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Online Parameters Estimation and Fault Detection of an Induction Machine

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ABSTRACT

This paper presents an approach for estimating the parameters of an induction machine during normal and faulty functionning. The approach is based on the Extended Kalman Filter . Simulations show that we can identify anomalies that can occur at any moment in the functionning such as load fault, power line default and broken bar fault. We can use this approach to reduce the rate of spurious stops, detect machine faults and false alarms and ameliorate the overall process efficiency. Besides, the disturbances that are estimated can be taken into account in the control system of the motor increasing the machine performance.

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Keywords Induction Machine, parameter, Extended kalman Filter

1. INTRODUCTION

Electrical motors, and in particular induction machines are at the heart of a wide varieties of industrial processes. As the International Energy Agency reports[9], around 40 % of the total energy consumed globally is due to electrical motors use. Therefore it is of significant interest to monitor their performance in order to ensure the efficiency of industrial processes[3]. The electrical induction machines of squirrel-cage are the most frequently used because of their hardiness, their simplicity of construction and because they are less costly. Nevertheless, they undergo during their life span a certain number of external or internal solicitations that can make them faltering.

The industrial constraints in reliability, availability and security of the facilities are otherwise very strong. That is why the industrial world is interested strongly by a set of techniques permitting to determine the state of health of these machines. The measure of key variables of a physical process is often of paramount importance when it is necessary to use some control strategies such as return of state , or the monitoring of the system , the diagnosis of shortcoming. However, for technical or economic reasons (difficulty of implementation or elevated cost of the sensors), it is not always possible to measure all state variables ,therefore it is necessary to make use of dynamic auxiliary system, named observer, or software sensor that is is used to estimate the states variable of the system.

The extended Kalman filter technique is suitable for overcoming the effects of uncertainties and nonlinearities of asynchronous motor model. Taking into consideration the system and observation noises, EKF algorithm can achieve the optimal estimation of parameters and states in a very short time for the discrete motor model[10].

The use of EKFs and special observers has proven to be a useful tool to determine parameter variations [7] and sensor faults [1] in electric motor systems. In this paper, it is shown through simulation that the EKF may be used to identify the disturbances present in the currents when the electric motor suffers a failure such as default of power line,load disturbance and a broken bar.

The paper is organized as follows; Section 2 describes the mathematical model of the Induction motor, followed by the description of the EKF in Section 3. Sections 4,5,6 show simulation results, finally Section 7 gives the conclusions.

2. MATHEMATICAL MODEL OF THE INDUCTION MACHINE

The well-known and established d-q dynamic model of a squirrel-cage induction motor is represented by its stator and rotor space phasors voltage equations and stator and rotor flux expressed in terms of stator and rotor currents space phasors[8].

The model presented below takes into account the following hypotheses:

- The fluxes are proportional to currents through the mutual inductances;
- Iron losses are negligible;
- The machine is modelled like a rotating machine, three-phase to the stator and to the rotor;
- The air-gap is uniform and smooth;
- Unsaturated and perfectly flaky magnetic circuit;
- Ferromagnetic losses negligible;

The mathematical model of the induction machine (referred to the d-q axis reference frame) can be expressed as follows:

$$\begin{bmatrix} \dot{i}_{sd} \\ \dot{i}_{sq} \\ \dot{\psi}_{rd} \\ \dot{\psi}_{rq} \\ \dot{\Omega} \end{bmatrix} = \begin{bmatrix} -\gamma i_{sd} + \omega_s i_{sq} + ab\psi_{rd} + bp\Omega\psi_{rq} \\ -\omega_s i_{sd} - \gamma i_{sq} - bp\Omega\psi_{rd} + ab\psi_{rq} \\ aM_{sr} i_{sd} - a\psi_{rd} + (\omega_s - p\Omega)\psi_{rq} \\ aM_{sr} i_{sq} - (\omega_s - p\Omega)\psi_{rd} - a\psi_{rq} \\ m(\psi_{rd} i_{sq} - \psi_{rq} i_{sd}) - c\Omega \end{bmatrix} + \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{1}{J} \end{bmatrix} \begin{bmatrix} u_{sd} \\ u_{sq} \\ T_l \end{bmatrix} \qquad (1)$$

$$\begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{sd} \\ i_{sq} \\ \psi_{rd} \\ \psi_{rq} \\ \Omega \end{bmatrix} \qquad (2)$$

In the d-q axis reference frame, the state vector, the input and output vectors are respectively:

$$x = \begin{bmatrix} i_{sd} \\ i_{sq} \\ \psi_{rd} \\ \psi_{rq} \\ \Omega \end{bmatrix}, u = \begin{bmatrix} u_{sd} \\ u_{sq} \\ T_l \end{bmatrix}, y = \begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix}$$

Where i_{sd} are i_{sq} the stator two-phase d-q axis components of stator currents; ψ_{rd} and ψ_{rq} are the rotor two-phase d-q axis components of rotor flux and Ω rotation speed of the rotor.

$$\gamma = \frac{R_s L_r^2 + R_r M_{sr}^2}{\sigma L_s L_r^2},\ a = \frac{R_r}{L_r},\ b = \frac{M_{sr}}{\sigma L_s L_r},$$

$$m_1 = \frac{1}{\sigma L_s},\ m = \frac{pM_{sr}}{JL_r},\ c = \frac{f_v}{J},\ \sigma = 1 - \frac{M_{sr}^2}{L_s L_r}$$

Here T_l, the load torque is considered like a disturbance.

3. EXTENDED KALMAN FILTER

The extended Kalman filter is a kind of stochastic observer algorithm. Based on the mathematical model of the induction machine, taking into account the statistical characteristics of system and observation noises. We can achieve real time optimal recursive states estimation from the stochastic state space model and measured output in multi-input, multi-output systems[10]. Let us describe the EKF algorithm according to [2].The derivative of the state vector is equal to:

$$\dot{x}(t) = f(x,u,\theta,t) + w(t) \qquad (3)$$

where w is a Gaussian noise of zero mean and covariance matrix Q. The measured outputs z are described by the model

$$z_k = h(x_k) + v_k \qquad (4)$$

where v_k is a Gaussian noise of zero mean and covariance matrix R_k. In this way, EKF is defined in the continuous-discrete form, i.e. the process is continuous and the outputs are discrete as they are measured at sampling times denoted by k, which are in general regularly, but not necessarily, spaced.

In this first approach, the model parameters θ are assumed to be perfectly known; the model can thus be written in simplified form

$$\dot{x}(t) = f(x,u,\theta,t) + w(t) \qquad (5)$$

The problem is to estimate at time k the unmeasured states by using the available process measurements at time $k-1$. The recurrent algorithm of the filter includes two stages:

1. Propagation of the state estimation and the error covariance matrix.

This means that the differential equations describing the variation of the state vector x and the error covariance matrix P are integrated in the time interval $[k-1,k]$ to obtain a prediction, whereas the measurement has not yet been realized. The predictions of $x(t_k)$ and $P(t_k)$ are respectively denoted by $\hat{x}_k(-)$ and $P_k(-)$. The differential equations to be integrated are

$$\dot{\hat{x}}(t) = f(\hat{x},u,t), \hat{x}(0) = x_0 \qquad (6)$$

$$\dot{P}(t) = F(\hat{x},t)P(t) + P(t)F^T(\hat{x},t) + Q(t), \quad \hat{P}(0) = P_0 \qquad (7)$$

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where F is the Jacobian matrix of f equal to

$$F(\hat{x},t) = \left(\frac{\partial f}{\partial x}\right)_{x=\hat{x}} \qquad (8)$$

2. **Update of the state estimation and the error covariance matrix**.

The measurements realized at instant t_k are used to correct the estimations $\hat{x}_k(-)$ and $P_k(-)$ by minimizing the estimation error. The estimations thus corrected, obtained at instant t_k, are denoted by $\hat{x}_k(+)$ and $P(+)$ and are equal to

$$\hat{x}_k(+) = \hat{x}_k(-) + K_k\left[z_k - h(\hat{x}_k(-))\right] \qquad (9)$$

$$P(+) = \left[I - K_k H_k(\hat{x}_k(-))\right]P_k(-) \qquad (10)$$

where H_k is the Jacobian matrix of h equal to

$$H_k(\hat{x}_k(-)) = \left(\frac{\partial h}{\partial x}\right)_{x=\hat{x}(-)} \qquad (11)$$

and K_k is the Kalman gain matrix equal to:

$$K_k = P_k(-)H_k^T(\hat{x}_k(-))\left[H_k(\hat{x}_k(-))P_k(-)H_k^T(\hat{x}_k(-)) + R_k\right]^{-1} \qquad (12)$$

Very frequently, the noise covariance matrices Q and R_k that represent the measurement of the model and measurement uncertainty are assumed to be diagonal. Their adjustment can be done by simulation.

The Kalman gain K can affect in different ways the various estimated states. Indeed, the elements of the Jacobian matrix F represent, through the model, the sensitivity of the different states one to each other.Because of its similarity with the linear Kalman filter, the extended Kalman filter (Fig. 1) i often used although it presents some drawbacks:

- P being only an approximation of the true covariance matrix, the extended Kalman filter performance cannot be guaranteed and its stability cannot be proved.
- The extended Kalman filter equations assume t the process model is exact. No robustness is guarante against modelling errors.

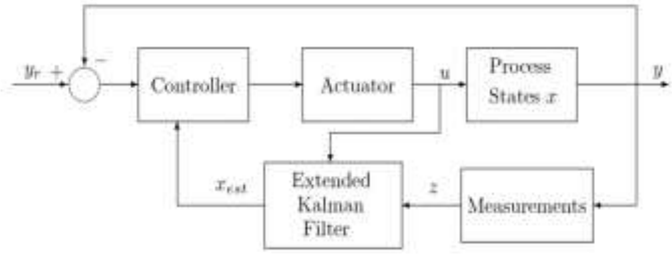

Figure 1: Implementation of the extended Kalman filter in a control scheme[2]

For these reasons, variants have been designed [4] such as the constant gain extended Kalman filter [5] which was essentially proposed to avoid the long calculations related to the update of the state and covariance matrix estimations.

4. PARAMETERS ESTIMATION

The EKF is a version of the Kalman Filter typically used for non-linear systems. The EKF makes use of a linearized version of the non-linear system to perform the state estimation at every time step k.

In additional, since it's a recursive evaluation method, of this fact, a discreet model of the machine is necessary and is gotten by using the Euler's formula.

Let us consider the discreet model with noise of the induction machine:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k) + w_k \\ y_k &= h(x_k) + v_k \end{aligned} \qquad (13)$$

with :

$x_{k+1} = \left[i_{sd|k+1} \quad i_{sq|k+1} \quad \psi_{rd|k+1} \quad \psi_{rq|k+1} \quad \Omega_{k+1}\right]$, the state variables at a time $k+1$.

$x_k = \left[i_{sd|k} \quad i_{sq|k} \quad \psi_{rd|k} \quad \psi_{rq|k} \quad \Omega_k\right]$, the state variables at a time k,

$y_k = \left[i_{sd|k} \quad i_{sq|k}\right]$, the output measurements at a time k.

$$f(x_k,u_k) = \begin{bmatrix} i_{sd|k}(1-\gamma T_s) + w_s i_{sq|k}T_s + ab\psi_{rd|k}T_s + bp\psi_{rq|k}\Omega_k T_s + m_1 u_{sd_k}T_s \\ -w_s i_{sd|k}T_s + i_{sq|k}(1-\gamma T_s) + ab\psi_{rq|k}T_s - bp\psi_{rd|k}\Omega_k T_s + m_1 u_{sq_k}T_s \\ aM_{sr} i_{sd|k}T_s + \psi_{rd|k}(1-aT_s) + (w_s - p\Omega_k)\psi_{rq|k}T_s \\ aM_{sr} i_{sq|k}T_s - (w_s - p\Omega_k)\psi_{rd|k}T_s + \psi_{rq|k}(1-aT_s) \\ m(\psi_{rd|k}i_{sq|k} - \psi_{rq|k}i_{sd|k})T_s - \frac{T_L}{J}T_s + (1-cT_s)\Omega_k \end{bmatrix}$$

The function of transition.

$u_k = \left[u_{sd_k}, u_{sq_k} \right]^T$: The voltages in d - q axis reference frame .

$h(x_k) = \left[i_{sd|k} \quad i_{sq|k} \right]$, the observation function.

w_k et v_k are control and measurement noises respectively .

$T_s = 10^{-4} s$, sampling time.

4.1 PARAMETERS OF THE EXTENDED KALMAN FILTER

Covariance matrices Q and R

It is through these matrices that the different measured states and their predicted valued will pass. Their goal is to minimize the errors due to modelling and the presence of measurement noises. This tuning requires a particular attention and only an on-line tuning permits to validate the functioning of the filter. However, some big lines permit to understand the influence of the adjusting of these values in relation to the dynamics and the stability of filtering. The matrix Q bound to the state noises, permits to adjust the quality estimated of our modelling and its discreet form. A strong value of Q gives a strong value of the gain K reducing the importance of the modelling and the dynamics of the filter. The measure possesses more important relative weight then. A too strong value of Q can create the observer's instability however. The matrix R adjusts the weight of the measures. A estimated of our modelling and its discreet form. A strong value of Q gives a strong value of the gain K reducing the importance of the modelling and the dynamics of the filter. The measure possesses more important relative weight then. A too strong value of Q can create the observer's instability however. The matrix R adjusts the weight of the measures. A strong value indicates a big uncertainty of the measure. On the other hand, a weak value permits to give an important weight to the measure. However, it is necessary to pay attention to the risk of instability to the weak values of R .

Parameters	Values
Number of measured output	2
Number of estimated states	5
Standard deviation of measurement noise	$\sigma = 0.001$
Covariance matrix Q	$Diag\left(10^{-5} 10^{-5} 10^{-6} 10^{-6} 10^{-6}\right)$
Covariance matrix R	$Diag\left(\sigma^2\right)$

Table 1: Adjusting parameters of Kalman filter

Initialization of the EKF algorithms:

$$\hat{x}(0) = \left[0.1 \quad 0.1 \quad 0 \quad 0 \quad 0 \right]^T,$$
$$P(0) = eye(5)$$

4.2 DETERMINATION OF MATRICES F and H

Matrices F and H are Jacobian matrices of $f(x_k, u_k)$ and $h(x_k)$ functions respectively and also called matrices of linearisation, they allow to linearise the system at each time. They are given as follows:

$$F = \begin{bmatrix} 1-\gamma T_s & w_s T_s & abT_s & bp\hat{\Omega}_k T_s & bp\hat{\psi}_{rq|k} T_s \\ -w_s T_s & 1-\gamma T_s & -bp\hat{\Omega}_k T_s & abT_s & -bp\hat{\psi}_{rd|k} T_s \\ aM_{sr} T_s & 0 & 1-aT_s & (-p\hat{\Omega}_k + w_s) T_s & -p\hat{\psi}_{rq|k} T_s \\ 0 & aM_{sr} T_s & -(-p\hat{\Omega}_k + w_s) T_s & 1-aT_s & p\hat{\psi}_{rd|k} T_s \\ -m\hat{\psi}_{rq|k} T_s & m\hat{\psi}_{rd|k} T_s & m\hat{i}_{sq|k} T_s & -m\hat{i}_{sd|k} T_s & 1-cT_s \end{bmatrix} \quad (15)$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \quad (16)$$

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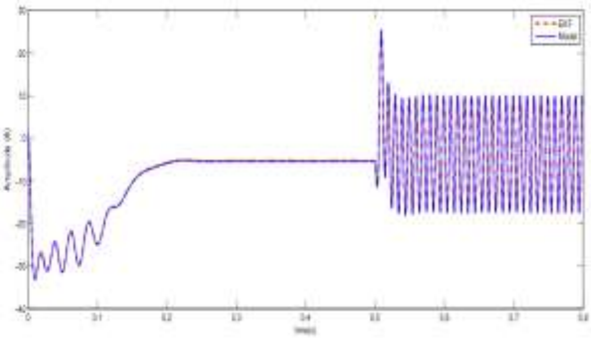
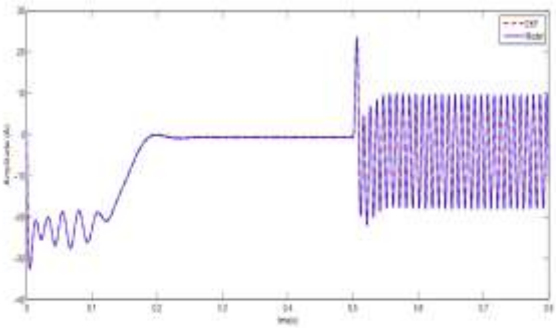
5. POWER LINE, LOAD DISTURBANCE ESTIMATION

5.1 DEFAULT OF POWER LINE

Fig. 2 and Fig. 3 show the behaviour of the currents and fluxes of the induction machine when occurs a power line default during its working. During the steady state, we apply a load torque to the induction machine at a time $t = 0.5s$ and at that time we remove a one of three-phase of the power supply; we notice that EKF always attains to rebuild induction machine parameters because (as seen on Fig. 1) the induction machine and the estimator both need to have the same power supply, That is why if the default occurs on the power supply directly the estimator will take into account anomaly as we can observe it on curves.

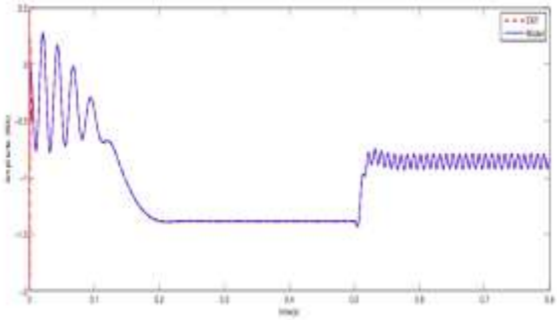


(a) i_{sd}

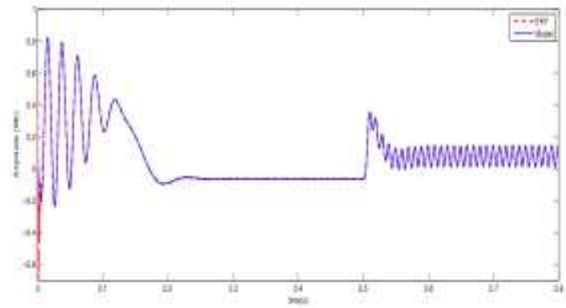


(b) i_{sq}

Figure 2: Stator currents of the model and EKF in the d - q axis reference frame case of power line default



(a) ψ_{rd}

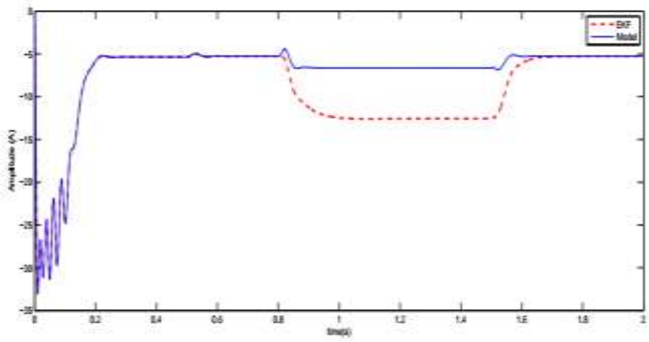


(b) ψ_{rq}

Figure 3: Rotor fluxes of the model and EKF in the d - q axis reference frame case of power line default

5.2 LOAD DISTURBANCE

We simulate a torque load varying during the working of the induction machine. Fig. 4 and Fig. 5 show estimated and true values of stator currents and rotor fluxes by extended Kalman filter. At a time $t = 0.5s$ (steady state), we introduce a torque load of $4.5N.m$ then at another time $t = 0.8s$, we increase the torque load value of 22.5% of its initial value, and the estimation error becomes very high, then we bring back the torque load value to its initial value at $t = 1.5s$, so we can observe a considerable decreasing of the error estimation at that time.



(a) i_{sd}

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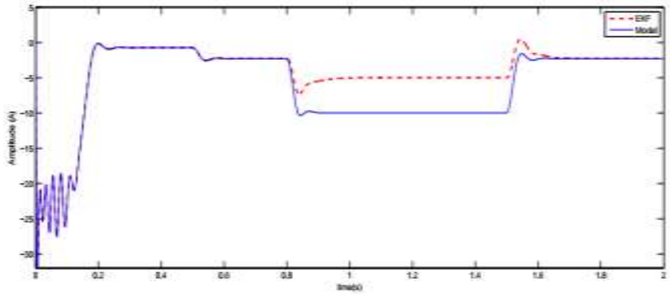
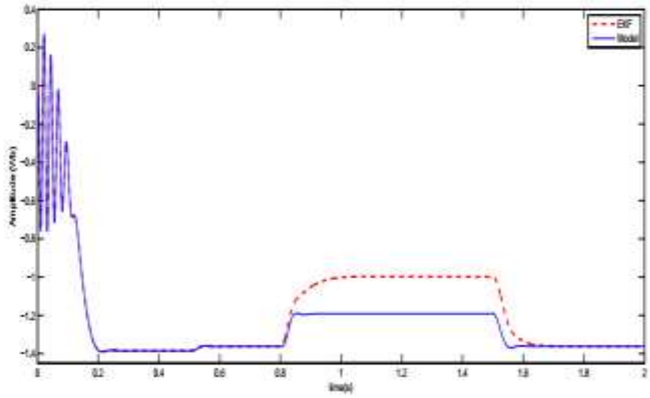
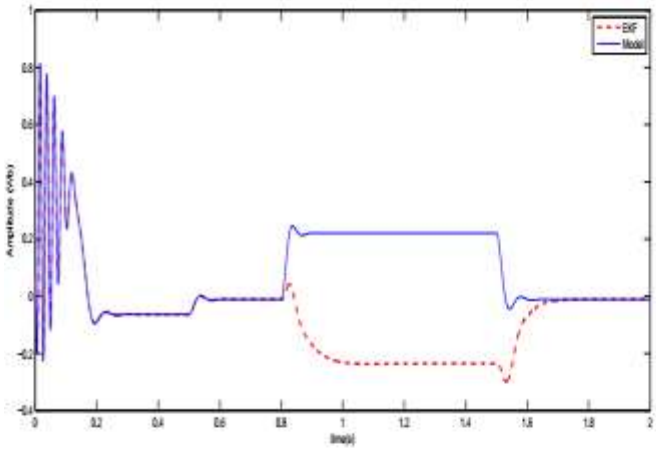


(b) i_{sq}

Figure 4: Stator currents of the model and EKF in the d - q axis reference frame case of load fault.



(a) ψ_{rd}



(b) ψ_{rq}

Figure 5: Rotor fluxes of the model and EKF in the d - q axis reference frame case of load fault

Table 2 shows the mean abs values and standard deviation values of induction under different operation condition. It is hard to make any decision based on these two values. To solve this problem, a specified fault index equation (16) is put forward

$$I = \frac{StandardDeviation}{Meanabs} \tag{17}$$

where SD represents standard deviation, Meanabs represents mean absolute values[6].

By calculating the fault index equation in (16) , it is much easier to judge the induction machine condition. As shown in Table 2 this index is higher when occurs the load fault and this fact is observed in rotor fluxes, on the other hand one can see the same effect on stator current in d axis but the reverse effect on the stator current in q axis.

	i_{sdreal}	i_{sdest}	i_{sqreal}	i_{sqest}
Mean abs	6.0470	9.4875	6.7695	3.8373
Standard Deviation	0.6878	3.3490	3.7451	1.6398
I	0.1137	0.3530	0.5532	0.4273

	ψ_{rdreal}	ψ_{rdest}	ψ_{rqreal}	ψ_{rqest}
Mean abs	1.978	1.0251	0.2163	0.2066
Standard Deviation	0.0293	0.0700	0.0288	0.0681
I	0.0148	0.683	0.1331	0.3296

Table 2: Simulation result analysis based on mean and Standard Deviation values

6. BAR FAULT DETECTION

When broken bar fault occurs in rotor, negative component at frequency $(1-2s)f$ (where s is the slip and f is the supply frequency) is generated in stator current. This component produces a torque ripple and causes rotor speed variation. This speed variation cause mechanical angular variation and lead to motor produces a phase modulation in the stator flux.

An obviously symptom about rotor bar breakage is rotor bar resistance will increase along with bar broken severity level. Broken rotor bars simulation under software normally run by increasing bar resistance trying to mimic the real current flow situation[6]. In order to show that the EKF is able to detect disturbances when the electric motor has a fault, the simulations were conducted using a model of a motor with a broken bar. As a consequence of this type of fault (the

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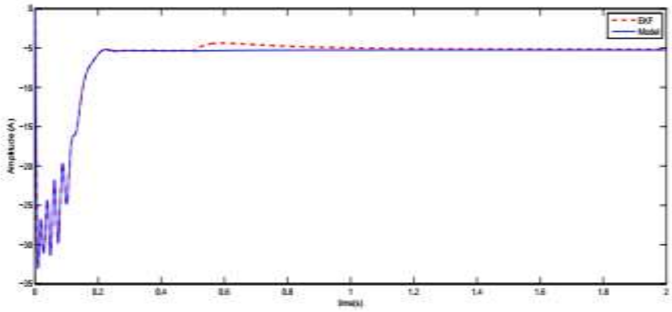
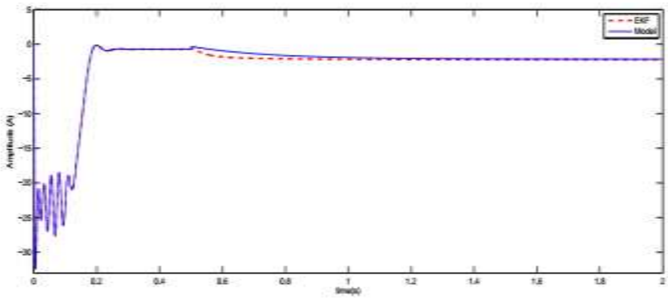
broken bar), the resistance of the rotor bar or ring segment will change, which will also lead to an increase in the equivalent resistance of the rotor. Typically these changes are modelled by increasing the initial resistance value of either the faulty bar or ring segment by a factor of 20[3].

Fig. 6 and Fig. 7 show the magnitude of the stator currents and the rotor fluxes d - q components obtained from the model and those estimated using the EFK.The fault occurs in full working of the machine during its steady-state when the torque load is introduced at $t = 0.5s$, however we notice that when the fault is there, the filter is not able to accurately estimate the variables of the machine as shown below.

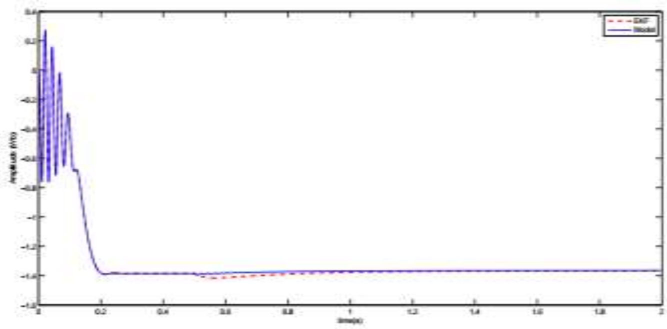


(a) i_{sd}

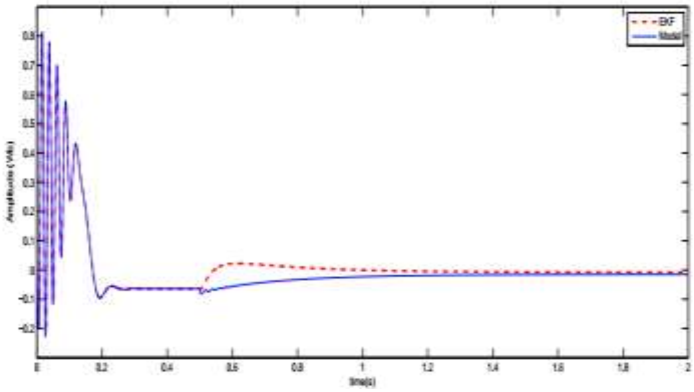


(b) i_{sq}

Figure 6: Rotor fluxes of the model and EKF in the stator reference frame case of broken bar



(a) ψ_{rd}



(b) ψ_{rq}

Figure 7: Rotor fluxes of the model and EKF in the stator reference frame case of broken bar

	i_{sdreal}	i_{sdest}	i_{sqreal}	i_{sqest}
Mean abs	5.2774	4.9973	1.8625	2.1281
Standard Deviation	0.0244	0.2350	0.4277	0.2453
I	0.0046	0.0470	0.2296	0.1153

	ψ_{rdreal}	ψ_{rdest}	ψ_{rqreal}	ψ_{rqest}
Mean abs	1.3686	1.3778	0.0250	0.0017
Standard Deviation	0.0063	0.0141	0.0145	0.0111
I	0.0046	0.0102	0.5800	6.5294

Table 3: Simulation result analysis based on mean and Standard Deviation values under broken rotor bar

7. CONCLUSION

In this paper, an approach for estimating the parameters of an induction machine is presented, the approach is based on an Extended Kalman Filter. We were able to come out with simultaneous state and parameter estimates and with these estimate we detected faulty functionning of the machine. Simulation were used and showed that a good standard of performance could be obtained even in the presence of measurement noise and model uncertainty.

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APPENDIX

The motor parameters and specifications are as follows:

$Pn = 4KW$, $p = 2$, $U = 380V$, $In = 2.86A$,
$n = 1600rpm$, $Rr = 3.08\Omega$, $Rs = 4.85\Omega$,
$Lr = 0.274H$, $Ls = 0.274H$, $Msr = 0.258H$,
$J = 0.031Kg.m^2$, $J = 0.031Kg.m^2$,
$f = 0.008N.m/s$

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A.T Boum is a Ph.D. holder in process control from the university of Lorraine, France in 2014. Currently, he is a senior lecturer and researcher in the university of Buea,.
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