Application of Moving Horizon Parameter Estimator in Fault Diagnosis of Broken Bars in Induction Motor

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ABSTRACT
The fault diagnosis and prediction of electrical machines and drives has become of importance because of its great influence on the operational continuation of many industrial processes. Correct diagnosis and early detection of incipient faults avoids harmful, sometimes devastative, consequences. In this work, on the basis of a model of an induction motor we study the approach for the detection of broken rotor bars problem using residual generators based in moving horizon estimator of the rotor resistance. Which the detection is based is that the failure events are detected by jumps in the estimated parameter values of the model. Upon breaking a bar the estimated rotor resistance is increased instantly, thus providing two values of resistance after and before bar breakage. Simulation and experimental results show the effectiveness of the proposed method for broken rotor bar detection in induction motors.

Keywords
Fault diagnosis, Moving horizon estimator, Induction motors, Residual generators, Rotor resistance.

1. INTRODUCTION
Induction motors are the most widely used motors among different electric motors because of their high level of reliability, efficiency and safety. However, these motors are often exposed to hostile environments during operation which leads to early deterioration leading to motor failure. It has also been observed that 5%–10% of faults are related to the rotor (broken bar) [4],[12]. The detection is based on the hypothesis that the rotor resistance of the induction motor will increase apparently when a rotor bar breaks. Using the existing observer state estimator, the implementation of a model-based fault detection scheme for induction motors can become more efficient and economical. In particular, rotor resistance is estimated and compared with its nominal value, at the same temperature and saturation conditions of the machine to detect broken bars [6]. Furthermore, the measurements obtained from stator voltages, currents and speed are processed for estimation of rotor resistance. For linear systems, this task is largely solved and powerful tools such as the Kalman Filter and Luenberger observer exists. The situation becomes more difficult for nonlinear systems. Here, most methods are extensions of linear state estimators, such as the Extended Kalman Filter (EKF) that does not guarantee convergence and stability. Moreover, the EKF needs statistical knowledge (covariance matrices) of the noises acting on the states and on the output, which can be difficult to obtain in non-linear cases. Others methods require special assumptions on the form of the process and observer models which should be satisfied in practice like high-gain-observers these algorithms need developments that can be mathematically complicated (very often exceeding the expertise of engineers or of non-specialists in process control) [5].
This paper presents a method that is designed to avoid these weaknesses, a method that guarantees convergence (by using non-linear models to carry out an estimation of states-given that the estimation strategy proposed allows the use of these models regardless of their structure), and that can be used by non-specialists as there are fewer parameters to configure. In order to achieve these objectives this article presents the development of an estimation algorithm for resistance and speed which is called Moving Horizon State Estimation or MHSE which consists of minimizing an output criterion on a time horizon.
The work is organized as follows: In Section 2, the non-linear estimation method MHSE is presented. This is followed by a presentation of the non-linear model of the induction motor which will be used for carrying out estimates. The non-linear estimation algorithm under consideration is then implemented, and applied to an induction motor (IM) through simulations that verify the benefits of the methods.

2. MOVING HORIZON ESTIMATION
In this section, the moving horizon estimation theory will be reviewed. The used observer is described by the following equations:

$$\begin{cases} \dot{x} = f(x(t), u(t)) \\ y = h(x(t)) \end{cases} \quad (1)$$

where $x \in R^n$ denotes the state vector $u \in R^m$, is the input variable and $y \in R^p$ is the vector of output (measurable), and *f* and *h* are known non-linear functions. However, the use of all available output measurements for the estimation leads to a numerical problem with a steadily growing size: the method becomes computationally unfeasible when time increases. This difficulty can be avoided by using a moving horizon formulation, also called receding horizon formulation, where the criterion is minimized only on a time horizon including the most recent measurements. The horizon moves forward at each sampling time in order to include the new measurement available (see Figure 1) [10].
The MHSE method solves the problem of state estimation of a dynamic system via a static problem of nonlinear optimization. The state estimation is performed by finding the

value of the state vector at the start of the time horizon (over an admissible domain for the state vector), so that the output trajectory generated from this state value is the same as the one measured from the output of the system. The criterion to minimize is the difference between the estimated output of the system and the measured output on the moving horizon. This corresponds to the sum of the square of the errors, over the time horizon [5].
The MHSE can be formulated as a non-linear programming problem with the following structure:

$$J(\theta)=\frac{1}{2}\sum_{k=1}^{N}\varepsilon_k^{\,2}=\sum_{k=1}^{N}(y_k-y_{mk})^2 \qquad (2)$$

where k denotes the current discrete sampling instant, N the number of measurements, J the criterion, θ is the parameter of system , y_k the measured output at time k and y_{mk} the output generated by the system for the initial state x_k .
The MHSE is given by the next algorithm [5]:

1. sh:=1
2. Compute the global MHSE solution. Solve the problem number (2) using the global optimization technique
   θ =Optimization (2).
3. Compute the estimated vector value at the end of the horizon.
4. Go to step 2, to calculate the next estimation
   sh: =sh + 1 (Horizon shift).

This algorithm can be divided into two main parts: prediction and global minimization.
The prediction computes an enclosure of the state and output set valued trajectory generated by an initial state using the model. The optimization technique consists of the minimization of the criteria given by (2) with gauss Newton algorithm described as follows [1]:

$$\theta_{i+1}=\theta_i+\lambda_i\Delta\theta_i=\theta_i-Hess(\theta_i)^{-1}.Grad(\theta_i)\lambda_i \qquad (3)$$

with
λ_i : Coefficient relaxation

$$Grad(\theta)=-2\sum_{k=1}^{N}\varepsilon_k.S_{\theta k} \qquad (4)$$

$$Hess(\theta)=2\sum_{k=1}^{N}S_{\theta k}^{\;2} \qquad (5)$$

and

$$S_{\theta k}=\frac{dy_{m_k}}{d\theta_i} \qquad (6)$$

The advantage of MHSE in the fact that disturbances in the form of unknown and slowly time-varying parameters can be estimated along with the states in a consistent way by adding them as single degrees of freedom to the optimization problem. This is in contrast to many other estimation approaches where parameters have to be reformulated as additional states [7].

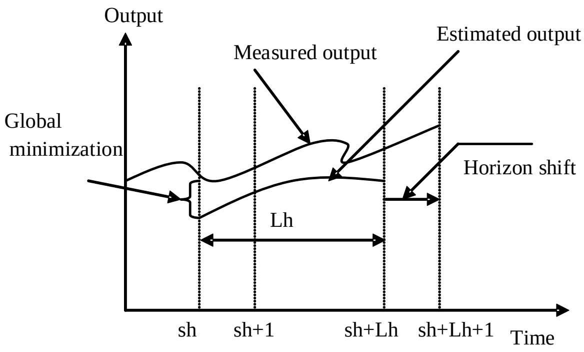

Fig 1: Moving horizon state estimation concept

3. MOTOR DYNAMIC MODEL

The moving horizon estimation algorithm requires a dynamic model of induction motor. The three phases-two phases Park's transformation is used to determine the model of the motor in the stator fixed α-β reference frame. The state equations of induction motor with four electrical variables (currents and fluxes), a mechanical variable (rotor speed), and two control variables (stator voltages) can be written as [8], [13] :

$$\begin{cases}\dot{x}=f(x)+g(u)\\ y=h(x)\end{cases} \qquad (7)$$

where

$x=[i_{s\alpha},i_{s\beta},\phi_{r\alpha},\phi_{r\beta},\Omega]^T$, is an *n* dimension state vector

$u=[u_{s\alpha},u_{s\beta}]^T$, is an *m* dimension control signal

$y=\Omega$, is an *p* dimension measurement vector.

$$f(x)=\begin{bmatrix}-\gamma i_{s\alpha}+\frac{K}{T_r}\phi_{r\alpha}+p\Omega K\phi_{r\beta}\\ -\gamma i_{s\beta}-p\Omega K\phi_{r\alpha}+\frac{K}{T_r}\phi_{r\beta}\\ \frac{M}{T_r}i_{s\alpha}-\frac{1}{T_r}\phi_{r\alpha}-p\Omega\phi_{r\beta}\\ \frac{M}{T_r}i_{s\beta}-\frac{1}{T_r}\phi_{r\beta}+p\Omega\phi_{r\alpha}\\ p\frac{M}{JL_r}(\phi_{r\alpha}i_{s\beta}-\phi_{r\beta}i_{s\alpha})-\frac{1}{J}(T_L+f\Omega)\end{bmatrix}$$

$$g=\begin{bmatrix}\frac{1}{\sigma L_s} & 0 & 0 & 0 & 0\\ 0 & \frac{1}{\sigma L_s} & 0 & 0 & 0\end{bmatrix}^T$$

$$K = \frac{M}{\sigma L_s L_r}, \sigma = 1 - \frac{M^2}{L_s L_r}, \gamma = \frac{R_s}{\sigma L_s} + \frac{R_r M^2}{\sigma L_S L_r^2}$$

$i_{s\alpha}; i_{s\beta}$ denote the stator currents, $\phi_{r\alpha}; \phi_{r\beta}$ the rotor fluxes, $u_{s\alpha}; u_{s\beta}$ the stator voltages, $L_s; L_r$ the stator and rotor inductances, $R_s; R_r$ the stator and rotor resistances, Ω the rotor speed, J the moment of inertia of the machine, M the mutual inductance, f the friction coefficient, p the number of poles pairs, T_L the load torque and finally $T_r = \frac{L_r}{R_r}$ is the rotor time constant.

In this model the voltage equations can be written in a stationary reference frame $\alpha\beta$. This can be done by using the following transformation.

$$T_{\alpha\beta}^{abc} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -0.5 & -0.5 \\ 0 & \sqrt{\frac{3}{2}} & -\sqrt{\frac{3}{2}} \end{bmatrix}$$

4. MODEL BASED DIAGNOSIS

Diagnosis and supervision are important in many applications. The task consists of the detection of faults in the processes, actuators and sensors by using the dependencies between different measurable signals. They are based either on the knowledge about the system or on the model of the system which is subject of this section. This consists of comparing the behaviour of the real system with that of its model. In an ideal case, the system and the model behave exactly the same and when a fault is detected the behaviours are different, this difference is termed as residual, this difference between real system and model behaviours, can be used to diagnose and isolate the malfunction [2]. Because some of variables are difficult to access or that are simply impossible to measure the real behaviour is obtained with estimation. Residual generation via parameter-estimation relies on the principle that possible faults in the monitored process can be associated with specific parameters and states of a mathematical model of a process given in general by an input-output relation. There are different estimating strategies based on measures. In this paper the moving horizon estimation is the method for given information about real system. The implementation procedure of the proposed FDI scheme is illustrated in Figure 2 [9], [11].

In this following, $r_k(t)$ represents the residual in each variable, that is the difference between the measurement parameter vector $\theta_k(t)$ and it's estimated $\hat{\theta}_k(t)$ at each time instant [3].

$$r_k(t) = \theta_k(t) - \hat{\theta}_k(t) \qquad (8)$$

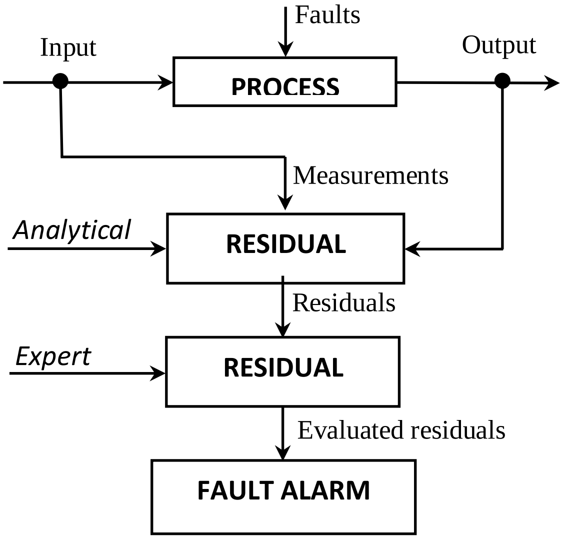

Fig 2: Block diagram representation of proposed FDI scheme problem formulation

5. SIMULATION RESULTS

The machine used is a 1.1kW, 220/380V, 50Hz, 1500rpm induction motor. The parameters nominal values of the studied motor are shown in Table 1.

Table 1: Induction motor parameters

p	2
$R_S(\Omega)$	10
$R_r(\Omega)$	5
$M(H)$	0.447
$J(kgm^2)$	0.029
$f(Nms)$	0.005
$L_r(H)$	0.47
$L_s(H)$	0.47
$T_L(Nm)$	5

The hypothesis on which detection is based is that the apparent rotor resistance of an induction motor will increase when a rotor bar breaks from it nominal value 5Ω to 5.1Ω at t=1.5s as illustrated by Figure 3.

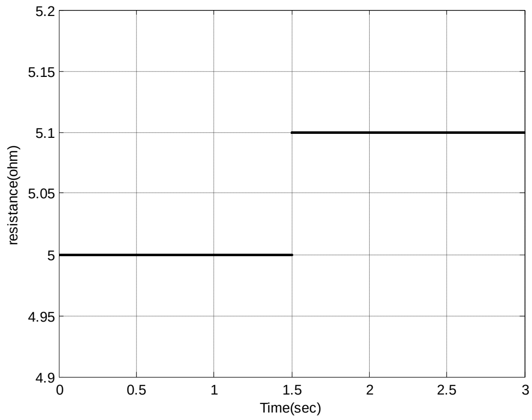

Fig 3: Induction motor resistance with 20% Rr stepwise at 1.5 s

To detect broken bars, measurements of speed are processed by moving horizon estimation for the speed (Figure 5) and rotor resistance simultaneous estimation (Figure 6). In particular, rotor resistance is estimated and compared with its nominal value to detect broken bars by residue generation (Figure 8).

To achieve the MHSE of rotor resistance by the measurement of speed it is necessary to detecting the sensitivity of the output of the variation of this parameter this sensitivity is given by:

$$\delta_{\Omega/R_r} = \frac{\partial \Omega}{\partial R_r} \tag{9}$$

or

$$\dot{\Omega} = p\frac{M}{JL_r}(\phi_{r\alpha} i_{s\beta} - \phi_{r\beta} i_{s\alpha}) - \frac{1}{J}(T_L + f\Omega) \tag{10}$$

$$= f_5$$

then the differential equation of the sensitivity of speed to rotor resistance is obtained by the next equation:

$$\dot{\delta}_{\Omega/R_r} = \frac{\partial f_5}{\partial i_{s\alpha}}\frac{\partial i_{s\alpha}}{\partial R_r} + \frac{\partial f_5}{\partial i_{s\beta}}\frac{\partial i_{s\beta}}{\partial R_r} + \frac{\partial f_5}{\partial \phi_{r\alpha}}\frac{\partial \phi_{r\alpha}}{\partial R_r} + \frac{\partial f_5}{\partial \phi_{r\beta}}\frac{\partial \phi_{r\beta}}{\partial R_r} + \frac{\partial f_5}{\partial \Omega}\frac{\partial \Omega}{\partial R_r} + \frac{\partial f_5}{\partial R_r} \tag{11}$$

with

$\delta i_{s\alpha/R_r} = \frac{\partial i_{s\alpha}}{\partial R_r}$: Is the sensitivity of $i_{s\alpha}$ to rotor resistance.

$\delta i_{s\beta/R_r} = \frac{\partial i_{s\beta}}{\partial R_r}$: Is the sensitivity of $i_{s\beta}$ to rotor resistance.

$\delta \phi_{r\alpha/R_r} = \frac{\partial \phi_{r\alpha}}{\partial R_r}$: Is the sensitivity of $\phi_{r\alpha}$ to rotor resistance.

$\delta \phi_{r\beta/R_r} = \frac{\partial \phi_{r\beta}}{\partial R_r}$: Is the sensitivity of $\phi_{r\beta}$ to rotor resistance.

then the last equation becomes:

$$\dot{\delta}_{\Omega/R_r} = p\frac{M}{JL_r}(\phi_{r\alpha}\delta i_{s\beta/R_r} - \phi_{r\beta}\delta i_{s\alpha/R_r} + i_{s\beta}\delta\phi_{r\alpha/R_r} - i_{s\alpha}\delta\phi_{r\beta/R_r}) - \frac{f}{J}\delta_{\Omega/R_r} \tag{12}$$

Using the ordinary differential equation (ODE) the sensitivity of the speed to the rotor resistance can be representing by the Figure 4 that is show that this output is sensible to the variation of this parameter.

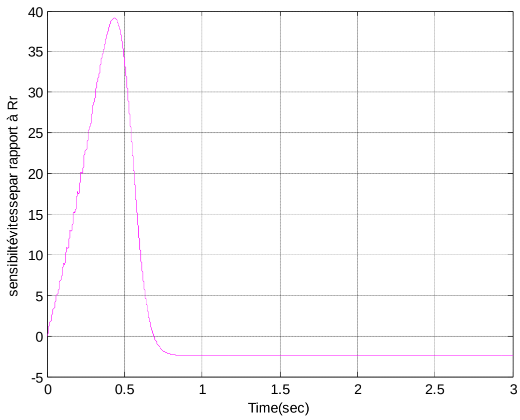

Fig 4: Sensitivity of speed to rotor resistance

In the last simulation result given by Figure 5 and Figure 6, the robustness of moving horizon state estimator with respect to a variation in the resistance value is investigated; the parameter and the state converge quickly to their respective true values. .

A zoom of Figure 6 shown on Figure 7 prove that the convergence time for the estimation method is less than *t* = 0.06 seconds.

As seen above, the obtained results demonstrate the high performance of MHSE especially with response times and precision.

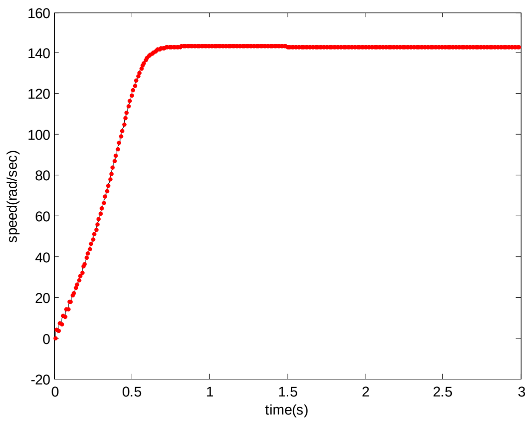

Fig 5: Estimated (in red) and real speed (in black)

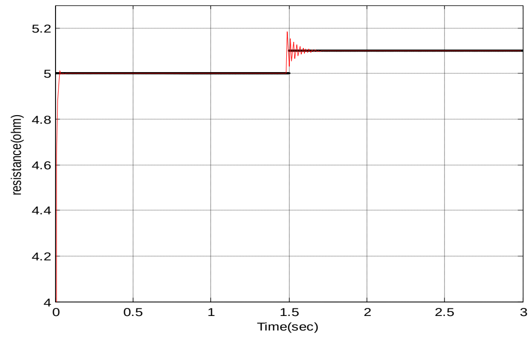

Fig 6: Estimated (in red) and real rotor resistance (in black)

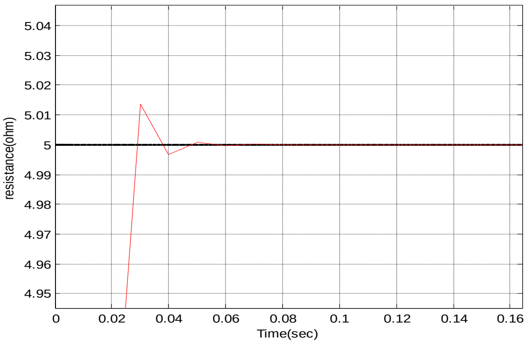

Fig 7: Response time of MHSE

The difference between the reference and the estimated value of the same variable at each time instant (the sample time is 0.1 s) is representing in the next figure, which is called residue which is used to decide about the faults. In the case of Figure 8, after almost 1.5 s, this residue value is jumping for zero to amplitude 0.1 which indicates the system is faulty.

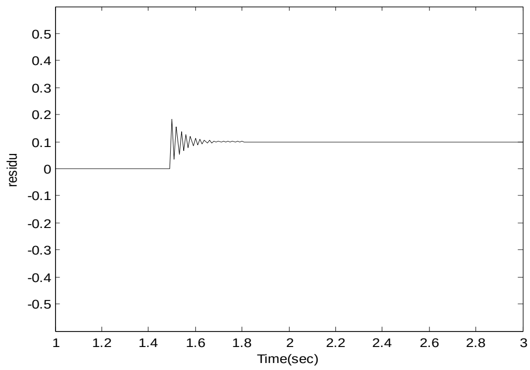

Fig 8: Residual in fault case

6. CONCLUSION

This paper presents an innovative method for the estimation of states in an IM based on a non-linear optimization. This method is called MHSE, and is based on the minimization of a non-linear criterion. In this case, the classic gauss Newton method has been used to solve the proposed optimization problem. This problem derives from the need to carry out estimation of the rotor resistance of an induction motor the simulations of a case of a variation of the resistance from the rated value have been presented, the presented algorithm show an excellent coherence between simulated and estimated process variables, as well as a good response time. These features lead us to believe that an experimental application of the MHSE technique, together with the control laws, may produce industrially useful results.

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