OVERCOMING SENSOR FAULTS IN CONTROLLED INDUCTION MOTORS USING EKF

Antonio Mendoza, Roberto Arnanz, Alicia Corrales, J.R. Perán*, L.J de Miguel*

C.A.R.T.I.F.
(Centro de Automatización,Robótica y Tecnologías de la Información y Fabricación)
Parque Tecnológico de Boecillo. Parcela 205 47151 Boecillo Valladolid. (Spain)
Tlf: ++34 983546504 Fax: +34 983 546521
e-mail: {antmen,robarn, alicor,,peran,luimig@cartif.es}
** (Departamento de Automática de la Universidad de Valladolid)*
Escuela Técnica Superior de Ingenieros Industriales

Abstract: Following CARTIF motors Group previous works, this paper proposes a new application for parameter online estimation for induction motors, which is used in a model-based fault diagnosis. The induction motor is described by non-linear differential equations and an Extended Kalman Filter (EKF) estimates three parameters (rotor resistance, stator resistance and magnetizing inductance). The diagnosis system proposed here is a parity equations scheme for sensor faults and multiplicative faults using parameter estimation. Reconfiguration of Kalman Filter is used to achieve acceptable control conditions when a sensor fault exists. Experimental results on a Field oriented controller (FOC) with 5.5kw motor are presented.

Keywords: Induction motors, Extended Kalman Filter, Fault diagnosis, Fault isolation, Control oriented models.

1. INTRODUCTION

Nowadays, induction motors are widely used in industry because they are cheaper than DC motors. Though the electromagnetic conversion is described by non-linear equations this is not an inconvenience because the mathematical model of the AC motor is well known (Leohnard, W. 1996; Sen, P. 1989; Krause P. et al 1986).

Recently, there has been an increasing interest in non-linear model-based diagnostic techniques. In the induction motor, research has developed non-linear parity equations for parametric faults diagnosis (Arnanz et al 2000; Getler J. 1998; Getler J. and Yongtong H. 2000; Patton R. J. 2000), multiple model fault-tolerant systems for sensor faults (Chen, J. and Patton, R.J. 1999) and AI techniques (Pacheco, M.A. et al 2001; Zamora, J.L. et al 2000; Filippetti, F. et al 2000). In this paper two methods are used. Residuals based on the MIMO model Parity Equation Implementation for sensor faults and parameter estimation for the detection of changes in the physical parameters of the motor

A model that consists of five state-variables: three measurable variables (stator currents and speed) and two non-measurable variables (rotor currents) have been used. The parameters need to be estimated via a non-linear estimator. The Extended Kalman Filter is a popular method to observe non-measurable variables and estimate physical parameters. (Eltabach M. et al 2002, Ouhrouche M.A. 2000, Hajiyev C. M. 1999, Lapeyre, F. et al 1997; Grover, R. and Hawng, P. 1985). Therefore, three variables {Stator Resistance Rotor resistance and Mutual Inductance} are included in the filter. This identification is used for the fault detection algorithm (Mendoza A. et al 2004; Bacher S. et al 2001; Bacher S. et al 2001b; Moreau S. et al 1999) and the implementation of the motor model on the rotor-flux-oriented control (FOC) of the induction machine. In this method, a good estimation of the parameters allows a marked improvement in the performance. A reconfiguration of the system is used in order to overcome sensor faults.

In this paper, section 2 reviews the model of the induction motor used for a FOC system. An EKF-based estimation is presented in section 3 and section 4 shows the diagnosis system. In section 5, the results of the residuals evolution and reconfiguration of the Kalman filter when a sensor fault appears are shown.

2. STATE EQUATIONS OF THE MOTOR

A fourth-order state-space model defines the relationship between stator and rotor currents and voltages. Thus, the three-phase system is linearly transformed into two orthogonal axes (a,b) using a time-invariant matrix and stator-fixed reference frame. Therefore, all variables are referred to the stator. Finally, the mechanical features of the motor are represented by a second-order system. The state variables of the induction motor are the rotor and stator currents (1), and the speed. The inputs are the line voltages and torque (2).

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} i_{Sa}(t) \\ i_{Sb}(t) \\ i_{Ra}(t) \\ i_{Rb}(t) \\ \omega(t) \end{bmatrix} \quad (1)$$

$$\mathrm{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} u_{Sa}(t) \\ u_{Sb}(t) \\ T_L(\varepsilon,\omega,t) \end{bmatrix} \quad (2)$$

The model equations can be expressed as follows:

$$\begin{cases} \dot{x}_1 = k\left(-R_S L_R x_1 + L_0 R_R x_3 + L_0 L_R x_4 x_5 + L_0^2 x_2 x_5\right) + k L_R u_1 \\ \dot{x}_2 = k\left(-R_S L_R x_2 + L_0 R_R x_4 - L_0 L_R x_3 x_5 - L_0^2 x_1 x_5\right) + k L_R u_2 \\ \dot{x}_3 = k\left(-R_R L_S x_3 - L_R L_S x_4 x_5 + L_0 R_S x_1 - L_0 L_S x_2 x_5\right) - k L_0 u_1 \\ \dot{x}_4 = k\left(-R_R L_S x_4 + L_R L_S x_3 x_5 + L_0 R_S x_2 + L_S L_0 x_1 x_5\right) - k L_0 u_2 \\ \dot{x}_5 = k_1\left(x_2 x_3 - x_1 x_4\right) - k_3 x_5 - k_2 u_3 \end{cases} \quad (3)$$

where:

$$k = \frac{1}{L_R L_S - L_0^2}$$

$$k_1 = \frac{3p^2 L_0}{2J}$$

$$k_2 = \frac{p}{J}$$

$$k_3 = fr \cdot \frac{p}{J}$$

with output vector (4)

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} i_{Sa}(t) \\ i_{Sb}(t) \end{bmatrix} \quad (4)$$

Where:
$L_s = L_{s1} + Lo$
$L_r = L_{r1} + Lo$
L_s L_r Stator and rotor inductance.
L_{s1} L_{r1} Stator and rotor auto-inductance.
R_s R_r Stator and rotor resistance
Lo : Mutual inductance
T_L: Mechanical shaft torque,
J: Combined rotor and mechanical load inertia.
ω: Rotor angular speed.
p: number of pole-pairs
fr: friction factor
ε: rotor angular

In this case, the system control model [14] is formulated in the reference frame fixed to the rotor flux-linkage space-phasor. There are many ways to obtain the stator voltage equations in this reference frame. The rotor magnetizing-current space-phasor (Imr) is obtained by dividing the rotor flux-linkage space-phasor established in this reference frame ($\psi_{r\psi r}$) by the mutual inductance (Lo). (5)

$$I_{mr} = \frac{\psi_{r\psi r}}{L_0} \quad (5)$$

Resolving rotor voltage equations formulated in this reference frame, in its real and imaginary axis components, the following two axis differential equations are obtained for the stator currents. (6).

$$Tr\frac{d\left|\mathrm{Im}r\right|}{dt} + \left|\mathrm{Im}r\right| = Isx$$

$$Wmr = \varpi + \frac{Isy}{Tr \cdot \left|\mathrm{Im}r\right|} \quad (6)$$

$$Tr = \frac{Lo}{Rr}$$

Isx, Isy, are the stator current formulated in the rotor flux oriented reference frame.

Wmr, is the rotor magnetizing current space phasor speed with respect to the direct axis of the stationary reference frame.
Tr rotor time constant.

The expression for the electrical torque *Te* in this reference frame is shown in 7.

$$Te = \frac{3}{2} p \frac{L^2 o}{Lr} |\mathrm{Im}r| \cdot Isy \tag{7}$$

3. ON LINE PARAMETER ESTIMATION

The Extended Kalman Filter (EKF) is the most popular algorithm for estimating physical parameters together with state variables. However, it is well known that in the induction motor model, it is not possible to identify all parameters.(Besacon G. 2001)

It allows the state-vector to be extended with three variables (Rs, Rr and L0).

Finally the state-vector is formed by eight variables (8):

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} = \begin{bmatrix} i_{Sa}(t) \\ i_{Sb}(t) \\ i_{Ra}(t) \\ i_{Rb}(t) \\ \omega(t) \\ Rs \\ Rr \\ Lo \end{bmatrix} \tag{8}$$

The model must be linearized with respect to the estimated extended state (9).

$$\begin{aligned} \hat{x}_{k+1} &= f(\hat{x}_k) \cdot \hat{x}_k + W \\ y_{k+1} &= h(\hat{x}_k) \cdot \hat{x}_k + V \end{aligned} \tag{9}$$

Where the process W and measurements V noise vector are assumed to be gaussian and characterised by mean null.

With $\tilde{x}_k = \hat{x}_k - x_k$ as the estimation error and with the following Jacobian matrices ∇f_{xk} y ∇h_{xk} (10)

$$\begin{aligned} \nabla f_{xk} &= \frac{\partial f(\hat{x}_k)}{\partial \hat{x}_k} \\ \nabla h_{xk} &= \frac{\partial h(\hat{x}_k)}{\partial \hat{x}_k} \end{aligned} \tag{10}$$

the extended Kalman filter equations are (11):

$$\hat{x}^*_k = f(\hat{x}_{k-1}, u_k, 0)$$

$$P^*_k = \nabla f_{xk} P_k \cdot \nabla f_{xk}^{\ T} + Q_k$$

$$K_k = P_k^* \cdot \nabla h_{xk}^T \cdot \left(\nabla h_{xk} \cdot P_k^* \cdot \nabla h_{xk}^T + R_k \right)^{-1}$$

$$\hat{x}_k = \hat{x}^*_k + K_k \cdot \left[z_k - h\left(\hat{x}^*_k, 0 \right) \right]$$

$$P^*_k = \left(I - K_k \cdot \nabla h_{xk} \right) P_k^* \tag{11}$$

where Q and R are the process and the measurement covariance matrices respectively. Z_k is the measurement and I the identity matrix.

The Runge-Kutta method (Mathews J. and Fink K. D. 1999) has been used to solve the discrete-time model of the motor in the equation (10).

As the correct matrices Q and R cannot be chosen based on classical theories, they are usually tuned experimentally by a trial-and-error method.

4. FAULT DETECTION METHOD

A classical scheme implemented for diagnosis based on an EKF can be seen in figure 1. The new scheme incorporates parity equations and parameter estimation blocks. In this implementation, parameter estimation and fault detection are feedback on the control system based on a FOC algorithm.

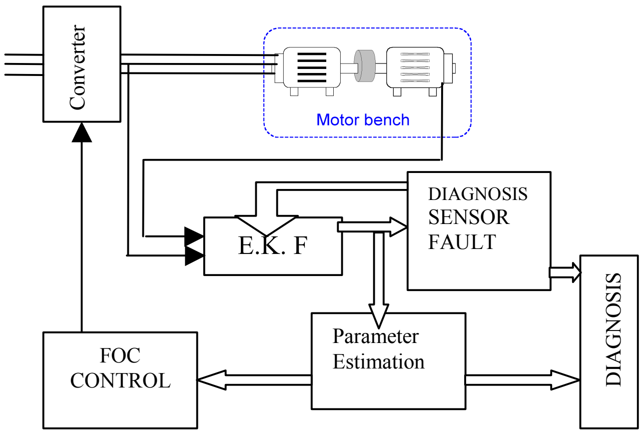

Fig. 1. Scheme of diagnosis and control System.

Two methods are used for fault detection. Parity relations are rearranged directly from input-output model equations for sensor faults and, on the other hand, changes of the electrical parameter associated to short circuits in the winding and broken rotor bars. (Mendoza A. et al, 2003; Moreau, S. et al 1999) are detected and isolated by parameter estimation.

We consider the follow faults:

- Additive faults
  - Current sensor
  - Velocity sensor
- Multiplicative faults
  - Changes in the parameters

4.1 Residual generation

Residuals are obtained from the state-space model. The model equations are written using a reference frame fixed to the stator, applying the Clarke transformation (12). It is analogous for rotor currents and voltage.

$$\begin{bmatrix} \hat{y}_R \\ \hat{y}_S \\ \hat{y}_T \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ -0.5 & \frac{\sqrt{3}}{2} \\ -0.5 & -\frac{\sqrt{3}}{2} \end{bmatrix} \cdot \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \end{bmatrix} \quad (12)$$

Primary set residuals are obtained by simple comparison of each of the discretized state equations, (resy1, resy2, resy2, resw) and resy0 is a general result obtained for balanced power systems. (13)

$$\begin{bmatrix} resy1 \\ resy2 \\ resy3 \\ resy0 \\ resw \end{bmatrix} = \begin{bmatrix} y_{Rm} \\ y_{Sm} \\ y_{Tm} \\ y_{Rm} + y_{Sm} + y_{Tm} \\ y_{3m} \end{bmatrix} - \begin{bmatrix} \hat{y}_R \\ \hat{y}_S \\ \hat{y}_T \\ 1 \\ \hat{y}_3 \end{bmatrix} \quad (13)$$

One more residual is defined for the mechanical equation. (14)

$$resmec = M_l + fr \cdot w - \frac{3 \cdot \hat{L}o \cdot p}{2 \cdot} \left(\hat{i}_{sb} \cdot \hat{i}_{ra} - \hat{i}_{sa} \cdot \hat{i}_{rb} \right) \quad (14)$$

4.2 Parameter estimation

Parameter estimation based on on-line identification is a natural approach to the detection of parametric faults. (Xiang-Qun, L. et al 2000; Attaianese, C. et al 1998) This allows the fault size to be measured independently of the operation point.

5.RESULTS

The motor bench is composed of two AC motors of 5.5 Kw placed one in front of the other with an elastic coupling.

Fig. 2. Motor bench

The motor bench is shown in Figure 2. It is composed of two motors. The first is the motor used in our research. The second acts as the load. A commercial ABB inverter controls this motor. The load torque can be selected in the control panel of the inverter, adding a chopper card to it and a group of resistors that act as a release for the absorbed energy of the load motor working in the fourth quadrant (positive speed and negative torque).

The Motor Parameters used are:

5.kW
Frequency=50 Hz.
Rs=1.15 Ohm
Rr=0.95 Ohm
Ls1= 0.0052 H
Lr1= 0.0028 H
L0=0.18 H
*J =0.225 kg*m^2*

The hardware used consists of an RTI real time control and acquisition card installed (DSPACE) in a Pentium II 450 MHz personal computer. The sampling time is 0.00015 s.

This hardware is programmed via Simulink using the standard Simulink blocks and a special toolbox, named RTI, which includes special Simulink blocks to manage input-output channels, generate PWM, manage the encoder etc...

5.1 Sensor faults.

Figure 3 shows a situation with a broken current sensor in R-phase. Residuals resy1 and resy0, allow this fault to be isolated.

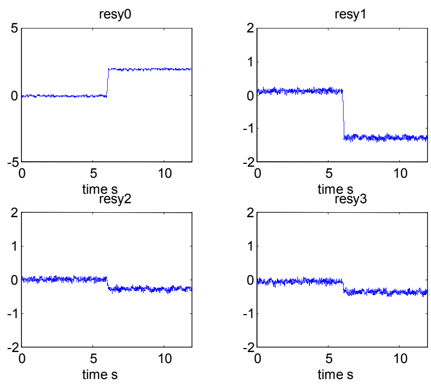

Fig. 3. Residual evolution (resy0, resy1, resy2, resy3)

This result can be generalised for S and T phases, where residuals resy2 and resy3 respectively allow these faults to be isolated. A good detection of a broken sensor or biased sensor has been obtained. The remaining residues are not modified.

Similar results are obtained for a speed sensor fault. In figure 4, residual evolution (resw and resmec) is shown for this situation. The residue resw is the only one that is modified when the failure appears in the speed sensor.

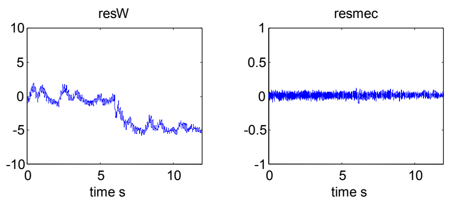

Fig. 4. Residual evolution (resy0, resy1, resy2, resy3)

Table 1 is the incidence matrix. The diagnostic structure is sensible and strongly isolates all sensor faults.

Table 1 Residual values for additive faults.

FAULT	RESIDUE resy0	resy1	resy2	Resy3	resw	resmec
Phase R Current sensor	1	1	0	0	0	1
Phase S Current sensor	1	0	1	0	0	1
Phase T Current sensor	1	0	0	1	0	1
Speed sensor	0	0	0	0	1	0

5.2 Decision module

When a fault occurs on the controlled motor, the parameters and state variables observed with EKF have unreal values and the system finally becomes unstable. For this reason, it is important to reconfigure the system to maintain the motor's good performance.

5.2.1 Speed sensor fault

When the speed sensor fails, the Extended Kalman Filter is substituted for a Kalman Filter that does not include the motor parameters (Rs, Rr and Lo) in the state vector. It allows the control conditions to be improved, but the FOC is not able to update with the estimated Kalman Filter parameters.

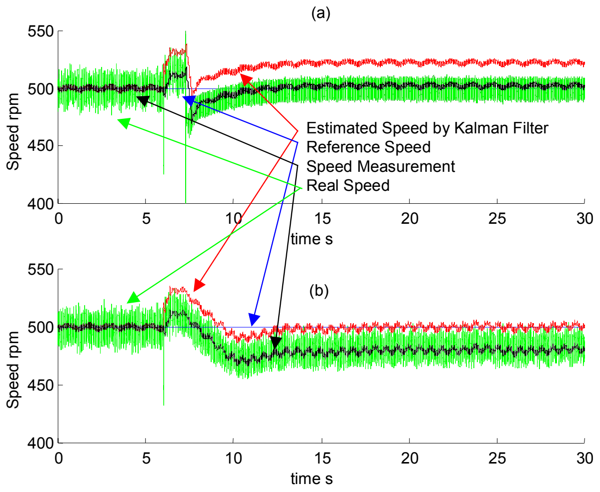

Fig. 5. Evolution when a fault appears at time 6s.
a) Reconfiguring Kalman Filter b) Without reconfiguring Kalman Filter.

In this case, the Kalman Filter is only used as a speed observer. In figure 5, a speed measurement fault with a 20 rpm bias is provoked at time 6s.

Figure 5.a) shows the speed when the fault is not detected. The control system uses a bad speed measurement, and finally the motor runs with a speed deviation. In figure 5.b) the fault is detected and a Kalman Filter is used as a speed observer. The motor achieves a speed reference, although the speed sensor gives an erroneous measurement.

5.2.2 A current sensor fault

In this case, when a current sensor fault exists, it makes the speed estimation worse. When the diagnosis system detects and isolates the faulty sensor, its signal is calculated with the other current measurements using Ir+Is+It=0. It is valid because the motor is connected on star without neutral connection

In table 2, the estimated speed variance is shown. It is reduced when the Extended Kalman Filter uses a calculated current measurement in the fault situation. When the fault is isolated, the reduction in the value of the estimated speed variance is greater than 50%.

Table 2 Speed estimated variance values

State of Motor	State diagnosis System	Estimated Speed Variance
Good condition.	No fault	58.97
R current sensor fault	No fault	711.99
R current sensor fault	Isolated Fault	**303.74**

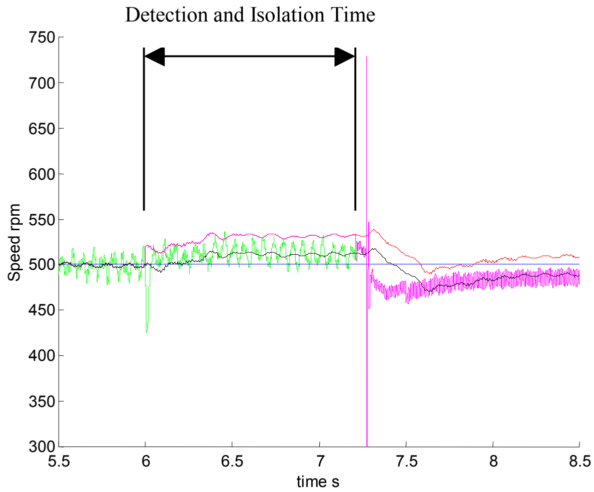

Fig. 6. Detection and Isolation Time when a fault occurs.

It is well known that the detection and isolation time is a fundamental characteristic of every diagnosis system to guarantee good performance. When a fault appears, especially if the diagnosis is used in the control system, a compromise between false alarms and decision time will be necessary. (Patton 93)(Patton 97)

In figure 6, the evolution of speed is shown. The fault takes place at time 6 seconds. Then, detection and isolation algorithm needs about 1.2 seconds to diagnose the fault. Just after diagnosis is carried out, the reconfiguring system based on Kalman filter is activated.

6. CONCLUSIONS.

Following CARTIF motors Group previous works, an extended Kalman Filter has been used simultaneously in two fields: control and diagnosis. Parameter estimation is used in the FOC and parity equations are used as a residual generator. In addition, a decision module is used to reconfigure the Kalman Filter. It allows an acceptable performance of the motor when a sensor fault occurs. The method has been tested on a real A.C. motor, obtaining good results.

Future work will include an active fault tolerant control based on the diagnosis information and on-line parameter estimation, of the whole converter-motor plant.

7. ACKNOWLEDGEMENT

This work was supported by the CICYT research project nº TAP2001-0725 titled "Diagnóstico automático de motores de A.C. Con variadores de velocidad".

REFERENCES

Arnanz, R. et al (2000). *Fault diagnosis in A.C. motors.* SAFEPROCESS2000 pp.1145-1150.

Attaianese, C. et al. (1998). *Induction motor drive parameters identification.* IEEE Transactions on power electronics, Vol. 13, No.6, pp.1112-1122.

Bacher S. et all (2001a) *Stator Fault Diagnosis in Induction Machines by Parameter Estimation* IEEE SDEMPED'01.

Bacher S. et all (2001b) Induction Motor *Modeling of Broken Rotors Bars and Fault Detection by Parameter Estimation* IEEE SDEMPED'01.

Besancon, G.(2001). *On line full state and parameter estimation in induction motor and application in control and monitoring.* ECC2001 pp.2313-2317

Chen J., Patton R.J., (1999). *Robust model-based fault diagnosis for dynamic systems.* Kluwer Academic Publishers.

Eltabach M., Charara M. Ismael Zein (2002), *Kalman filtering and torque spectral analisys for borken bar detection in induction motors.* IFAC2002

Filippetti, F. et al (2000). *Recent Developments of induction motor drives fault diagnosis using AI techniques.* IEEE Transactions on industrial electronics, Vol. 47, No.5, pp.994-1004.

Getler J., (1998). *Fault Detection and Diagnosis in Engineering en Systems.* Marcel Dekker.

Getler J.and Yongtong H.(2000).*Diagnosing parametric fault in induction motors with nonlinear parity relations.* SAFEPROCESS2000 pp.992-997

Grover R., Hwang P., (1985). *Introduction to random signals and applied Kalman filtering.* John Wiley & Sons

Hajiyev C. M. and Caliskan F., (1999) *Fautl diagnosis in dynamic systems via kalman filter innovation sequence. IFAC1999.*

Lapeyre, F. et al.(1997) *Fault detection in induction motor via parameter estimation techniques.* SAFEPROCESS1997. pp.270-275

Leonhard, W. (1996). *Control of Electrical Drivers* Springer-Verlag. Berlin.

Mathews J. H., Fink K. D. (1999) *Métodos numéricos con Matlab.* Prentice Hall.

Mendoza A. et al (2003). *Online Diagnosis of induction motor for additive and short-circuit windings with extended Kalman filter* SAFEPROCESS2003.

Moreau S. et al (1999). *Diagnosis of Induction Machines: a procedure for electrical fault detection and localization.* IEEE SDEMPED'99.

Ouhrouche, M. A.(2000) *EKF-Based Estimation of Rotor Flux,Speed and Rotor Resistance in Cage Induction Motor Sensorless Drive.* MS'2000

Pacheco, M.A. et al. (2001). *Diagnosis of A.C. motor with parity equations and neural networks.* ECC2001. pp.499-503.

Patton R. J. (1993). *Robustness issues in fault-tolerant control. TOOLDIAG'93*. Plenary paper.

Patton, R. J. (1997). *Fault-Tolerant control: the 1997 situation (survey).* SAFEPROCESS'97. pp. 1029-1052.

Patton, R. J. (2000). *Multiple model fault tolerant control of an induction motor in the presence of uncertainty.* SAFEPROCESS2000. pp.1139-1144.

P.Krause, O. Wasynczuk,S. Sudhoff (1986). *Analysis of Electric Machinery.* McGraw-Hill.

Sen, P. (1989). *Principles of electrical machines and Power Electronics.* John Wiley & Sons.

Xiang-Qun L. et al (2000). *Fault detection and diagnosis of permanent-magnet DC motor based on parameter estimation and neural network.* IEEE Transactions on industrial electronics, Vol. 47, No.5, pp.1021-1030.

Zamora J.L. et al.(2000). *Online estimation of the stator parameters in an induction motor using only voltage and current measurements.* IEEE Transactions on industry applications, Vol. 36, No.3, pp.805-816.