2005 American Control Conference
June 8-10, 2005. Portland, OR, USA

On-line Identification and Robust Fault Diagnosis for Nonlinear PMSM Drives

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Abstract—**The performance of model-based fault diagnosis (FD) algorithms is degraded by modeling errors caused by process uncertainties. FD robustness against process uncertainties is discussed in this paper. In the proposed FD schematics, robustness is improved by using adaptive residual generators, in which the advanced on-line identification plays a key role. The approach is investigated on a Permanent Magnet Synchronous Motor drive system with inherent nonlinearity and time-varying parameters caused by process uncertainties. Stator resistance and *q*-axis inductance are considered as possible sources of system uncertainties under different operating conditions. Mathematical decoupling simplifies both identification and fault detection designs for the drive monitoring process. Preliminary simulation results are provided.**

I. Introduction

Model-based diagnosis is one of the most widely used methods in engineering process monitoring. It utilizes a mathematical model to construct residuals for the subsequent decision-making logic [1]-[3]. In the fault diagnosis (FD) field, residuals are a set of functions constructed to generate symptoms indicating the difference between nominal and faulty status. An ideal residual signal should remain zero in the fault-free case and non-zero when faults occur. For this purpose, the model must be an accurate representation of the supervised process. However, practical processes are always subjected to unexpected changes such as variations under different operating conditions. The term *uncertainty* is used to refer to the differences or errors between models and reality. Robust fault detection has been firmly established since 1989 [2] and has been practiced soon after the Kalman filter was first presented in [4][5].

In general, uncertain systems can have both structured uncertainties and unstructured uncertainties. Structured uncertainties can usually be expressed as model parameter variations, while unstructured ones indicate that we have no idea about how they impact the nominal model. Both categories degrade the FD performance and cause robustness problems. Only structured uncertainties are considered in this stage.

Manuscript received March 1, 2005. This work was supported by the Office of Naval Research under Grant N000140210623.

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This paper addresses the problem of improving the system robustness against structured uncertainties by synthesizing adaptive parameter identification and residual generation. The application of the proposed approach is investigated on a Permanent Magnet Synchronous Motor (PMSM) drive.

Reliability and safety become crucial when the PMSM drives are utilized in high performance applications such as a marine ship-based propulsion system. Early detection of process faults provides significant time for protective strategies or performance moderations to act, before a catastrophic failure is precipitated. Hence, the system reliability and safety are increased. However, the application of FD theories to the highly coupled PMSM drives is challenging due to the inherent system nonlinearity. While the structure of the adaptive residual generation has been existent (e.g. [6]), the application to the PMSM has not been explored.

Section II formulates the problem and briefly introduces the monitored process. An overview of the proposed FD methodology is illustrated in section III. Preliminary simulation results in section IV evaluate the effectiveness of the approach. Conclusions as to the effectiveness of the model-based FD to PMSM are preliminary and discussed in section V.

II. Problem Formulation

Fig. 1 describes a typical variable-speed PMSM Drive system, on which the proposed FD scheme is investigated. The system dynamics in PMSM can be described by a set of nonlinear third-order differential equations in *dq*-axis synchronous rotating reference frame, in which the process uncertainties are reflected by time-varying parameters [7]. Specifically, the electrical model of the PMSM can be derived from the *d-q* equivalent circuits shown in Fig. 2, or directly from [7]:

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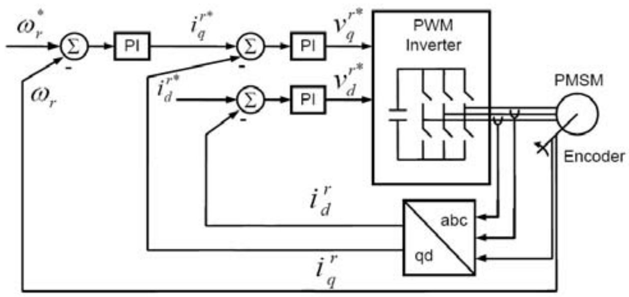


Fig. 1. PMSM Drive Schematics [14]

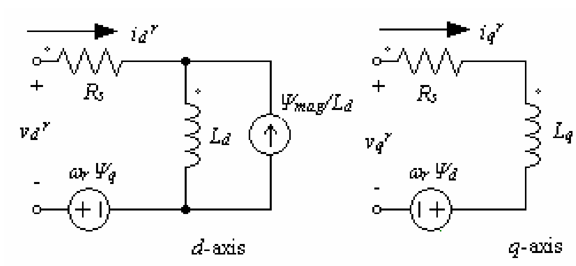


Fig. 2. *d-q* Equivalent Circuit Model of PMSM

$$\frac{di_d^r}{dt} = \frac{1}{L_d}\left[v_d^r - R_s i_d^r + \omega_r L_q i_q^r\right]$$
$$\frac{di_q^r}{dt} = \frac{1}{L_q}\left[v_q^r - R_s i_q^r - \omega_r L_d i_d^r - \omega_r \psi_{mag}\right] \qquad (1)$$

where $i_{dq}{}^r$ and $v_{dq}{}^r$ are the *dq*-axis currents and voltages in the rotor reference frame; ω_r is the rotor electrical angular speed; R_s, L_q, L_d and ψ_{mag} are the stator resistance, *d*-axis and *q*-axis inductance, and the permanent magnet flux linkage, respectively. The electromechanical torque production of the machine is given by:

$$T_e = \frac{3}{4}P\left[i_q^r \psi_{mag} + \left(L_d - L_q\right) i_q^r i_d^r\right] \qquad (2)$$

Neglecting the mechanical losses, the rotor electrical speed ω_r is thus expressed with the following differential equation:

$$\frac{d\omega_r}{dt} = \frac{P}{2}\frac{1}{J}\left[T_e - T_L\right] \qquad (3)$$

In equation (2) and (3), J denotes the inertia of the rotor; P is the number of poles of the machine and T_L is the load torque. Equations (1)-(3) complete the description of system dynamics for the PMSM. Obviously, this model is a highly coupled nonlinear 2-input 3-output system in *d-q* axis reference frame with i_d^r, i_q^r and ω_r as state variables; v_d^r and v_q^r as control signals (inputs). Literature reveals the existence of Hopf bifurcations, limit cycles and even chaotic attractors in this system (e.g. [8][9]) and therefore the system can exhibit complex behaviors. In this paper, the major sources of uncertainties under consideration are the stator resistance R_s and *q*-axis inductance L_q. R_s is directly related to motor temperature fluctuations under different operating conditions; while L_q is susceptible to the magnetic saturation effect, especially during flux-weakening operation [7].

The PWM inverter in Fig. 1 is ideally modeled as a constant gain factor; the faults and uncertainties within the inverter are beyond the scope of this work.

In established fault diagnosis, possible faults in a supervised process are classified into two different categories according to their influence with respect to the process model. Faults are called additive if they are represented as unknown extra system inputs. While, the yare called multiplicative if they are represented as changes in some process parameters [1]. Both types are generally illustrated in the transfer-function process model (4) [10]:

$$y = (G_u(s) + \Delta G_u(s))u + G_d(s)d + G_f(s)f \qquad (4)$$

where $y \in \Re^{n\times 1}$ is the measurements, $u \in \Re^{m\times 1}$ is the known control signal input, $d \in \Re^{k\times 1}$ is disturbances and $f \in \Re^{v\times 1}$ is the monitored additive faults. Hence, G_u, G_d and G_f are the proper transfer function matrices of corresponding dimensions; ΔG_u represents the parametric uncertainties or internal process faults.

This paper investigates the robustness for the fault diagnosis of the PMSM drive. Both sensor faults and internal process faults are considered.

III. Structure Of Robust Fault Diagnosis

A general structure of the proposed robust fault diagnosis system is shown in Fig. 3. In the diagram, signal u and y are the measurable inputs and outputs; u^* denotes the process control signal after the feedback decoupling; if denoting actual process parameters as p_i, then the estimated counterparts of y and p_i are expressed as $\hat{y}$ and $\hat{p}_i$ respectively. At last, signal r_i represents the residual output for the detection of additive sensor faults, which is sent to the fault diagnosis block for decision-making about process status.

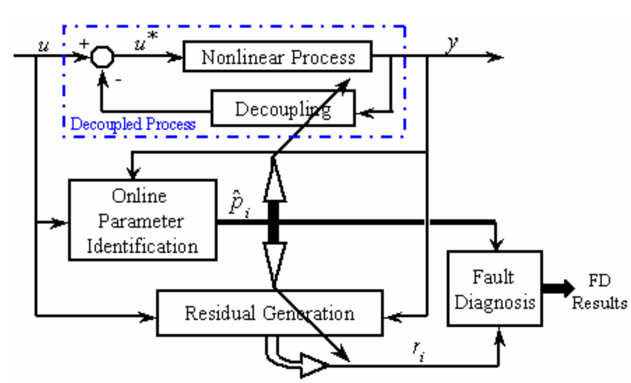


Fig. 3. General Robust Fault Diagnosis Structure

As mentioned in the previous section, the nonlinearity and coupling effects usually complicate the system dynamics, and thus cause difficulties in most goal-oriented designs. In practical applications, the most widely adopted method is the so-called *quasi-dynamic* approach with pseudo constant speed characteristics [16]. Under the assumption that the PMSM mechanical time constant is much larger than the electrical time constant, the currents equation (1) becomes linear as ω_r is treated as a pseudo constant. Equation (1) is then rewritten in a transfer function as in (5), where the only issue to be dealt with is the coupling effect.

$$\begin{bmatrix} i_d^{\,r} \\ i_q^{\,r} \end{bmatrix} = Y(s) \begin{bmatrix} v_d^{\,r} \\ v_q^{\,r} - \omega_r \psi_{mag} \end{bmatrix} \tag{5}$$

with
$$Y(s) = \frac{1}{P(s)} \begin{bmatrix} L_q s + R_S & L_q \omega_r \\ -L_d \omega_r & L_d s + R_s \end{bmatrix}; \tag{6}$$
$$P(s) = (L_q s + R_s)(L_d s + R_s) + L_q L_d \omega_r^{\,2}$$

A new decoupled system is achieved by applying a decoupling block in feedback loop as illustrated in Fig. 3. Some advanced multivariable control techniques already utilize state decoupling technique (e.g. [11][12]), which simplifies the controller design in general and improves the system performance. Similarly, the on-line identification and the residual generation designs based upon this decoupled system can also be simplified.

The on-line parameter identification uses a model-based technique based upon the decoupled model, in which the model parameters are adaptively estimated. Inside of the parameter identification block, the estimated output $\hat{y}$ is calculated based on the decoupled model and is compared with the measured value of y. The estimator then takes as inputs the errors between y and $\hat{y}$ to regulate the values of the estimated parameters ($\hat{p}_i$) with a commonly used regulator, i.e.:

$$\hat{p}_i(t) = \hat{p}_i(t_0) + \gamma \int_{t_0}^{t} \big(\hat{y}(\tau) - y(\tau)\big) u(\tau) d\tau \tag{7}$$

where $\gamma>0$ represents tuning factor referred as the adaptive gain [13]. u, y *and* $\hat{y}$ in (7) are measurements (estimations) of the specific input and output of the decoupled system corresponding to the identified parameter. The implementation of the adaptive regulator is illustrated in Fig. 4.

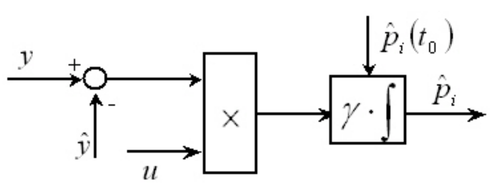


Fig. 4. Schematics of the Adaptive PI-Regulator

The residual generation block in Fig. 3 is designed to detect additive faults. In this work, the minimal polynomial basis approach is chosen to generate residuals of the additive faults. The method produces the low order properties of the residual generator that reduces its dependence on the model. This is important when process uncertainties have nontrivial impact on the mathematical model. Briefly, the residual (r_i) for additive faults can be obtained by finding the null space of matrix *M(s)* following the definition in (4) according to [10], which provides a complete description of this approach.

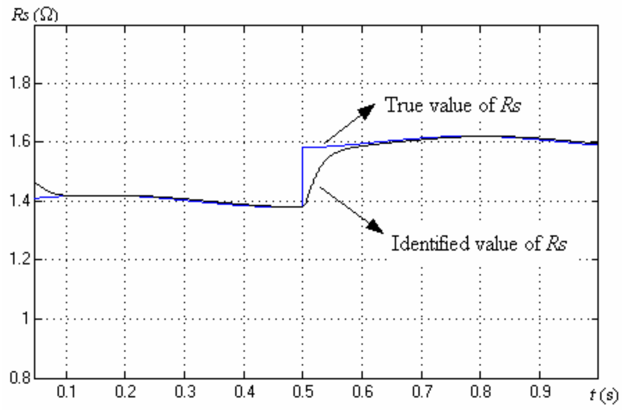
$$M(s) = \begin{bmatrix} G_u(s) & G_d(s) \\ I & 0 \end{bmatrix} \tag{8}$$

In the residual generation design, the load torque T_L is decoupled as an external disturbance so that the system robustness is not degraded with the load variations. This feature is also important when the load torque is unknown.

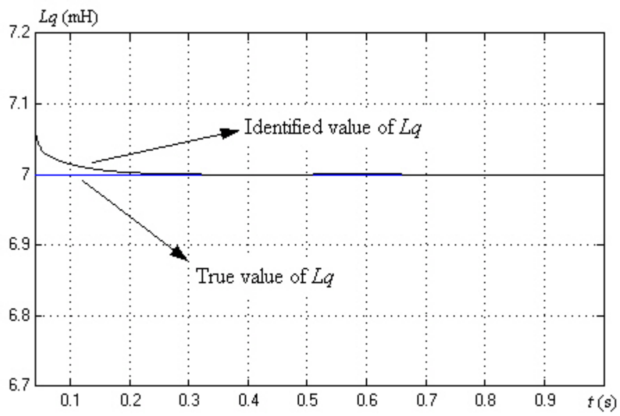
Assuming the on-line parameter identification has obtained a good tracking of the realistic process, we can utilize its output ($\hat{p}_i$) for two different goals simultaneously. On one hand, it is applied to the offline-designed residual generator to keep it consistent to the process under the current operating condition. On the other hand, the parameter changes are sent directly to the fault diagnosis block as an indication of internal process faults. Under normal operations, the residual generation block and parameter identification block function in parallel continuously and synchronously online. When faults are determined, the adaptation of the residual generation is interrupted by fault alarms from the diagnosis block and remedial strategies should follow.

IV. Application To PMSM Drives

The application of the robust FD structure described in the previous section is investigated on a variable-speed PMSM drive system (Fig. 1). This 2-input 3-output system can be decoupled with the decoupling block in the loop, based upon which the model-based parameter identifier is designed. The decoupling block used here and the proof of identification convergence are fully described in [14]. Successful system decoupling and on-line parameter identification have been verified through simulation in MATLAB/Simulink®. Due to the complex dynamics of the nonlinear PMSM drives, special attention has to be paid to the tuning of the adaptive gains for a good balance between the convergence speed and system stability. Fig. 5 provides the identification results for stator resistance R_s and q-axis inductance L_q. In (a), it is clearly seen how the identification process tracks the slow parameter variations (R_s) under different operation status, as well as an



(a)



(b)

Fig. 5. Simulation Results of On-line Identification of PMSM Drives
(a) Stator Resistance R_s (b) q-axis Inductance L_q

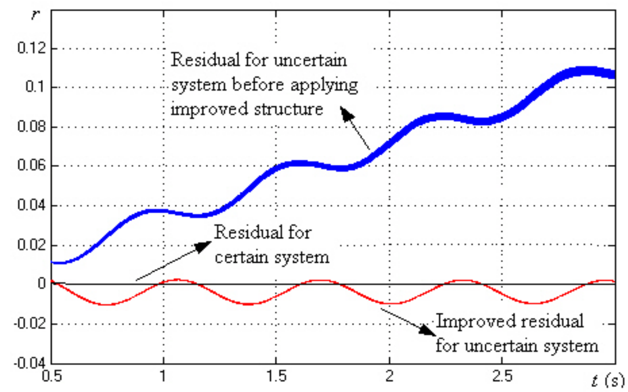


Fig. 6. Fault-free Residuals for process with and without uncertainties

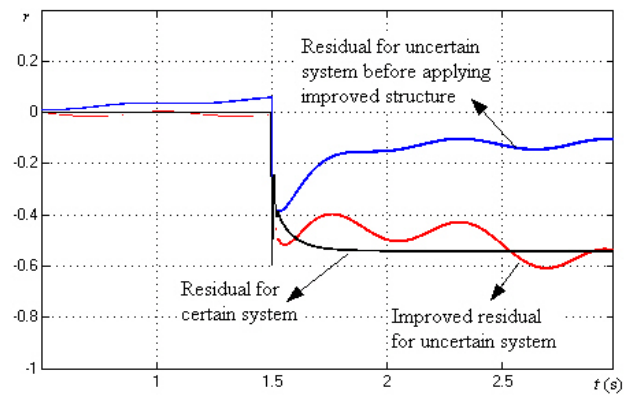


Fig. 7. Fault-Case Residuals for process with and without uncertainties
----- Sensor Fault at *t=1.5s*

identified abrupt change caused by a unique internal process fault, e.g. a fault leading to sudden temperature rise. Convergence within 0.1 second is satisfactory considering the electrical time constant of electric machines.

Fig. 6 presents the comparison of residuals for the current sensor fault diagnosis before and after applying the robust structure. The ideal residual for a healthy process without uncertainties is also displayed as a benchmark. For simulation purpose only, sinusoidal fluctuations are introduced to parameter R_s in the model. Clearly, without the improvement, the residual in the fault-free case is significantly impacted by process uncertainties so that it deviates from zero and builds up quickly. This is not desirable because the residual will eventually run over the preset threshold leading to false alarms. After applying the proposed structure, the residual generator can be adapted with the identification output. Although the residual will not stay zero-valued as the ideal case does due to the existence of identification errors, it does constrain itself within a relatively small range. Accordingly, the threshold has to be raised to some non-zero value, which is usually a tradeoff between the rates of false alarms and missed detection of faults. The improvement on system robustness against uncertainties is obvious in Fig. 6. In our example, if the threshold for this specific fault is set as ±0.02, without the robust feature, we will receive a false alarm soon after the process uncertainty appears (at about 0.3s), whereas this threshold is still conservative for the improved system.

In order to verify that the revised structure will not impact the system performance in faulty conditions, Fig. 7 gives the residual signals for the current sensor fault. In this demonstration, the sensor fault is simulated with a bias magnitude at *t=1.5s*. While being more robust during normal operations, the revised structure produces similar response for faulty case compared with the unimproved version. This strengthens the validity of the improved methodology.

V. CONCLUSION

The paper investigates robustness against process uncertainties in the diagnosis system for a variable speed PMSM drive. It presents a synthesis of the advanced on-line parameter identification and the model-based fault detection techniques based upon successful system decoupling. The system can deal with both sensor/actuator faults and internal process faults based on different approaches. The combination of the two approaches enhances the robust feature of the diagnosis system. Preliminary results from MATLAB/Simulink® simulation verify that the proposed fault diagnosis structure is effective on the improvement of PMSM FD system robustness against process uncertainties.

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