

Demagnetization Fault Detection in PMSMs with Online Inductance Estimation

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Demagnetization Fault Detection in PMSMs with Online Inductance Estimation

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Index Terms—Motor, Observer, Demagnetization, Detection.

I. INTRODUCTION

Permanent magnet synchronous motors (PMSMs), offering high efficiency, strong dynamic performance, high precision, and high reliability, have been widely used in modern industry and transportation applications [1], [2]. However, PMSMs are prone to permanent magnet demagnetization faults resulting from environmental, mechanical, thermal, and electrical stresses or a combination of them. Demagnetization faults can be classified into uniform demagnetization and partial demagnetization. Uniform demagnetization refers to a condition in which all permanent magnets installed in the motor experience an identical degree of demagnetization [3]. This typically occurs when all magnets are subjected to similar operating conditions, such as a uniform temperature increase throughout the machine. In contrast, partial demagnetization (also referred to as localized demagnetization) affects only specific regions and is usually caused by local variations [4]

such as localized heating or partial magnet damage. Both types of demagnetization can cause unbalanced magnetic pull, torque derating, and reduced efficiency and reliability of the overall motor drive system [5]. Consequently, demagnetization fault detection is essential for ensuring safe motor operation and has attracted significant attention in industrial applications.

The most accurate approach for monitoring permanent magnet (PM) health is direct flux measurement, such as using a Gaussmeter [6]. However, this method requires motor disassembly, making it impractical for many applications. Another accurate offline technique estimates PM condition by measuring the rotor back electromotive force (back-EMF) from open-circuit terminals while operating in generating mode [7]. Nevertheless, back-EMF is not directly accessible when the PMSM operates as a motor, and maintaining constant-speed rotation requires additional equipment, which limits its applicability. With the development of artificial intelligence, machine learning (ML) based methods [8]–[10] for demagnetization fault detection have been developed. To identify the PMSM demagnetization fault, in [8], the gathered stator current data are used to train a convolutional neural network (CNN). However, for machine-learning-based methods, selecting appropriate fault indicators can be challenging, and large amounts of data under diverse operating conditions may not always be available.

Model-based fault-diagnosis methods have also been widely used for PM motors; these methods estimate states or parameters using mathematical PMSM models. [11]–[14]. Two SMOs are designed for sensor fault and uniform demagnetization fault detection in PMSM [11]. A temperature-insensitive irreversible demagnetization fault diagnosis based on dual-state flux estimation for permanent magnet synchronous motors considering temperature influence is proposed in [12]. In [13], the inductance values of the motor are obtained from the convergence behavior of the sliding-mode observer (SMO). Once the observer reaches the sliding surface and the estimation error converges to zero, the equivalent control yields the

inductance estimate, which converges to the actual parameter value. However, this approach often requires retuning the observer gains under different operating conditions, and the use of differential current signals can make the method sensitive to measurement noise. In addition, most existing model-based methods primarily target uniform demagnetization, while their capability to detect localized demagnetization has not yet been fully investigated.

In this work, an observer-based framework is proposed for detecting both uniform and localized demagnetization faults in PMSMs. An SMO is first designed to estimate the motor flux linkage and generate a demagnetization fault indicator. To address inductance uncertainty, two adaptive observers are then developed to estimate the d - and q -axis inductances online, and the estimated inductances are incorporated into the SMO-based fault detection scheme. In addition, a flux-estimation-based fault-tolerant control (FTC) strategy is introduced to compensate for the effect of demagnetization on the drive system. Unlike existing sliding-mode inductance estimation methods, such as [13], where inductance values are inferred from the convergence of the sliding surface and are therefore sensitive to gain selection, the proposed adaptive observers directly estimate the inductances using measured current signals. This reduces computational complexity and relaxes gain-tuning requirements, improving the robustness and practicality of the proposed framework for real-world motor drive applications.

The rest of this paper is organized as follows. Section II introduces the PMSM model and the uniform and localized demagnetization fault models. Sections III and IV present the SMO design for flux-linkage estimation and the adaptive observer design for inductance estimation, respectively. Section V describes the proposed flux-estimation-based FTC strategy. Simulation results are presented in Section VI. Section VII presents experimental validation, and Section VIII concludes the paper.

II. PMSM AND FAULT MODEL

A. PMSM Dynamic Model

This study focuses on fault detection for a permanent-magnet synchronous motor (PMSM) drive, whose overall control architecture is illustrated in Fig. 1. The motor is operated under field-oriented control. In this configuration, the speed controller determines the reference command for the q -axis current, while the inner current-control loops track the commanded d - and q -axis currents. The electrical rotor position and rotor speed are assumed to be available for feedback control and coordinate transformation. By transforming the three-phase stator variables into the rotor-synchronous d - q coordinate system, the electrical dynamics of the PMSM are described by the following voltage equations [15]:

$$\begin{aligned} u_d &= R_s i_d + L_d \dot{i}_d - \omega_e L_q i_q - \omega_e \psi_q, \\ u_q &= R_s i_q + L_q \dot{i}_q + \omega_e L_d i_d + \omega_e \psi_d, \end{aligned} \quad (1)$$

where i_d and i_q are the d - and q -axis stator currents, u_d and u_q are the corresponding stator voltages, R_s is the stator

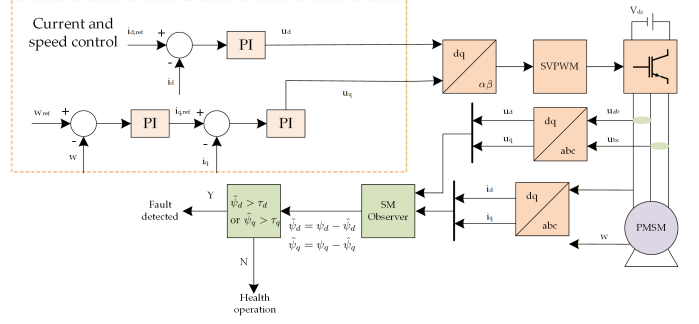


Fig. 1. Block diagram of the PMSM drive, controller, and observer structure.

resistance, L_d and L_q are the d - and q -axis inductances, ω_e is the electrical rotor speed, and ψ_d and ψ_q denote the permanent-magnet flux-linkage components projected onto the d - q frame.

The mathematical model of the current can be obtained from system (1) as

$$\begin{aligned} \dot{i}_d &= -\frac{R_s}{L_d} i_d + \frac{L_q}{L_d} \omega_e i_q + \frac{1}{L_d} u_d + \frac{\omega_e}{L_d} \psi_q, \\ \dot{i}_q &= -\frac{R_s}{L_q} i_q - \frac{L_d}{L_q} \omega_e i_d + \frac{1}{L_q} u_q - \frac{\omega_e}{L_q} \psi_d. \end{aligned} \quad (2)$$

Defining the state vector and input vector as

$$x = [i_d \ i_q]^T, \quad u = [u_d \ u_q]^T, \quad (3)$$

the current dynamics can be written in compact state-space form as

$$\dot{x} = Ax + Bu + B_\psi \psi, \quad (4)$$

where the flux vector is defined as $\psi = [\psi_q \ \psi_d]^T$. The matrices in the model are:

$$A = \begin{bmatrix} -\frac{R_s}{L_d} & \frac{\omega_e L_q}{L_d} \\ -\frac{\omega_e L_d}{L_q} & -\frac{R_s}{L_q} \end{bmatrix}, \quad B = \begin{bmatrix} \frac{1}{L_d} & 0 \\ 0 & \frac{1}{L_q} \end{bmatrix}, \quad B_\psi = \begin{bmatrix} \frac{\omega_e}{L_d} & 0 \\ 0 & -\frac{\omega_e}{L_q} \end{bmatrix}. \quad (5)$$

Under healthy operating conditions, the permanent-magnet flux is aligned with the rotor d -axis, and therefore $\psi_q = 0$ and $\psi_d = \psi_0$, where ψ_0 is the nominal permanent-magnet flux linkage. A demagnetization fault changes the effective permanent-magnet flux linkage and may introduce abnormal flux components in the d - q frame. Therefore, deviations in ψ_d and ψ_q are used in this work as fault-sensitive terms for observer-based residual generation.

B. Uniform Demagnetization Fault Modeling

Uniform demagnetization in a PMSM is modeled as a spatially symmetric reduction of the permanent-magnet flux linkage caused by irreversible magnetic degradation [16]. Since the air-gap flux distribution remains symmetric, the PMSM model structure is unchanged, while the effective flux linkage decreases.

A demagnetization severity factor λ is introduced, and the flux linkage is expressed as

$$\psi_d = (1 - \lambda) \psi_{d0}, \quad \psi_q = (1 - \lambda) \psi_{q0}, \quad (6)$$

where ψ_{d0} and ψ_{q0} are the nominal healthy flux-linkage components, and $\lambda \in [0, 1]$ denotes the fault severity. Here, $\lambda = 0$ corresponds to the healthy case, while larger λ indicates greater flux weakening. For an ideal PMSM, $\psi_{q0} \approx 0$, so uniform demagnetization mainly reduces ψ_d .

C. Localized Demagnetization Fault

Unlike uniform demagnetization, localized demagnetization occurs when only part of the permanent magnet is weakened or damaged. This fault produces a spatially nonuniform air-gap flux distribution along the rotor circumference, leading to rotor-position-dependent variations in the permanent-magnet flux linkage. As a result, additional harmonic components appear in the synchronous d - q reference frame. The localized demagnetization introduces asymmetric flux weakening and causes harmonic variations in both d - and q -axis flux linkages. Similar to the localized demagnetization flux behavior in [17], the localized demagnetization can be modeled as

$$\begin{aligned}\psi_d(t) &= \psi_{dc} + \sum_{h \geq 2} \Delta\psi_h \cos((h-1)\theta_e(t) + \phi_h) \\ \psi_q(t) &= \sum_{h \geq 2} \Delta\psi_h \sin((h-1)\theta_e(t) + \phi_h),\end{aligned}\quad (7)$$

where ψ_{dc} is the dc component of the permanent-magnet flux linkage, $\theta_e(t)$ is the electrical rotor position, and $\Delta\psi_h$ and ϕ_h are the amplitude and phase angle of the h th harmonic component, respectively. The $h = 1$ fundamental component becomes the dc d -axis flux after the Park transformation; therefore, only the components with $h \geq 2$ appear as periodic variations in the dq frame. These harmonic variations are used as fault signatures for detecting localized demagnetization.

III. SLIDING MODE OBSERVER DESIGN

A. Flux Linkage Estimation

The proposed observer estimates the flux-linkage components online together with the motor states. Therefore, prior knowledge of the fault severity, harmonic amplitude, or phase information is not required. The state, input, and speed variables are defined as

$$x \triangleq \begin{bmatrix} i_d \\ i_q \end{bmatrix}, \quad u \triangleq \begin{bmatrix} u_d \\ u_q \end{bmatrix}, \quad \omega_e = p\omega_m, \quad (8)$$

and the permanent-magnet flux linkages are denoted by ψ (true) and $\hat{\psi}$ (estimate). Define the estimation error

$$s \triangleq \hat{x} - x = \begin{bmatrix} s_d \\ s_q \end{bmatrix}. \quad (9)$$

The nonlinear injection function is chosen [11]:

$$f_p(s) = \begin{cases} \tanh(s) & |s| \geq \sigma \\ \tanh(s) \left(\frac{|s|}{\sigma} \right)^\sigma & |s| < \sigma. \end{cases} \quad (10)$$

The function is applied to the estimation error vector as

$$f_p(s) = \begin{bmatrix} f_p(s_d) \\ f_p(s_q) \end{bmatrix}. \quad (11)$$

A diagonal gain matrix $F = \text{diag}(F_d, F_q)$ scales the injection signal and governs the sliding convergence, and F_d, F_q are the gains of the observer. The SMO is designed as:

$$\dot{\hat{x}} = A\hat{x} + Bu + B_\psi\hat{\psi} - Ff_p(s). \quad (12)$$

The last term enforces the sliding condition and ensures strong robustness to disturbances and parameter mismatches, including those induced by faults. To eliminate the requirement of pre-known fault signatures, the flux estimate is updated by

$$\dot{\hat{\psi}} = -\gamma_\psi B_\psi s, \quad (13)$$

where $\gamma_\psi > 0$ is an adaptation gain. This mechanism compensates for flux mismatches online and guarantees convergence of the estimated flux toward its true value. A projection operator may be incorporated to enforce physical bounds on $\hat{\psi}$ and prevent estimator drift.

B. Stability Analysis

The estimation error of the SMO in (12) is defined as

$$e = \hat{x} - x. \quad (14)$$

The corresponding error dynamics are obtained as

$$\begin{aligned}\dot{e} &= A\hat{x} + Bu + B_\psi\hat{\psi} - Ff_p(s) - (Ax + Bu + B_\psi\psi) \\ &= Ae + B_\psi(\hat{\psi} - \psi) - Ff_p(s).\end{aligned}\quad (15)$$

The flux-linkage estimation error is defined as $\tilde{\psi} = \hat{\psi} - \psi$. To analyze stability, consider the standard quadratic Lyapunov candidate

$$V(e, \tilde{\psi}) = \frac{1}{2}e^T e + \frac{1}{2\gamma_\psi}\tilde{\psi}^T \tilde{\psi}, \quad (16)$$

which is positive definite. Differentiating V along the error dynamics yields

$$\begin{aligned}\dot{V} &= e^T \dot{e} + \frac{1}{\gamma_\psi}\tilde{\psi}^T \dot{\tilde{\psi}} \\ &= e^T (Ae + B_\psi\tilde{\psi} - Ff_p(s)) + \frac{1}{\gamma_\psi}\tilde{\psi}^T (-\gamma_\psi B_\psi e) \\ &= e^T Ae - F e^T f_p(s).\end{aligned}\quad (17)$$

To ensure $\dot{V} \leq 0$, the following condition must hold:

$$e^T Ae - e^T F \leq 0. \quad (18)$$

Thus, selecting the observer gain F sufficiently large guarantees that the Lyapunov derivative is non-positive, ensuring stability of the SMO.

IV. ADAPTIVE OBSERVER FOR INDUCTANCE ESTIMATION

In practical applications, the motor inductances L_d and L_q may not be accurately known for controller and observer design. Although measured inductance values can be used in the proposed sliding mode observer for flux-linkage estimation, these values may vary with operating conditions. Inaccurate inductance information can degrade the flux estimation accuracy and, consequently, affect the reliability of demagnetization fault diagnosis. To address this issue, two adaptive Luenberger-like observers are developed in this section to update the d - and q -axis inductance estimates online.

A. L_q Estimation

Considering that the differential equations of the d-current contains the information of L_q . Besides, L_q is a numerator, while L_d is a denominator in d-current model, making it more suitable to estimate the q-axis inductance [18]. The d-axis current dynamics of a PMSM can be written as:

$$\dot{i}_d = -\frac{R_s}{L_d}i_d + \frac{\omega_e L_q}{L_d}i_q + \frac{1}{L_d}u_d. \quad (19)$$

First, the measured d-axis inductance L_d and resistance R_s are used to construct the adaptive current observer for L_q estimation:

$$\dot{\hat{i}}_d = -\frac{R_s}{\hat{L}_d}\hat{i}_d + \frac{\omega_e \hat{L}_q}{\hat{L}_d}i_q + \frac{1}{\hat{L}_d}u_d - K_1(\hat{i}_d - i_d), \quad (20)$$

where $\hat{i}_d$ and $\hat{L}_q$ denote the estimates of i_d and L_q , respectively, and $K_1 > 0$ is the observer gain.

Define the current estimation error and the parameter estimation error as

$$e_d \triangleq \hat{i}_d - i_d, \quad \tilde{L}_q \triangleq \hat{L}_q - L_q. \quad (21)$$

Subtracting (19) from (20) yields the error dynamics

$$\dot{e}_d = -\left(K_1 + \frac{R_s}{L_d}\right)e_d + \frac{\omega_e i_q}{L_d}\tilde{L}_q. \quad (22)$$

The adaptation law is chosen as

$$\dot{\tilde{L}}_q = -\gamma_{L_q} e_d \frac{\omega_e i_q}{L_d}, \quad (23)$$

where $\gamma_{L_q} > 0$ is the adaptation gain. Since L_q is constant, $\dot{\tilde{L}}_q = \dot{\hat{L}}_q$. Consider the Lyapunov candidate

$$V_1 = \frac{1}{2}e_d^2 + \frac{1}{2\gamma_{L_q}}\tilde{L}_q^2, \quad (24)$$

which is positive definite. Differentiating (24) and substituting (22) and (23) gives

$$\begin{aligned} \dot{V}_1 &= e_d \dot{e}_d + \frac{1}{\gamma_{L_q}}\tilde{L}_q \dot{\tilde{L}}_q \\ &= -\left(K_1 + \frac{R_s}{L_d}\right)e_d^2 + e_d \frac{\omega_e i_q}{L_d}\tilde{L}_q - \tilde{L}_q e_d \frac{\omega_e i_q}{L_d} \\ &= -\left(K_1 + \frac{R_s}{L_d}\right)e_d^2 \leq 0. \end{aligned} \quad (25)$$

Therefore, $V_1(t)$ is nonincreasing and $e_d(t)$ and $\tilde{L}_q(t)$ are bounded for all $t \geq 0$. Hence, the proposed observer guarantees boundedness of the estimation errors and convergence of the d-axis current estimation error. It should be noted that this result guarantees convergence of the current estimation error, while convergence of the inductance estimation error $\tilde{L}_q$ requires a persistent excitation of $\omega_e i_q / L_d$.

B. L_d Estimation

To estimate the value of the L_d , the current model of q-frame is used:

$$\dot{i}_q = -\frac{R_s}{L_q}i_q - \frac{L_d}{L_q}\omega_e i_d + \frac{u_q}{L_q} - \frac{\psi_d}{L_q}\omega_e. \quad (26)$$

The designed adaptive observer model can be expressed as:

$$\dot{\hat{i}}_q = -\frac{R_s}{\hat{L}_q}\hat{i}_q - \frac{\hat{L}_d}{\hat{L}_q}\omega_e i_d + \frac{u_q}{\hat{L}_q} - \frac{\psi_d}{\hat{L}_q}\omega_e - K_2(\hat{i}_q - i_q), \quad (27)$$

where the adaption rule for the $\hat{L}_d$ dynamics is

$$\dot{\hat{L}}_d = \gamma_{L_d}(\hat{i}_q - i_q) \frac{\omega_e i_d}{L_q}. \quad (28)$$

For the proposed adaptive observer, $\hat{i}_q$ denotes the estimated q-axis current derivative, K_2 is the observer gain, and $\hat{L}_d$ is the estimated d-axis inductance. Note that the implementation requires the flux linkage ψ_d and the q-axis inductance L_q . In this work, L_q is provided by the adaptive observer in (20), while ψ_d is obtained from the SMO in (12). Therefore, the required parameters L_q and ψ_d are available for the d-axis inductance estimation. With both adaptive observers integrated with the SMO in (12), the motor flux linkage can be estimated reliably while simultaneously updating L_d and L_q online.

The current estimation error and L_d estimation error are defined as:

$$e_q = \hat{i}_q - i_q, \quad \tilde{L}_d = \hat{L}_d - L_d, \quad (29)$$

then the error dynamics combined with flux linkage estimation $\hat{\psi}$ in (12) and $\tilde{L}_q$ estimation from (20) can be:

$$\begin{aligned} \dot{e}_q &= -\left(\frac{R_s}{\hat{L}_q} + K_2\right)e_q - \frac{\tilde{L}_d}{\hat{L}_q}\omega_e i_d \\ &\quad + \left(\frac{1}{\hat{L}_q} - \frac{1}{L_q}\right)\left(R_s i_q + L_d \omega_e i_d - u_q + \psi_d \omega_e\right) - \frac{\tilde{\psi}_d}{\hat{L}_q}\omega_e. \end{aligned} \quad (30)$$

Assume that the q-axis inductance estimation error $\tilde{L}_q$ and the flux-linkage estimation error $\tilde{\psi}_d$ are bounded. Consider the Lyapunov function

$$V_2(e_q, \tilde{L}_d) = \frac{1}{2}e_q^2 + \frac{1}{2\gamma_{L_d}}\tilde{L}_d^2. \quad (31)$$

Differentiating along (30) and the parameter dynamics gives

$$\dot{V}_2 = e_q \dot{e}_q + \frac{1}{\gamma_{L_d}}\tilde{L}_d \dot{\tilde{L}}_d = -\left(\frac{R_s}{\hat{L}_q} + K_2\right)e_q^2 + e_q \tilde{\Delta}(t), \quad (32)$$

and the part related to the estimation of flux linkage and L_q is defined as

$$\tilde{\Delta}(t) = \left(\frac{1}{\hat{L}_q} - \frac{1}{L_q}\right)\left(R_s i_q + L_d \omega_e i_d - u_q + \psi_d \omega_e\right) - \frac{\tilde{\psi}_d}{\hat{L}_q}\omega_e. \quad (33)$$

Since currents, voltages and ω_e are bounded, and $L_q, \hat{L}_q$ remain in known positive intervals, and there exist constants $k_l, k_\psi > 0$ such that

$$|\tilde{\Delta}(t)| \leq k_l |\tilde{L}_q| + k_\psi |\tilde{\psi}_d|. \quad (34)$$

Using the bound (34) and Young's inequality [19], for any $\varepsilon_1, \varepsilon_2 > 0$, it satisfies that

$$\begin{aligned} |e_q \tilde{\Delta}(t)| &\leq |e_q| (k_l |\tilde{L}_q| + k_\psi |\tilde{\psi}_d|) \\ &\leq \frac{\varepsilon_1}{2} e_q^2 + \frac{k_l^2}{2\varepsilon_1} \tilde{L}_q^2 + \frac{\varepsilon_2}{2} e_q^2 + \frac{k_\psi^2}{2\varepsilon_2} \tilde{\psi}_d^2. \end{aligned} \quad (35)$$

Choosing $\varepsilon_1 = \varepsilon_2 = K_2/2$ gives the coupled inequality

$$\dot{V}_2 \leq -\left(\frac{R_s}{\hat{L}_q} + \frac{K_2}{2}\right) e_q^2 + c_{L_q} \tilde{L}_q^2 + c_\psi \tilde{\psi}_d^2, \quad (36)$$

where $c_{L_q} = \frac{k_l^2}{K_2}$ and $c_\psi = \frac{k_\psi^2}{K_2}$. Since $\hat{L}_q$, $\tilde{L}_q$, and $\tilde{\psi}_d$ are bounded, the q -axis current estimation error is uniformly ultimately bounded. Moreover, the ultimate bound decreases as $\tilde{L}_q$ and $\tilde{\psi}_d$ decrease, and can be reduced by increasing K_2 .

V. FAULT-TOLERANT CONTROL

After demagnetization fault detection, an FTC strategy is applied to compensate for the flux-linkage variation and maintain stable motor operation. The proposed FTC uses the estimated flux information from the observer to generate voltage compensation terms in the dq reference frame. The main objective is to reduce the influence of demagnetization-induced voltage disturbances while satisfying the inverter current limitation.

In the PMSM drive system, the inverter current is limited by the over-current protection constraint

$$I_s = \sqrt{i_d^2 + i_q^2} \leq I_{\max}, \quad (37)$$

where $I_{\max}$ is the maximum allowable stator current. Under the conventional $i_d = 0$ control strategy, this constraint becomes

$$|i_q| \leq I_{\max}. \quad (38)$$

Therefore, when a demagnetization fault occurs, the available q -axis current margin becomes important for maintaining torque production without exceeding the inverter current limit.

The observer provides the estimated flux linkages in the dq reference frame, denoted by $\hat{\psi}_d$ and $\hat{\psi}_q$. Let ψ_d and ψ_q represent the nominal healthy flux linkages. The flux deviations caused by demagnetization are defined as

$$\tilde{\psi}_d = \hat{\psi}_d - \psi_d, \quad \tilde{\psi}_q = \hat{\psi}_q - \psi_q. \quad (39)$$

These deviations represent the difference between the estimated faulty flux linkage and the nominal healthy flux linkage.

In the dq -frame voltage equations, the flux-linkage deviations appear as equivalent disturbance voltage terms. The corresponding disturbance voltages are expressed as

$$\begin{aligned} \Delta u_d &= \omega_e \tilde{\psi}_q, \\ \Delta u_q &= -\omega_e \tilde{\psi}_d, \end{aligned} \quad (40)$$

where ω_e is the electrical angular speed. Therefore, the demagnetization fault can be interpreted as an additional voltage disturbance acting on the nominal PMSM model.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Pole pairs, p_m	4
Rated speed (rad/s)	314
Armature resistance, R_s (Ω)	5.04
d -axis inductance, L_d (mH)	8
q -axis inductance, L_q (mH)	8
Flux linkage, ψ_n (Wb)	0.83

To compensate for these disturbances, the commanded dq voltages are modified by subtracting the estimated disturbance voltages. The compensated voltage commands are given by

$$\begin{aligned} u_d^c &= u_d - \Delta u_d = u_d - \omega_e (\hat{\psi}_q - \psi_q), \\ u_q^c &= u_q - \Delta u_q = u_q + \omega_e (\hat{\psi}_d - \psi_d), \end{aligned} \quad (41)$$

where u_d and u_q are the original voltage commands and u_d^c and u_q^c are the compensated voltage commands applied to the inverter. The proposed FTC uses the observer-estimated flux linkages to calculate the flux deviations and equivalent disturbance voltages. These disturbances are compensated in the dq -axis voltage commands through (41), reducing the influence of demagnetization on the drive system. Without requiring additional flux sensors, the method can be integrated into the existing field-oriented control framework, and the compensated voltage commands are sent to the PWM module for inverter switching.

VI. SIMULATION VERIFICATION

In order to comprehensively verify the proposed observer-based framework for demagnetization fault detection, Simulink simulation is conducted and the parameter of the PMSM motor is shown in Table. I. In this motor, the reference current i_d is set to be 1 A, the sampling period T_s is set as 5 μ s. The PI controller is adopted by the speed control loop, in which the proportional and integral gains are 800 and 0.3, respectively. In the nominal operation, the given speed is 314 rad/s, and the given load torque is 800 N·m. To better reflect practical applications, measurement noise is added to the current signal to evaluate the robustness of the proposed observers.

A. Simulink Simulation Results

In the first scenario, at time $t = 0.3$ s, a step change is applied to the load torque. The SMO estimates the flux linkage accurately, matching the nominal value of (0.83 Wb), and the estimated inductances (L_d) and (L_q) both match the true values of (8 mH). Notably, the flux linkage estimate remains essentially unchanged during the load disturbance, indicating that typical load-torque variations do not trigger a false alarm. Then a uniform fault is introduced by reducing the motor flux linkage from 0.83 Wb to 0.6 Wb. As shown in Fig. 2, the uniform demagnetization fault is applied at $t = 1$ s, and the estimated flux linkage correspondingly drops to 0.6 Wb. Because the flux linkage decreases, the controller increases the i_q current to maintain the same load torque and speed. Consequently, at $t = 1$ s, i_q exhibits a transient overshoot

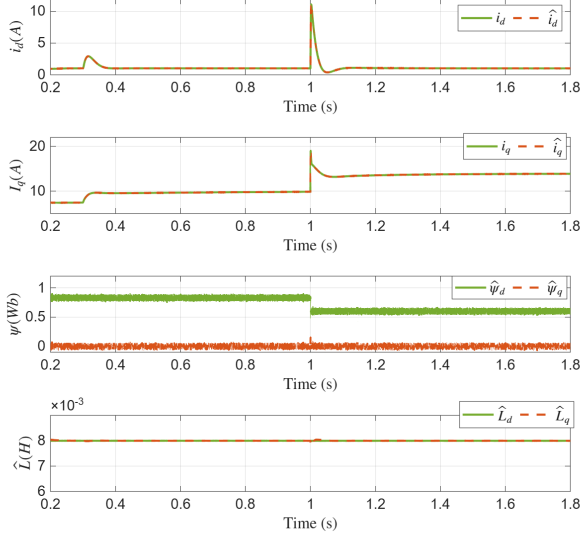


Fig. 2. Simulation result of uniform demagnetization fault.

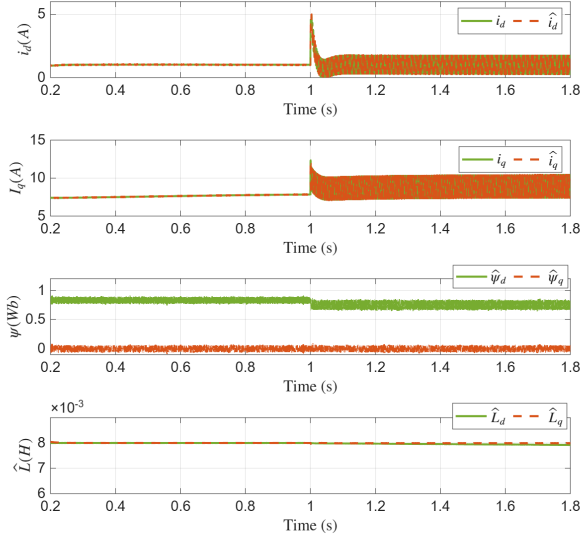


Fig. 3. Simulation result of localized demagnetization fault.

and rises from 10 A to approximately 14 A. The inductance estimation result is still accurate under this faulty operating condition. In the second scenario, a localized demagnetization fault is introduced with center angle 120° , demagnetization ratio 0.2, and span angle 180° . As shown in Fig. 3, the localized fault induces oscillations in both i_d and i_q , and the i_q also increases during this fault. The proposed SMO-based flux estimator captures the localized fault behavior, and the two adaptive observers accurately track the inductance parameters.

B. Real-time Simulation

Real-time simulations of the system in Fig. 1 are conducted using dSPACE with a $20 \mu\text{s}$ time step, implementing

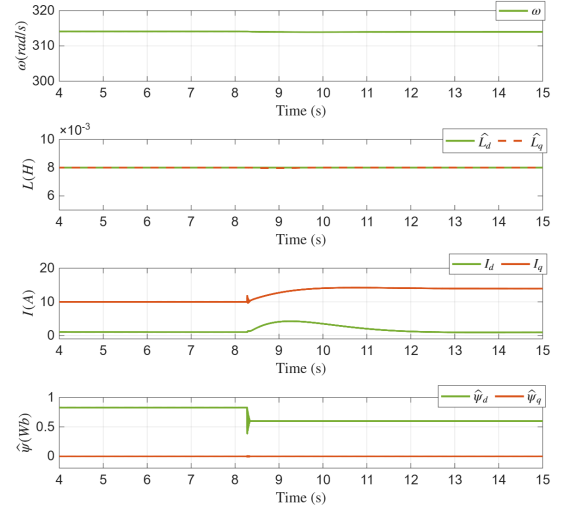


Fig. 4. Real-time simulation result of uniform demagnetization fault.

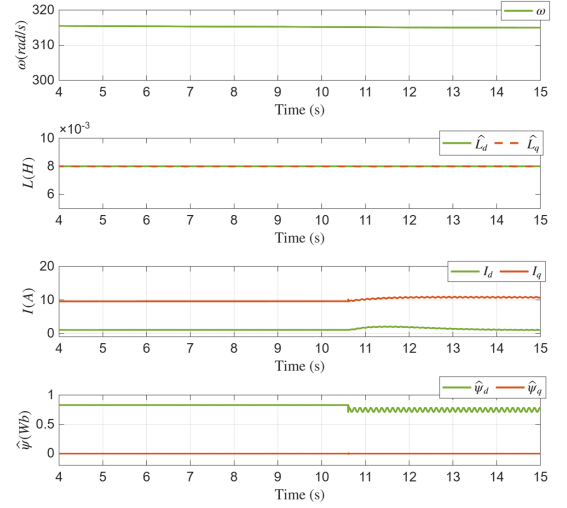


Fig. 5. Real-time simulation result of localized demagnetization fault.

the proposed fault-tolerant control. In the first scenario, a uniform demagnetization fault reduces the flux linkage from 0.83 to 0.6, resulting in an increase of i_q from 10 A to 16 A (Fig. 4). The SMO-based flux estimation accurately detects the fault while inductance estimates remain unchanged. In the second scenario, a localized demagnetization fault is introduced, and the corresponding flux variation is successfully identified (Fig. 5). The results show that uniform demagnetization primarily causes a constant reduction in the d-axis flux linkage, whereas localized demagnetization produces periodic flux-linkage variations. In both cases, the proposed FTC ensures a smooth transient response and maintains stable motor operation.

VII. EXPERIMENTAL VALIDATION

To further verify the proposed observer-based demagnetization fault detection method, an experimental test was conducted using a surface-mounted permanent magnet syn-

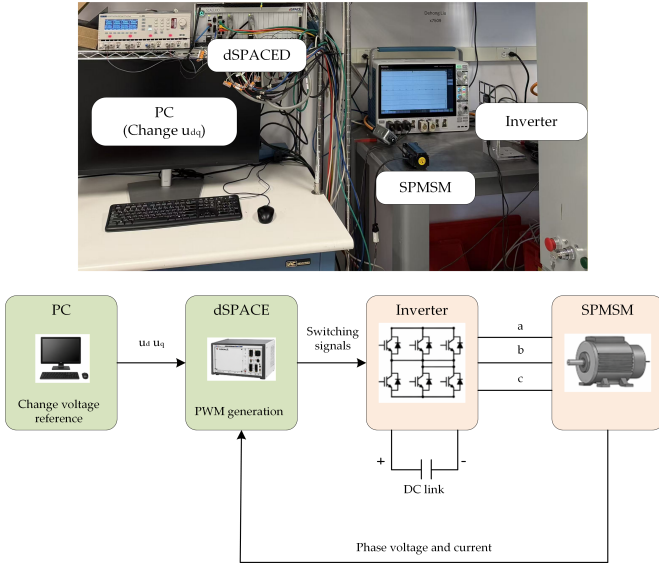


Fig. 6. Experimental setup for emulated demagnetization fault detection.

chronous motor (SPMSM) drive platform. As shown in Fig. 6, the setup consists of a host PC, a dSPACE real-time controller, a three-phase voltage-source inverter, and an SPMSM machine under test. The host PC sets the d - and q -axis voltage references, u_d and u_q , while the dSPACE controller implements the control algorithm and the proposed observer in real time. The dSPACE controller also generates the PWM signals for the inverter, which drives the SPMSM. The measured phase voltages and currents are fed back to the controller for observer implementation and fault detection.

The experiment was carried out under no-load operating conditions. Since physically demagnetizing the permanent magnets may permanently damage the machine, a virtual demagnetization fault was emulated by injecting voltage variations into the d - and q -axis voltage commands. The SPMSM current dynamics in the dq reference frame are expressed as

$$\begin{aligned} L_d \dot{i}_d &= -R_s i_d + (L_q i_q + \psi_q) p \omega + u_d \\ L_q \dot{i}_q &= -R_s i_q - (L_d i_d + \psi_d) p \omega + u_q, \end{aligned} \quad (42)$$

where p is the number of pole pairs, and ω is the mechanical speed. To emulate a demagnetization fault, a virtual flux variation $\Delta\psi_{pm}$ is introduced. The virtual flux variation is converted to an equivalent d -axis current variation as

$$i_d = \frac{\Delta\psi_{pm}}{L_d}. \quad (43)$$

Based on this, the voltage commands for generating the virtual demagnetization fault are

$$u_d = \frac{R_s \Delta\psi_{pm}}{L_d}, \quad (44)$$

$$u_q = (\psi_d + \Delta\psi_{pm}) p \omega. \quad (45)$$

By changing u_d and u_q according to the desired virtual flux variation, the experiment produces an equivalent flux-linkage

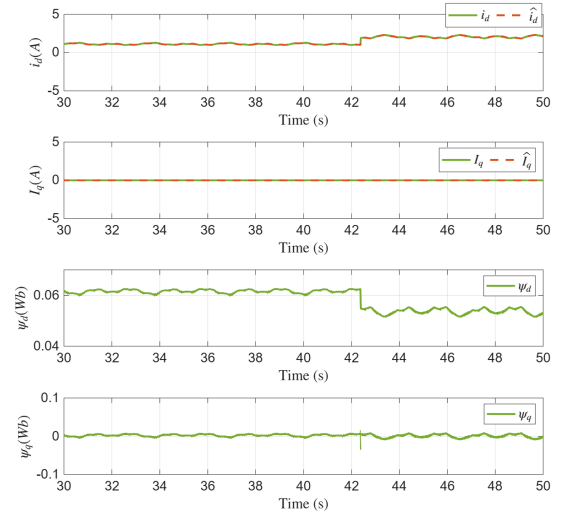


Fig. 7. Experiment result of uniform demagnetization fault.

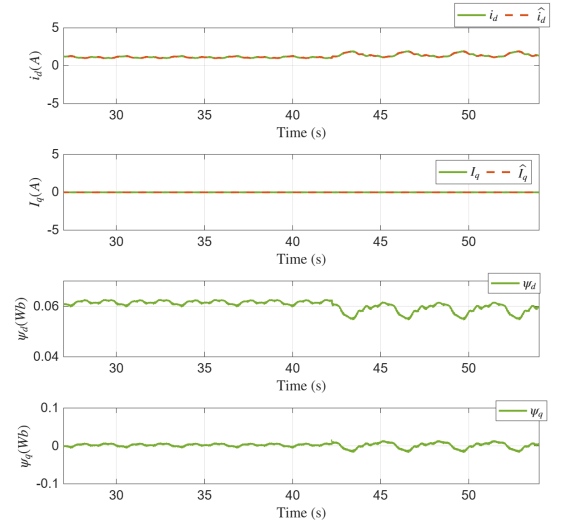


Fig. 8. Experiment result of localized demagnetization fault.

change without physically damaging the rotor magnets. The nominal flux linkage of the tested motor is 0.062 Wb.

The experimental results for the virtual uniform and localized demagnetization faults are shown in Fig. 7 and Fig. 8. Before the fault injection, the estimated flux components remain nearly constant, indicating healthy operation. After the virtual fault is injected, the d -axis flux component ψ_d decreases noticeably, while the q -axis flux component ψ_q remains close to zero with small oscillations. This behavior agrees with the expected flux reduction caused by demagnetization. Compared with the uniform fault case, the localized fault produces a more oscillatory flux response due to the spatially nonuniform flux variation. These results demonstrate that the proposed observer can capture the flux-linkage change caused by both uniform and localized demagnetization faults.

VIII. CONCLUSION

This paper presented a fault diagnosis strategy for detecting PMSM demagnetization under a wide range of operating conditions. The proposed approach employs a SMO for flux-linkage estimation and demagnetization fault detection, and two adaptive observers for online inductance estimation to improve practicality under parameter variations. By continuously updating the inductance estimates, the proposed framework mitigates flux-estimation errors caused by inductance mismatches and enhances the reliability of fault detection. The proposed SMO provides accurate flux-linkage estimation and enables effective detection of demagnetization faults. The adaptive inductance observer estimates L_d and L_q online, improving robustness to parameter changes and increasing applicability in practical implementations. Simulation and experimental results demonstrate consistent fault-detection performance and improved estimation accuracy under different operating conditions. Overall, the proposed observer-based diagnosis strategy offers a practical and robust solution for PMSM condition monitoring, with the potential to improve motor performance and reliability in real-world applications. Future work will extend the proposed diagnosis framework to interior PMSMs (IPMSM) and incorporate temperature-dependent permanent-magnet flux linkage to improve the robustness of flux estimation and demagnetization diagnosis.

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