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A Fault Diagnosis Approach for Electrical Induction Motors via Energetic Based Scheme

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Abstract— **In this paper an energetic based approach is presented for a class of Linear Parameter Varying (LPV) systems subject to sensor and component faults. The main purpose of this research is to estimate the stator winding faults of an electrical induction motor. To this end, a quasi-LPV model is derived, on the basis of the nonlinear model of induction motor. Then, an algebraic technique is addressed to derive a regressor description of the system energy balance, where the regressor coefficients are stator winding fault. This formulation provides the possibility of using the Least Square(LS) technique to component fault estimation. The effectiveness of the proposed method is illustrated in a final numerical example.**

Keywords-dissipativity; induction motor; component fault; fault estimation; linear matrix inequality; linear parameter varying

1 INTRODUCTION

Induction Motors(IM) are widely used in modern industry and thus monitoring and detecting of electrical and mechanical damages for them become an important issue in industrial applications. According to [1], the major faults of IM can be categorized as bearing related faults(40%), stator winding faults(38%), rotor related faults(10%) and other faults(10%), among many, the stator winding faults are quite difficult to be detected online at early stages during the normal operation of the motor. With this in mind, several stator winding related fault detection and isolation(FDI) techniques have been proposed in the literature [2–21]. An online monitoring technique based on motor current signature analysis(MCSA) was demonstrated in [2,3] and [4] for fault diagnosis in induction motors. The main disadvantage of the method is that knowledge on the design and operation of induction motors are crucial ingredients for correct data interpretation and reliable diagnosis of the faults. Furthermore, this technique requires the motor operation at steady state. In [5], a novel technique is presented to detect turn faults in a single phase of the stator of an induction machine. This scheme needs an accessibility to the machine electrical neutral in its wye-configuration, which strictly limit its application. The extended park vector approach has been considered by [6] to detect a change in the unbalance in operating three-phase motors which may lead to diagnosis the occurrence of stator winding faults. They did not take into consideration that any of the motor non-idealities that causes a change in the unbalance may influence the fault detection method. The proposed method in [7] addresses a sensor-less fault detection method based on sum of ac components of phase power indicator. A high degree of attention must be used in this scheme to avoid false alarm. The negative sequence current and voltage based fault detection is considered in [8,9] and [10]. The proposed strategy is very sensitive to supply voltage unbalances which may produce false alarms. Modern techniques based on artificial intelligence approach have also been applied in [11,21] to detect inter turn faults of the motor. Although some researches has been done for diagnosis of stator winding faults, model based fault detection strategies have received a growing attention in the past years, due to the early fault detection properties [13,14,16–21]. For example, an adaptive observer is proposed in [17] to generate a vector of specific residual. This allows for a fast detection of incipient faults. In [16], a parametric low differential order model was coupled with an adaptive Kalman filter for recursively estimating the states and parameters of continuous time model with discrete measurements for fault detection ends. In [19], the nonlinear model of the electrical motor was first approximated in a quasi-LPV model. Then an FDI filter was designed to achieve a compromise between disturbance decoupling and fault sensitivity over a prescribed frequency range. The subject of model based inter-turn short circuit fault detection in the stator of an induction motor was proposed in [13]. The Set Membership Identification approach was

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suggested in [18] to diagnose short circuit faults in stator winding. Although most of the strategies that have been proposed in this area are based on residual generation and evaluation, but fault detection, based on the identification method, is a motivation for work.

Recently, considerable attention has been focused on the area of fault detection and estimation based on dissipativity approach. One of the salient features of this technique is the potential of extending to non-linear systems. In fault diagnosis area, see e.g. [22,23] that extend energetic approaches to fault detection. In [22], a bond graph system model is used to generate residual signals for fault diagnosis. The proposed method is based on the observation of energetic exchanges amongst system components. The main disadvantage of the method is that it is not robust with respect to measurement noise and uncertainty. An energy balance based fault detection method was considered also in [23], for sensor fault detection in steel galvanizing process. It does not take into account the effect of disturbances on the proposed scheme.

Dissipativity is characterized by the presence of a storage function and an energetic supply rate. The basic assumption is that the energy stored in the passive systems can not be more than the energy supplied by the environment outside. In [24], this characteristic is used in fault diagnosis in the sense that when this inequality fails then it is supposed that faults appear in the system. The passivity based fault detection method was extended to an energy based framework in [25], where, besides the stored energy and supplied energy, the dissipated energy has also been modeled for the dissipative systems and an optimal fault detection approach based on the energy balance was suggested.

The problem of robust fault tolerant control for dissipative Hamiltonian systems subject to actuator faults is considered in [26]. They proposed an energy based robust controller to ensure local uniform asymptotic stability of the equilibrium point and the disturbance attenuation performance of the faulty system. The main disadvantage of this method is that the proposed controller has the drawback of being discontinuous, which may lead to the chattering effect sometimes. The energy balance framework has been used by [27], to exploit LQ control characteristics in fault detection. It does not take into account the state un-measurable case. An energy monitoring based fault detection and isolation method is proposed in [28]. They investigate how the energy monitoring of robotic systems can be applied for detection and isolation of robot actuator faults. In [29], an Unknown Input Observers based approach using a bond graph model is proposed. The dissipativity theory is used in [30, 31] to develop a fault detection and diagnosis scheme for process systems in linear and non-linear contexts respectively. One major disadvantage of this method is that it is not sensitive to individual faults. The problem of robust dissipative fault tolerant control for discrete-time systems with actuator faults is investigated in [32]. In [33], the energy balance framework is used to estimate the faults. The idea behind is to design a dissipative fault estimation observer for multi-agent systems based on Galerkin method and singular perturbation theory.

In this paper, a novel polytopic fault estimation technique is developed for an electrical induction motor which is subjected to stator winding faults. To this end, the nonlinear model of the

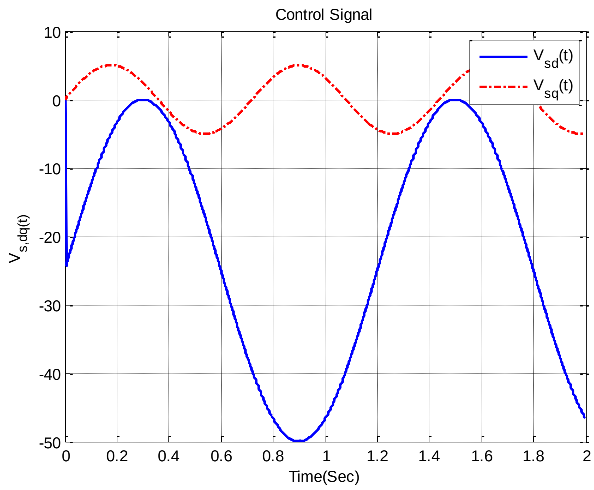

Figure1. The control signal u(t)

electrical motor is first approximated in a quasi LPV model as demonstrated in [19]. Then, the fault energy is represented as a function of the stored energy, supply energy and dissipated energy. The design objective is to develop a polytopic scheme which can estimate winding faults. Differently from [29,33], where fault detection based on dissipativity observer has been considered, here we develop the energy based fault diagnosis approach of [25] for LPV systems. The key difference of our approach with respect to [33] is that the dissipativity properties of the system is determined from process input/output data. Another specific feature of our scheme is to perform the fault estimation approach, which has not been addressed in [13, 14, 16–21, 25]. Beside, our setup is capable of fault isolation, along with disturbance rejection. The polytopic fault estimation scheme is based on the Lyapunov function, thus it can be applied to either linear or non-linear systems. Moreover, properties of the presented observer are formally proved and discussed.

2 IM MODEL WITH STATOR FAULTS

This section has been assigned to derive an LPV model approximation of IM model, which will be used for diagnosis purposes.

2.1 Nonlinear Model of IM

Induction motors are the essential components in the vast majority of industrial processes, which have been considered as a theoretically interesting and practically important class of nonlinear systems due to the highly coupled nature of them. It is well known that the dynamic d-q frame, the space vector and the spiral vector modulation are the most used to model and study the transient behavior of induction machines under dynamic conditions [34]. Here, the rotating d-q frame model is taken into account. This model is being carried out through the utilization of Park’s transform[35]. It is worth pointing out that, the subscripts ‘s’ and ‘r’ denote, respectively, stator and rotor quantities. By defining $x_n^T = [\omega \quad \Phi_{rd} \quad \Phi_{rq} \quad i_{sd} \quad \mathrm{i}_{sq}]^T$ as the state variables, the IM model with stator fault can be represented in an stationary reference dq-frame, as follow

$$\begin{cases} \dot{x}_{n_1} = \frac{pL_M}{JL_r}(\mathrm{x}_{n_5}\mathrm{x}_{n_2} - \mathrm{x}_{n_4}\mathrm{x}_{n_3}) - \frac{k}{J}x_{n_1} - \frac{C_r}{J} + \frac{pL_M}{JL_r}[(\mathrm{x}_{n_2} - 2\mathrm{L}_M\,\mathrm{x}_{n_4})\mu_q f_d] \\ \quad -\frac{pL_M}{JL_r}[(\mathrm{x}_{n_3} - 2\mathrm{L}_M\,\mathrm{x}_{n_5})\mu_d f_d] \\ \dot{x}_{n_2} = \frac{L_M R_r}{L_r}x_{n_4} - \frac{R_r}{L_r}x_{n_2} + (\omega_a - \mathrm{x}_1)\mathrm{x}_{n_3} - \frac{2}{3}L_M \frac{R_r}{L_r}\mu_d f_d \\ \dot{x}_{n_3} = \frac{L_M R_r}{L_r}x_{n_5} - \frac{R_r}{L_r}x_{n_3} - (\omega_a - \mathrm{x}_{n_1})\mathrm{x}_{n_2} - \frac{2}{3}L_M \frac{R_r}{L_r}\mu_q f_d \\ \dot{x}_{n_4} = \gamma x_{n_4} + \omega_e x_{n_5} + \frac{L_M}{L_r L_s \sigma}(\frac{R_r}{L_r}x_{n_2} + \mathrm{x}_{n_1}\mathrm{x}_{n_3}) + \frac{1}{L_s\sigma}v_{sd} \\ \quad + \frac{2}{3}\mu_d f_d + \frac{2}{3}\frac{L_r^2 R_s + L_M^2 R_r}{(L_s L_r - L_M^2)L_r}\mu_d f_d \\ \dot{x}_{n_5} = \gamma x_{n_5} - \omega_e x_{n_4} + \frac{L_M}{L_r L_s \sigma}(\frac{R_r}{L_r}x_{n_3} - \mathrm{x}_{n_1}\mathrm{x}_{n_2}) + \frac{1}{L_s\sigma}v_{sq} \\ \quad + \frac{2}{3}\mu_q f_d + \frac{2}{3}\frac{L_r^2 R_s + L_M^2 R_r}{(L_s L_r - L_M^2)L_r}\mu_q f_d \end{cases} \tag{1}$$

$$\begin{cases} y_1 = x_{n_1} + b \\ y_2 = x_{n_4} \\ y_3 = x_{n_5} \end{cases}$$

Where p denotes the number of pole pairs, K the damping coefficient, J is the moment of inertia, ω_a is the angular speed of the rotating d-q frame, C_r is the load torque and $\gamma = -(\frac{1}{\sigma})(\frac{R_s}{L_s} + (1-\sigma)\frac{R_r}{L_r})$. Moreover, σ is the leakage factor which can be computed as follow:

$$\sigma = 1 - \frac{L_M^2}{L_r L_s} \tag{2}$$

Furthermore, R_r and R_s are the rotor and stator resistances, respectively. L_s, L_r and L_M represent the stator, rotor and rotor/stator mutual inductances, respectively. It is worth of pointing that, the fault f_d refers to stator winding short circuit current and b represents for bias fault. Also, the vector $\mu_{qd} := [\mu_q \quad \mu_d]^T$ represents the percentage of short circuited windings and the vector direction corresponds to the faulted phase. Further details on this model can be found in [36].

2.2 LPV Approximation of Nonlinear Model of IM

In what follows, we describe a simple way to achieve a quasi-LPV approximation of IM. Such a model is based on the well-known Jacobian linearization approach, where the nonlinear plant behavior is approximated by a family of linear systems. As a result, a quasi LPV model approximation is constructed by suitably blending a set of linearized model of the nonlinear system holding around suitable equilibrium points. In this way, one can rewrite the nonlinear model of IM in a compact form as follow:

$$\begin{cases} \dot{x}_n(t) = \phi(\mathrm{x}_n(\mathrm{t}), f_d(\mathrm{t})) + \mathrm{Bu(t)} \\ y(t) = Cx_n(t) + \mathrm{Fb(t)} \end{cases} \tag{3}$$

Consider the following state variables:

$$x_n^T = [\omega \quad \Phi_{rd} \quad \Phi_{rq} \quad i_{sd} \quad \mathrm{i}_{sq}]^T \tag{4}$$

One can derive the following quasi-LPV model similar to the method which has been described in [36]:

$$\begin{cases} \dot{x}_n(t) = \sum_{i=1}^{l}\rho_i(t)A_i x_n(t) + \sum_{i=1}^{l}\rho_i(t)B_i\,\mathrm{u}(t) \\ \qquad + (\delta_1 x_n(t) + \delta_2)\,\mathrm{f}_d(t) - \sum_{i=1}^{l}\rho_i(t)\gamma_{x,i} \\ y(t) = Cx_n(t) + \mathrm{Fb(t)} \end{cases} \tag{5}$$

Where $x_n(\mathrm{t}) \in \mathrm{R}^n$ is the *state vector*, $u(\mathrm{t}) \in \mathrm{R}^{n_u}$ is a known input. Moreover, $y(\mathrm{t}) \in \mathrm{R}^m$ represents the *plant output* provided by the physical redundant sensors possibly effected by bias fault $b(\mathrm{t}) \in \mathrm{R}^q$. Additionally, $\rho(t) = [\rho_1(\mathrm{t}), ..., \rho_l(\mathrm{t})]$ is the set of normalized scheduling terms as follow:

$$0 \le \rho(t) \le 1, \forall i, \sum_{i=1}^{l}\rho_i(t) = 1 \tag{6}$$

Notice that, the coefficients δ_1 and δ_2 is governed by

$$\delta_1 = \begin{bmatrix} 0 & \frac{pL_M}{JL_r}\mu_q & -\frac{pL_M}{JL_r}\mu_d & -2\frac{pL_M}{JL_r}L_M\mu_q & 2\frac{pL_M}{JL_r}L_M\mu_d \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{7}$$

$$\delta_2 = \begin{bmatrix} 0 & -\frac{2}{3}L_M\frac{R_r}{L_r}\mu_d & -\frac{2}{3}L_M\frac{R_r}{L_r}\mu_q & \frac{2}{3}(1+\frac{L_r^2 R_s + L_M^2 R_r}{(L_s L_r - L_M^2)L_r})\mu_d & \frac{2}{3}(1+\frac{L_r^2 R_s + L_M^2 R_r}{(L_s L_r - L_M^2)L_r})\mu_q \end{bmatrix}'$$

Besides, for each equilibrium point $(x_{n_i}, u_i), \mathrm{i} = 1, ..., \mathrm{l}$, the term $\gamma_{x,i} \triangleq A_i x_i + B_i u_i$ needed to be added in the formulation as a corresponding offset.

Additionally, the v_{sd} and v_{sq} of stator voltage are considered as scheduling variables, where

$$\Pi: \begin{cases} v_{sd} \in [\underline{v}_{sd}, \overline{v}_{sd}] \\ v_{sq} \in [\underline{v}_{sq}, \overline{v}_{sq}] \end{cases} \tag{8}$$

Moreover, the scheduling parameters have been defined as follow:

$$\begin{cases} \rho_1 = p_1 * p_2, \qquad \rho_2 = p_1 * (1-p_2) \\ \rho_3 = (1-p_1) * p_2, \quad \rho_4 = (1-p_1) * (1-p_2) \end{cases} \tag{9}$$

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Where the measurable parameters p_i obtained by normalizing and centering the physical signals v_{sd} and v_{sq} as follow:

$$p_1(t) = \frac{v_{sd}(t) - \underline{v}_{sd}}{\overline{v}_{sd} - \underline{v}_{sd}}; \; p_2(t) = \frac{v_{sq}(t) - \underline{v}_{sq}}{\overline{v}_{sq} - \underline{v}_{sq}} \tag{10}$$

In order to exploit a simple quasi-LPV model description, one can re-describe the quasi-LPV model (5) as follow:

$$\begin{cases} \dot{x}_n(t) = A_\rho x_n(t) + B_\rho u(t) + \mathrm{Ef(t)} \\ \quad + \mathrm{Gd(t)} - \sum_{i=1}^{l} \rho_i(t)\gamma_{x,i} \\ y(t) = Cx_n(t) + F\,\mathrm{b(t)} \end{cases} \tag{11}$$

where

$$E = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{2}{3}L_M \frac{R_r}{L_r} \\ -\frac{2}{3}L_M \frac{R_r}{L_r} & 0 \\ 0 & \frac{2}{3}(1 + \frac{L_r^2 R_s + L_M^2 R_r}{(L_s L_r - L_M^2)L_r}) \\ \frac{2}{3}(1 + \frac{L_r^2 R_s + L_M^2 R_r}{(L_s L_r - L_M^2)L_r}) & 0 \end{bmatrix} \tag{12}$$

$f(t) = \mu_{qd} f_d(t), \; d(t) = \delta_1 x_n(t) \mathrm{f}_d(t)$

Notice that $f(t)$ considered as the fault effect, including the percentage of short circuit winding and the vector direction among its parameters. Moreover, in order to exploit the unknown input structure, we consider $d(t)$ as an unknown input.

3 PROPOSED STRATEGY FOR STATOR FAULT DIAGNOSIS

3.1 *Problem Statement*

Let us consider plant whose dynamics is described by (11). Of particular interest will be those systems in which the system matrices are described in polytopic framework whose mathematical description depends on parameters that change values over time. These parameters are generally considered as bounded and taking values inside a set Δ, often assumed to be a compact and convex polytope. This means that the system matrix

$$S_\rho := (\mathrm{A}_\rho, \mathrm{B}_\rho) \tag{13}$$

can be expressed as

$$S_\rho = \sum_{i=1}^{l} \rho_i(t) \mathrm{S}_i, \; \sum_{i=1}^{l} \rho_i(t) = 1 \tag{14}$$

where

$$S_i := (A_i, B_i) \tag{15}$$

are constant system matrices of appropriate dimension. In particular, this implies that the system matrices $S(t), \quad t \in R^n$ belong to the convex hull of $S_1, \cdots, S_N$,i.e.

$$S(t) \in Conv(S_1, \cdots, S_N) \tag{16}$$

The objective of this paper is to present an energetic based approach to estimate the component fault which can be coupled with a polytopic observer to estimate the bias fault.

To this end, an augmented unknown input structure has been used to decouple the component fault effect from the bias fault and unknown inputs.

Then, the energy based framework in [25] has been extended to the following new structure

$$\varepsilon_{fault} = \varepsilon_{sup} - \varepsilon_{stor} - \varepsilon_{diss} \tag{17}$$

which implies that the fault rate energy(ε_{fault}) can be expressed as a function of stored energy(ε_{stor}), supply rate energy(ε_{sup}) and dissipated rate energy(ε_{diss}). This energy balance points out that fault estimation can be carried out, if we have been provided by the stored, supplied and dissipated energy value. While the aforementioned energies are function of system states, we proposed an algebraic technique to describe them by the input and output measured variables. Next, the energy balance has been re-described in a regression form where the regression coefficients are component fault matrix elements.

Before describing the proposed scheme, let us recall first the usual concept of dissipativity and assumptions that are made.

Definition1: Consider the process defined by (11) without fault. This process is said to be dissipative with respect to the supply rate $S(u, y)$, if there exist a function $V(x, \rho) = x'(t)Q(\rho)x(t) > 0$, called the storage function, and input function $u(t)$ such that the dissipation inequality

$$\partial_x V(x, \rho)\dot{x}(t) + \partial_\rho V(x, \rho)\dot{\rho}(t) \le S(u, y) \tag{18}$$

holds true for all signals (x, u, y, ρ) satisfies

A1: It is assumed that the input and the output variables of the system are bounded before and after the fault occurrence. So, there exist compact sets $\mathbb{U} \subset \mathbb{R}^{n_u}$ and $\mathbb{Y} \subset \mathbb{R}^m$ such that the input and the output variables remain bounded before and after the fault occurrence, i.e., for all $t, u \in \mathbb{U}$ and $y \in \mathbb{Y}$.

A2: It is assumed that the pair (A_ρ, C) is observable.

A3: It is assumed that the trajectories $\rho(.)$ are continuously differentiable while

$$\rho(t) \in \Delta, \quad \dot{\rho}(t) \in \Gamma, \quad \forall t \in R \tag{19}$$

where Γ is a compact set. This implies that there exists positive scalars μ_i such that the

$$|\dot{\rho}_i| \le \mu_i \tag{20}$$

A4: It is assumed that the bias fault is varying slowly, i.e.

$$\dot{b}(t) \approx 0 \tag{21}$$

3.2 Energetic Approach for Fault Diagnosis

In order to estimate the short circuit winding fault, one can consider the bias fault as an actuator fault, following the procedure described in [38], by adding an auxiliary state variable having a faster response than all other physical system states as follow:

$$X(t) = \begin{bmatrix} x_n(t) \\ b(t) \end{bmatrix} \tag{22}$$

As a result, the related augmented model can be described as

$$\begin{cases} \dot{X}(t) = \bar{A}_\rho X(t) + \bar{B}_\rho u(t) \\ +\bar{G}\bar{d}(t) + \bar{\mathrm{E}}\bar{\mathrm{f}}(t) - offset \\ y(t) = \bar{C}X(t) \end{cases} \tag{23}$$

Where

$$\bar{A}_\rho = \begin{bmatrix} A_\rho & 0 \\ 0 & \alpha \end{bmatrix}, \quad \bar{B}_\rho = \begin{bmatrix} B_\rho \\ 0 \end{bmatrix} \tag{24}$$

$$\bar{G} = \begin{bmatrix} G & 0 \\ 0 & 1 \end{bmatrix}, \quad \bar{C} = \begin{bmatrix} C & F \end{bmatrix}, \quad \bar{\mathrm{E}} = \begin{bmatrix} E \\ 0 \end{bmatrix}$$

$$offset = \begin{bmatrix} \sum_{i=1}^{l} \rho_i(t)\gamma_{x,i} \\ 0 \end{bmatrix}, \quad \bar{\mathrm{f}}(t) = \begin{bmatrix} f(t) & 0 \end{bmatrix}'$$

$$\bar{d}(t) = \begin{bmatrix} d(t) & \eta(t) \end{bmatrix}'$$

In order to decouple the multiplicative fault effect from the unknown input, following the procedure described in [39], we assumed to be provided by the matrices $H = \bar{G}(\bar{C}\bar{G})^{\dagger}$ and $T = I - H\bar{C}$ such that

$$rank(\bar{C}\bar{G}) = rank(\bar{G}) \tag{25}$$

then a possible structure for unknown input description of (23) is given by

$$\begin{aligned} \dot{X}(t) &= T\bar{A}_\rho X(t) + T\bar{B}_\rho u(t) + T\bar{E}\bar{f}(t) \\ &+ T\bar{G}\bar{d}(t) + H\dot{y}(t) - T\ \text{offset} \\ y(t) &= \bar{C}X(t) \end{aligned} \tag{26}$$

Equation (26) is equivalent to

$$\begin{aligned} \dot{x}(t) &= T\bar{A}_\rho X(t) + \bar{F}_w w(t) \\ y(t) &= \bar{C}x(t) \end{aligned} \tag{27}$$

where $w(t)$ is the input vector as follow

$$\bar{F}_w = \begin{bmatrix} T\bar{B}_\rho \\ T\bar{E} \\ H \\ -T \end{bmatrix}, \quad w(t) = \begin{bmatrix} u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ offset \end{bmatrix} \tag{28}$$

Notice that the condition $rank(\bar{C}\bar{G}) = rank(\bar{G})$ guarantees that $T\bar{G} = 0$.

To design the passivity based fault detection method for (27), the passivity conditions should be investigated. The following Lemma gives us the passivity conditions for (27).

Lemma1: The system (27) with supply rate

$$\varepsilon_{sup} = \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix}' \begin{bmatrix} 0 & N_\rho\bar{C}T\bar{B}_\rho & N_\rho\bar{C}T\bar{E}_\rho & N_\rho\bar{C}H & N_\rho\bar{C}T \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix} \tag{29}$$

and storage function $V(X,\rho) = X'(t)Q(\rho)X(t)$ is passive if assumption **A3** holds and there exist a symmetric positive definite matrix Q_i, symmetric matrix Q_0 and the matrix N_i such that

$$\begin{aligned} &\bar{A}_i' T' Q_j + Q_j T\bar{A}_i + \sum_{i=1}^{N} \mu_i (Q_i - Q_0) < 0, Q_i - Q_0 > 0 \\ &Q_i = \bar{C}' N_i \bar{C}, i = 1,\cdots,N, \quad j = 1,\cdots,N \end{aligned} \tag{30}$$

Proof: To construct the energy balance (17) for system (27), consider the following kind of storage function

$$V(X,\rho) = X'(t)Q(\rho)X(t) \tag{31}$$

The rate of change of storage function along trajectories of the system will be appear as follow

$$\begin{aligned} \dot{V}(X,\rho) &= \dot{X}'(t)Q(\rho)X(t) \\ &+ X'(t)Q(\rho)\dot{X}(t) + X'(t)Q(\dot{\rho})X(t) \end{aligned} \tag{32}$$

Considering (26), one can re-write (32) as

$$\dot{V}(X,\rho) = X'(t)(\bar{A}'_\rho T'Q_\rho + Q_\rho T\bar{A}_\rho)X(t) + u'(t)\bar{B}'_\rho T'Q_\rho X(t) + X'(t)Q_\rho T\bar{B}_\rho u(t) + \bar{f}(t)\bar{E}'T'Q_\rho X(t) + X'(t)Q_\rho T\bar{E}f(t) + \dot{y}'(t)H'Q_\rho X(t) + X'(t)Q_\rho H\dot{y}(t) - \text{offset}'T'Q_\rho X(t) - X'(t)Q_\rho T\text{offset} + X'(t)\dot{Q}_\rho X(t) \tag{33}$$

which is equivalent to

$$\dot{V}(X,\rho) = \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix}' \begin{bmatrix} \bar{A}'_\rho T'Q_\rho + Q_\rho T\bar{A}_\rho + \dot{Q}_\rho & Q_\rho T\bar{B}_\rho & Q_\rho T\bar{E} & Q_\rho H & Q_\rho T \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix} \tag{34}$$

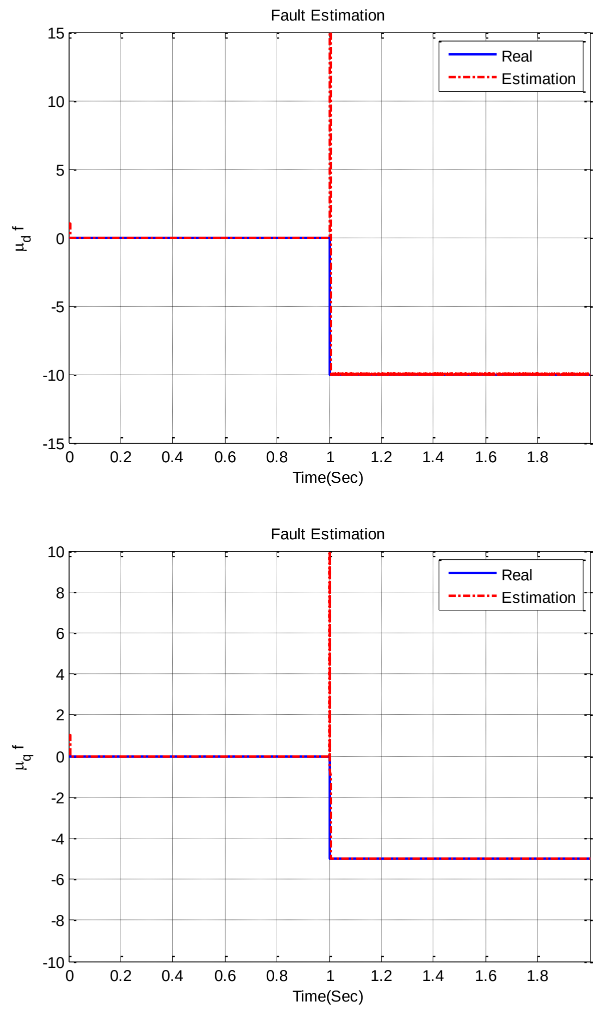

Figure 2. The stator winding fault estimation results

Assuming to be provided by the matrix N_ρ such that

$$Q_\rho = \bar{C}'N_\rho\bar{C} \tag{35}$$

then (34) is equivalent to

$$\dot{V}(x,\rho) = \begin{bmatrix} y(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix}' \begin{bmatrix} 0 & N_\rho\bar{C}T\bar{B} & N_\rho\bar{C}T\bar{E} & N_\rho\bar{C}H & N_\rho\bar{C}T \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} y(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix} + \begin{bmatrix} y(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix}' \begin{bmatrix} \bar{A}'_\rho T'Q_\rho + Q_\rho T\bar{A}_\rho + \dot{Q}_\rho & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} y(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix} \tag{36}$$

In addition, expression (36) is equivalent to

$$\varepsilon_{stor} = \varepsilon_{sup} - \varepsilon_{diss} - \varepsilon_{fault} \tag{37}$$

With

$$\varepsilon_{stor} = \dot{V}(X,\rho) \tag{38}$$

$$\varepsilon_{sup} = \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix}' \begin{bmatrix} 0 & N_\rho\bar{C}T\bar{B}_\rho & N_\rho\bar{C}T\bar{E} & N_\rho\bar{C}H & N_\rho\bar{C}T \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \\ \star & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix} \tag{39}$$

$$\varepsilon_{diss} + \varepsilon_{fault} = \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix}' \begin{bmatrix} \bar{A}_\rho' T' Q_\rho + Q_\rho T \bar{A}_\rho + \dot{Q}_\rho & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \\ o & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X(t) \\ u(t) \\ \bar{f}(t) \\ \dot{y}(t) \\ \text{offset} \end{bmatrix} \tag{40}$$

The necessary and sufficient condition for system (27) to be dissipative is that $\varepsilon_{stor} - \varepsilon_{sup} < 0$ which implies that

$$\bar{A}_\rho' T' Q_\rho + Q_\rho T \bar{A}_\rho + \dot{Q}_\rho < 0 \tag{41}$$

Due to (14), it obviously follows

$$\sum_{i=1}^{N} \dot{\rho}_i = 0 \quad \Rightarrow \quad \sum_{i=1}^{N} \dot{\rho}_i Q_0 = 0 \tag{42}$$

with assumption **A3** and (42), $\dot{\rho}_i$ is bounded by

$$\dot{Q}_\rho = \sum_{i=1}^{N} \dot{\rho}_i (Q_i - Q_0) \le \sum_{i=1}^{N} |\dot{\rho}_i| (Q_i - Q_0) = \sum_{i=1}^{N} \mu_i (Q_i - Q_0) \tag{43}$$

for any matrix Q_0 such that $Q_i - Q_0 \ge 0$. The matrix Q_0 is a slack variable introducing an additional degree of freedom. Then, inequality (41) holds if

$$\bar{A}_\rho' T' Q_\rho + Q_\rho T \bar{A}_\rho + \sum_{i=1}^{N} \mu_i (Q_i - Q_0) < 0 \tag{44}$$

which can be expressed as (30).

Q.E.D.

Now we have all ingredients to design a passivity based fault detection method. More formally, given the set of input ($u(t)$) and output ($y(t)$) of the plant, we are interested to estimate the component fault. To this end, consider the following Theorem.

Theorem1: Let the conditions expressed in (30) be held. Also assume to be provided by a matrix $M(t)$ such that

$$\bar{C}' M(t) \bar{C} = \bar{A}_\rho' T' Q_\rho + Q_\rho T \bar{A}_\rho \tag{45}$$

Then, the system described in (23) will take the following innovation form

$$Y(t) = \varphi(t) \bar{f}(t) \tag{46}$$

where

$$\begin{aligned} Y(t) &= \dot{y}'(t) N_\rho y(t) + y'(t) N_\rho \dot{y}(t) \\ &\quad - y'(t) M(t) y(t) - 2\dot{y}'(t) H \bar{C}' N_\rho y(t) \\ &\quad - 2u'(t) \bar{B}_\rho' T' \bar{C}' N_\rho y(t) \\ &\quad + 2\,\text{offset}' \bar{C}' T' N_\rho y(t) \\ \varphi(t) &= 2y'(t) N_\rho' \bar{C} T \bar{E} \end{aligned} \tag{47}$$

Proof:

Assuming that the conditions expressed in (30) hold, one can re-write (33) as follow

$$\begin{aligned} \dot{V}(X,\rho) &= \dot{y}'(t) N(\rho) y(t) + y'(t) N(\rho) \dot{y}(t) \\ &\quad + X'(t) Q(\dot{\rho}) X(t) \\ &= X'(t) (\bar{A}_\rho' T' Q_\rho + Q_\rho T \bar{A}_\rho + \dot{Q}_\rho) X(t) \\ &\quad + 2\dot{y}'(t) H \bar{C}' N_\rho y(t) + 2u'(t) \bar{B}_\rho' T' \bar{C}' N_\rho y(t) \\ &\quad + 2\bar{f}'(t) \bar{E}' T' \bar{C}' N_\rho y(t) - 2\,\text{offset}' T' Q_\rho X(t) \end{aligned} \tag{48}$$

Moreover, assuming to be provided by the matrix $M(t)$ at each instant of time t such that

$$\bar{C}' M(t) \bar{C} = \bar{A}_\rho' T' Q_\rho + Q_\rho T \bar{A}_\rho \tag{49}$$

Then, one can re-describe (48) as

$$\begin{aligned} &\dot{y}'(t) N_\rho y(t) + y'(t) N_\rho \dot{y}(t) + X'(t) \dot{Q}_\rho X(t) \\ &= y'(t) M(t) y(t) + 2\dot{y}'(t) H \bar{C}' N_\rho y(t) \\ &\quad + 2X'(t) \dot{Q}_\rho X(t) + 2u'(t) \bar{B}_\rho' T' \bar{C}' N_\rho y(t) \\ &\quad + 2\bar{f}'(t) \bar{E}' T' \bar{C}' N_\rho y(t) - 2\,\text{offset}' T' \bar{C}' N_\rho y(t) \end{aligned} \tag{50}$$

Expression (50) is equivalent to

$$\begin{aligned} 2y'(t) N_\rho' \bar{C} T \bar{E} \bar{f}(t) &= \dot{y}'(t) N_\rho y(t) + y'(t) N_\rho \dot{y}(t) \\ &\quad - y'(t) M(t) y(t) - 2\dot{y}'(t) H \bar{C}' N_\rho y(t) \\ &\quad - 2u'(t) \bar{B}_\rho' T' \bar{C}' N_\rho y(t) + 2\,\text{offset}' T' \bar{C}' N_\rho y(t) \end{aligned} \tag{51}$$

which can be written in compact form as

$$Y(t) = \varphi(t) \bar{f}(t) \tag{52}$$

Where

$$
\begin{aligned}
Y(t) = {} & \dot{y}'(t)N_\rho y(t) + y'(t)N_\rho \dot{y}(t) \\
& - y'(t)M(t)y(t) - 2\dot{y}'(t)H\bar{C}'N_\rho y(t) \\
& - 2u'(t)\bar{B}_\rho' T'\bar{C}'N_\rho y(t) \\
& + 2\,\text{offset}' T'\bar{C}'N_\rho y(t) \\
\varphi(t) = {} & 2y'(t)N_\rho' \bar{C}T\bar{E}
\end{aligned} \tag{53}
$$

Q.E.D.

Based on the regression form (46), the optimization algorithm developed by [37], is still applicable here.

To this end, we will search solutions that minimize the estimation error as follow

$$
\hat{\bar{f}}(t) = \arg\min_{\bar{f}(t)} \int_0^t (Y(\tau) - \varphi(\tau)\bar{f}(t))^2 d\tau \tag{54}
$$

Remark1: It is worth of pointing that, following the procedure described in [40], the LS technique could be coupled with an LPV Unknown Input Observer (LPV-UIO), to estimate the stator winding faults, simultaneously with system states and bias faults

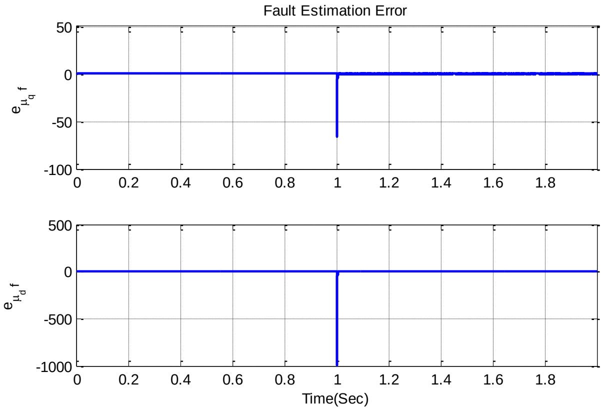

Figure3. The stator winding fault estimation error

4 Conclusion

In this paper, a novel polytopic fault estimation technique is developed for an electrical induction motor which is subjected to stator winding faults. To this end, the nonlinear model of the electrical motor is first approximated in a quasi LPV model. Then, the fault energy is represented as a function of the stored energy, supply energy and dissipated energy. The design objective was to develop a polytopic scheme which can estimate winding faults. Property of the presented observer are formally proved and discussed.

5 Illustrative Example

In this section, the effectiveness of the proposed scheme is investigated by considering the linear stable model which has been described in (5), where

$$
A_1 = \begin{bmatrix} 0 & 63 & 13 & -3 & 0 \\ 0 & 4 & 0 & 0 & 0 \\ 0 & 0 & -4 & 0 & 0 \\ 48 & 765 & 38603 & -0047 & 377 \\ 5 & -38603 & 765 & -377 & -47 \end{bmatrix} \tag{57}
$$

$$
A_2 = \begin{bmatrix} 0 & 64 & -1 & -3 & 0 \\ 0 & -4 & 0 & 0 & 0 \\ 0 & 0 & -4 & 0 & 0 \\ 48 & 765 & 38603 & -47 & 377 \\ -6 & -38603 & 765 & -377 & -47 \end{bmatrix} \tag{58}
$$

$$
A_3 = \begin{bmatrix} 0 & -41 & 1 & 0 & 0 \\ 0 & -4 & 28 & 0 & 0 \\ 0 & -28 & -4 & 0 & 0 \\ 0 & 765 & 33683 & -47 & 377 \\ 6 & -33683 & 765 & -377 & -47 \end{bmatrix} \tag{59}
$$

Table1. Chosen equilibrium configuration for LPV interpolation

$u = [u_1 \quad u_2]'$	$x = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5]'$
$u^1 = [-70 \quad -8]'$	$x^1 = [219.5527 \quad -0.0282 \quad 0.2751 \quad -1.4128 \quad 6.8054]'$
$u^2 = [-70 \quad 8]'$	$x^2 = [219.5527 \quad 0.0346 \quad 0.2744 \quad 0.1591 \quad 6.9487]'$
$u^3 = [0 \quad -8]'$	$x^3 = [191.5748 \quad -0.0369 \quad 0.0502 \quad -0.0637 \quad -4.4144]'$
$u^4 = [0 \quad 8]'$	$x^4 = [191.5748 \quad 0.0369 \quad -0.0502 \quad 0.0637 \quad 4.4144]'$

$$A_4 = \begin{bmatrix} 0 & 41 & -1 & 0 & 0 \\ 0 & -4 & 28 & 0 & 0 \\ 0 & -28 & -4 & 0 & 0 \\ -9 & 765 & 33683 & -47 & 377 \\ -6 & -33683 & 765 & -377 & -47 \end{bmatrix} \quad (60)$$

$$B_{1...4} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 189.011 & 0 \\ 0 & 189.011 \end{bmatrix}, \text{C}= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (61)$$

$$E = \begin{bmatrix} 0 & 0 \\ 0 & \text{-0.0116} \\ \text{-0.0058} & 0 \\ 0 & 32.0195 \\ 32.0195 & 0 \end{bmatrix}, G = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (62)$$

Moreover, in the estimator design we pick $\alpha = -0.0056$ to ensure a faster response for the auxiliary state defined in (22).

Notice that for the LPV interpolation, the equilibrium configuration has been chosen as Table (1).

Furthermore, the input $u(t) = \begin{bmatrix} v_{sd}(t) & v_{sq}(t) \end{bmatrix}'$, e.g. provided by a controller is depicted in Fig(1). Also, the short circuit winding fault will affect the system as follow

$$\mu_{qd} = \begin{bmatrix} 5 & 10 \end{bmatrix}' \quad (63)$$

The corresponding fault estimation results and the estimation error are reported in Fig(2) and (3).

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