

States Estimation and Fault Detection of a Doubly Fed Induction Machine by Moving Horizon Estimation

A. T. Boum, L. Bitjoka, N. N. Léandre, S. Bennet

Abstract—This paper presents the estimation of the key parameters of a double fed induction machine (DFIM) by the use of the moving horizon estimator (MHE) for control and monitoring purpose. A study was conducted on the behavior of this observer in the presence of some faults which can occur during the operation of the machine. In the first case a stator phase has been suppressed. In the second case the rotor resistance has been multiplied by a factor. The results show a good estimation of different parameters such as rotor flux, rotor speed, stator current with a very small estimation error. The robustness of the observer was also tested in the practical case of DFIM by using another model different from the real one at a constant close. The very small estimation error makes the MHE a good software sensor candidate for monitoring purpose for the DFIM.

Keywords—Doubly fed induction machine, moving horizon estimator parameters' estimation.

I. INTRODUCTION

THE AC machines have revolutionized the industrial world that used to use DC machines. The presence of the ball-collector system penalized the use of DC machine. They cannot be used in the field of high power, in a corrosive environment and also they need a lot of maintenance due to the presence of the collector [1]. Among these AC machines, there is DFIM which operates in a somewhat particular mode. It is very popular as it has advantages [2]-[4] over all other types of electrical machine with variable speed [5]. The interest in this machine continues to grow especially in the field of renewable energies [6].

In the different applications of doubly fed induction machine such as compressors, pumping systems, generation of electrical energy etc..., the online measurements of parameters are often difficult to be carried out or rarely done. To optimize the control of these systems despite the absence of physical sensors, it is frequently necessary to know the values not directly accessible to the measurement [7]. For this purpose, the use of a software sensor called observer is one of the appropriate solutions. The observer estimates the missing values using the inputs and outputs of the system and its

model [7]. The observer is developed from a linear or nonlinear dynamic model. The estimation of the state of the DFIM is done by means of the observer with a moving horizon.

II. MODELLING

A. System Description

The interconnexion of the MHE and the DFIM is shown on Fig. 1. In Fig. 1, Speed r represents the rotation speed and X_{est} represents the estimated state.

An observer is an algorithm that uses the input and the output of a system to provides estimate of parameters or states that can be measured or for which we cannot have access due to lack of sensors or inaccessible environment [7]. The MHE will therefore use the inputs of the DFIM (three-phase power supply) and outputs (current, rotation speed) to provide an estimation of the entire state of the system (current, flux, rotation speed) as shown in Fig. 1.

B. Dynamic Model

The first appearance of the double-fed asynchronous machine DFIM dates to 1899 [8], [9]. It is a new mode of supply and not a new structure. The asynchronous double-fed machine has a stator similar to that of the conventional three-phase machines (asynchronous with cage or synchronous) generally constituted by stacked magnetic laminations provided with a notch in which the windings are inserted [10]. The originality of this machine stems from the fact that the rotor differs radically because it is not composed of magnets or a squirrel cage but of three-phase winding arranged in the same way as the stator windings (wound rotor) [11], [12]. The wound rotor comprises a three-phase winding similar to that of the star-connected stator and the free end of each winding of which is connected to a ring and allows external connection of the windings to the rotor. This connection is an external power supply connection which makes it possible to carry out a control of the rotor magnitudes. In order to estimate the state of this machine, it is necessary to give its mathematical model taking into account certain simplifying hypotheses in order to obtain a model simpler than possible. The electrical equations are mostly derived from [13]. The voltage equations are:

At the stator

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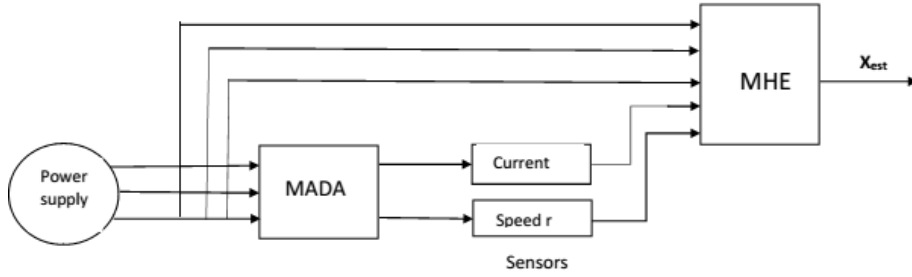


Fig. 1 The estimation's system

$$\begin{bmatrix} U_{sa} \\ U_{sb} \\ U_{sc} \end{bmatrix} = [R_s][I_{sabc}] \left[\frac{d}{dt} \right] \begin{bmatrix} \varphi_{sa} \\ \varphi_{sb} \\ \varphi_{sc} \end{bmatrix} \quad (1)$$

At the rotor

$$\begin{bmatrix} U_{ra} \\ U_{rb} \\ U_{rc} \end{bmatrix} = [R_r][I_{rabc}] \left[\frac{d}{dt} \right] \begin{bmatrix} \varphi_{ra} \\ \varphi_{rb} \\ \varphi_{rc} \end{bmatrix} \quad (2)$$

With the flux:

$$[\varphi_s] = [L_s][I_s] + [M_{sr}][I_r] \quad (3)$$

$$[\varphi_r] = [L_r][I_r] + [[M_{sr}]^T][I_s] \quad (4)$$

We thus obtain the equations of the voltages of the DFIM in the frame (d, q) [14]

$$\begin{cases} U_{sd} = R_s I_{sd} + \frac{d\varphi_{sd}}{dt} - \omega_s \varphi_{sq} \\ U_{sq} = R_s I_{sq} + \frac{d\varphi_{sq}}{dt} + \omega_s \varphi_{sd} \\ U_{rd} = R_r I_{rd} + \frac{d\varphi_{rd}}{dt} - (\omega_s - \omega_r) \varphi_{rq} \\ U_{rq} = R_r I_{rq} + \frac{d\varphi_{rq}}{dt} + (\omega_s - \omega_r) \varphi_{rd} \end{cases} \quad (5)$$

Using the flux φ_{rd} , φ_{rq} , and the currents I_{sd} , I_{sq} and Ω as state variables and using the linear magnetic circuit, the two equivalent phases of the DFIM model are represented in the (d,q) reference frame connected to the stator are given by the equations:

$$\dot{I}_{sd} = -\gamma I_{sd} + \omega_s I_{sq} + bp\Omega \varphi_{rq} + ab\varphi_{rd} + m_1 U_{sd} + bU_{rd} \quad (6)$$

$$\dot{I}_{sq} = -\gamma I_{sq} - \omega_s I_{sd} - bp\varphi_{rd}\Omega + ab\varphi_{rq} + bU_{rq} + m_1 U_{sq} \quad (7)$$

$$\varphi_{rd} = U_{rd} - a\varphi_{rd} + aM_{sr}I_{sd} + (\omega_s - p\Omega)\varphi_{rq} \quad (8)$$

$$\varphi_{rq} = U_{rq} - a\varphi_{rq} + aM_{sr}I_{sq} - (\omega_s - p\Omega)\varphi_{rd} \quad (9)$$

$$\dot{\Omega} = m(\varphi_{rd}I_{sq} - \varphi_{rq}I_{sd} - c\Omega T_l/J) \quad (10)$$

where

$$\begin{aligned} \gamma &= (R_s L_r^2 + R_r M_{sr}^2) / \sigma L_s L_r^2, \quad a = R_r / L_r \\ b &= M_{sr} / \sigma L_r L_s, \quad m_1 = 1 / \sigma L_s \\ m &= 3pM_{sr} / 2JL_r, \quad c = f_v / J \end{aligned}$$

and I_{sd} , I_{sq} , φ_{rd} , φ_{rq} , Ω , ω_s , $\omega_r = p\Omega$ are the components of the stator currents, the rotor fluxes, the rotation velocity, the angular velocity of the Park transformation respectively. The indices s and r refer to the stator and the rotor respectively. R_s and R_r are the resistances to the stator and the rotor. L_s and L_r are the self inductances. M_{sr} is the mutual inductance between the stator and the rotor. f_v is the coefficient of viscous friction. T_l is the load torque. J is the inertia moment.

III. THE MOVING HORIZON ESTIMATOR

MHE has the principle of minimizing a criterion on a time window from an earlier time to the current time, this time is shifted at each sampling step [15]. The criterion is a measure of the difference between the estimated output and the actual output.

Suppose the process is represented by the following continuous time model:

$$\begin{cases} \dot{x}(t) = f(x(t), u(t)) + Gw(t) \\ y(t) = h(x(t)) + v(t) \end{cases} \quad (11)$$

where v and w are Gaussian noises of zero mean.

The nonlinear continuous model above is approximated by the discrete linear model:

$$\begin{cases} x_{k+1} = A_k x_k + B_k u_k + Gw_k \\ y_k = h(x_k) + v_k \end{cases} \quad (12)$$

where A and B are the Jacobian matrices of f respectively with respect to x_k and u_k

The measurement model is linearized according to:

$$y_{k+1} = C_k x_{k+1} + v_{k+1} \quad (13)$$

where C is the Jacobian of h with respect to x_k .

The criterion J_k is given by:

$$J_k = (x_0 - \hat{x}_0)^T \pi_0^{-1} (\hat{x}_0 - x_0) + \sum_{i=0}^{k-1} (v_{i+1}^T R^{-1} v_{i+1} + w_i^T Q^{-1} w_i) \quad (14)$$

It is minimized with respect to the initial state x_0 and the sequence of noises $\{w_0 \dots w_{k-1}\}$ then the states \hat{x}_i are obtained using (13).

The estimate of the state at time k computed at instant $k \geq N$ is obtained by solving:

$$\min_{\hat{x}_{k-N/k}, \{\hat{w}_{k-N+i/k}\}_{i=0}^{N-1}} J_k(\hat{x}_{k-N/k}, \{\hat{x}_{k-N+i/k}\}_{i=0}^{N-1}, \hat{x}_{k-N/k}, y_{k-N}^k) \quad (15)$$

$$J_k = \left\| \hat{x}_{k-N/k} - \hat{x}_{k-N/k}^- \right\|_P^2 + \sum_{i=0}^{N-1} \left\| \hat{w}_{k-N+i/k} \right\|_Q^2 + \sum_{i=0}^N \left\| y_{k-N+i} - h(\hat{x}_{k-N+i/k}) \right\|_R^2 \quad (16)$$

Subject to constraints:

$$\hat{x}_{k-N+i/k} = f(\hat{x}_{k-N+i/k}) + \hat{w}_{k-N+i/k}, \forall i \in [0, N-1] \quad (17)$$

$$\hat{x}_{k-N+i/k} \in X, \hat{w}_{k-N+i/k} \in W, y_{k-N+i} - h(\hat{x}_{k-N+i/k}) \in V, \forall i \in [0, N-1] \quad (18)$$

P, Q and R are the definite positive weighting matrices. Q and R can be chosen to be equal respectively to the inverse of the covariance matrices and of state and measurement noises, i.e. Q^{-1} and R^{-1} .

For our process we have chosen $Q = \text{Diag} [10 \ 5 \ 20 \ 15 \ 30 \ 100]$ and $R = \text{diag} [200 \ 100]$. Let $(\hat{x}_{k-N+i/k}^0, \{\hat{w}_{k-N+i/k}^0\}_{i=0}^{N-1})$ problem (15) at time k. The a priori estimate at the beginning of the horizon $\hat{x}_{k-N+i/k}$ is computed using the solution of (15) at the previous instant $(\hat{x}_{k-N/k-1}^0, \{\hat{w}_{k-N/(k-1)}^0\})$ and (17). $\hat{x}_{k/k}$ denotes the estimate of x_k calculated at the instant k given by the MHE. $\hat{x}_{k/k}$ is calculated by propagating the optimal solution $\hat{x}_{k-N+i/k}^0, \{\hat{w}_{k-N+i/k}^0\}_{i=0}^{N-1}$ using the state equation (17) set of constraints on the MHE. For $k < N$, (15) is always valid but with a horizon of increasing length equal to each instant [16].

Two design approach can be envisaged for the MHE: the stochastic approach [17] [18] and the determinist approach [19]. In the stochastic approach, x_0, w_k, v_k are random variables according to specific statistical laws. In the deterministic approach, the initial state x_0 , the state noise w_k and the measurement noise v_k are considered as unknown deterministic variables of unknown characteristics which assume a value in a known compact set. In view of all this we can have the algorithm of the mobile estimate of the state as costume as shown in [20]:

1-Initialization

- Initialize matrices states of the criterion
- Initializes the state vector

$$\hat{x}(0) = (I_{sd}(0) \ I_{sq}(0) \ \varphi_{rd}(0) \ \varphi_{rq}(0) \ \Omega(0))^T$$

2-Storage of data

- Obtain the measurements $y(k)$
- store the manipulated inputs and the previous measured outputs.

3-If $k \leq N$ we have the total estimation of the state, otherwise we have the mobile estimation of the state.

4- Call the initial parameters

5- Realize non-linear optimization

The minimization made by the cost function to calculate the optimal value of the criterion.

- the management of constraints on the model.
- the management of noise constraints.

6-Compute new estimated states

- 7- Update the covariance matrix
- 8-The estimated states and the optimum value of the criterion calculated previously are stored
- 9-Return to step 2.

The Jacobian matrices of f and h are obtained by:

$$F_k = (\partial f / \partial x) / x_k, \quad F_k = (\partial h / \partial x) / x_k$$

which gives:

$$F = \begin{pmatrix} -\gamma T_s & \omega_s T_s & abT_s & bp\hat{\Omega}_k T_s & bp\hat{\Omega}_k T_s \\ -\omega T_s & -\gamma T_s & -bp\hat{\Omega}_k T_s & abT_s & -bp\hat{\varphi}_{rd/k} T_s \\ aM_{sr} T_s & 0 & aT_s & (-p\hat{\Omega}_k + \omega_s) T_s & -p\hat{\varphi}_{rq/k} T_s \\ 0 & aM_{sr} T_s & (p\hat{\Omega}_k - \omega_s) T_s & aT_s & p\hat{\varphi}_{rd/k} T_s \\ -m\hat{\varphi}_{rq/k} T_s & m\hat{\varphi}_{rd/k} T_s & ml_{sq/k} T_s & -ml_{sd/k} T_s & cT_s \end{pmatrix}$$

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{pmatrix}$$

with T_s the sampling time.

IV. RESULTS AND ANALYSIS

The simulations were performed under the MATLAB/Simulink environment. The parameters of the DFIM are given in Table I.

TABLE I
PARAMETERS OF THE DFIM

characteristics	symbols	values
Stator rated voltage	U_{sn}	380 V
Rotor rated voltage	U_{rn}	225 V
Stator resistance	R_s	1.75 Ω
Rotor resistance	R_r	1.68 Ω
stator inductance	L_s	0.295 H
Rotor inductance	L_r	0.104 H
Mutual Inductance	M_{sr}	0.165 H
Number of pole pairs	P	2
Moment of inertia	J	0.0426 Nm/Rad/s ²
friction	f_v	0.0027 m.N.s/Rad

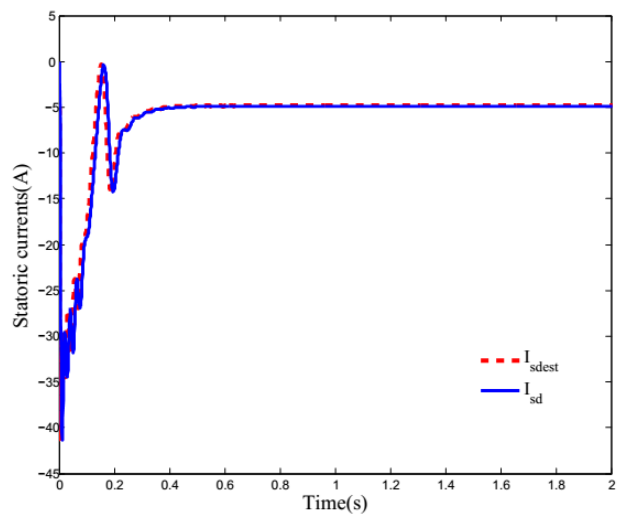


Fig. 2 Stator current along axis q

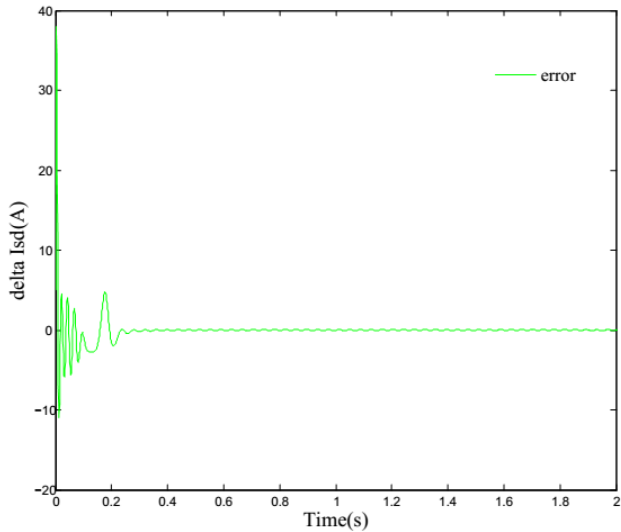


Fig. 3 Estimation error of stator current along axis d

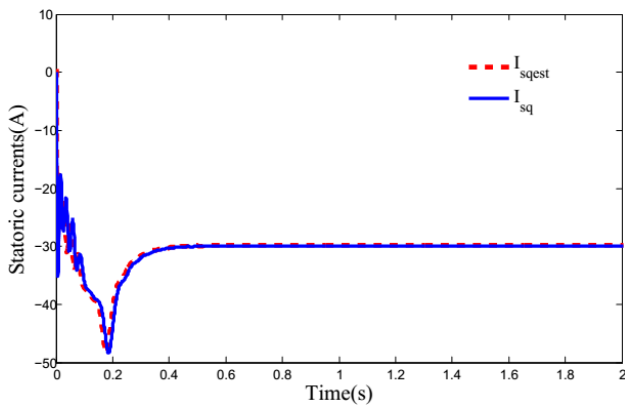


Fig. 4 Stator current along axis q

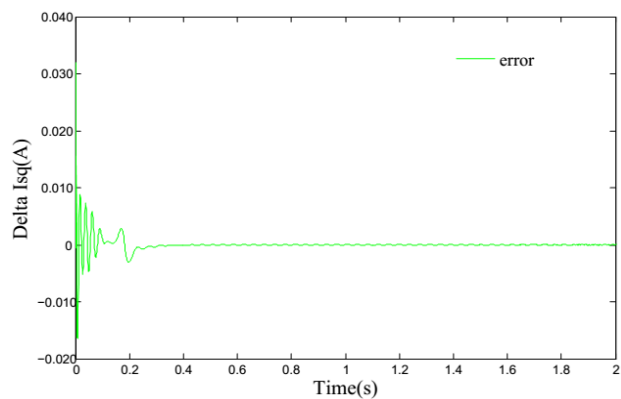


Fig. 5 Estimation error of stator current along axis q

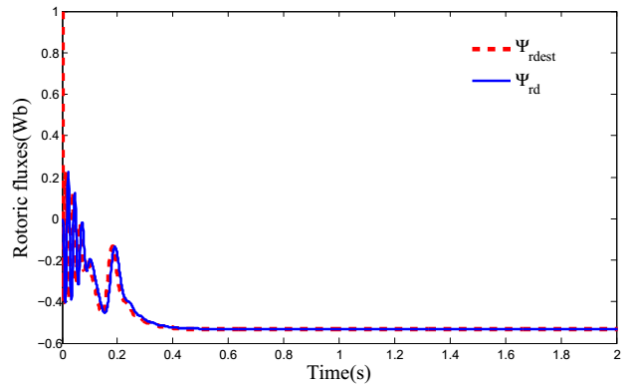


Fig. 6 Rotor flux along axis q

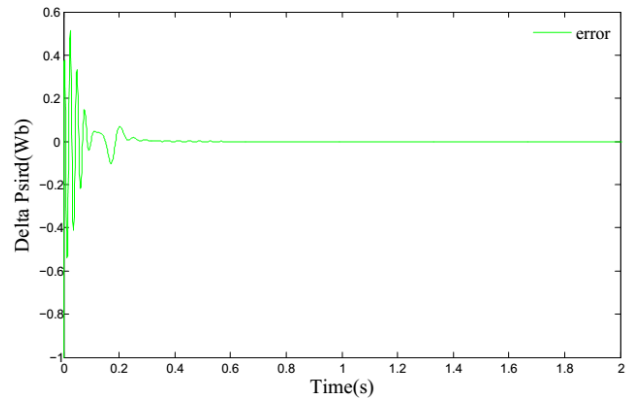


Fig. 7 Estimation error of rotor flux along axis d

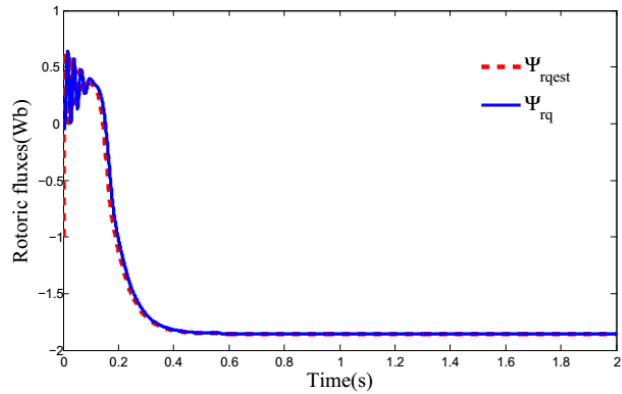


Fig. 8 Rotor flux along axis d

$$std = \sqrt{(\bar{x}^2) - (\bar{x})^2} \quad (19)$$

In Figs. 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, real values are in blue line and their estimations are in dash-dotted red line. The simulations are done with the hypothesis of a normal functioning of the machine. The mean values and standard deviations are given in Table II.

Figs. 2-11 show that the sliding horizon reconstructs the state of the machine very well at every moment, with very good accuracy. The estimated error is zero from the instant $t = 0.25$ s. The estimate made by the observer is optimal during the operation of the machine in the steady state but, what if defects occur? Simulations were carried out with some defects. Its behavior against defects makes it more interesting.

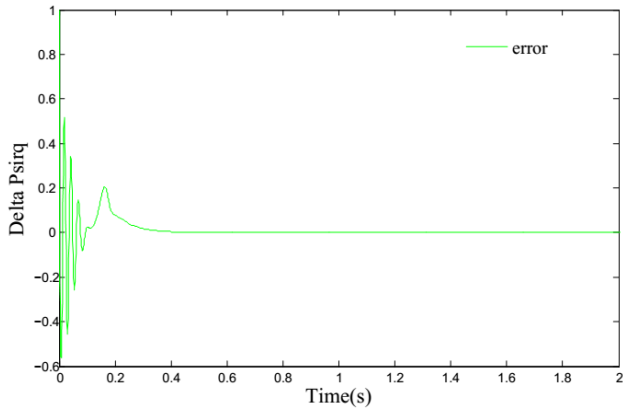


Fig. 9 Estimation error of rotor flux along axis d

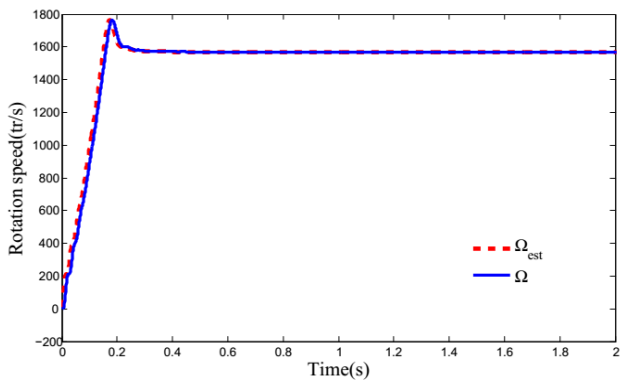


Fig. 10 Rotation speed

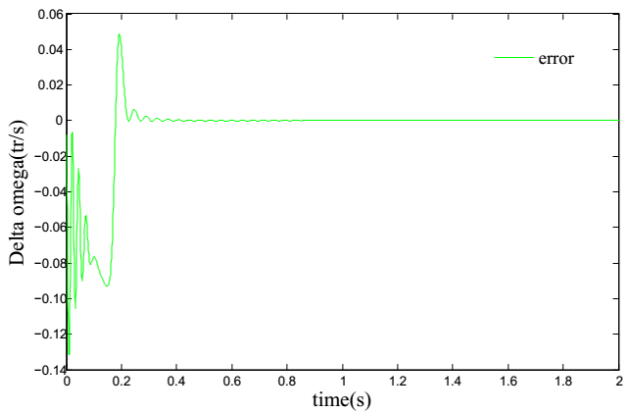


Fig. 11 Estimation error

In Table II, the mean and the standard deviation are calculated for each parameter. By comparing the real data and their estimates, we see that there is a difference of the order of 10^{-2} or 10^{-3} depending on the case.

The following results are obtained taking into account different faults that can occur during the functioning of a machine.

TABLE II
THE MEAN VALUES AND THE STANDARD DEVIATION OF PARAMETERS

	mean	std
I_{sd}	-5.888	4.387
I_{sdest}	-5.8	4.307
I_{sq}	-30.46	2.706
I_{sqest}	-30.38	2.635
Ψ_{rd}	-0.5068	0.09103
Ψ_{rdest}	-0.5094	0.0929
Ψ_{rq}	-1.708	0.4998
Ψ_{rqest}	-1.712	0.4918
Ω_{rd}	1528	218.8
Ω_{rdest}	1532	204.4

A. Line Failure

During operation of the machine, one phase of the network can be disconnected unexpectedly. By removing a stator phase at $t=0.5$ s, Figs. 12-18 are obtained. The mean values and standard deviation of the fluxes and rotation are given in Table III. Table IV shows the mean value and standard deviation of currents and flux.

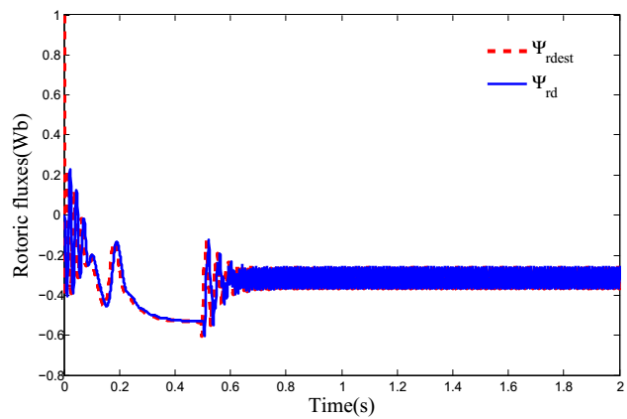


Fig. 12 Rotor flux along axis d

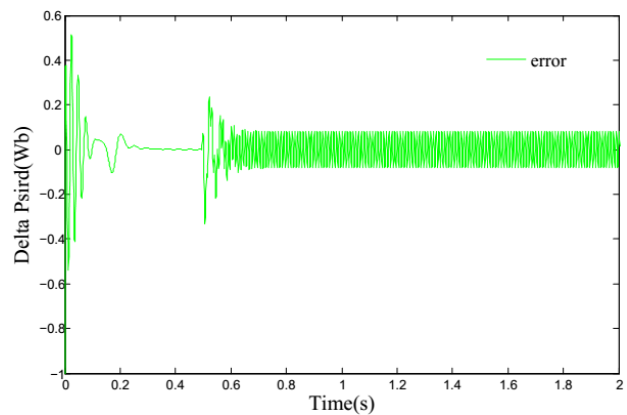


Fig. 13 The estimation error

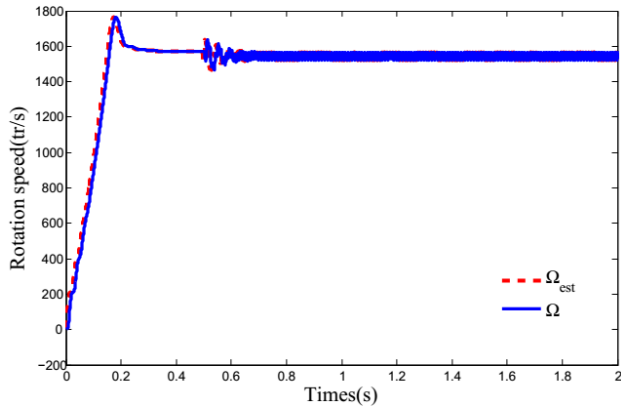


Fig. 14 Rotation speed

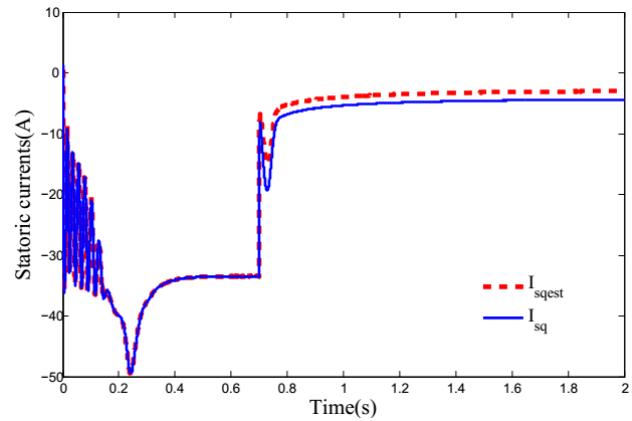


Fig. 16 Rotor flux along axis d

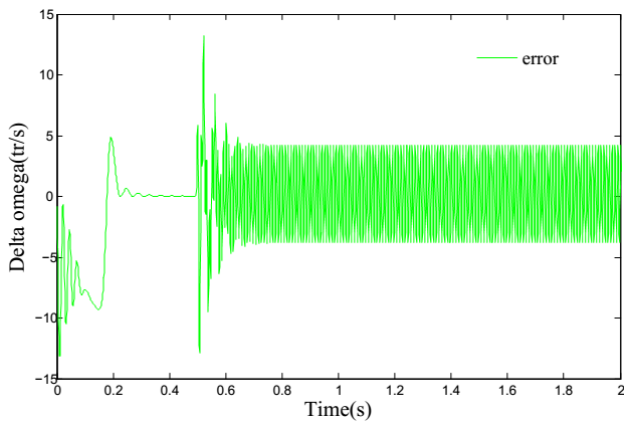


Fig. 15 Estimation error of rotor flux along axis d line failure

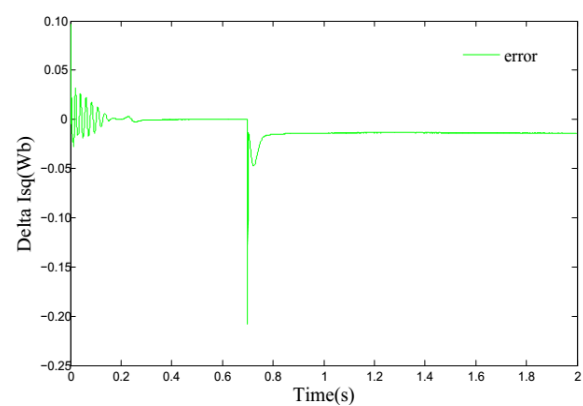


Fig. 17 Estimation error with rotor bar breaking

The observer has difficulty reconstructing the parameters of the machine following the occurrence of the fault. He succeeds in making a good estimate once the machine has stabilized, since it minimizes the estimation error as much as possible. The estimates at steady-state are quite accurate. It thus allows to give an alarm of appearance of the defect in the machine.

TABLE III
THE MEAN VALUES AND THE STANDARD DEVIATION OF FLUXES AND ROTATION SPEED

	mean	std
Ψ_{rd}	-3.268	0.08371
Ψ_{rdest}	-0.3286	0.08609
Ω_{rd}	1508	215.6
Ω_{rdest}	1511	201.4

In Table III, the difference $|\Psi_{rd} - \Psi_{rdest}|$ is equal to 0.00238 Wb. It shows that the MHE gives a quite good estimation although the defect appears.

B. Rotor Bar Breaking

It is also possible to envisage the case where a rotor bar breaks, the load on the rotor increases by a factor of 20 for example at $t=0.7s$.

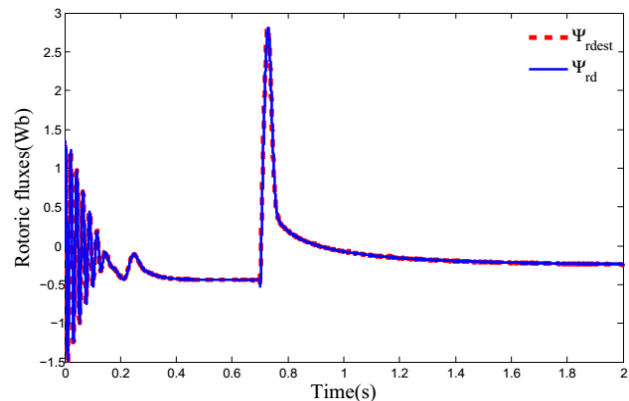


Fig. 18 Rotor flux along axis d

We see that the observer endeavors to reconstruct the state of the system by approximating as closely as possible to the real values. This difference between the estimated values and the actual values reflect the difficulty of the observer to reconstruct the parameters of the DFIM. But the error curve shows that after the time of occurrence of the fault, the observer manages to give a very good estimate as shown in Fig. 9. Once again, this fault can be detected.

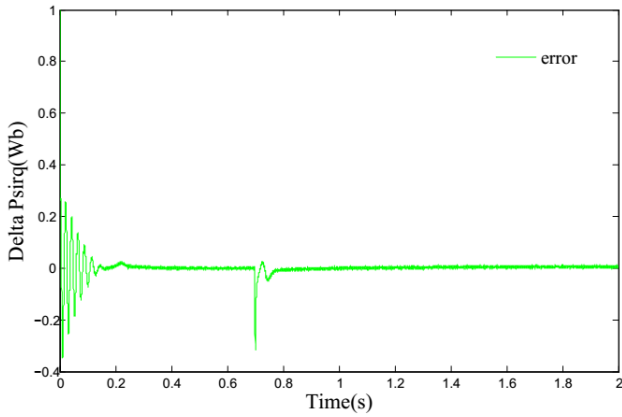


Fig. 19 Estimation error with rotor bar breaking

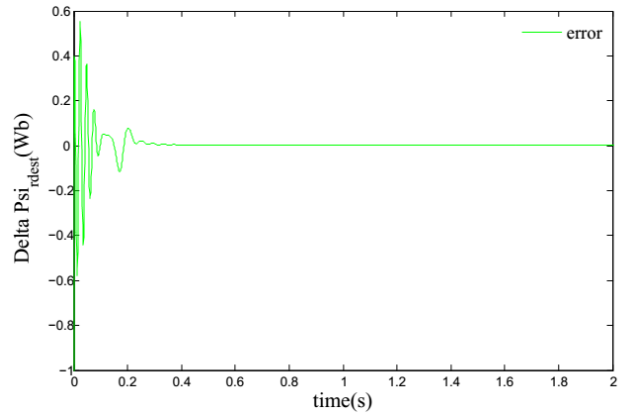


Fig. 21 Estimation error in robustness case

 TABLE IV
 THE MEAN VALUES AND THE STANDARD DEVIATION OF CURRENTS AND FLUXES

	mean	std
I_{sq}	-15.43	14.28
I_{sqest}	-14.47	14.91
Ψ_{rd}	2.81	0.4057
Ψ_{rdest}	2.812	0.4061

In Table IV, the difference $|\Psi_{rd} - \Psi_{rdest}|$ is equal to 0.0004 Wb. It shows that the MHE gives a quite good estimation although the defect appears.

C. The Robustness

The robustness of this observer has been proven by [18], [19], [21], and his convergence by [22]. In the case of doubly fed induction machine it will be interesting to verify it.

The results are shown on Figs. 20-23.

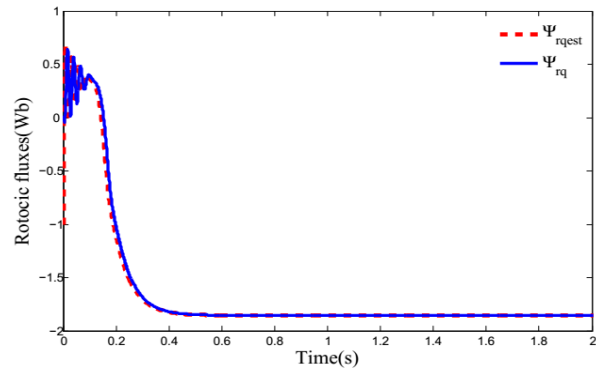


Fig. 22 Rotor flux along axis d

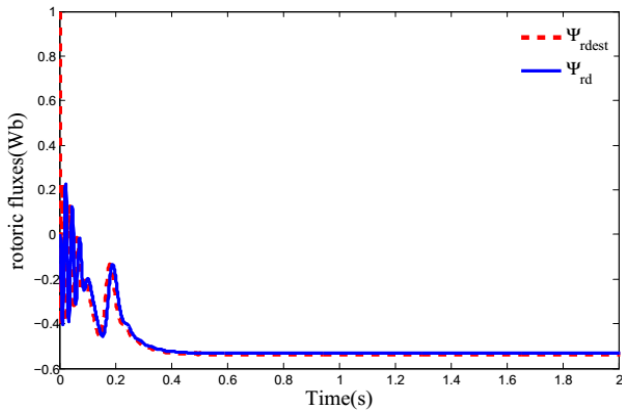


Fig. 20 Rotor flux along axis d

The model used to test the robustness of the moving horizon is different from the real model to a constant close. Using a model different from that of the real model, the observer manages to reconstruct the state of the system with very good accuracy. It has the same behavior as with the real model. Figs. 20 and 21 confirm the robustness of the observer.

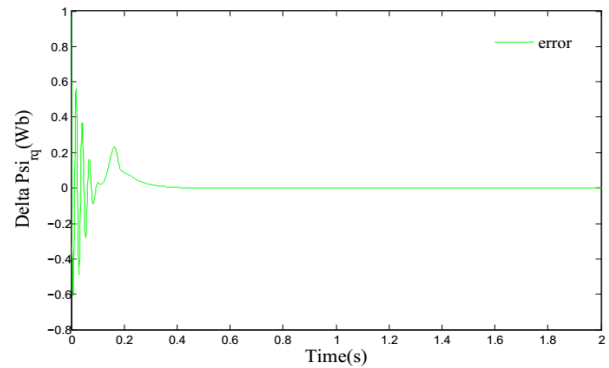


Fig. 23 Estimation error of rotor flux along axis d

 TABLE V
 THE MEAN VALUES AND THE STANDARD DEVIATION OF FLUXES

	mean	std
Ψ_{rd}	-0.5068	0.09103
Ψ_{rdest}	-0.5096	0.0929
Ψ_{rq}	-1.708	0.4998
Ψ_{rqest}	-1.712	0.4918

In Table V, by calculating the difference $|\Psi_{rq} - \Psi_{rqest}|$ which is equal to 0.94162 Wb, we see that the MHE gives good estimates with good accuracy even in the presence of defects.

V.CONCLUSION

The goal of this article is to estimate the parameters of the doubly fed asynchronous machine by the moving horizon observer. This estimation was carried out first without faults, then in the presence of faults. The results obtained show that the observer succeeds in reconstructing the state of the system very well. But in the presence of a fault, he endeavors to approximate the real values with a fairly good precision, by minimizing the estimation error. This can be used as information to detect the different faults that can occur in the machine. The robustness of the observer with an MHE is very effective which reassures its use for the diagnosis and control of the functioning of the DFIM.

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