitudes on the generated residuals r_i (*i*=1to2) is illustrated in Fig. 4. These residuals stay approximately at zero until 1.59s. At t=1.59s, when a fault is injected on phase 'b' current sensor, the residual r_2 deviate from zero. Its value overcomes the defined threshold just after fault occurrence, and remains upper the threshold during this fault case. If one of the residual r_1 and r_2 exceeds a preset threshold, the flag *i* is set as shown in Fig.5. So, the current sensor fault is detected. As it is seen in Fig. 5, the faulty phase 'b' sensor is identified by using the logic presented in Fig. 2 since the corresponding flag (flag i_b) is set. The fault in phase 'b' current sensor is removed at t=3.59s, when the fault in phase 'a' current sensor has been introduced. As shown in Fig. 4, this fault affects the residuals r_1 and r_2 associated respectively to the first and second observers, where they deviate from theirs actual values. Since these current residuals exceed the preset thresholds, the current fault flags (flag *i* and flag i_a) are set as illustrated in Fig.5. So, the fault on phase 'a' current sensor is detected and isolated.

The current measurement, as shown in Fig. 6 and 7, is instantly triggered by the fault detection signal flag *i*, displayed in Fig. 5. In fact, after current faults application, it is seen that DC components appear in the stator measured phase currents with faulty sensors. But, the reconfigured currents used in the PMSM current control are respectively switched to the healthy observed currents. Therefore, the control reconfiguration is successful.

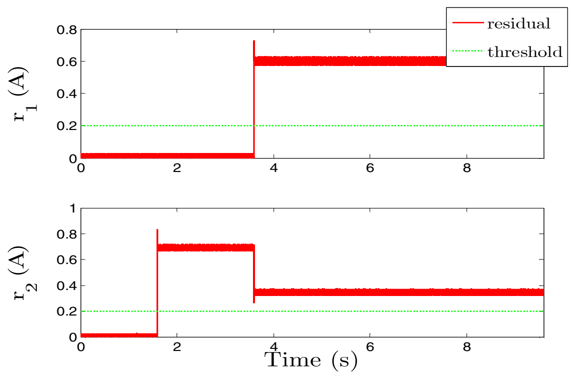

Fig. 4. Current residuals during current sensors failures.

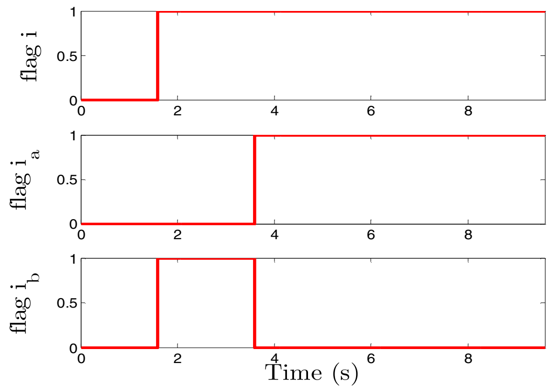

Fig. 5. Fault flags during current sensors failures.

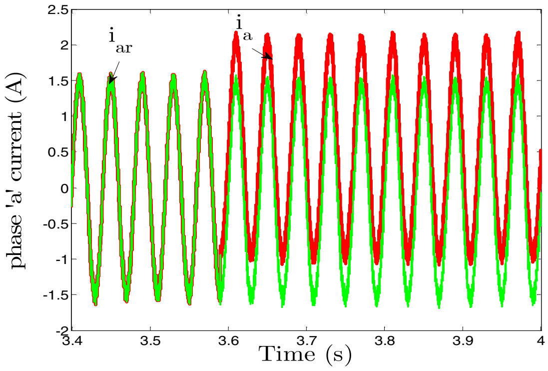

Fig. 6. Comparison of the currents in phase ‘a’ when offset fault is applied to the phase ‘a’ current sensor. Red: measured current i_a in phase ‘a’ with faulty sensor; Green: reconfigured current i_{ar} in phase ‘a’.

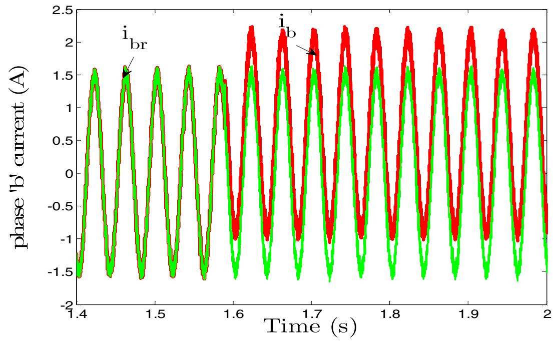

Fig. 7. Comparison of the currents in phase ‘b’ when offset fault is applied to the phase ‘b’ current sensor. Red: measured current i_b in phase ‘b’ with faulty sensor; Green: reconfigured current i_{br} in phase ‘b’.

VI. CONCLUSION

An approach utilizing a bank of adaptive observers with an augmented state vector was developed for PMSM sensors faults detection, isolation and reconfiguration of the current control loops. 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 sensors faults related to the above signals. After sensor fault detection and isolation, the control is reconfigured using the healthy observer’s outputs. The performance of the control reconfiguration is demonstrated through simulation tests. For further verification, experimental study is to be performed in the future work.

VII. APPENDIX

TABLE I
PERMANENT MAGNET SYNCHRONOUS MOTOR SPECIFICATIONS

Parameters		Rated characteristics	
R	6.2 Ω	power	1.1 kW
L_d	25.025 mH	voltage	400 V
L_q	40.17 mH	current	2.53 A
Φ_v	0.305 Wb	p	3
J	0.0036 $Kg.m^2$	speed	3000 rpm
f	0.0011 $Nm.s.rad^{-1}$	torque	4.1 N.m

REFERENCES

[1] B. A. Welchko, T. M. Jahns, and S. Hiti, "IPM Synchronous machine drive response to a single-Phase open circuit fault," *IEEE Trans. on Power Electron*, vol. 17, no. 5, pp. 764–771, Sep. 2002.

[2] A. Khlaief, M. Boussak, M. Gossa, "Open phase faults detection in PMSM drives based on current signature analysis," in *Proc. Int. Congress of Electrical Machines (ICEM ‘2010)*, Rome, 6–8 september 2010, pp.1–6.

[3] A. Akrad, M. Hilairet, D. Diallo, "Design of a Fault-Tolerant Controller Based on Observers for a PMSM Drive," *IEEE Trans. on Ind. Electron,* vol. 58, no. 4, pp. 1416–1427, Apr. 2011.

[4] H. Berriri, M. W. Naouar, and I. S. Belkhodja, "Easy and Fast Sensor Fault Detection and Isolation Algorithm for Electrical Drives," *IEEE Trans. on Power Electronics*, vol. 27, no. 2, pp. 490–499, Feb. 2012.

[5] M. Trabelsi, M. Boussak, M. Gossa, "PWM-Switching pattern-based diagnosis scheme for single and multiple open-switch damages in VSI-fed induction motor drives," *ISA Trans.*, vol. 51, no. 2, pp. 333–344, 2012.

[6] K. Jemli, M. Gossa, M. Jemli, M. Boussak, "Diagnosis of an IGBT inverters weakness in vector controlled Induction Machines drives," in *Proc. Second Int. Conf. on Signals Systems Decision and Information Technology SSD’03*–Sousse, Tunisia, March 26-28, 2003, CD-ROM.

[7] W. Liu, L. Liu, Il-Y. Chung, D.A. Cartes, W. Zhang, "Modeling and detecting the stator winding fault of permanent magnet synchronous motors," *Simulation Modelling Practice and Theory*, vol.27, pp. 1–16, 2012.

[8] M. Benbouzid, D. Diallo, and A. Makouf, "A fault-tolerant control architecture for induction motor drives in automotive applications," *IEEE Trans. Veh. Technol.*, vol. 53, no. 6, pp. 1847–1855, Nov. 2004.

[9] M. Benbouzid, D. Diallo, and M. Zeraouila, "Advanced fault-tolerant control of induction-motor drives for EV/HEV traction applications: From conventional to modern and intelligent control techniques," *IEEE Trans.Veh. Technol.*, vol. 56, no. 2, pp. 519–528, Mar. 2007.

[10] T. A. Nadjafabadi, R. Salmasi, and P. J. Maralani, "Detection and isolation of speed, DC-link voltage and current sensors faults based on an adaptive observer in induction motor drives," *IEEE Trans. Industrial Electronics*, vol. 58, No.5, pp. 1662 – 1672, May. 2011.

[11] K. Rothenhagen and F. W. Fuchs, "Current sensor fault detection by bilinear observer for a doubly-fed induction generators," in *Proc. 2006 IEEE Ind. Electron., – 32nd Annu. Conf.*, pp. 1369–1374.

[12] K. Rothenhagen and F. W. Fuchs, "Current sensor fault detection and reconfiguration for a doubly fed induction machine," in *Proc. IEEE PESC*, Orlando, FL, 2007, pp. 2732–2738.

[13] K. Rothenhagen and F. W. Fuchs, "Current Sensor Fault Detection, Isolation, and Reconfiguration for Doubly Fed Induction Generators," *IEEE Trans. Industrial Electronics*, Vol. 56, No. 10, pp. 4239- 4245, Oct. 2009.

[14] K. Rothenhagen and F. W. Fuchs, "Advanced Sensor Fault Detection and Control Reconfiguration of Wind Power Plants using Doubly Fed Induction Generators," in *Proc. 2008 Power Electronics Specialists Conf.,*pp. 913– 919.

[15] K. Rothenhagen and F. W. Fuchs, "Model-based fault detection of gain and offset faults in doubly fed induction generators," in *Proc. 2009 IEEE Int. Symp. Diagnostics for Electric Machines, Power Electronics and Drives*, pp. 1–6.

[16] Y. Jeong, S. Sul, S. Schulz, and N. Patel, " Fault detection and fault-tolerant control of interior permanent-magnet motor drive system for electric vehicle, " *IEEE Trans. Ind. Appl.*, vol. 41, no. 1, pp. 46–51, Jan./Feb. 2005.

[17] L. Li, "Robust Fault Detection and Diagnosis for Permanent Magnet Synchronous Motors," Ph.D. dissertation, Dept. of Mechanical Engineering, Florida State University College of Engineering, USA, 2006.

[18] G. Heredia, A. Ollero, R. Mahtani, M. Bejar, V. Remuss, and M. Musial, "Detection of Sensor Faults in Autonomous Helicopters," in *proc. 2005 IEEE Int. Conf. on Robotics and Automation (ICRA 2005)*, pp. 2229 -2234.

[19] W. Chen, and M. Saif, "An actuator fault isolation strategy for linear and nonlinear systems," in *Proc. 2005 IEEE American Control Conf. (IEEE- ACC'05)*, pp. 3321-3326.

[20] M. Blanke, M. Kinnaert, J. Lunze and M. Staroswiecki, *Diagnosis and Fault-Tolerant Control*, Berlin, Germany: Springer-Verlag, 2003.

[21] D. Fragkoulis, G. Roux, and B. Dahhou, "A global scheme for multiple and simultaneous faults in system actuators and sensors," in *Proc. 2009 IEEE – 6th Int. Multi. Conf. on Systems, Signals and Devices SSD'09*, pp. 1- 6.

[22] D. Fragkoulis, G. Roux, and B. Dahhou, "Sensor fault detection and isolation observer based method for single, multiple and simultaneous faults: application to a waste water treatment process," in *Proc. 2009 5th IFAC Int. Symp. on Advanced Control of Chemical Processes (ADCHEM 2009)*, pp. 934-939.

[23] M. Ben Hamed, and L. Sbita, "Speed sensorless indirect stator field oriented control of induction motor based on Luenberger observer," in *Proc. 2006 IEEE-ISIE Conf.*, pp. 2473-2478.