Genetic Algorithms Based Parameters Identification of Induction Machine ARMAX Model

A. Mansouri, F. Krim, *Senior Member, IEEE*
Laboratory of Power Electronics and Industrial Control
Faculty of Technology, University of Sétif, Route de Béjaïa,
19000 Sétif, Algeria
email : MANSOURI51@yahoo.com; krim_f@ieee.org

***Abstract* - For a high dynamic performance induction machine (IM) control, parameters have to be precisely known. In this paper we propose a detailed study of the extensive recursive least squares (ERLS) method to estimate these parameters in real time. We use this algorithm with its various extensions to identify the parameters of the Autoregressive Moving Average with Extra Inputs (ARMAX) model associated to the IM. This method is based on the minimization of a quadratic criterion. As advanced technique, this paper proposes Genetic Algorithms (GA) to identify model parameters with biased estimations. A comparison of these two methods confirms the effectiveness of the last one.**

***Keywords:* Parameter Identification, ARMAX Model, Induction Machine, Extensive Recursive Least Squares, Genetic Algorithms, optimization.**

I. Introduction

All procedures of control methods need the knowledge of a system mathematical model. Any deviation between the parameters real values and those belonging to any electrical apparatus induces the control performances deterioration. Hence, it is indispensable to use a high performance method to identify the IM parameters. In industrial control, it is the method used for the choice of classes of adopted models and than to obtain the set of parameter values. Identifying an unknown dynamic system can be defined as an experimental process of building a mathematical model belonging to a class of models presented which reflects precisely its behavior. Considering the referred objective and accuracy, the candidate model will satisfy, in an equivalent manner the process to identify, when submitted to the same constraints leading to the definition of the identification method.

In other words, it is the art of creating a mathematical description of an unknown dynamic system. In everyday life, most of the observed phenomena have dynamic components.

The most used optimization methods are based on the minimization of a quadratic criterion to obtain the best possible set of parameter values. It will be reasonable to confirm that the best parameter values will be those which minimize the quadratic criterion J which will be defined in section 4, often called cost function, also referred to as an index of performance.

Nevertheless, it is not always possible to evaluate these derivatives when the real measures are noisy. Consequently, we use the GA method which needs only to compute the function and not its gradient or other auxiliary knowledge [1].

Many conventional identification methods were published such as based on the least mean squares LMS and RLS. Nowadays, more precise computing of real machine parameters is necessary for Direct Torque Control DTC, Field Oriented Control FOC, and speed sensorless control. For this reason, to efficiently identify the IM phase model, when high dynamic performance in control techniques for adjustable-speed drives is required, GA method is preferred [2-8].

In this paper, two different techniques, the ERLS and the GA for identification of the FOC tetra polar squirrel-cage IM's ARMAX dynamic model including the parameters minimum number, are applied under the same conditions. In the first one, we use the most popular RLS algorithm with its various extensions (ERLS) to identify IM parameters. In the second, we apply GA method for the estimation of these parameters. The proposed approach is employed in fitting characteristics of the block diagram of FOC IM drive using data curves representing angular speed versus supplying voltage and a second order transfer function of the ARMAX model with only four parameters reducing complexity of resolution and computing time. Simulation results obtained from these two methods will also be compared to conclude our study.

II. IM PHASE MODEL

The IMs are the most commonly used in industrial applications to equip all power actuators as machine tools, robots and in variable speed for ship propulsion, TGV, electrical vehicles and so on…. In fact, they are reliable and need low maintenance, regarding their low cost, simplest and robust construction. However; this easiness is accompanied by a physical complexity du to electromagnetic interactions between stator and rotor. It concerns a representation by two coupled magnetic circuits.

Otherwise, knowledge of a per phase equivalent circuit model of the IM becomes necessary to acquire a best understanding to its behavior. To study an electrical machine, the aim of the electro-technician is to elaborate an accurate model to well behave the reality. Then, modeling electrical machines is a primordial step to observe and analyze various electro-mechanical quantities evolution on the one hand and on the other, to elaborate control laws.

Generally, the IM's model is represented by a per-phase real equivalent circuit referred to stator [9] as shown in

978-1-4577-0354-6/11/$26.00 ©2011 IEEE

Fig.1. It is a very important nonlinear type to evaluate the steady state IM's performances, facilitates the computing of various operating quantities, such as stator and rotor currents, electro-mechanical power and losses, developed torque, and efficiency. This simplified equivalent circuit is obtained by referring the rotor elements to stator. As for a per-phase real transformers equivalent circuit, rotor elements will be divided by m^2 in stator.

Considering a tight coupling ($k=1$); the transform ratio rotor/stator:

$$m = \frac{N_r}{N_s} = \frac{M}{\mathcal{L}_s} = \frac{\mathcal{L}_r}{M} \; ;$$

Then $M = \sqrt{\mathcal{L}_s \mathcal{L}_r}$ And $m^2 = \frac{\mathcal{L}_r}{\mathcal{L}_s}$

Rotor resistance referred to the stator: $R = \frac{R_r}{m^2}$

Leakage reactance X_{fs} totalized in the stator:

$$X_{fs} = \frac{X_{fr}}{m^2} = \frac{\mathcal{L}_{fr}}{m^2}.\omega = N.\omega \quad \text{And} \quad \overline{X}_{fs} = jN\omega$$

Hence, the global *leakage* inductance referred to stator:

$$N = \frac{\mathcal{L}_{fr}}{m^2} \quad \text{With } \mathcal{L}_{fr} = \boldsymbol{\sigma}.\boldsymbol{\mathcal{L}_r} \quad \text{where} \quad \sigma = 1 - \frac{M^2}{\mathcal{L}_s \mathcal{L}_r}$$

$\boldsymbol{\sigma}$: *Blondel leakage coefficient which* represents the leakage flux referred to the rotor such that $\mathcal{L}_{fr}$ *is the leakage inductance referred to the rotor*.

R_C and L_m denote the iron core resistor and the magnetizing inductance. R_S denotes the stator resistance.

The steady state IM simplified equivalent circuit is reduced to:

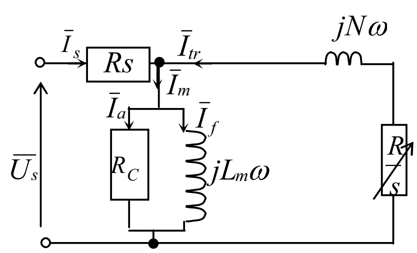

Fig.1. Per-phase equivalent circuit referred to the stator of an I.M

R/s : *Motional resistance*; it means that rotor is rotating accompanied by any slip *s*. It is the reason that this ratio is variable. Hence, it is the source of rotor Joule's losses:

$$P_{JR} = \frac{R}{g} I_{tr}^2$$

and mechanical friction losses: $P_{mf} \;\; (s \neq 0)$

$\overline{I}_{tr} = m\overline{I}_r$: Rotor current referred to stator.

The parameters R_S, (R_{Fer}, L_m), then (R, N) of the equivalent circuit can be obtained respectively from the dc, no load (in o.c: $s = 0$) and blocked-rotor (in s.c: $s = 1$) simple tests using the nominal values from the Y – connected IM's nameplate and the active, reactive power expressions in a typical laboratory experiment. This parameter vector will be used as initial data vector for the minimization based algorithms between the output quantities of the real system and the estimated ones.

III. OUTPUT ERROR BASED METHOD

The model parameters identification procedure could be illustrated by the block diagram of fig.2, where the prediction error ε_k between the output process $y(k)$ and $\hat{y}(k)$ predicted by the model, is used by a parametric adaptation algorithm (P.A.A) based on an optimization quadratic criterion permitting to modify the model parameters $\hat{\theta}$ at each instant k to minimize the output error:

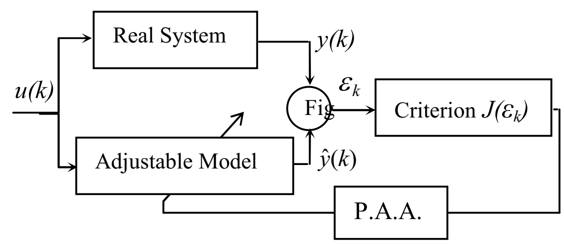

Fig.2. Output error based identification principle.

IV. OPTIMIZATION QUADRATIC CRITERION

The least mean squares method has been introduced by Karl Gauss in 1809. It has been the basic one of all identification methods and parameters estimation. This method is based on the minimization of a quadratic function J defined in (1).

It is the LMS method which permits to find the parameters optimal values $\hat{\theta}$ of linear prediction which minimize the quantity J.

The mean squared error J « MSE » is the prediction distance based on the difference between the output of the real system and that predicted by the model in a same instant *k*:

$$J = \sum_{k=1}^{N} [\varepsilon_k]^2 = \sum_{k=1}^{N} \left[\hat{y}(k) - y(k)\right]^2 \qquad (1)$$

N : number of measurement points

$\varepsilon(k)$: prediction error committed on the estimation.

It concerns to find the parameters vector $\hat{\theta}$ minimizing this function J of the error which is a non linear function of the last ones.

The prediction made using the model depends on the form of this one (AR, MA, ARMA, ARMAX, NARMAX…) that we will choice in section 6.

The model is a function of n parameters θ_k , k varying from 1 to n . The question is then to determine the parameters θ_k so that the criterion J will be minimal.

These algorithms based on the parametric estimation are numerous, here are the most used:

- LMS,
- RLS,
- Recursive Prediction Error Method (RPEM)

In the following sections, we present the equation error methods using the basic RLS algorithm with its various extensions called Extensive RLS (ERLS): the generalized least squares (GLS), the recursive maximum likelihood (RML) and the instrumental variable (IV) methods.

The search of optimal parameters $\hat{\theta}_k$ is made by non linear programming. It concerns to use an algorithm which from non optimal parameters θ_k and a criterion J provides the parameters $\hat{\theta}_k$ of the model.

V. RECURSIVE LEAST SQUARES ALGORITHM (RLS)

It is often desirable to dispose of methods which permit to adjust on line the digital model of a physical process or any signal for the prediction and /or the systems control. These methods are qualified as adaptive. They must be of a high performance concerning rate of convergence, stability, robustness and execution speed since they must be completed within one sample interval.

The RLS method is used for adaptive identification to search, in real time, a digital model of any physical system, of an industrial process (DC motors, synchronous and induction machines…).

The principle of the method consists on minimizing the quadratic criterion J corresponding to the squared error (Mean Square Error: MSE) at the present instant, between the model output and the process output (for example the IM) to determine the best parameters.

In identification, the aim of a recursive algorithm is to find the new estimate of parameters $\hat{\theta}(k)$ from the past one $\hat{\theta}(k-1)$ without making all calculus.

VI. THE ARMAX MODEL

Considering a noisy digital model to simulate a real process, very useful in industrial control, with single input $u(k)$ -single output $y(k)$ and a delay d described by its linear digital recurrent difference equation:

$$y(k) = -\sum_{i=1}^{na} a_i\, y(k-i) + \sum_{i=0}^{nb} b_i\, u(k-d-i) + w(k) \qquad (2)$$

Application of the Z-Transform to (2), leads to the output of a system for which the model « process + perturbation » is ARMAX - type described by:

$$y(k) = Z^{-d}\frac{B(z)}{A(z)}u(k) + w(k) \qquad (3)$$

$w(k)$ represents the effect of the noise in the output, because a system is submitted to perturbations with the result that we can never perfectly calculate the output knowing the input. $w(k)$ could be due to measurement noise of non controlled input. In addition, $w(k)$ has the same dynamic specified by the denominator $A(z)$ of the system TF.

Hence, in the ARMAX model as in the ARX one, the model and the perturbation $e(k)$ have the same dynamic, specified by the denominator $A(z)$ which leads to the structure represented by the fig.3.

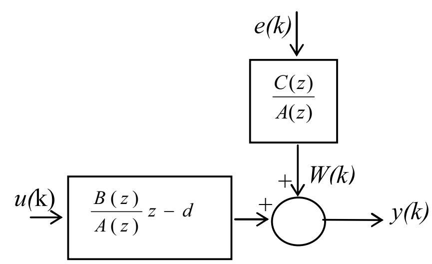

Fig.3. Model structure with equation error ARMAX.

$A(z)$ and $B(z)$ are the polynomials of respectively degree n and m so as $m \prec n$ to be realized . The equation (3) is given by:

$$A(z)y(k) = Z^{-d}B(z)u(k) + w(k) \qquad (4)$$

Hence, this ARMAX model contains AR term $A(z)y(k)$, a control term $B(z)u(k)$ of moving average MA. The output signal $y(k)$ of this system is composed of a determinist part attached to the excitation input $u(k)$ and a stochastic part attached to perturbations $w(k)$ in (5) below (GLS).

$$w(k) = \sum_{i=1}^{n_c} c_i\,.e(k-i) + e(k) \qquad (5)$$

Knowing that the perturbation is not reproducible (unpredictable); it can not be described only in independent random manner specified by two parameters: Its mean μ and its variance σ^2 of the effectuated measurements.

The output of a system for which the model <<process + perturbation>> ARMAX-type will be:

$$y(k) = Z^{-d}\frac{B(z)}{A(z)}.u(k) + \frac{C(z)}{A(z)}.e(k) \qquad (6)$$

Where $e(k)$ is often taken to be Gaussian discrete white noise (RML) with zero mean $\mu = 0$ and variance $\sigma^2 = constant$.

Practically, these models with output error filtering observations represents the 2/3 of the cases, hence the most of the applications.

Using the Z-polynomials, the equation (2) will be written as a model of the form:

$$A(z).y(k) = z^{-d}.B(z)u(k) + w(k) \qquad (7)$$

With the z-polynomials:

$$A(z) = 1 + a_1.z^{-1} + ... + a_{na}.z^{-na} = 1 + z^{-1}.A^*(z)$$

$$B(z) = b_1.z^{-1} + ... + b_{nb}.z^{-nb} = z^{-1}.B^*(z) \qquad (8)$$

(2) can also be written as:

$$y(k) = A^*(z).y(k-1) + B^*(z)u(k-d-1) + w(k)$$

$$= \varphi^T(k).\theta(k) + w(k) \qquad (9)$$

Where $\theta = [a_1 ... a_{na},\ b_1 ... b_{nb}]^T$: (10.a)

is the parameters vector.

$\varphi^T(k) = [-y(k-1)...-y(k-na), u(k-d-1)..u(k-d-nb)]$: (10.b)

is the measurement vector (regressor).

If the model actual parameters are known so as $\hat{\theta} = \theta$, we can define the equation of mean square predictor:

$$\hat{y}(k/\theta) = \varphi^T(k).\theta(k) \qquad (11)$$

VII. THE EXTENSIVE RLS METHOD

In the case of a noisy system, we effectuate N observations measurements (IV), we can write the equation (9) in matrix form:

$$Y_N = \phi_N.\theta_N + W_N \qquad (12)$$

Y_N and ϕ_N represent respectively the whole output and input available data, with Y_N a vector of dimension $Nx1$ and ϕ_N a matrix of dimension NxN enclosing the vectors φ for all experiences.

We define now the equation of the vectorial prediction error presented in matrix form:

$$\varepsilon_N = [\varepsilon(N)...\varepsilon(1)]^T = Y_N - \phi_N.\hat{\theta}_N \qquad (13)$$

Then, the mean square criterion will be written as:

$$J_N(\hat{\theta}) = \frac{1}{N}\varepsilon_N^{\ T}.\varepsilon_N = \frac{1}{N}\left[Y_N - \phi_N.\hat{\theta}_N\right]^T.\left[Y_N - \phi_N.\hat{\theta}_N\right] \qquad (14)$$

Computing the criterion gradient, we find for the condition of optimality:

$$-\frac{2}{N}\phi_N^{\ T}\left[Y_N - \phi_N.\hat{\theta}_N\right] = 0 \qquad (15)$$

With $\hat{\theta}_N$ the estimated parameter vector using N measures. We obtain the analytic solution of the problem:

$$\hat{\theta}_N^* = \left[\phi_N^{\ T}.\phi_N\right]^{-1}.\phi_N^{\ T}Y_N \qquad (16)$$

Remarks:

- We observe that the matrix $\phi_N^{\ T}.\phi_N$ is of a large dimension, if the samples number N is important. The calculus of its inverse poses hence numerical problems. For that, we use the mean square recursive estimation which is well adapted for on line estimation.
- The condition (15) could be interpreted as the search of an orthogonal linear projection of Y_N in the space defined by ϕ_N :

$$\hat{Y}_N = \phi_N.\hat{\theta}_N \qquad (17)$$

The solution by the mean square is then optimal.

To implement the recursive algorithm, we pose:

$$P^{-1}(k) = \sum_{i=1}^{k}\phi(i).\phi^T(i)$$

$$= \sum_{i=1}^{k-1}\phi(i).\phi^T(i) + \phi(k).\phi^T(k)$$

$$= P^{-1}(k-1) + \phi(k).\phi^T(k) \qquad (18)$$

Observing that: $\phi(k)\phi^T(k) \succ 0$ and as the inverse P^{-1} of the gain increases along the time k, the gain P then decreases.

Next, we try to express $\hat{\theta}(k)$ in term of $\hat{\theta}(k-1)$:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \Delta\hat{\theta}(k)$$

Then using (16), we operate for the following transformation:

$$\sum_{i=1}^{k} Y(i)\phi(i) = P^{-1}(k).\hat{\theta}(k)$$

$$= \sum_{i=1}^{k-1} Y(i)\phi(i) + Y(k).\phi(k)$$

$$= P^{-1}(k-1).\hat{\theta}(k-1) + Y(k).\phi(k)$$

$$+ \phi^T(k)\phi(k).\hat{\theta}(k-1) - \phi^T(k)\phi(k).\hat{\theta}(k-1)$$

$$= P^{-1}(k-1).\hat{\theta}(k-1) + \phi(k)\left[y(k) - \hat{\theta}^T(k-1)\phi(k)\right]$$

$$= P^{-1}(k-1).\hat{\theta}(k-1) + \phi(k)\varepsilon^0(k)$$

Hence, we obtain the recurrence for the parameters vector:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k).\phi(k).\varepsilon^0(k) \qquad (19)$$

We have already observed that the gain $P(k)$ is decreasing because we had:

$$P^{-1}(k) = P^{-1}(k-1) + \phi(k)^T.\phi(k) \qquad (20)$$

Along the on line operations, we avoid the matrix inversion due to possible numerical difficulties and we use the matrix inversion lemma, concerning the matrix A, B, C, D which provide the following equality:

$$\left(A + BCD\right)^{-1} = A^{-1} - A^{-1}B\left(C^{-1} + DA^{-1}B\right)^{-1}DA^{-1}$$

With:

$$A = P^{-1}(k-1)\,;\, B = \phi(k)\,;\, C = I\,;\, D = \phi^T(k)$$

This lemma is applied below, in a simplified form to deduct a recursive formula of $P(k)$ using (20) for $P^{-1}(k)$:

$$P(k)=P(k-1)-\frac{P(k-1)\phi(k)\phi^{T}(k)P(k-1)}{1+\phi^{T}(k)P(k-1)\phi(k)}$$

Where it appears yet on an simplest manner that the gain is decreasing.

The RLS algorithm based on the priori error is then constituted by the following three formulas [10]:

$$\hat{\theta}(k)=\hat{\theta}(k-1)+P(k).\phi(k).\varepsilon^{0}(k) \tag{21}$$

$$P(k)=P(k-1)-\frac{P(k-1)\phi(k)\phi^{T}(k)P(k-1)}{1+\phi^{T}(k)P(k-1)\phi(k)} \tag{22}$$

$$\varepsilon^{0}(k)=y(k)-\theta^{T}(k-1)\phi(k) \tag{23}$$

VIII. ESTIMATION OF THE IM ARMAX BY ERLS ALGORITHM

The nominal values from the tetra polar squirrel-cage IM's nameplate were:

$P_{uN}=1.1kW\ (1.5hp), U_{N}=380V,\ f=50Hz,\ n_{N}=1410rpm$

The parameters obtained from the dc, no load and blocked-rotor tests:

$R_{s}=10\Omega, R_{r}=3.5\Omega, L_{s}=0.38H, L_{r}=M=0.3H,$

$J=0.02kgm^{2}$

The IM ARMAX model can be described by the following transfer function:

$$\frac{Y(z)}{U(z)}=\frac{z^{-1}(b_{1}+b_{2}.z^{-1})}{1-a_{1}.z^{-1}-a_{2}.z^{-2}} \tag{24}$$

We choice $Y(z)=\hat{\Omega}(z)$ the output as the IM angular speed and $U(z)=U_{as}(z)$ its supply voltage. a_{k}, b_{k} depends on the IM's parameters of the circuit in fig.1.

Applying the inverse transformation *TZI*, we obtain the following discrete difference equation:

$$\hat{\Omega}(k)=a_{1}\Omega(k-1)+a_{2}\Omega(k-2)+b_{1}U_{as}(k-1)+b_{2}U_{as}(k-2) \tag{25}$$

We can express (25) in the form of a scalar product of parameters vector $\theta(k)$ and anterior measurements vector $\phi(k-1)$ so as:

$$\hat{\Omega}(k)=\theta^{T}(k).\phi(k-1) \tag{26}$$

With $\theta(k)^{T}=[a_{1}\ a_{2} b_{1}\ b_{2}]$

And $\phi(k-1)=[\Omega(k-1)\ \ \Omega(k-2)\ \ U_{as}(k-1)\ \ U_{as}(k-2)]^{T}$

A. Parameters evolution

Applying the ERLS algorithm given the equations (21-23), we obtain the final values of the estimated parameters:

$\{a_{1}=0.4851; a_{2}=0.4843; b_{1}=0.0062; b_{2}=0.0044\}$

Their evolutions are represented by fig. 4.

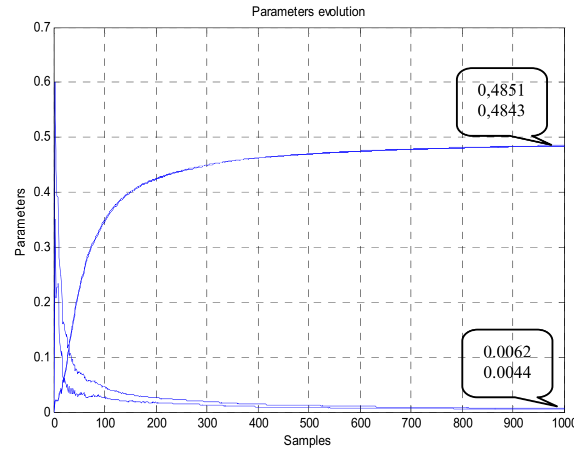

Fig.4. Parameters evolution $a_1 \approx a_2$ et b_1, b_2.

The evolution of the estimated and measured rotor speed with ERLS and the identification residue are shown in fig.5 and fig.6 respectively.

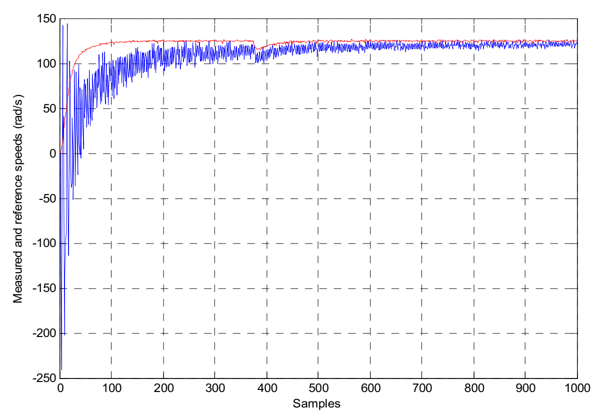

Fig.5. ERLS Estimated (blue) and measured (red) speeds.

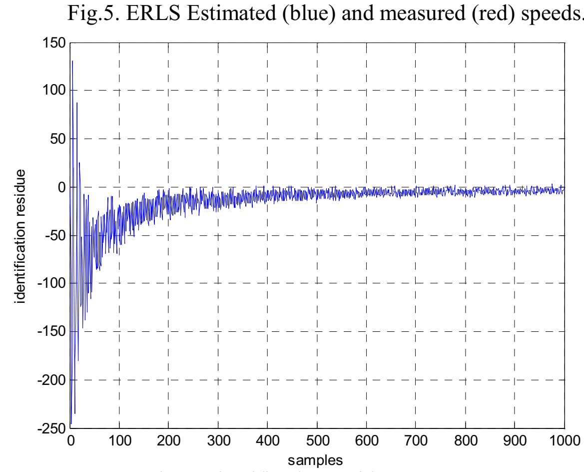

Fig.6. Identification residue

IX. APPLICATION OF GA

A. *GA* method

As a result of rapid industrial developments, the GA technique could be used for many applications in electrical design. This technique can be so considered as an optimization method for a learning process (fig.7) [11-13]. Recently, they are applicable for the identification procedures as the ac and dc machines [6-8], [14-18].

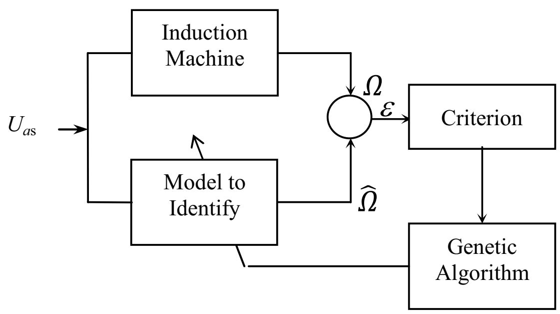

Fig.7. Identification scheme using GA

The GA is based on the natural selection. It is based on its working on the evaluation of a great number of points (parameters) in the research space. From this point of view, it is suitable for searching a global minimum to solve the optimization problems.

As simplified basic principal which produces good results in many practical problems, the GA use three fundamental operators [19-20]:

- Selection - Crossover - Mutation

Fig. 8 shows the necessary steps for the evolution of the algorithm. In the first stage, an initialisation of the population is elaborated by its random generation with a length of *N* individuals so as: $N \in [20,....,100]$ Generally, it depends on the application.

For our study, the individuals are the parameters of a TF *G (z)* of the IM ARMAX model:

$$G(z) = \frac{\Omega(z)}{U_{as}} = \frac{z^{-1}(b_1 + b_2.z^{-1})}{1 - a_1.z^{-1} - a_2.z^{-2}} \qquad (27)$$

Each parameter represents a gene with considerations on the bounds of their variation using initial range [0;1].

To study the quality of individuals a fitness function F is settled on. This is made through an objective function which is computed as the sum of squared errors between the model and the real system outputs for the global response. This function F is evaluated and defined as the maximum in a maximisation problem, because the genetic algorithm minimizes the error. This function *F* is obtained by inversing the mean squared criterion *J*: $J = \sum_{1}^{N} \varepsilon^2$

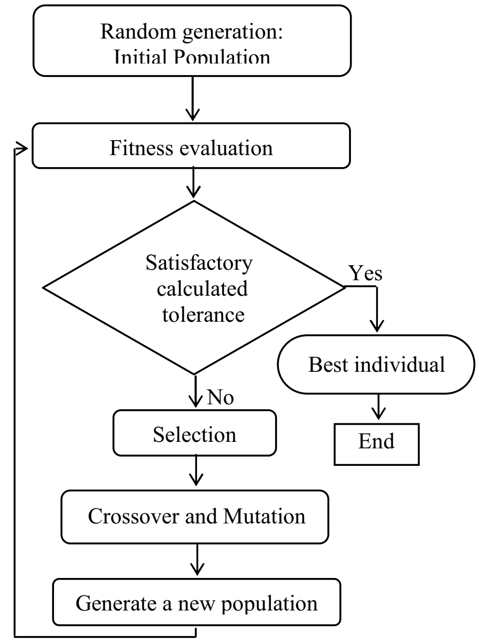

Fig.8. Evolution flowchart of the AG

Hence we find the maximal criterion: $F = \frac{1}{J}$

The selection operator effectuates a filtering on the individuals which guarantees the best fitness to copy directly for the next generation.

In the other hand, the crossover operator guarantees the creation of two new individuals. Generally, the crossover probability p_c varies from 0.6 to 1.

Using the genes of two individuals belonging to the following generation and for what the natural phenomena of permutation and extraction are accomplished for mutation operator. The individuals are attained by changing the nature of one of their gene. This gene is randomly selected. The mutation operator is applied bit by bit and by generation. It randomly modifies the value of some genotype's bits with low probability (practically $P_m \leq 1\%$).

In the final stage, we will try to change individuals with a very low fitness by other mutations to have a high diversity. To finalise the method in the identification process, we can use as stopping criterion, the number of iterations when the value of the tolerance is reached.

B. *Program using MATLAB G.A Toolbox*

We apply GA program using MATLAB GA Toolbox for the estimation of the ARMAX model parameters in (27) depending on those of the equivalent circuit of fig.1. We choice $Y(k) = \hat{\Omega}(k)$ the output as being the IM angular speed and $U(k) = U_{as}(k)$ as being its supply voltage. Hence, we have predicted speed value:

$$\hat{\Omega}(k) = a_1.\Omega(k-1) + a_2.\Omega(k-2) + b_1.U_{as}(k-1) + b_2.U_{as}(k-2)$$

Where $\theta = [a_1\, a_2\, b_1\, b_2]$: the parameters vector.

The error: $\varepsilon = \Omega(k) - \hat{\Omega}(k)$

The criterion: $$J = \sum_{1}^{N=1000} \varepsilon^2 \qquad (28)$$

- The genetic algorithms automatically optimise the four parameters of this model.

- In the first step we create the adaptation function in the work of MATLAB which calculate the error ε between the IM output speed and that predicted by the model on the horizon $N = 1000$. Then, we apply the Fitness Function F *by* mean of the objective function J.
The fitness F searches the maximum: $F = 1/J$ (29)

- The second step, consists to declare in the command WINDOW the input and output variables and also the parameters vector:
$(U_{as}(k)$ $\Omega(k)$ $\theta)$ Globally in MATLAB as follow: *global (U, Y, V)*
With $U = U_{as}$; $Y = \Omega(k)$; $V = [a_1\, a_2 b_1\, b_2]$

- In the third step, we use the AG toolbox on the WINDOW command line as follow: *gatool*
The GA Toolbox being opened, we use the graphical interface in the GA by applying their toolbox.

C. Results and discussion

We obtain the following results of GA method (fig.9-11):

Fitness function value: 310091.0024375879
Parameters best values:
$\{a_1 = 0.48247, a_2 = 0.51118, b_1 = 0.03452, b_2 = 0.04896\}$

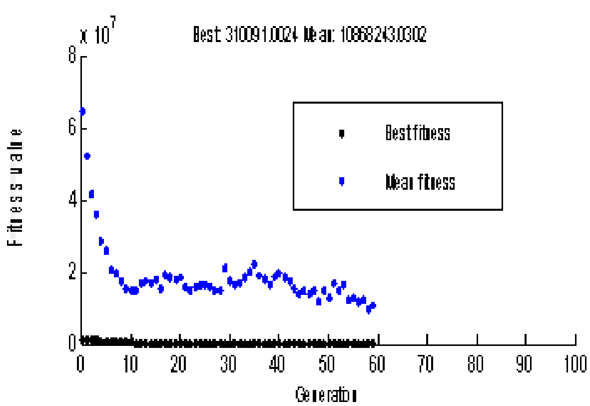

Fig.9. Fitness values.

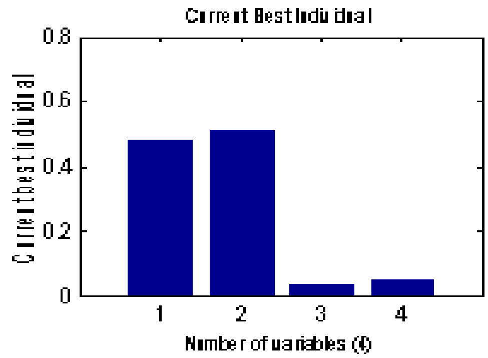

Fig.10. Parameters best values.

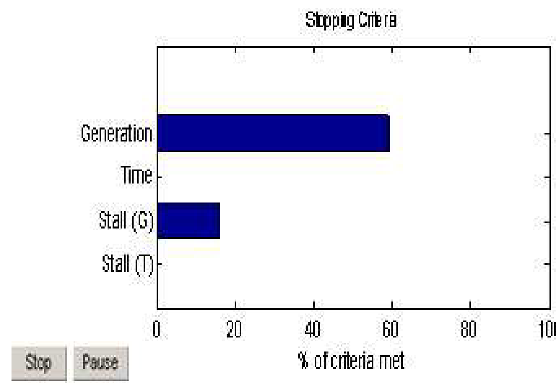

Fig.11. Stopping Criteria

The evolution of the estimated rotor speed with GA is shown in fig.12.

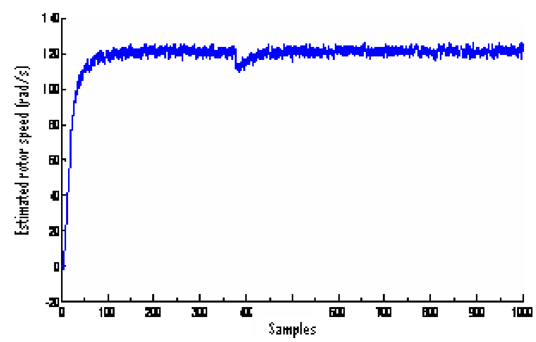

Fig.12. Estimated speed

Applying the ERLS algorithm for a sampling period Ts =8ms, after a short transient state, parameters values converge very quickly (fig.4). The exam of temporal response curves for all amplitudes of the system, permit to estimate a time to establish response time $t_r = 0.8s$.

Observing the estimated speed responses of fig. 5 and 12, confirm the effectiveness of the GA compared to the ERLS method.

The output measured speed of the block diagram of FOC IM drive (fig.13) in steady state is quickly being stabilised to 125 rad/s near the reference value. After application of the mechanical load of $10\,Nm$ at $t = 3s$, we observe a short disturbance to return to its initial value.

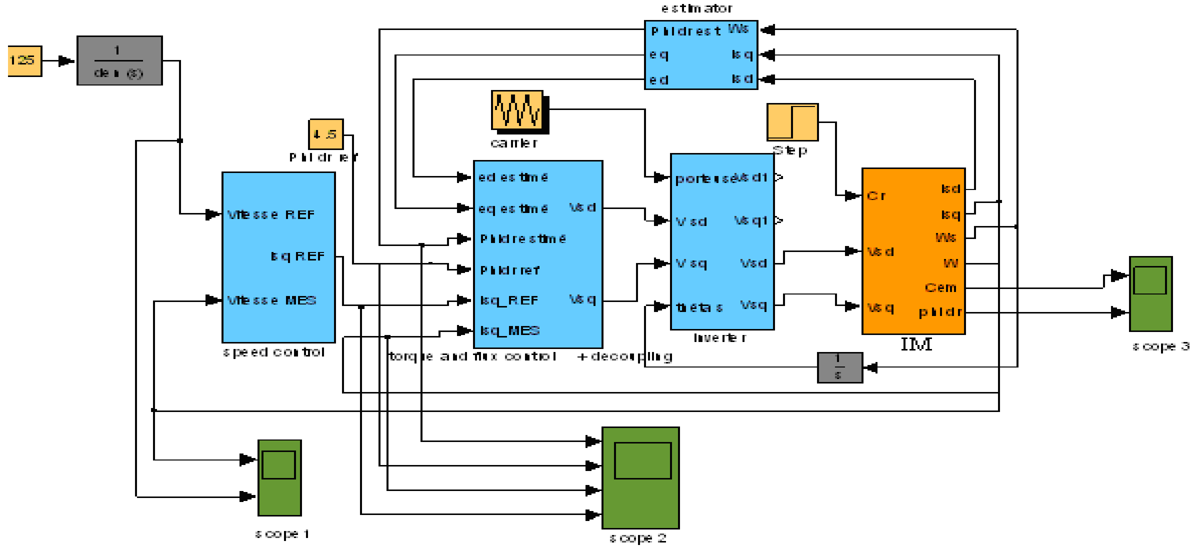

Fig.13. Block diagram of FOC IM drive.

X. CONCLUSION

As shown in this paper the GA applied to the parameter identification of the FOC IM dynamic model is an efficient tool. The power and the robustness of the GA reside in its simple implementation, the necessity of reduced number of iterations for its rapid convergence. For a high efficiency, the IM parametric identification technique using the GAs has given encouraging results. This technique could be extended to other ac and dc machines. Our results will be validated on an experimental test bench. Other optimization functions could be used in the near future.

REFERENCES

[1]. K.F. Man, K.S. Tang, S. Kwong, Genetic Algorithms, Springer-Verlag, London, 1999.

[2]. F. Allonge, F. D´Ippolito, G. Ferrante, F. M. Raimondi "Parameter identification of induction motor model using genetic algorithm", IEE Proc. Control Theory, vol.145, pp.587-593, 1998.

[3]. F. Alonge, F.D'Ippolito, and F. M. Raimondi, "Least squares and genetic algorithms for parameter identification of induction motors," *Contr. Eng. Practice*, vol. 9, no. 6, pp. 647–657, Jun. 2001.

[4]. P. Y Chung, M. Doelen, R. D. Lorenz, "Parameter identification for induction machines by continuous genetic algorithms", ANNIE Conf., pp.1-13, St. Louis 2000.

[5]. H. Razik, A. Rezzoug, "An application of genetic algorithm to the identification of electrical parameters of an induction motor", PEMC, vol.6, pp.1-5, Košice 2000.

[6]. K.S. Huang, Q.H. Wu, D.R. Turner "Effective Identification of Induction Motor Parameters Based on Fewer Measurements", IEEE Transaction on energy conversion , vol. 17, No.1, pp.55-60, March 2002.

[7]. B. Abdelhadi, A. Benoudjit, and N. Nait-Said, "Application of Genetic Algorithm With a Novel Adaptive Scheme for the Identification of Induction Machine Parameters," IEEE Trans. Energy Convers. , Vol. 20, no. 2, June 2005.

[8]. J.-W. Kim, and S. W. Kim,"Parameter Identification of Induction Motors Using Dynamic Encoding Algorithm for Searches (DEAS)", IEEE Trans. Energy Convers. Vol. 20, no. 1, March 2005.

[9]. S. Ayasun, and C. O. Nwankpa, "Induction Motor Tests Using MATLAB/Simulink and Their Integration Into Undergraduate Electric Machinery Courses IEEE Trans. On Education, Vol. 48, no. 1, Febuary 2005.

[10]. K. J. Aström, B. Wittenmark, *Adaptive Control*, Addisson Wesley, USA 1989.

[11]. G. Clerc, D. Choutier, C. Besson, M. Bellaa, N. Rabet, J. Retifm "Comparative study of identification methods for induction machine ", *EPE' 97, Trondheim, p.1.524-528, 1997.*

[12]. Cvetkoski, L. Petrovska, M. Cundev, "Mathematical Model of Permanent Magnet Axial Fed Synchonous Motor for a Genetic Algorithm Optimization," ICEM' *98, Istanbul, pp.1172- 1117, 1998.*

[13]. P. Wang, D. Kwok, "Optimal design of PID process controllers based on Genetic Algorithm," *Control Eng. Practice, vol.2, n°4, pp.641-648m 1994.*

[14]. R. Nolan, P. Pillay, T. Haque, "Application Synchronous of Genetic Algorithm to Motor Parameter Determination," *IAS' 94, New York, pp.47- 54, 1994.*

[15]. P. Pilay, R. Rohan T. Haque, "Application of Genetic Algorithms to Motor Parameter Determination for transient torque calculations," *IEEE Transactions on Industry Applications, vol.33, pp.1273-1282, 1997.*

[16]. F. Alonge, F. D'Ippolito G. Ferrante, and F.M. Raimondi "Parameter Identification of Induction Motor Model Using Genetic Algorithms," *Proc. Inst. Elect. Eng .Contr. Theory Applications, vol.145, pp.587-593, 1998.*

[17]. R. R. Bishop, G. G. Richard, "Identifying Induction Machine Parameters Application Using Genetic Optimization Algorithms," *Southeastcon' 90, vol.2, pp.476-479, New Orleans, USA 1990.*

[18]. R. S. Steven and B. L. Steven, "Identification of induction motor parameters from transient stator current measurements," *IEEE Trans. Ind. lectron.*, vol. 46, no. 1, pp. 139–149, Feb. 1999.

[19]. E. B. S. Filho, A. M. N. Lima, and C. B. Jacobina, "Characterization of induction machines with a genetic algorithm," in *Proc. IEEE Int. Electric Machines Drives Conf.*, Seattle, WA, pp. 446–448, 1999.

[20]. N. Bianchi and S. Bolognani, "Brushless DC motor design: An optimization procedure based on genetic algorithms," in *Proc. Inst. Elect. Eng. International Electric Machines Drives Conf.*, Cambridge, U.K., pp. 16–20, 1997.