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Demagnetization fault detection in permanent magnet synchronous motors based on sliding observer

Jing He[a,b], Changfan Zhang[a,*], Songan Mao[c], Han Wu[a], Kaihui Zhao[a]

[a] *School of Electrical and Information Engineering, Hunan University of Technology, Zhuzhou, 412007, Hunan, China.*
[b] *School of Mechatronic Engineering and Automation, National University of Defense Technology, Changsha, 410073, Hunan, China.*
[c] *School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN 47907, USA.*

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Abstract

This paper considers a robust multiple fault detection method for actuator failures in nonlinear systems. The actuator failures model is initially put forward. By employing the unique advantage that the sliding mode variable structure is invariance to uncertainties, a sliding mode state observer is designed to isolate the unknown input disturbance effect on residual generation. The parameters of the observers being designed are determined by the use of linear matrix inequalities techniques. Accordingly, the generated residual is only sensitive to the specific fault signals, and the fault detection accuracy is improved. This paper verifies the proposed method by its application in demagnetization fault detection for a permanent magnet synchronous motor (PMSM). Simulation and experiment results illustrate the high detection accuracy and robustness.

Keywords: Fault detection, sliding mode variable structure, state observer, residual, permanent magnet synchronous motor.
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1. Introduction

Technology of state-estimation-based residual generation and identification is one of the key approaches for system fault detection and diagnosis. Residual signal is generated by comparing the measured value

*Corresponding author
Email addresses: hejing@263.net (Jing He), zhangchangfan@263.net (Changfan Zhang), songan@purdue.edu (Songan Mao), wuhan90@163.com (Han Wu), zhaokaihui@outlook.com (Kaihui Zhao)

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of actual system with the estimated value from an observer, and it is low or approaches zero if fault free. However, the residual signal shows a significant change whenever fault occurs. A threshold is set in this situation to describe the changes and identify the fault. The unknown inputs, such as modeling error, parameter perturbation, external noise, disturbance, et al, may greatly affect the residual signal in an actual system, thereby increasing the difficulty in selecting the threshold, leading to an increase of fault false alarm rate and fault missing alarm rate [1, 4, 10]. The present state estimation methods focus on reaching a best coordination between robustness and sensitivity in the fault detection system, that is, increase the robustness of the system to unknown inputs and simultaneously maintain its high sensitivity to incipient faults and glitches. Relevant studies that used generalized likelihood ratio, adaptive nonlinear observer, Kalman filter, or other methods have provided solutions from various perspectives [6, 7, 10]. The uncertainties, including modeling error, parameter variation and disturbance, do not influence the systems in the sliding mode if a certain condition, the so-called '*matching condition*' holds, thus the invariance of these systems to uncertainties is much more robust than robustness [2, 3, 12].

Permanent magnet synchronous motors have been increasingly used in recent years. Nonetheless, when compared with induction motors and other electro-magnetic motors, PMSM faces a big challenge because of the demagnetization risk on permanent magnetic material. Magnetic field ripple or demagnetization of permanent magnetic may decrease torque performance, abnormally overheat the motor, and may even ruin the motor in serious situations [13]. This issue greatly restricts the use of permanent magnet motors. Xiao et al. proposed a Kalman filter-based on-line monitoring method for permanent magnetic flux linkage [14]. Gritli et al. proposed a wavelet algorithm-based on-line monitoring method [5]. Lu et al. presented a demagnetization fault detection method based on artificial neural networks [11]. However, how to remove the stator resistance and other parameter uncertainties effect on demagnetization fault detection accuracy, and how to provide a fast and efficient algorithm for demagnetization fault detection still require further studies.

In this paper, a multiple actuator fault detection and isolation method based on sliding mode variable structure for a class of nonlinear systems is presented. The essential feature of the sliding mode variable structure technology, that is, being completely invariance to unknown input disturbances, is used to isolate the various unknown inputs effect on residual generation. Accordingly making the residual approaches zero if fault free, enhancing the system sensitivity to fault signals and simultaneously ensuring strong detection robustness.

The remainder of this paper is arranged as follows. In Section 2, the nonlinear system is introduced. A multiple actuator fault detection and isolation method based on sliding mode variable structure is presented in Section 3. In Section 4, the method is employed for demagnetization fault detection of permanent magnet motors and a brief conclusion is drawn in Section 5.

2. System Description

The nonlinear systems considered are of the following form

$$\begin{cases} \dot{x}(t) = Ax(t) + f(x,u,t) + Ef_a + Dd(x,u,t) + Bu(t), \\ y(t) = Cx(t), \end{cases} \tag{2.1}$$

where $x(t) \in R^n$, $u(t) \in R^m$ and $y(t) \in R^p$ denote, the state variables, inputs and outputs, respectively. $A \in R^{n\times n}$, $B \in R^{n\times m}$ and $C \in R^{p\times n}$ are known matrices. The non-linear continuous term $f(x,u,t) \in R^n$ is assumed to be known. The unknown non-linear term $d(x,u,t) \in R^r$ models the lumped uncertainties and disturbances experienced by the system, collectively referred to system unknown input disturbance. $f_a(x,u,t) \in R^q$ denotes actuator fault. The known term $D \in R^{n\times r}$ and $E \in R^{n\times q}$ denote disturbance distribution matrix and fault distribution matrix respectively.

For the objective of achieving actuator fault detection, the following assumptions are made throughout:

Assumption 2.1. E is a full column rank matrix.

Suppose that Assumption 2.1 is not satisfied, i.e. $rank(E) = q_1 < q$, it thus follows E can be factorized into $E = E^{'}E^{''}$, where $E^{'}$ is a full column rank matrix, $\tilde{f}_a = E^{''}f_a$ represents the new actuator failure, $\tilde{f}_a \in R^{q_1}$.

Assumption 2.2. (A, C) is observable.

Assumption 2.3. System failures and unknown inputs are bounded functions and there exist positive constants γ_{1i}, γ_2 such that $\|f_{ai}\| \le \gamma_{1i}$, $\|d\| \le \gamma_2$, where $f_{ai}\,(i = 1, 2, \cdots, q)$ is the ith row of f_a, represents the ith type of actuator failure.

Assumption 2.4. $f(x, u, t)$ is a nonlinear function and satisfies the Lipschitz condition, with a positive Lipschitz constant γ_3, one has $\|f(x, u, t) - f(y, u, t)\| \le \gamma_3 \|x - y\| = \gamma_3 \|\varepsilon\|$, where $\varepsilon = x - y$.

Lemma 2.5 ([8]). *If $f(x, u, t)$ satisfies the Lipschitz condition, then for any positive values of σ, the following inequation holds*

$$2\varepsilon^T P(f(x, u, t) - f(y, u, t)) \le \sigma\varepsilon^T PP\varepsilon + \frac{1}{\sigma}\gamma_3^2\varepsilon^T\varepsilon, \tag{2.2}$$

where P is a symmetric positive matrix.

Assumption 2.6. Matrices P, F_1, F_2 satisfy the equation $PE = C^T F_1^T$, $PD = C^T F_2^T$.

The target of this paper is to detect and isolate the actuator failures for nonlinear systems, with unknown input disturbances by employing the measurable input $u(t)$ and output $y(t)$.

3. State Observer Design

Definition 3.1. $E = \begin{bmatrix} E_1 & \cdots & E_i & \cdots & E_q \end{bmatrix}$, where E_i is the ith column of E.

Definition 3.2. $f_a = \begin{bmatrix} f_{a1} & \cdots & f_{ai} & \cdots & f_{aq} \end{bmatrix}$, where f_{ai} is the ith type of actuator failure, if the ith type of actuator failure takes place, $f_{ai} \neq 0$, otherwise $f_{ai}=0$.

From Definition 3.1 and Definition 3.2, one has

$$Ef_a = \sum_{j=1}^{q} E_j f_{aj} = E_i f_{ai} + \bar{E}_i \bar{f}_{ai}, \tag{3.1}$$

where $\bar{E}_i$ is the column of E except E_i, $\bar{f}_{ai}$ refers to all faults except f_{ai}.

Therefore, Equation (2.1) can be rewritten as the following form

$$\begin{cases} \dot{x}(t) = Ax(t) + f(x, u, t) + Dd(x, u, t) + Bu(t) + E_i f_{ai} + \bar{E}_i \bar{f}_{ai}, \\ y(t) = Cx(t). \end{cases} \tag{3.2}$$

Under the design principle of the Walcott-Zak observer [2], we can propose the following observer for the ith type of fault f_{ai}, which are particularly designed for actuator fault isolation purposes.

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x}(t) + L(y - \hat{y}) + f(\hat{x}, u, t) + Bu(t) + E_i w_1 + Dw_2, \\ \hat{y}(t) = C\hat{x}(t), \end{cases} \tag{3.3}$$

where the superscript " ˆ " denotes the observed value of relevant variables, $e = \hat{x} - x$ is state error, $e_y = \hat{y} - y$ is output error, w_1 and w_2 are the output signals of sliding mode variable structure, where

$$w_1 = \begin{cases} -\rho_{1i}\frac{F_1^i e_y}{\|F_1^i e_y\|} & if \quad e_y \neq 0, \\ 0 & if \quad e_y = 0, \end{cases} \tag{3.4}$$

and

$$w_2 = \begin{cases} -\rho_2 \frac{F_2 e_y}{\|F_2 e_y\|} & if \quad e_y \neq 0, \\ 0 & if \quad e_y = 0, \end{cases} \tag{3.5}$$

where F_1, F_2 and L are being designed matrices, ρ_{1i}, ρ_2 are being designed positive constants, F_1^i is the *ith* row of F_1.

Subtracting (3.2) from (3.3) gives the error system

$$\dot{e} = A_0 e + f(\hat{x}, u, t) - f(x, u, t) + E_i(w_1 - f_{ai}) - \bar{E}_i \bar{f}_{ai} + D(w_2 - d), \tag{3.6}$$

where $A_0 = A - LC$.

Theorem 3.3. *Let* Assumptions 2.1-2.6 *hold, for error system* (3.6)*, if the sliding mode variable structure parameters satisfy $\rho_{1i} > \gamma_{1i}$, $\rho_2 > \gamma_2$, and if the following inequation holds,*

$$\begin{bmatrix} A_0^T P + P A_0 + \frac{1}{\sigma}\gamma_3^2 I & P \\ P & -\frac{1}{\sigma} I \end{bmatrix} < 0,$$

then for any kth ($k = i$, $1 \leq k \leq q$) type of fault, the observer given by equation (3.3)-(3.5) *can make e converge to zero exponentially and will not if $k \neq i$.*

Proof. Consider the Lyapunov function

$$V = e^T P e. \tag{3.7}$$

In the first case, when only the *ith* type of fault f_{ai} takes place, i.e. $f_{ai} \neq 0$, $\bar{f}_{ai} = 0$ from (3.6), we have

$$\dot{e} = (A - LC)e + f(\hat{x}, u, t) - f(x, u, t) + E_i(w_1 - f_{ai}) + D(w_2 - d). \tag{3.8}$$

Differentiate(3.7) with respect to time along with Equation (3.8), we obtain

$$\begin{aligned} \dot{V} &= e^T(A_0^T P + P A_0)e + 2e^T P(f(\hat{x}, u, t) - f(x, u, t)) + 2e^T P E_i(w_1 - f_{ai}) + 2e^T P D(w_2 - d) \\ &\leq e^T(A_0^T P + P A_0)e + 2e^T P(f(\hat{x}, u, t) - f(x, u, t)) - 2\left\|F_1^i e_y\right\|(\rho_{1i} - \gamma_{1i}) - 2\left\|F_2 e_y\right\|(\rho_2 - \gamma_2). \end{aligned} \tag{3.9}$$

If $\rho_{1i} > \gamma_{1i}$, $\rho_2 > \gamma_2$ hold, then from Lemma 2.5, one has

$$\dot{V} \leq e^T(A_0^T P + P A_0 + \sigma P P + \frac{1}{\sigma}\gamma_3^2 I)e. \tag{3.10}$$

Suppose

$$\begin{bmatrix} A_0^T P + P A_0 + \frac{1}{\sigma}\gamma_3^2 I & P \\ P & -\frac{1}{\sigma} I \end{bmatrix} < 0 \tag{3.11}$$

is satisfied, so that $e(t)$ will make a global asymptotic convergence to zero, that is $\lim_{t\to\infty} e = 0$.

Remark 3.4. The linear matrix inequality (LMI) (3.11) can easily be solved using the Matlab LMI toolbox.

In the second case, when the *ith* type of fault f_{ai} does not take place, from (3.6), we have

$$\dot{e} = ((A - LC)e + f(\hat{x}, u, t) - f(x, u, t) + E_i(w_1 - f_{ai}) + D(w_2 - d)) - \bar{E}_i \bar{f}_{ai}. \tag{3.12}$$

Under Assumption 2.1, E_i and $\bar{E}_i$ are linearly independent, thus $\lim_{t\to\infty} e \neq 0$.

This completes the proof. □

In accordance with the above principles, a total of q sliding mode observers are designed for the q fault models and accordingly constructing an observer array.

The observer corresponding to the ith type of fault model is given by

$$\begin{cases} \dot{\hat{x}}^i(t) = A\hat{x}^i(t) + L(y - \hat{y}^i) + f(\hat{x}^i, u, t) + Bu(t) + E_i w_1^i + D w_2^i, \\ \hat{y}^i(t) = C\hat{x}^i(t), \end{cases} \tag{3.13}$$

where

$$w_1^i = \begin{cases} -\rho_{1i} \frac{F_1^i e_y^i}{\|F_1^i e_y^i\|} & if \quad e_y^i \neq 0, \\ 0 & if \quad e_y^i = 0, \end{cases} \tag{3.14}$$

and

$$w_2^i = \begin{cases} -\rho_2 \frac{F_2 e_y^i}{\|F_2 e_y^i\|} & if \quad e_y^i \neq 0, \\ 0 & if \quad e_y^i = 0, \end{cases} \tag{3.15}$$

where $e_y^i = \hat{y}^i - y$, w_1^i is used to isolate the effect upon the system by the fault f_{ai}, and w_2^i is used to isolate the effect upon the system by the unknown input disturbance d.

Remark 3.5. To reduce chattering in the sliding mode, a sign function $sgn\,(s)$ can be used to replace the sigmoid function in equation (3.14) and (3.15).

$$sgn(s) = \frac{s}{\|s\|} \approx \frac{2}{1 + e^{-as}} - 1, \tag{3.16}$$

where a is positive constant.

Definition 3.6. Let residual be $r_i = \left\|e_y^i\right\| (i = 1, 2, \cdots, q)$.

The above analysis shows that residual r_i generated by the ith observer is not sensitive to the ith type of fault among the total q generated residuals, and r_i maintains zero even if the ith type of fault occurs. However, the residual r_i is much more sensitive to the other $(q-1)$ types of faults. By showing a value deviating from zero, it indicates that the type or types of fault have taken place. Different types of fault may take place alone or together in actual projects. For the total q types of fault that have been modeled, each combination of the generated q residuals corresponds to a possible fault case. Therefore, a logical judgment table can be established for all fault cases. Concurrent faults can be detected and isolated by checking this table.

4. Application and Verification

4.1. Mathematical Model

The voltage equation of a PMSM in $d-q$ reference frame which is fixed on the direction of the rotor permanent magnetic is given by [9]

$$\begin{cases} u_d = R_s i_d + \dfrac{d\psi_d}{dt} - \omega\psi_q, \\ u_q = R_s i_q + \dfrac{d\psi_q}{dt} + \omega\psi_d, \end{cases} \tag{4.1}$$

where

u_d, u_q : Voltage in $d-q$ reference frame;
R_s : Stator winding phase resistance;
i_d, i_q : Current in $d-q$ reference frame;
ψ_d, ψ_q : Stator winding flux linkage components in $d-q$ reference frame;
ω : Rotor electrical angular velocity.

Suppose equation (4.1) is a surface-mounted permanent magnet synchronous motor, then the stator winding shows the same electrical inductance on both d and q axes, i.e. $L_d = L_q = L$, the corresponding flux linkage equation is

$$\begin{cases} \psi_d = Li_d + \psi_{r0}, \\ \psi_q = Li_q, \end{cases} \tag{4.2}$$

where

ψ_{r0} : Nominal value of rotor permanent magnetic flux linkage.

If a PMSM encounters demagnetization failure, as shown in Figure 1, the amplitude and direction of the flux linkage vector is accordingly changed. The flux linkage vector changes from the nominal value ψ_{r0} to ψ_r, Equation (4.2) is converted to

$$\begin{cases} \psi_d = \psi_{r0} + \Delta\psi_{rd} + Li_d, \\ \psi_q = \Delta\psi_{rq} + Li_q, \end{cases} \tag{4.3}$$

where $\Delta\psi_{rq}$ is the flux component generated by permanent magnetic flux linkage ψ_r on q axes, $\Delta\psi_{rq} > 0$, whereas ψ_{rd} is the flux component generated by permanent magnetic flux linkage ψ_r on d axes, here $\psi_{rd} = \psi_{r0} + \Delta\psi_{rd}$, $\Delta\psi_{rd} < 0$.

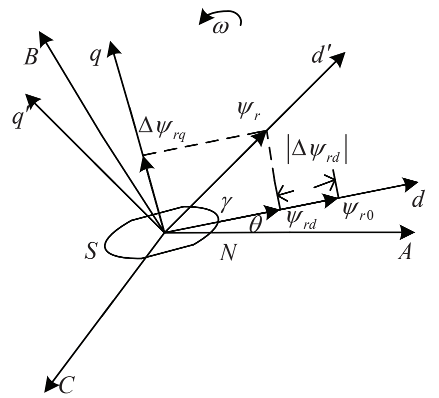


Figure 1: Variation of PMSM flux linkage

Substituting (4.2) into (4.1), we get the voltage equation

$$\begin{cases} u_d = R_s i_d - \omega L i_q + L\dfrac{di_d}{dt} - \omega\Delta\psi_{rq} + \dfrac{d\Delta\psi_{rd}}{dt}, \\ u_q = R_s i_q + L\dfrac{di_q}{dt} + \omega(\psi_{r0} + \Delta\psi_{rd}) + \omega L i_d + \dfrac{d\Delta\psi_{rq}}{dt}. \end{cases} \tag{4.4}$$

When compared with the current and other state variables, the flux linkage on both d and q axes may be treated as a steady value because the permanent magnetic linkage variation rate is much slower in actual projects, i.e. $\frac{d\Delta\psi_{rq}}{dt} \approx 0, \frac{d\Delta\psi_{rd}}{dt} \approx 0$. Stator winding resistance may be subject to great perturbation if the temperature changes, let $R_s = \bar{R}_s + \Delta R_s$, where $\bar{R}_s$ is nominal value of stator resistance, ΔR_s is the perturbation value.

From (4.4), we obtain the current equation

$$\begin{cases} \dfrac{di_d}{dt} = \dfrac{u_d}{L} - \dfrac{\bar{R}_s}{L} i_d + \omega i_q + \omega\dfrac{\Delta\psi_{rq}}{L} - \dfrac{\Delta R_s}{L} i_d, \\ \dfrac{di_q}{dt} = \dfrac{u_q}{L} - \dfrac{\bar{R}_s}{L} i_q - \omega i_d - \omega\dfrac{\psi_{r0}}{L} - \omega\dfrac{\Delta\psi_{rd}}{L} - \dfrac{\Delta R_s}{L} i_q. \end{cases} \tag{4.5}$$

Let stator current be the state variable, the Equation (4.5) represents the state equation in $d-q$ reference frame when demagnetization failure shown in Figure 1 occurs. Referring to (2.1), parameter matrixes of (4.5) shall be

$$x = \begin{bmatrix} i_d \\ i_q \end{bmatrix},\ u = \begin{bmatrix} u_d \\ u_q \end{bmatrix},\ y = \begin{bmatrix} i_d \\ i_q \end{bmatrix},\ f(x,u,t) = \begin{bmatrix} 0 \\ -\omega\frac{\psi_{r0}}{L} \end{bmatrix},\quad f_a = \begin{bmatrix} f_{a1} \\ f_{a2} \end{bmatrix} = \begin{bmatrix} \Delta\psi_{rd} \\ \Delta\psi_{rq} \end{bmatrix},$$

$$A = \begin{bmatrix} -\frac{\bar{R}_s}{L} & \omega \\ -\omega & -\frac{\bar{R}_s}{L} \end{bmatrix},\quad B = \begin{bmatrix} \frac{1}{L} & 0 \\ 0 & \frac{1}{L} \end{bmatrix},\quad C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},\quad D = \begin{bmatrix} -\frac{x_1}{L} \\ -\frac{x_2}{L} \end{bmatrix},$$

$$E = \begin{bmatrix} E_1 & E_2 \end{bmatrix} = \begin{bmatrix} 0 & \frac{\omega}{L} \\ -\frac{\omega}{L} & 0 \end{bmatrix},\quad d(x,u,t) = \Delta R_s.$$

The parameters for a PMSM are given in Table 1.

Table 1: Nominal value for PMSM

Parameters	Nominal Value
Stator resistance / Ω	2.875
Number of pole pairs	4
Stator inductance / H	0.0085
Rotor PM flux / Wb	0.175
Rotor moment of inertia / Kgm^2	0.008

4.2. Demagnetization Fault Detection Algorithm

(**1**) The observer for failure $f_{a1} = \Delta\psi_{rd}$ is designed as

$$\begin{cases} \dot{\hat{x}}^1(t) = A\hat{x}^1(t) + L(y - \hat{y}^1) + f(x^1,u,t) + Bu(t) + E_1 w_1^1 + D w_2^1, \\ \hat{y}^1(t) = C\hat{x}^1(t), \end{cases} \tag{4.6}$$

where

$$w_1^1 = \begin{cases} -\rho_{11}\frac{F_1^1 e_y^1}{\|F_1^1 e_y^1\|} & if \quad e_y^1 \neq 0, \\ 0 & if \quad e_y^1 = 0, \end{cases} \tag{4.7}$$

and

$$w_2^1 = \begin{cases} -\rho_2\frac{F_2 e_y^1}{\|F_2 e_y^1\|} & if \quad e_y^1 \neq 0, \\ 0 & if \quad e_y^1 = 0, \end{cases} \tag{4.8}$$

where $e_y^1 = \hat{y}^1 - y$, and the residual is $r_1 = \left\|e_y^1\right\|_2$.

(**2**) The observer for failure $f_{a2} = \Delta\psi_{rq}$ is designed as

$$\begin{cases} \dot{\hat{x}}^2(t) = A\hat{x}^2(t) + L(y - \hat{y}^2) + f(x^2,u,t) + Bu(t) + E_2 w_1^2 + D w_2^2, \\ \hat{y}^2(t) = C\hat{x}^2(t), \end{cases} \tag{4.9}$$

where

$$w_1^2 = \begin{cases} -\rho_{12}\frac{F_1^2 e_y^2}{\|F_1^2 e_y^2\|} & if \quad e_y^2 \neq 0, \\ 0 & if \quad e_y^2 = 0, \end{cases} \tag{4.10}$$

and

$$w_2^2 = \begin{cases} -\rho_2\frac{F_2 e_y^2}{\|F_2 e_y^2\|} & if \quad e_y^2 \neq 0, \\ 0 & if \quad e_y^2 = 0, \end{cases} \tag{4.11}$$

where $e_y^2 = \hat{y}^2 - y$, and the residual is $r_2 = \left\|e_y^2\right\|_2$.

Similarly, the sign functions in equations (4.7)-(4.8) and equations (4.10)-(4.11) are also replaced by the sigmoid function (3.16), respectively.

The aforementioned matrices and parameters are given by

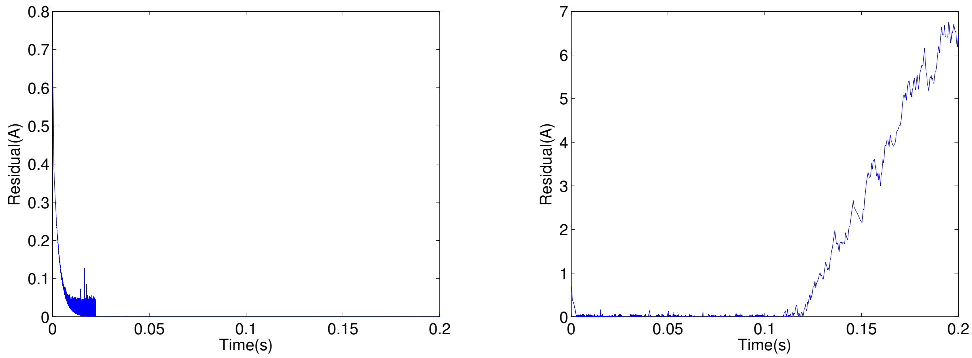
$$F_1 = \begin{bmatrix} F_1^1 \\ F_1^2 \end{bmatrix} = \begin{bmatrix} 0 & -\frac{\omega}{L} \\ \frac{\omega}{L} & 0 \end{bmatrix},\quad F_2 = \begin{bmatrix} -\frac{x_1}{L} & -\frac{x_2}{L} \end{bmatrix},\quad L = \begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix},\quad k_1 > 0,\quad k_2 > 0.$$

4.3. Simulation Results

The initial simulation conditions are $x_1(0) = 0$, $x_2(0) = 0$, $\hat{x}_1(0) = 0.5$ and $\hat{x}_2(0) = 0.5$, the parameters are chosen as: $\rho_{11} = 0.3$, $\rho_{12} = 0.3$, $\rho_2 = 1$, $k_1 = 1$, $k_2 = 1$ and a=1, setting $T_L = 5N$. Random noises with amplitudes within ± 0.7 are selected to simulate ΔR_s, i.e. stator winding resistance perturbation.

Case 1: Only amplitude demagnetization occurs, i.e. $f_{a1} \neq 0$, $f_{a2} = 0$.

In the first case, let the fault be a ramp function, that is, $f_{a1} = -t\,Wb$. Assume that f_{a1} begins at time instant of 0.1 second, and $f_{a1} = 0$ when $t < 0.1$ second. The residual generations shown in Figure 2 indicates that residual r_1 remains unchanged at zero threshold, whereas r_2 greatly varies, that is, amplitude demagnetization occurs because residual r_2 deviates from zero threshold.

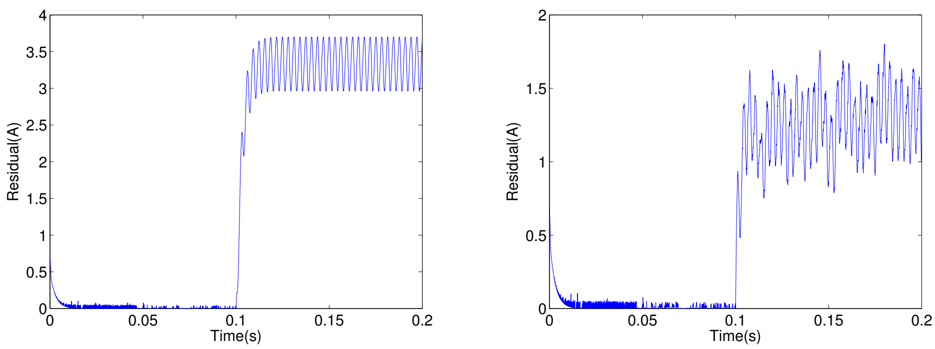


(a) The residual r_1 generation (b) The residual r_2 generation

Figure 2: Detection of fault f_{a1} with fault f_{a2} free

Case 2: Demagnetization occurs on d and q axes simultaneously, i.e. $f_{a1} \neq 0$, $f_{a2} \neq 0$.

In the second case, two sinusoidal signals are selected to illustrate that the faults detection are sensitive to incipient faults, that is, $f_{a1} = -\left|0.05\cos(1000t)\right| Wb$, $f_{a2} = \left|0.05\sin(1000t)\right| Wb$. Assume that $f_{ai}(i = 1, 2)$ begins at time instant of 0.1 seconds. The corresponding residual generations shown in Figure 3 indicates that both r_1 and r_2 vary greatly at 0.1s when f_{a1} and f_{a2} simultaneously occur. This method is successful for fault source identification purposes.



(a) The residual r_1 generation (b) The residual r_2 generation

Figure 3: Detection of fault f_{a1} and fault f_{a2} simultaneously

4.4. Experimental Results

RT-Lab is a modular real-time simulation platform which can achieve hardware-in-the-loop simulation (HILS). Figure 4 shows the RT-lab HILS configuration diagram for PMSM control systems. TMS320F2812 is selected as the controller, and RT-lab OP5600 is selected to simulate the inverter and the PMSM. The HILS of the PMSM can be realized by downloading the compiled code from the PMSM and the inverter model for running in OP5600, and by downloading the C-code generated from the designed controller model for running in DSP. PWM carrier frequency is set to 5 KHz, the sampling period is set to 50 μs.

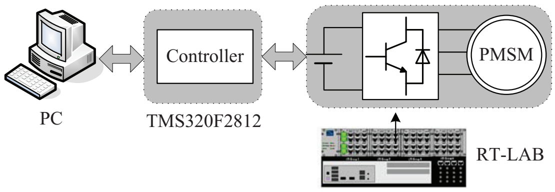


Figure 4: The RT-lab HILS configuration

The fault models are chosen the same as above in order to compare the experiment results with simulation results. Figure 5 shows the experimental results of residual generations when fault signal $f_{a1} = -t\,Wb$ is introduced at 0.1 s with f_{a2} free. The same as Figure 2, residual r_1 remains unchanged at zero threshold, whereas r_2 varies greatly. Therefore, amplitude demagnetization can be confirmed because residual r_2 deviates from zero threshold. Figure 6 shows the experimental results of residual generations when fault signal $f_{a1} = -\left|0.05\cos(1000t)\right| Wb$ and $f_{a2} = \left|0.05\sin(1000t)\right| Wb$ are both introduced at 0.1 s. Figure 6 shows that both r_1 and r_2 significantly vary at 0.1 s when f_{a1} and f_{a2} simultaneously occur. Therefore, fault source is identified successfully.

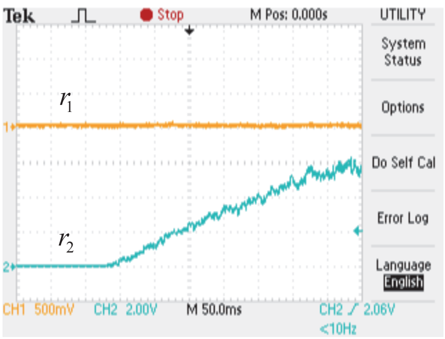


Figure 5: Detection of fault f_{a1} with fault f_{a2} free

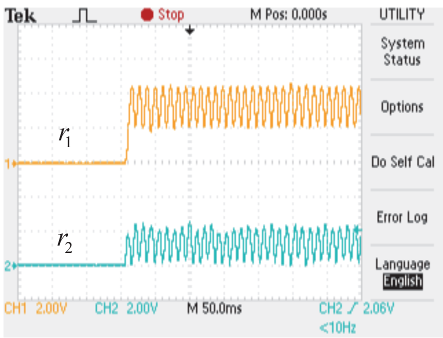


Figure 6: Detection of fault f_{a1}, fault f_{a2} simultaneously

The judgment rules are shown in Table 2, where '1' represents $r_i \neq 0$, '0' represents $r_i = 0$.

Table 2: Fault diagnosis decision rules

r_2	r_1	Fault Decisions
0	0	fault free
0	1	fault f_{a2}
1	0	fault f_{a1}
1	1	fault f_{a1}, f_{a2} simultaneously

5. Conclusion

This paper designs a sliding mode observer for residual generations by employing the specific feature of sliding mode variable structure technology, that is, being completely invariant to unknown input disturbances. By removing unknown input disturbances from the system residual signals, the residual-based fault detection cannot be affected by the unknown input disturbances, thereby a low threshold can be selected to improve the fault detection sensitivity. The sliding mode observer can make the residual value approach zero threshold with unknown input disturbances if fault free, and the system can accurately detect and locate the faults if several faults simultaneously occur. By employing the proposed method in the demagnetization fault detection for PMSM, series convincingly simulation and experiment results have verified the efficiency of the method.

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