

OPTIMIZATION OF A SPACE VECTOR CONTROL USING MOAM ALGORITHM AND EXTENDED KALMAN FILTER

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Abstract

This paper proposes a new application of parameter estimation for induction motors. Induction motor is described by non-linear differential equations and an Extended Kalman Filter (EKF) estimates three parameters needed for the control (rotor resistance, stator resistance and magnetising inductance). A Modified Random Optimisation Method, MOAM, is used to optimize the covariance matrix in Extended Kalman Filter, rotor and stator autoinductances, friction factor and moment of inertia. It is used to achieve the best performance in the Vector control. Simulation studies on a field oriented controller (FOC), under different variations on the parameter model, and experiments with 5.5 kW motor are presented.

1 Introduction

Nowadays, induction motors are widely used in industry because they are cheaper than DC motors. Though electromagnetic conversion is described by non-linear equations this is not an inconvenience because the mathematical model of the AC motor is well known [6,8,11]

Induction machines represent an alternative to synchronous machines in high performance servo-drive applications. Different configurations are used to implement field oriented control. The rotor-flux-oriented control of induction machines is presented in this case when a pulse-width-modulated (PWM) voltage source inverter supplies the machine[14]. In this case, an induction motor model is necessary for obtaining good performance.

A model that consists of five state-variables: three measurable variables (stator currents and speed) and two non-measurable

variables (rotor currents) has been used. The parameters need to be estimated via a non-linear estimator. The Extended Kalman Filter is a popular method to observe non-measurable variables and estimate physical parameters. [3,4,5,7,10,15]. Three variables {Rs Rr y Lo} are therefore included in the filter.

A large class of optimization problems can be handled by random search techniques. These methods become competitive in some circumstances, for instance when the function characteristics are difficult to compute or are highly desirable to find the global minimum of a function having many local minima. In the problem we are dealing with, both circumstances are present. Since the system is in a closed loop, a more conventional method would not be accurate enough, or even feasible. Moreover, a global minimum is always preferable because a local minimum would not lead to the desired solution.

These algorithms allow the parameter estimation to be improved. Other techniques, such as genetic algorithms, have been used in previous works, [12]. In this case, the Moam algorithm is used to optimise the process and noise covariance matrix of the EKF, and parameters of the induction motor.

In this paper, section 2 reviews the model of the induction motor used for a FOC system. An EKF-based estimation is presented in section 3. In section 4 simulation results are shown with a deficient control due to regular parameter estimation and section 5 shows the optimized EKF to achieve a better identification. Experimental results in a motor bench with a 5.5. KW A.C. motor are presented in section 6.

2 State equations of the motor

A fourth-order state-space model defines the relationship between stator and rotor currents and voltages. Thus, the three-phase system is linearly transformed into two orthogonal axes (a,b) using a time-invariant matrix and stator-fixed reference frame . Therefore, all variables are referred to

the stator. Finally, the mechanical features of the motor are represented by a second-order system. The state variables of the induction motor are the rotor and stator currents (1), and the speed. The inputs are the line voltages and torque (2).

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

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

The model equations can be expressed as follows:

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

where:

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

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

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

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

with output vector (4)

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

Where:

$$L_s = L_{s1} + L_0$$

$$L_r = L_{r1} + L_0$$

L_s L_r Stator and rotor inductance.

L_{s1} L_{r1} Stator and rotor auto-inductance.

R_s R_r Stator and rotor resistance

L_0 : Mutual inductance

T_L : Mechanical shaft torque,

J : Combined rotor and mechanical load inertia.

ω : Rotor angular speed.

Z_p : number of pole-pairs

fr : friction factor

In this case, the system control model [14] is formulated in the reference frame fixed to the rotor flux-linkage space-phasor. There are many ways to obtain the stator voltage equations in this reference frame. Rotor magnetizing-current space-phasor (I_{mr}) is obtained by dividing the rotor flux-linkage space-phasor established in this reference frame ($\Psi_{r\psi r}$) by the mutual inductance (L_0). (5)

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

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

$$\begin{aligned} Tr \frac{d|\text{Im } r|}{dt} + |\text{Im } r| &= I_{sx} \\ W_{mr} &= W + \frac{I_{sy}}{Tr \cdot |\text{Im } r|} \\ Tr &= \frac{L_0}{Rr} \end{aligned} \quad (6)$$

I_{sx} , I_{sy} , stator current formulated in the rotor flux oriented reference frame.

W_{mr} , rotor magnetizing current space phasor speed with respect to the direct axis of the stationary reference frame.

Tr rotor constant.

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

$$Te = \frac{3}{2} Z_p \frac{L_0^2}{Lr} |\text{Im } r| \cdot I_{sy} \quad (7)$$

In figure 1, rotor flux-oriented control schematic of a voltage-source inverter-fed induction machine is presented. The function generation FG allows field weakening to be achieved and its output is the reference value of the flux controller. A decoupling circuit is necessary, because there are dead-time components due to the delay of the inverter and signal processing. For simplicity, it is assumed that the total dead time (T) is concentrated at the end of the signal process.

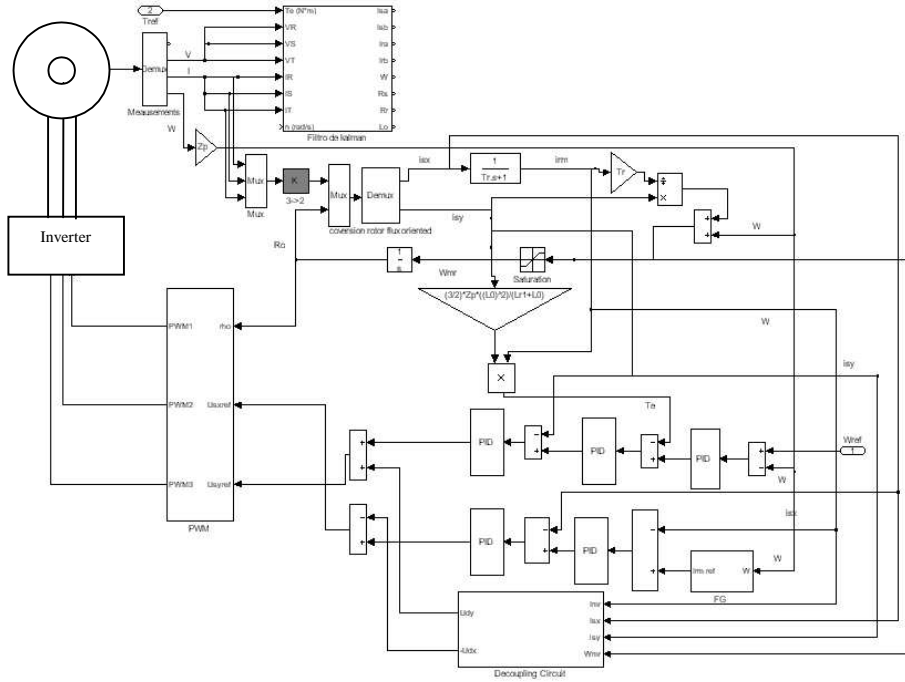


Figure 1- Rotor flux oriented control schematic of a voltage-source inverter-fed induction machine and implementation of Extended Kalman Filter

3 On line parameter estimation

The Extended Kalman Filter (EKF) is the most popular algorithm for estimating physical parameters together with state variables. However, it is well known that in the induction motor model it is not possible to identify all parameters.[1].

It allows the state-vector to be extended with three variables (R_s , R_r and L_0). Therefore, it is not enough to obtain the complete set of parameters.

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

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} = \begin{bmatrix} i_{Sa}(t) \\ i_{Sb}(t) \\ i_{Ra}(t) \\ i_{Rb}(t) \\ \omega(t) \\ R_s \\ R_r \\ L_0 \end{bmatrix} \quad (8)$$

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

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

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

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

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

the extended kalman filter equations are (11):

$$\begin{aligned} \hat{x}_k^* &= f(\hat{x}_{k-1}, u_k, 0) \\ P_k^* &= \nabla f_{xk} P_k \nabla f_{xk}^T + Q_k \\ K_k &= P_k^* \nabla h_{xk}^T (\nabla h_{xk} P_k^* \nabla h_{xk}^T + R_k)^{-1} \\ \hat{x}_k &= \hat{x}_k^* + K_k \cdot [z_k - h(\hat{x}_k^*, 0)] \\ P_k^* &= (I - K_k \nabla h_{xk}) P_k^* \end{aligned} \quad (11)$$

Where Q and R are the process and the measurements covariance matrices respectively. Z_k are the measurements and I the identity matrix.

The Runge-kutta method [9] has been used to solve the discrete-time model of the motor in the equation (10).

As the correct matrices Q and R cannot be chosen based on classical theories, they are usually tuned experimentally by a trial-and-error method, which may not give accurate results. The Moam algorithm is used for improving these values.

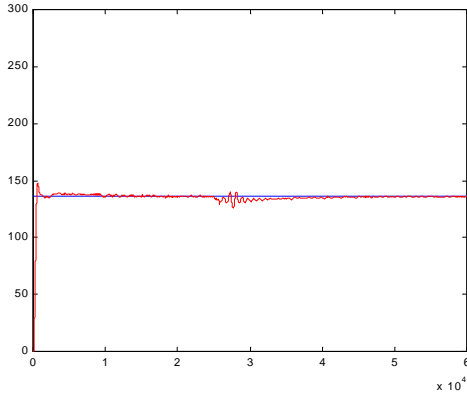


Figure 2. Vector control with a good parameter estimation

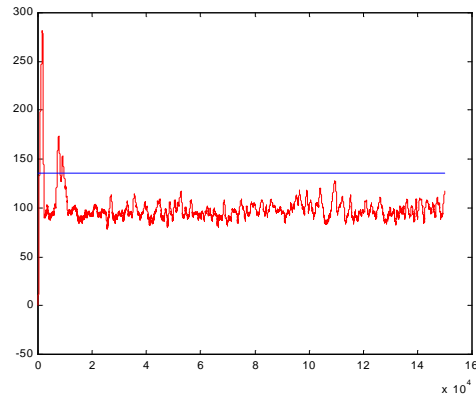


Figure 3. Vector control with deficient parameter estimation

4 Simulation

The system shown above has been simulated with MATLAB 5.3.0 [2].

Some different simulations are made in order to show how a bad parameter estimation effects to the control.

Figure 3 shows a deficient control because the parameters used in the flux model are not precise enough. The parameters used in the simulation are shown in table 1. Figure 3 presents the response for a reference speed step when traditional test parameters are used and figure 2 presents the same test for EKF parameters.

Improving the identification of the motor parameter is the main objective of this work. Estimation with EKF and its optimization are used to achieve this.

5 Optimizing of EKF using a MOAM algorithm

The method that has been used in this paper was proposed by [13] and assures the convergence to a global minimum. The convergence proof and the properties of the algorithm can be found in [13]. In order to implement it, the algorithm has been expressed as follows:

Let $f(\vec{x})$ be the function to minimise and X the search region. The procedures are outlined as follows:

Step 1

Choose an initial point $\vec{x}(0)$ and make $k = 0$. k is the iteration counter and M is its limit.

Step 2

Generate a random gaussian vector $\vec{\xi}(k) = \vec{b}(k) + \vec{r}$, where $\vec{b}(0) = 0$ and \vec{r} is a random gaussian vector. If $\vec{x}(k) + \vec{\xi}(k) \in X$ go to Step 3, if not go to Step 4.

Step 3.

i) If $f(\vec{x}(k) + \vec{\xi}(k)) < f(\vec{x}(k))$, then make

$$\vec{x}(k+1) = \vec{x}(k) + \vec{\xi}(k) \text{ and} \\ \vec{b}(k+1) = 0.4\vec{\xi}(k) + 0.2\vec{b}(k).$$

ii) If $f(\vec{x}(k) + \vec{\xi}(k)) \geq f(\vec{x}(k))$ and

$$f(\vec{x}(k) - \vec{\xi}(k)) < f(\vec{x}(k)), \text{ then make}$$

$$\vec{x}(k+1) = \vec{x}(k) - \vec{\xi}(k) \text{ and} \\ \vec{b}(k+1) = \vec{b}(k) - 0.4\vec{\xi}(k).$$

If neither i) nor ii), applies then make $\vec{x}(k+1) = \vec{x}(k)$ and $\vec{b}(k+1) = 0.5\vec{b}(k)$.

Step 4.

If $k = M$, the end of algorithm is reached. If $k < M$, make $k = k + 1$ and go to Step 2.

Note that the only way in which constraints can be set on \vec{x} is by sizing the X search region.

In our case, the initial values are obtained with classical tests. The function to minimise $f(\vec{x})$ is the sum of the mean squared errors of the process covariance matrix elements for the Rs, Rr and Lo variables

The X Search region is selected in ranges close to the initial estimation of the parameters. (Rr, Rs, Lo, Lr1, Lr1, j, fr), because the classical test is a good approximation.

$\vec{x}(0)$ is computed for a 12 variable. (12)

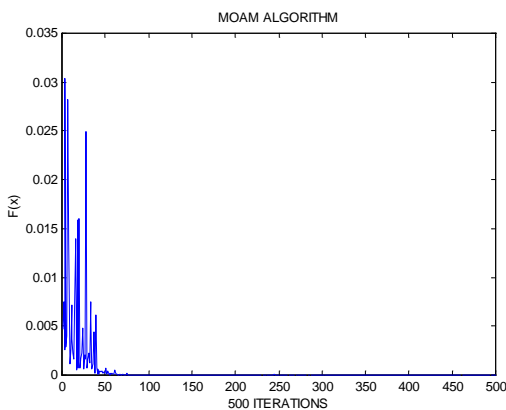
$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \\ x_{10} \\ x_{11} \\ x_{12} \end{bmatrix} = \begin{bmatrix} q1 \\ q3 \\ q5 \\ q6 \\ q7 \\ q8 \\ r1 \\ r3 \\ fr \\ j \\ Ls1 \\ Lr1 \end{bmatrix} \quad (12)$$

$q1, q3, q5, q6, q7, q8$ are process covariance values of the current stator, rotor stator, angular speed, stator resistance, rotor resistance and mutual inductance, respectively.

$r1$ and $r3$, are noises measurement covariance values of the current stator and angular speed.

Figure 3 shows the values $f(x)$ after 500 iterations. The minimum value for $f(x)$ is found in the 465 iteration number. These values are used as the new parameter estimation and a better performance in our vector control can be observed. Table 1 shows the initial parameters versus Moam parameter estimation.

$f(x)$ is minimized, value $f(1) = 0.0047$, after using the Moam algorithm $f(465) = 1.0388e-010$, therefore the algorithm used



is a good method for obtaining a better parameter estimation, improving the process and noise matrices values of an EKF.

Figure 4. Values obtained with Moam algorithm

6 Experimental results

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

The first of them is the motor which is used in our research The second acts as the load. A commercial ABB inverter controls this motor. The load torque can be selected in the control panel of the inverter adding a chopper card and a group of resistors that act as a loser of the absorbed energy of

the load motor that is working in the fourth quadrant (positive speed and negative torque).

PARAMETER	TRADITIONAL TESTS	MOAM ALGORITHM
R_s	1.3	1.28
R_r	2.3	2.332
L_0	0.0226	0.5787
L_{s1}	0.00149	0.00029071
L_{r1}	0.00149	0.000107089
F	0	1e-12
J	0.068	0.66349

Table 1-. Parameter estimation Values with traditional test and optimized-EKF.

The hardware used consists of a Real Time Control and Acquisition Card DSPACE installed in a Pentium II 450 MHz personal computer. The sampling time is 0.0002 s.

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

Figures 5 and 6 show some results for the vector control of the induction motor. The first response has been obtained using parameters calculated with a traditional test and the second has been calculated with EKF and Moam algorithm. Some tests with different values in load and speed have been developed.. The best performance of the control is obtained for FOC when the flux model uses optimised parameters.

The Moam parameters achieve better performance for changes in speed reference. Figure 5 shows the time response of the speed when the reference is set from 800 r.p.m to 1300r.p.m with the load being null.

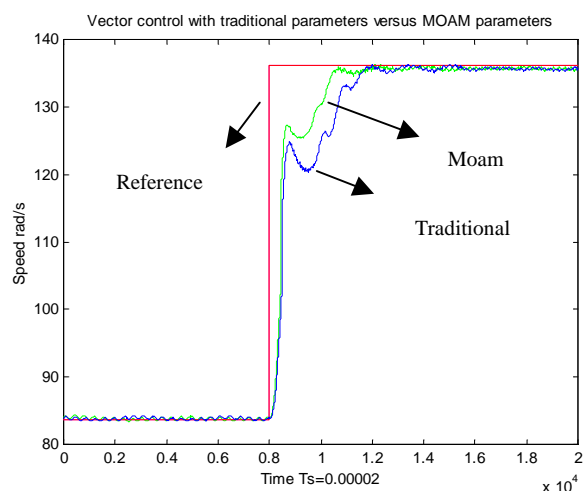


Figure 5. Speed time response with a change in the speed reference

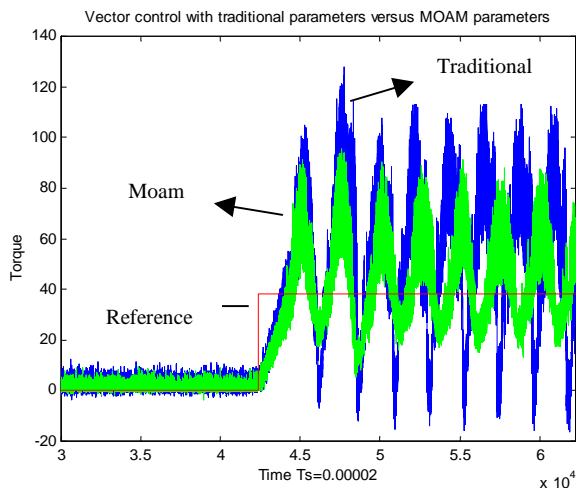


Figure 6. Torque time response with a change in the load reference

Figure 6 shows a load change at 800r.p.m., in this case the reference torque is incremented up to 35% of the nominal load.

In this case, both controls have difficulties to get the load reference but it is the Moam algorithm makes the motor work with less stress, because the reference torque changes of the space vector control will be lower. The speed time response is similar to that shown in figure 6.

Thus it can be seen that control using Moam optimised parameters gives the best performance for the motors for both speed and torque changes.

5 Conclusions

The classical vector space controls do not perform well without the suitable set of parameters, and it has been shown by means of simulation that the traditional techniques are not good enough to obtain them. This paper follows a new optimising method for parameter estimation in induction motor. An Extended Kalman Filter has been used for parameter estimation and the Moam algorithm is used for improving this estimation. The method has been tested with a real A.C. motor, and it has been validated for load and speed changes.

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