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Observer-based IM stator fault diagnosis: Experimental validation

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ABSTRACT

In this paper, an experimental validation of an efficient approach to the Fault Detection and Isolation (FDI) of Induction Motor (IM) is proposed. The problem of Inter-turn short circuits (ITSC) in the stator windings is addressed. By introducing fault factors in the IM model an observer-based residual generator is designed, allowing the detection of ITSC in stator windings. The residual generator is built around an extended Kalman Filter (EKF) in order to estimate state variables and fault factors, which permits the evaluation of the severity of the fault. To overcome the problem of tuning the EKF a Partcile swarm Optimisation (PSO) algorithm is developed. It carries out a heuristic search of the noise matrices by optimizing a cost function. The proposed solution is validated by computer simulations and by real-time implementation on dSPACE 1104 Digital Signal Processor (DSP) test-bench under the healthy and the faulty conditions of IM. To perform tests under faulty conditions, an IM with customized design is built and the stator is rewound permitting to create ITSC. The results reveal the quick detection of the faults, the quantification of its severity and confirm the efficacy of this observer-based FDI algorithm.

Keywords: Fault Detection and Isolation, Induction motor model, Inter-turn short circuit, Extended Kalman Filter, PSO algorithm

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1. Introduction

The detection of incipient fault at an early stage is amongst the most important characteristic of a diagnostic system. Fulfilling this task permits avoiding detrimental stopping of the supervised system and accompanying corrective or preventive maintenance. Induction motors are the horsepower of the modern industry, and they are driving a majority of equipment at fixed or variable speed. IM is easy to build, with low cost and is highly reliable. It is subjected to electrical, mechanical and thermal stresses, leading to ITSCs in stator windings, rotor broken bars and static and /or dynamic eccentricity [1], [2]. These abnormalities may cause unacceptable performance degradation and ultimately the IM may fail. Consequently, the condition monitoring of IM is of primordial importance.

Overheating can cause the destruction of the turn insulation, which induces ITSC of stator windings. Therefore, their early detection would reduce the damage to adjacent coils and the down time. Condition monitoring of IM has been reported in many scientific works. Some of them have been traditionally used in industry, as Motor Current-Signature Analysis (MCSA) and Park's Vector in order to extract fault signatures [3], [4], which are widely used thanks to their inherent simplicity. As an alternative, Discrete Wavelet transform (DWT) combined with Hilbert transform is performed in [5] to study faulty motor higher statistical parameters; however a good spectral resolution is required. In [6], a FFT based method is used, in real time, for the detection of IM broken bar. These methods necessitate IM working at constant speed. Furthermore, they are sensitive to supply-voltage unbalance. Signal vibration, combined with classification method, was also used to construct a motor fault diagnosis system based on neural network [7], [8]. However, vibration sensors are expensive and fragile. All the methods cited above are model free and not use the information of the rotor side of IM. The concept of analytical redundancy provides strategies for IM model-based diagnosis [9], [10]. Firstly, dedicated IM models are developed to take into account the fault effects [11], [12]. Thus, Observer-based methods for IM condition monitoring have been developed [13], [14], [15]. In [15], by using sliding mode observer an ITSC in the stator windings detection approach is presented.

Specific vector residuals, obtained by states observers, allowing fault detection and fault severity estimation is proposed in [13], [14]. In [16], [17], the extended Kalman filter (EKF) is used to estimate the rotor resistance, with the aim to detect broken bars. For stator related faults, the state variables and some parameters of the IM model are estimated recursively using EKFs allowing the detection of such faults [18], [19].

The extended Kalman filter (EKF) is an efficient observer which is widely applied to jointly estimate the state vector and some IM parameters[20]. Rotor speed and rotor or stator resistances have been estimated by the EKF or by using an adaptive KF [21], [22], [23], [24]. EKF is also applied to fault-tolerant vector control of PMSM by estimating stator currents, rotor speed and position [25].The most important concern with EKF is the tuning of the state and noise covariance matrices. They are assumed to be white and Gaussian, however no knowledge of theirs values is available. These noises matrices are crucial for the optimal performance of the EKF since they have a great impact on the computation of EKF gain. Trial-and-error method for tuning the EKF, which is commonly used [25] is a tedious one. A Memetic Algorithm is applied [26] in order to adjust the value of the state noise covariance matrix. In [24] the PSO algorithm was used to optimize both the state and measurement noise matrices. A Genetic algorithm has been proposed to estimate EKF parameters in [27].

In this work and to overcome this drawback, a PSO algorithm is developed and applied to the test bed in order to compute the noise covariance matrices. Several experimental tests offer the best covariance noises that permit an optimal EKF functioning.

The contributions, in this work, are as follows:

- An improved IM model is presented in, that three fault factors (fraction of the not short-circuited turns on the stator windings) take into account inter-turn short circuits in stator windings. This model is effective in either healthy or faulty cases. A model of an IM with only one fault factor is then deduced.
- An experimental validation of the proposed IM model is presented. The IM is rewound and different tests are elaborated under the test-bed. The analysis of the experimental results concludes of the effectiveness of the proposed IM model in healthy and faulty situations.
- An EKF-based FDI approach is developed which estimates the fault factor, jointly with the state vector. EKF is tuned via PSO algorithm. An experimental test-bench, based on dSPACE 1104 kit, is used in order to validate this approach.
- Fault detection based on EKF is experimentally validated. Diverse amount of short-circuited turns are applied to the stator winding of the rewound IM. The results recorded via dSPACE1104 kit and Fault detection based on EKF algorithm are analyzed.
- A residual generation is carried out during the experimental tests and permits the detection of the ITSC on stator windings and the evaluation of the severity of the fault on the damaged phase.

This paper is organised as follow: in section 2 an improved IM model is developed in which fault factors are introduced to take account of ITSC in stator windings. The fault detection based on Extended Kalman Filter (EKF) is presented in section 3. Then, the procedure to tune EKF by PSO algorithm and the residual generator are developed. In section 4, computer simulation and implementation on dSPACE 1104 kit are carried out allowing experimental validations of the IM model and the EKF-based fault detection technique. A conclusion ends this work.

2. IM model with stator winding faults

Modelling of IM with ITSCs in stator windings is the first step in the design of the fault detection systems. Many models describing IM with additive or multiplicative faults have been proposed in the literature in [11], [12], [15].

In this section, an IM model which takes into account explicitly the ITSC in stator windings is developed. This model is used to analyze the behavior of IM in healthy and faulty conditions. It provides a simulation tool which permits to avoid the inherently destructive nature of inter-turn short-circuits. For this end, three fault factors f_a, f_b and f_c, defined by (1), are introduced in the IM model.

$$f_i = \frac{n_s - n_{cci}}{n_s},\ i = a, b, c \qquad (1)$$

n_s is the total number of turns in one stator phase. $i = a, b, c$ are the quantity indexes related to phase *A*, *B* or *C* respectively. $n_{cci}$is the number of short-circuited turns in the stator phase i.
The fault factors f_i are the amount of healthy turns to the total number of turns in one stator phase (1). $f_i < 1$ stands for the faulty case and $f_i = 1$ stands for the no faulty one.
The fault factors f_i are included in the stator matrices of resistances, mutual inductances and self-inductances of IM model as follows.

$$R_s = r_s\begin{pmatrix} f_a & 0 & 0 \\ 0 & f_b & 0 \\ 0 & 0 & f_c \end{pmatrix}; M_{sr} = M\begin{pmatrix} f_a c_1 & f_a c_2 & f_a c_3 \\ f_b c_3 & f_b c_1 & f_b c_2 \\ f_c c_2 & f_c c_3 & f_c c_1 \end{pmatrix}; M_{rs} = M_{sr}^T$$

$$M_{ss} = M_s + L_{s\sigma}$$

$$M_s = M\begin{pmatrix} f_a^2 & -0.5 f_a f_b & -0.5 f_a f_c \\ -0.5 f_b f_a & f_b^2 & -0.5 f_b f_c \\ -0.5 f_c f_a & -0.5 f_c f_b & f_c^2 \end{pmatrix}$$

$$L_{s\sigma} = l_{s\sigma}\begin{pmatrix} f_a^2 & 0 & 0 \\ 0 & f_b^2 & 0 \\ 0 & 0 & f_c^2 \end{pmatrix}$$

Where:

$$c_1 = \cos(\theta)\,; c_2 = \cos\left(\theta + \frac{2\pi}{3}\right);\ c_3 = \cos\left(\theta - \frac{2\pi}{3}\right)$$

θ: Stator/rotor angle.

$$R_r = r_r\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}; L_{r\sigma} = l_{r\sigma}\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$M_r = M\begin{pmatrix} 1 & -0.5 & -0.5 \\ -0.5 & 1 & -0.5 \\ -0.5 & -0.5 & 1 \end{pmatrix}; M_{rr} = M_r + L_{r\sigma}$$

$$M\begin{pmatrix} 1 & -0.5 & -0.5 \\ -0.5 & 1 & -0.5 \\ -0.5 & -0.5 & 1 \end{pmatrix}; M_{rr} = M_r + L_{r\sigma}$$

Where: r_s, *M* and $l_{s\sigma}$are the nominal values of the stator resistance, the mutual inductance and the stator leakage inductance, respectively.
r_r is the rotor resistance and $l_{r\sigma}$ is the rotor leakage inductance.
The IM model is based on the conventional assumptions (no saturation of magnetic circuit, sinusoidal distribution of magnetomotive forces and skin effect neglected) [28]. It is described by the following set of equations.

$$U_s = R_s I_s + \frac{d}{dt}(\Phi_s); U_r = R_r I_r + \frac{d}{dt}(\Phi_r) = 0 \qquad (2)$$

$$\Phi_s = M_{ss} I_s + M_{sr} I_r;\ \Phi_r = M_{rr} I_r + M_{rs} I_s \qquad (3)$$

By using (2) and (3), cited before, the state equation of IM model which takes into account the stator faults is then given by:

$$\begin{pmatrix} \dot{I}_s \\ \dot{\Phi}_r \end{pmatrix} = \begin{pmatrix} A_1 & A_2 \\ A_3 & A_4 \end{pmatrix}\begin{pmatrix} I_s \\ \Phi_r \end{pmatrix} + \begin{pmatrix} B_0 \\ 0_3 \end{pmatrix} U_s \qquad (4)$$

Where:

$$I_s = (I_{sa} \quad I_{sb} \quad I_{sc})^T \; ; \Phi_r = (\Phi_{ra} \quad \Phi_{rb} \quad \Phi_{rc})^T$$

$I_s$andΦ_r are the stator currents and rotor fluxes vectors respectively.
The matrices A_1, A_2, A_3, A_4 and $B_0$are given thereafter:

$A_1 = (M_{ss} - M_{sr}M_{rr}^{-1}M_{rs})^{-1}\left(\dot{M}_{sr}M_{rr}^{-1}M_{rs} + M_{sr}M_{rr}^{-1}R_rM_{rr}^{-1}M_{rs} + M_{sr}M_{rr}^{-1}\dot{M}_{rs} - R_s\right).$
$A_2 = (M_{ss} - M_{sr}M_{rr}^{-1}M_{rs})^{-1}\left(-\dot{M}_{sr}M_{rr}^{-1} + M_{sr}M_{rr}^{-1}R_rM_{rr}^{-1}\right).$
$A_3 = R_rM_{rr}^{-1}M_{rs}.$
$A_4 = -R_rM_{rr}^{-1}.$
$B = (M_{ss} - M_{sr}M_{rr}^{-1}M_{rs})^{-1}.$
0_3: 3×3 zero matrix.

These matrices are not symmetric and depend on the angle *θ,* which is time varying. To obtain a model with constant matrices, the *T* transform described by (5) is proposed. This matrix is bloc-diagonal, invertible and orthogonal.

$$T = \begin{pmatrix} P_0 & 0_3 \\ 0_3 & P_0T_0 \end{pmatrix} \qquad (5)$$

P_0 is the Concordia matrix and *T_0* is the matrix proposed in [11], [15].

$$P_0 = \sqrt{\frac{1}{6}}\begin{pmatrix} 2 & -1 & -1 \\ 0 & \sqrt{3} & -\sqrt{3} \\ \sqrt{2} & \sqrt{2} & \sqrt{2} \end{pmatrix}$$

$$T_0 = \frac{2}{3}\begin{pmatrix} c_1 & c_2 & c_3 \\ c_3 & c_1 & c_2 \\ c_2 & c_3 & c_1 \end{pmatrix} + \frac{1}{3}\begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \qquad (6)$$

The coefficients c_1, c_2, and c_3 have been expressed above.
We propose an improved compact form of the IM state space model (7) resulting from the application of the *T* transform to (4). This model is characterized by two important features; it is able to account the faulty or healthy situations and its matrices are independent on the stator / rotor angle *θ*.

$$\begin{cases} \dot{X}(t) = f(X(t), f_i, U(t)) = f_1(X(t), f_i)X(t) + g(f_i)U(t) \\ Y(t) = CX(t) \end{cases} \qquad (7)$$

Where:

$$f_1 = \begin{pmatrix} P_0A_1P_0^{-1} & P_0A_2T_0^{-1}P_0^{-1} \\ P_0T_0A_3P_0^{-1} & P_0\dot{T}_0T_0^{-1}P_0^{-1} + P_0T_0A_4T_0^{-1}P_0^{-1} \end{pmatrix}$$

$$g(f_i) = \begin{pmatrix} P_0B_0P_0^{-1} \\ 0_3 \end{pmatrix}$$

The input vector is: $U(t) = (U_{ds} \quad U_{qs})^TandC = (I_3 \quad 0_3)$
The transformed state vector X is defined by the following equation.

$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = T\begin{pmatrix} I_s \\ \Phi_r \end{pmatrix}$$

Where: $X_1 = (I_{ds}^* \quad I_{qs}^*)^T$ and $X_2 = (\Phi_{dr}^* \quad \Phi_{qr}^* \quad \Phi_{or}^*)^T$

By examining the IM model (7), we note that the third component of X_2 (the homopolar rotor flux) is decoupled from all the other state variables; therefore it is not necessary to include it in the final model.
In the next part, the IM model with an ITSC in the stator windings in the phase A is deduced from (7). Its matrices are given on the appendix B.

2.1. IM stochastic model with stator winding faults

A discrete stochastic IM model is derived taking account of noise effects on state and output variables. The noises are assumed to be zero-mean, white and uncorrelated between them, similarly between the state vector and the input vector. In addition, under the assumption that the rotor speed is measured and is constant between two sampling times, the discretization of the improved IM model given on appendix B is computed using second order Taylor expansion; the obtained model is given below.

$$\begin{cases} X(k+1) = f(X(k), f_a, U(k)) + W_d(k) \\ Y(k+1) = CX(k+1) + V_d(k) \end{cases} \quad (8)$$

Where: W_d and V_d is the covariance of state and measurement noise vector respectively.
The discretized improved IM model (8) has a multiplicative fault form and is assumed to be detectable. It is used to design the EKF for the estimation of the fault factor on phase A.

3. Fault detection based on EKF

The fault diagnosis task is a main issue in the global design of a process. It permits to increase safety and reliability. Early detection, isolation and evaluation of the severity of the fault are of great consequence. An observer-based FDI approach, using an EKF, is proposed here to detect inter-turn short circuits on the stator winding.
An important feature of the EKF is its ability to jointly estimate the state vector and some parameters of the model. In this work, EKF is developed to estimate state variables and a fault factor f_a. This is done by considering the improved IM model (8) and is obtained by appending unknown fault factor into the state vector (10) with the assumption that it has no dynamic (13). The extended IM model becomes, then, nonlinear. The implementation of EKF algorithm is performed by a linearization that is achieved by the computation of the Jacobean matrices with respect to the extended state estimated vector.
The EKF gain K is provided through a solving of Riccati equation, given by equation (12). Then, the variance of the error between state variables and their estimates P (11) will be minimal [29].

$$X_e(k) = (x_1 x_2 x_3 x_4 f_a)^T = \left(I_{ds}^* I_{qs}^* \Phi_{dr}^* \Phi_{qr}^* f_a\right)^T \quad (10)$$

$$P(k) = E[(X_e - \hat{X}_e)(X_e - \hat{X}_e)^T] \quad (11)$$

$$\dot{P} = \left(\frac{\partial f_e(X_e,\Omega)}{\partial X_e}\bigg|_{X_e}\right) P \left(\frac{f_e(X_e,\Omega)}{\partial X_e}\bigg|_{X_e}\right)^T + W_d \quad (12)$$

Where:

$$f_e(X_e, \Omega) = \begin{pmatrix} f_1(X_e, \Omega) & 0_{4\times1} \\ 0_{1\times5} & 1 \end{pmatrix} X_e(k) + \begin{pmatrix} g(f_a) \\ 0 \end{pmatrix} U(k) \quad (13)$$

$$\hat{X}_e(k) = (\hat{x}_1 \hat{x}_2 \hat{x}_3 \hat{x}_4 \hat{f}_a)^T = (\hat{I}_{ds}^* \hat{I}_{qs}^* \hat{\Phi}_{dr}^* \hat{\Phi}_{qr}^* \hat{f}_a)^T \quad (14)$$

The EKFs algorithm is then summarized below:

Initialization step

$$\hat{X}_{e0}(k/k) = (\hat{I}^*_{dqs_0} \quad \widehat{\Phi}^*_{dqr_0} \quad 1)^T;\ P(k/k) = P_0 \ (15)$$

Prediction step

$$\hat{X}_e(k+1/k) = f(\hat{X}_e(k/k)), U(k)) \quad (16)$$

$$P(k+1/k) = \frac{\partial f_e}{\partial \hat{X}_e}\bigg|_{\hat{X}_e(k+1/k))} P(k/k) \frac{\partial f_e}{\partial \hat{X}_e}\bigg|^T_{\hat{X}_e(k+1/k))} + W_d \quad (17)$$

Computation of EKF gain step

$$K(k+1/k+1) = P(k+1/k)C_d^T(C_d P(k+1/k)C_d^T + V_d)^{-1}(18)$$

Correction step

$$\hat{X}_e(k+1/k+1) = \hat{X}_e(k+1/k) + K(Y(k+1/k+1) - \hat{Y}(k+1/k))(19)$$

$$\hat{Y}(k+1/k) = C_d \hat{X}_e(k+1/k)$$

Computation of the estimation error variance step

$$P(k+1/k+1) = (I_5 - KC_d)P(k+1/k) \quad (20)$$

Where: $P(k+1/k)$ is the covariance of the prediction error matrix $P(k+1/k+1)$ is the variance of the estimation error matrix. $P_0$and X_{e0} are the initial values of the covariance of the prediction error matrix and the prediction state vector respectively. K is the EKF gain. I_5 is the (5x5) identity matrix.

3.1. EKF tuning by PSO algorithm

The particle swarm optimization (PSO) is a metaheuristic search approach inspired by the communication of a set of birds or fish during their food search; firstly, it was introduced by [30]. PSO is global search algorithm. It was applied to solve the optimization problem encountered in the parameters Identification of the IM by [31]. PSO was also applied in order to tune the EKF and AKF, which permits the estimation of the IM rotor speed [24].

PSO is a global optimization technique in which the swarm (the population) is constituted by a number of particles. The particles coordinates are the candidate solutions of the optimization issue. In this work, PSO is applied for EKF tuning issue; the covariance of the state and measurement noise W_d and V_d are the required particles coordinates as shown in Figure 1. The detailed structure of PSO algorithm is developed in [31].

The appreciation of EKF performance is evaluated by the cost function J given in (21); it is carried out, automatically by PSO algorithm, under various values of $W_d$and V_d.

$$J = \min \frac{1}{N}\sum_{k=1}^{N}\left(I_{sd}(k) - \hat{I}_{sd}(k)\right)^2 + \left(I_{sq}(k) - \hat{I}_{sq}(k)\right)^2 + \left(f_a - \hat{f}_a(k)\right)^2 \quad (21)$$

N : is the number of sampled data in iteration.

In addition of the measured stator currents, the fault factor is introduced in the cost function J to increase the precision of the PSO algorithm. Firstly, the EKF tuning method by PSO is applied in the case of healthy IM, is to say $f_a = 1$ (no fault), as presented in the Figure 1. Since various iterations are necessary to PSO to reach the best solution, it must be running off line using the IM stator currents collected under the test-bed. Then, the obtained values of the covariance of the state and measurement noise W_d and V_d are introduced in the EKF to estimate, on line, the extended state vector in the case of healthy and faulty IM resumed in table 1 and in§3.2. The studies of the obtained results with several applied stator ITSC (short circuited) show the effectiveness of the EKF tuning by PSO method.

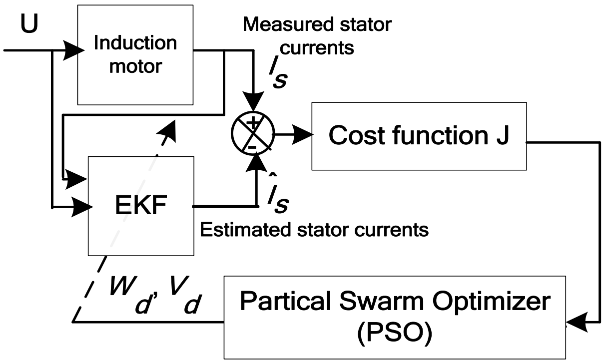


Figure 1.Schematic representation of EKF tuning by PSO algorithm.

3.2. Residual generation

The generation of residuals is an important step in FDI based on analytical redundancy. Residuals are signals indicating the inconsistency between measured data and those provided by the model of the supervised system [32]. In no fault case, residuals are identically zero; when a fault occurs they become different from zero. In addition, residuals must be insensitive to disturbances.
In this work, the residual is based on (22). It traduces the discrepancy between estimated fault factor, provided by EKF, and its value in healthy case, that is equal to 1.

$$r = f_a - \hat{f}_a = 1 - \hat{f}_a \qquad (22)$$

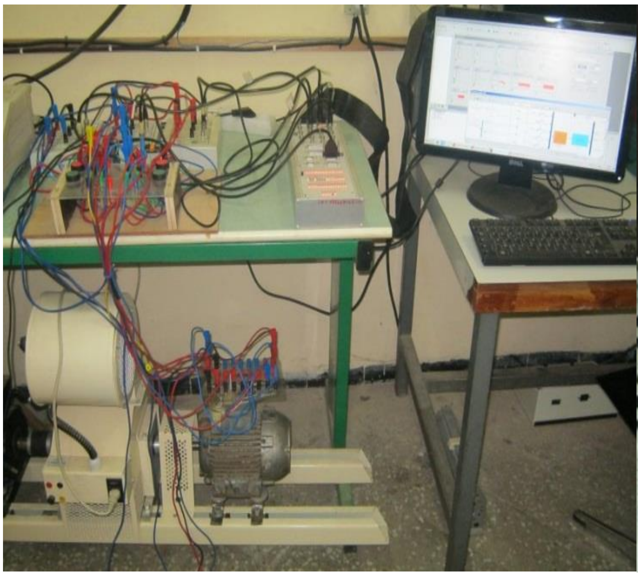
For a healthy IM, the fault factor is equal to one; therefore the residual signal is zero when no fault has occurred. When an ITSC in stator windings takes place, the residual becomes different from zero. The amplitude of this residual permits the evaluation of the fault severity.

4. Experimental validation results

In this section, numerical simulation and experimental validation of the proposed EKF-based FDI approach are presented. First, the validation of IM mathematical model is carried out. Then, several scenario of the occurrence of the fault are experimented, by numerical simulation and with the test-bench. The test-bench given in Figure 2.a is used to make easy experimental investigation. The three-phase squirrel cage IM, PEDROLLO K80A4, 0.55 kW, 380 V, 4 poles is opted for in this work. Each stator phase contains 4 coils of 132 turns connected in series. The IM is rewound, and a small amount of stator turn outputs are made to create a number of short circuits as shown in the Figure 2.b. The star connected IM is fed by a 50Hz sinusoidal source voltage via a three-phase autotransformer. The IM used in simulation and in the test-bench have the same parameters, listed in the appendix A.
The stator phase currents and voltages are measured via Hall-Effect sensors, and an encoder of 1024 counts/r is used to measure the IM speed. Two A/D converters, 12 bits four channels and 16 bits four channels multiplexed, were used. The measured signals were filtered by the anti-aliasing low pass filters. EKF observer is implemented, by means of C-Language, on the dSPACE1104 platform operating on a host PC linked to external signals by an interface board.

4.1. Validation of IM model with ITSC

The experimental validation of the IM mathematical model given by (8) is presented. Next, ITSCs on the phase *A* are provoked. After that, different tests for the detection of the fault and the estimation of its severity are performed by EKF-based FDI.
Short-circuits of respectively 6, 24 and 30 stator turns are applied to the phase *A* of the IM. They correspond to the values of the fault factor f_a, defined by (1) and given in the first column of the table 1. The test-bed previously presented allows recording the three stator currents. They are compared to those obtained by simulation. The RMS values of the measured and simulated stator currents in healthy and faulty situations are recapitulated in the table 1.



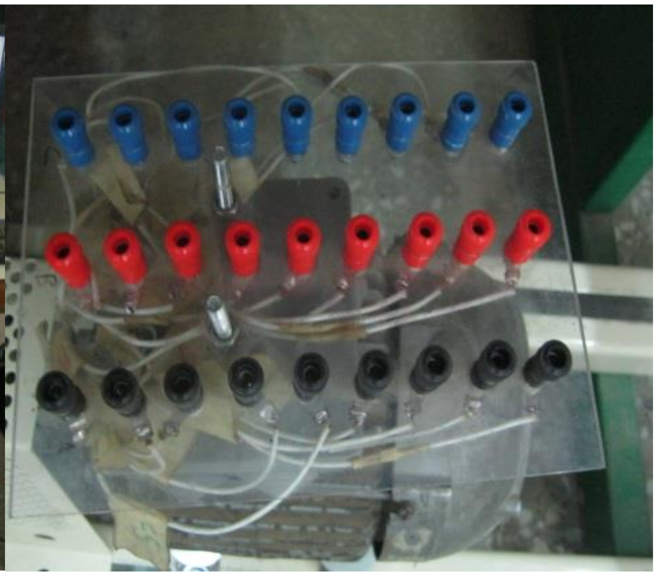


Figure 2.aThe test-bed Figure 2.b Rewound IM

Table 1 RMS values of the measured and simulated currents on phase *A*, *B* and *C*.

f_a	Number of turns Short-circuited on phase *A*	Percentage of ITSC on phase *A*	$\bar{I}_{sa\_m}$	$\bar{I}_{sb\_m}$	$\bar{I}_{sc\_m}$	$\bar{I}_{sa\_s}$	$\bar{I}_{sb\_s}$	$\bar{I}_{sc\_s}$
1	0	0	1.057	1.138	1.031	1.074	1.074	1.074
0.98	6	1.13	1.231	1.154	1.098	1.156	1.04	1.036
0.95	24	4.54	1.504	1.085	1.09	1.422	0.938	0.9197
0.94	30	5.68	1.606	1.058	1.082	1.517	0.904	0.8804

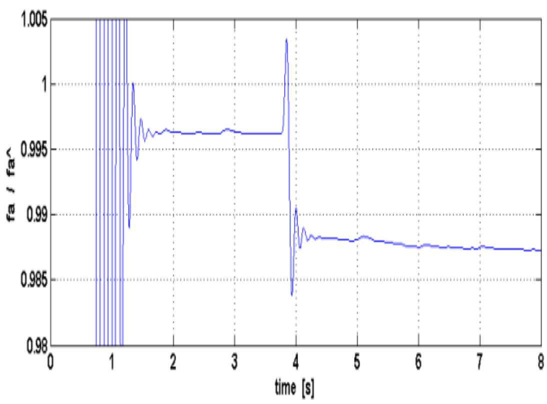
Where: $\bar{I}_{si\_m}$ is the RMS value of the measured three stator current of the rewound IM and $\bar{I}_{si\_s}$ is the RMS value of the simulated one by the proposed mathematical IM model, *i* = *a*, *b* or *c*.

The results illustrated in table 1, show that the RMS values of measured currents are close to those given by IM model in healthy and faulty situation. The difference between them has several sources, such as the inherit imperfection of conditioning circuits and the modeling errors. The obtained results show the well matching between the simulated and the experimental data. Therefore, the improved IM model used in this work has good prediction of the behavior of the IM under healthy and faulty conditions, permitting to validate the effectiveness of the proposed IM model.

4.2. Experimental of the EKF-based residual generation FDI approach

In this section, experimental results, obtained in test-bench, are provided in order to confirm the effectiveness of the EKF-based FDI approach. EKF estimates state variables and fault factor, permitting residual generation. The severity of the fault is then evaluated.

Two set of tests were carried out. In The first one, a unique fault, at different level of severity, occurs in the phase *A* of the rewound IM. In fact, an amount of 0 (healthy), 6, 24, and 30 ITSC turns were intentionally provoked including the transient state. The estimated fault factor $\hat{f}_a$ and the residual r, achieved with this scenario are shown in the Figures 2.a to 4.a and in the Figures 2.b to 4.brespectively. The obtained results show, in all cases of ITSC considered above, the good estimation of the fault factor and the residuals which permit the evaluation of the fault severity.



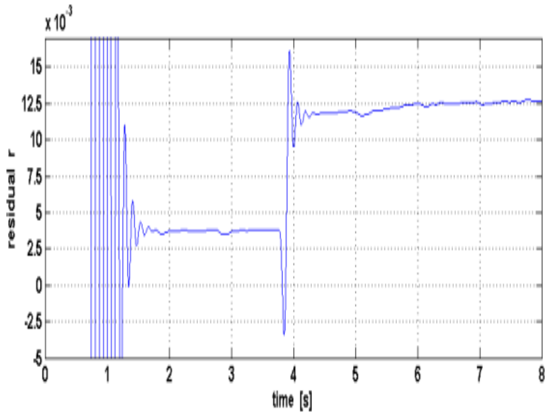
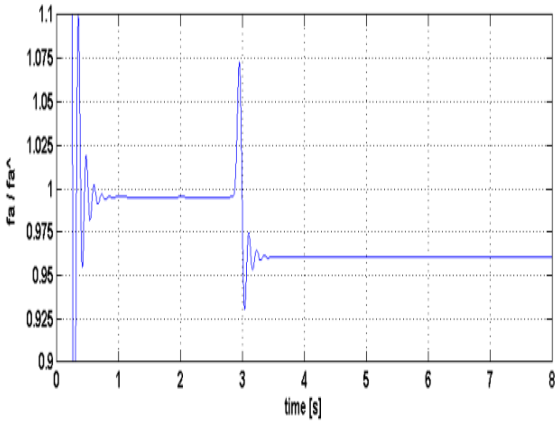


Figure 2.a. $\hat{f}_a$ behaviour in healthy IM case and in SITSC of 6 turns

Figure 2.b. Residual behaviour in healthy IM case and in SITSC of 6 turns



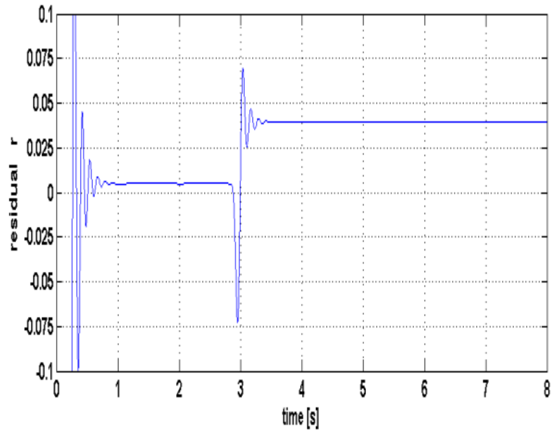
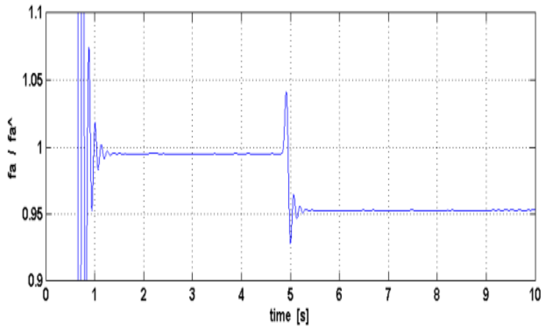


Figure 3.a. $\hat{f}_a$ behaviour in healthy IM case and in SITSC of 24 turns

Figure3. b. Residual behaviour in healthy IM case and in SITSC of 24 turns



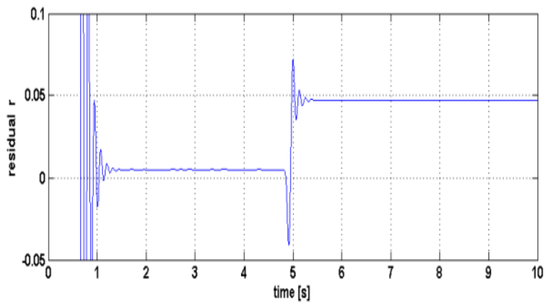
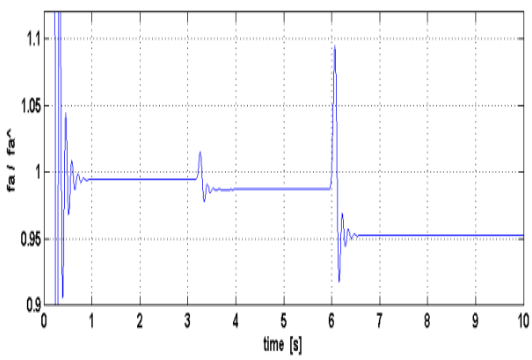


Figure 4.a. $\hat{f}_a$ behaviour in healthy IM case and in SITSC of 30 turns

Figure 4.b. Residual behaviour in healthy IM case and in SITSC of 30 turns

The scenario adopted for the second set is as follows: the IM is run healthy (without ITSC), after 3 seconds a fault of 6 ITSC turns occurs, followed by a fault of 30 ITSC turns at about 6 seconds.

The Figure 3 and Figure 4 illustrate the obtained results by means of the test-bench.



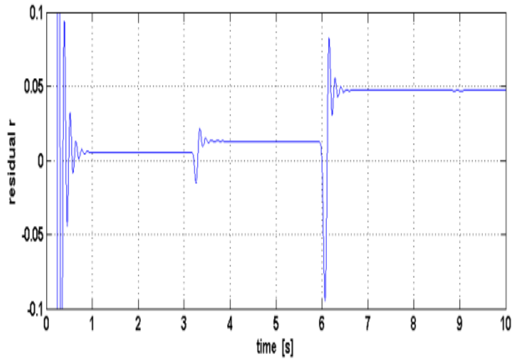


Figure.5.a.$\hat{f}_a$behaviour in healthy IM case and in SITSC of 6 and 30 turns

Figure. 5.b. Residual behaviour in healthy IM case and in SITSC of 6 and30 turns

The Figure 6 shows the three-phase stator currents recorded during this experience. The consequence of the ITSC of 6 turns provoked on the rewound IM appears by a little rise on the magnitude of the faulty phase current. On the other hand, the current magnitude of the phase under an ITSC of 30 turns increases more. This fact is more significant in the residual r, which is more interesting in the sense that, it indicates the occurrence of the fault.

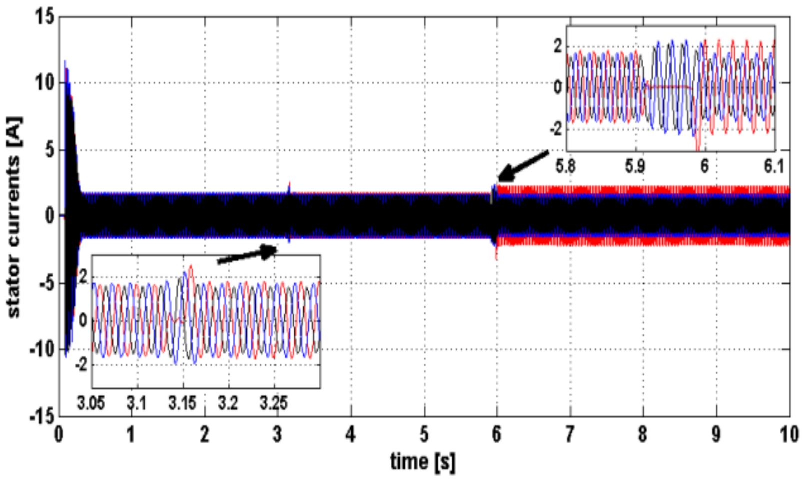


Figure 6. Filtred stator currents in healthy IM and in SITSC of 6 and 30 turns

5. Conclusion

Fault diagnosis became an important topic in electrical machine. The quick detection of fault can avoid detrimental breakdown and save safety of persons and equipment.

In this work, an EKF-based FDI approach has been developed. First, an improved IM model with ITSC in stator windings has been performed and experimentally validated on a rewound IM. This model has allowed analyzing the behavior of IM in both healthy and faulty circumstances. Next, the proposed EKF-based FDI approach has been implemented (programmed in C-Language) on dSPACE 1104 environment. A PSO algorithm was used to tune the EKF permitting suitably selecting the noise covariance matrices. EKF has provided the estimation of the state vector and the fault factors. It has permitted the residual generation which has achieved not only the fault detection but also the fault severity evaluation. Experiments and computer simulation have highlighted the effectiveness of the proposed approach and have validated successfully its well working.

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Appendix A

The parameters of the IM used in Benchmark are given below.
Stator resistance r_s= 13.63 Ω, Rotor resistance r_r = 13.31 Ω.
Stator inductance M_s = 0.678 H, Rotor inductance M_r = 0.678 H
Stator leakage inductance $l_{s\sigma}$ = 0.039 H, Rotor leakage inductance $l_{r\sigma}$= 0.039 H.
Maximal value of the mutual inductance M = 0.664 H.
Viscous friction coefficient f_v = 0.000643 Ns / rad, Moment of inertia J = 0.002 kg m^2.
Rated speed Ω=1440 rpm. Rated phase current I = 1.6 A, Rated line voltage U = 380 V.
Rated Power P = 0.55 kW, Pole pairs p = 2.

Appendix A

The matrices evolved in the improved IM model described by (7) are detailed beneath.

$$A(f_a, f_b, f_c, \Omega) = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix};\ B(f_a, f_b, f_c) = \begin{pmatrix} B_1 \\ B_2 \end{pmatrix}$$

$$A_{11}(1,1) = \frac{-a_1 - 3a_2 + a_3 + a_4}{3} - \frac{2a_1 - 2a_3 + 2a_4}{3f_a} - \frac{2a_4 f_a}{3}$$

$A_{11}(1,2) = 0$

$A_{11}(2,1) = 0$; $A_{11}(2,2) = -a_2 - a_4 - a_{13}$

$$A_{11}(3,1) = \frac{\sqrt{2}(2a_1 - 3a_4)}{6} + \frac{2\sqrt{2}}{3}a_4 f_a + \frac{\sqrt{2}(-2a_1 + 2a_3 - a_4)}{6f_a}$$
$$A_{11}(3,2) = \frac{\sqrt{6}(a_1 - a_3 + a_4)}{3}$$
$$A_{11}(3,3) = -a_2 + 2\frac{-a_1 - 2a_3 + a_4}{3} + \frac{2a_4 f_a}{3}$$
$$A_{12}(1,1) = a_5 + \frac{2a_5}{f_a};$$
$$A_{12}(1,2) = -\sqrt{3}\frac{a_5 - a_6 p\Omega}{3} + 2\sqrt{3}\frac{a_6 p\Omega}{3f_a}$$
$$A_{12}(2,1) = -\sqrt{3}a_6 p\Omega; A_{12}(2,2) = 3a_5$$
$$A_{21}(1,1) = a_7(2f_a + 1);\ A_{21}(1,2) = 0$$
$$A_{21}(1,3) = -\sqrt{2}a_7(-f_a + 1)$$
$$A_{21}(2,1) = 0; A_{21}(2,2) = 3a_7; A_{21}(2,3) = 0$$
$$A_{22}(1,1) = a_8 - a_9;\ A_{22}(1,2) = -p\Omega;$$
$$A_{22}(2,1) = p\Omega;\ A_{22}(2,2) = a_8 - a_9$$
$$B(1,1) = \frac{b_1}{3}\left(\frac{2}{{f_a}^2} + 1\right) + \frac{b_2}{3}$$
$$B(1,2) = B(2,1) = 0;\ B(2,2) = b_1 - b_2;\ B(4:5,1:2) = 0$$
$$a_1 = \frac{r_s}{3l_r} + \frac{6M^2 r_s + \frac{8}{3}r_s l_r^2 + 8Mr_s l_r}{d_0 d_1};\ a_2 = \frac{6M^2 r_r}{d_0 d_1}$$
$$a_3 = \frac{Mr_s l_r}{d_1 l_s};\ a_4 = \frac{3M^2 R_r}{d_0 d_1};\ a_5 = \frac{2Mr_r}{d_0 d_1}$$
$$a_6 = \frac{\sqrt{3}M}{d_1};\ a_7 = \frac{Mr_r}{d_0};\ a_8 = \frac{-r_r(M + 2l_r)}{l_r d_0}$$
$$a_9 = \frac{-r_r M}{l_r d_0};\ b_1 = \frac{Ml_r + l_s d_0}{l_s(3Ml_r + l_s d_0)};\ b_2 = \frac{Ml_r}{l_s(3Ml_r + l_s d_0)}; d_0 = 3M + 2l_r;\ d_1 = 3Ml_r + l_s$$

Appendix C

List of Symbols

r_s (r_r)	Stator (rotor) resistance (Ω)
$l_{s\sigma}$ ($l_{r\sigma}$)	Stator (rotor) leakage inductance (H)
M	Maximal value of mutual inductance (H)
U_s	Three-phase stator voltages vector (V)
U	Stator voltage in Park frame (V)
I_s	Three-phase stator currents vector (A)
I_r	Three-phase rotor currents vector (A)
Φ_s	Three-phase stator fluxes vector (Wb)
Φ_r	Three-phase rotor fluxes vector (Wb)
I^*_{dqs}	Transformed stator currents vector
Φ^*_{dqr}	Transformed rotor fluxes vector
$\hat{I}^*_{dqs}$	Estimated transformed stator currents vector
$\widehat{\Phi}^*_{dq0r}$	Estimated transformed rotor fluxes vector
θ	Stator/rotor angle.
Ω	Rotor speed

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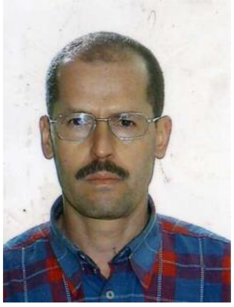

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