Characterization of Induction Machines with a Genetic Algorithm

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Abstract: **In this paper, the characterization of the induction machine is formulated as a nonlinear estimation problem. The solution of the estimation problem is achieved with a genetic algorithm that aims at minimizing a quadratic cost function. The data sources used in the proposed formulation correspond to the values of the current and power absorbed by the machine in standard laboratory tests. The characterization obtained with the proposed technique is compared with that obtained with the classical no-load a locked rotor tests either by simulation and experimentally.**

I. Introduction

It has been established that the quality of the parameters issued from the classical characterization tests must be improved in order to be successfully employed in the design of an inverter fed ac drive system [1–4].

The classical characterization tests are based on the equivalent circuit of the induction machine. An interesting alternative to improve the quality of the classical tests has been proposed in [4]. The technique proposed in [4] essentially solves a non-linear parameter estimation problem by employing the laboratory measurements of the steady-state characteristic curves of the input current and input power as functions of the machine slip. This technique has some practical advantages with respect to previous works since it uses the machine terminal quantities and does not require any mechanical device to measure the electromagnetic torque. However, as the basic formulation is non-linear the choice of the initial parameter vector has to be carefully selected because it has strong influence over the final converging parameter. It is not so hard to find a good initial parameter vector that provide consistent final results, however it requires repeated iterations and some experience of the user. Then, to seek for techniques that could be less sensitive to the initial parameter choice is a relevant topic. In that respect, the use of a genetic algorithm appears as good alternative to overcome this problem. The use a genetic algorithm to determine the induction machine parameters has been recently proposed in [2].

The technique proposed in the present paper is based on the V4 version given in [2] but with significant differences with respect to the definition of the fitness function as well as in the number and type of measurements employed. In the present technique only the quantities which can be measured at the machine terminals are required.

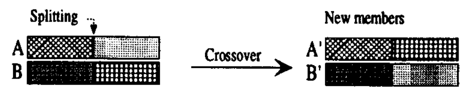

Fig. 1. The crossover mechanics.

II. Genetic algorithm

A genetic algorithm is search technique that is based on the Darwinian evolution model [5]. In a genetic algorithm the individuals are represented as binary strings and it is necessary to define the size of the initial population upon which the genetic operators will be used to generate successive populations. The basic version of a genetic algorithm employs three different operators which are briefly described below. The operators are reproduction, crossover and mutation.

For a given a randomly selected individual of the initial population the reproduction operator is applied. The reproduction operator simply copies the selected individual to the new generation if it satisfies a prescribed criterion. In the jargon that criterion is the fitness function which represents some measure of goodness to be maximized. After reproduction, the crossover operator is employed in a pair of randomly selected individuals of the new generation. The crossover operator splits the two individuals into two parts and then exchange the equivalent parts to create two new individuals. Fig. 1 shows how the crossover operator works by generating two new individuals A' and B' from the initial pair A and B.

The mutation operator takes some selected individual of the new generation obtained after crossover and mutates some bits of its representation, i.e. some zeros may become ones and vice-versa. It is possible to define other genetic operators. However, the three operators presented here are computationally simple but very effective for parameter optimization problems [5].

III. Machine model

For the purposes of the present investigation the induction machine is assumed to be described by

$$\mathbf{v}_s = r_s\mathbf{i}_s + j\omega_s l_s\mathbf{i}_s + j\omega_s l_m\mathbf{i}_r \tag{1}$$

$$0 = r_r\mathbf{i}_r + j(\omega_s - \omega_m)l_r\mathbf{i}_r + j(\omega_s - \omega_m)l_m\mathbf{i}_s. \tag{2}$$

The equivalent circuit shown in Fig. 2 may be derived from these equations. The equations and the equivalent circuit are valid in sinusoidal steady-state with ω_m representing the speed and ω_s the stator frequency, r_s and r_r the stator and rotor resistances and $l_{\sigma s} = l_s - l_m$, $l_{\sigma r} = l_r - l_m$

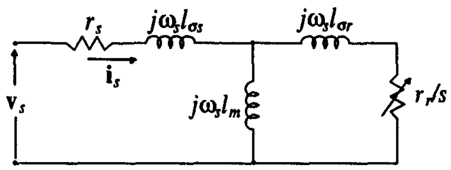

Fig. 2. Steady-state equivalent circuit.

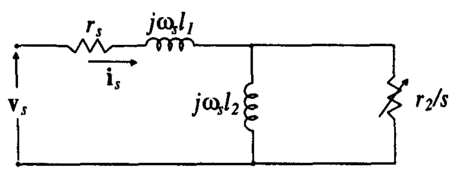

Fig. 3. Equivalent circuit in a rotor flux rotating frame.

and l_m the stator and rotor leakage inductances and the magnetizing inductance, respectively.

Equations (1) and (2) may Por quê? [illegible] the rotor flux given by $\phi_r = l_r \mathbf{i}_r + l_m \mathbf{i}_s$ in a rotating reference frame aligned along the d-axis component of the rotor flux. This rewriting yields another equivalent circuit that will be used in the present paper. This equivalent circuit is shown in Fig. 3.

The parameter vector of the optimization problem is $\theta = [r_s \quad x_1 \quad x_2 \quad r_2]^T$ with $x_1 = \omega_s l_1$, $x_2 = \omega_s l_2$., $\sigma = 1 - l_m^2/(l_s l_r)$, $l_1 = \sigma l_s$, $l_2 = (1-\sigma) l_s$, $r_2 = r_r/(1+\sigma_r)^2$ and $\sigma_r = l_r/l_m - 1$.

It is assumed that the data available to determine the parameter vector are obtained from the measurements of the stator current and stator power as function of the slip. These curves are defined as the steady-state characteristics curves and its relationship with the parameter vector and the slip is given by:

$$I(s,\theta) = \frac{V_s\left[1 + (\frac{r_2}{s}\frac{1}{x_2})^2\right]}{\sqrt{\left(r_s A + \frac{r_2}{s}\right)^2 + \left[x_1 A + (1-A) x_2\right]^2}} \tag{3}$$

$$P(s,\theta) = \frac{V_s^2\left[1 + (\frac{r_2}{s}\frac{1}{x_2})^2\right]\left(r_s A + \frac{r_2}{s}\right)}{\left(r_s A + \frac{r_2}{s}\right)^2 + \left[x_1 A + (1-A) x_2\right]^2} \tag{4}$$

$$A = 1 + \left(\frac{r_2}{s}\frac{1}{x_2}\right)^2 \tag{5}$$

In the present paper the fitness function is

$$f(\theta) = \frac{1}{J(\theta)} \tag{6}$$

which defined as the inverse of the cost function given by

$$J(\theta) = \sum_{i=1}^{N} [I(s_i) - I(s_i,\theta)]^2 + \sum_{i=1}^{N} [P(s_i) - P(s_i,\theta)]^2 \tag{7}$$

TABLE 1. Parameter coding

0	..	10	11	..	21	22	..	32	33	..	43
	r_s			x_1			x_2			r_2	

where $s_i \in [0,1]$. In the above expression $I(s_i)$ and $P(s_i)$ stand for the measured variables. Some authors prefer to include the electromagnetic torque data in parameter optimization problem [1,2]. Evidently, as more measurement data is available the more believable is the final parameter vector. However, the instrumentation required for providing the torque measurement adds significant complexity to the experimental setup. The basic motivation for choosing only electrical quantities is the simplicity of experimental apparatus anchored by a powerful search technique that would compensate the lack of the information related with the measurement of the torque.

The components of the parameter vector are coded as binary numbers of 11 bits. So, the parameter vector is compacted into a 44 bit word as indicated in Table 1.

The components of the parameter vector vary during the optimization process. The maximum value of a given component occurs when all the bits are set to 1 and naturally the minimum corresponds to all bits set to 0. The maximum and minimum values are $\pm 50\%$ of the values determined via the locked rotor and no-load tests, respectively.

The selection of the individuals for the next generation follows a deterministic rule. Also, the crossover operator is applied to every component of the parameter vector which means that there are four splitting points. In all the tests presented in the following the size of the ini[illegible] Como assim? was set to 400 individuals i.e., 400 strings [illegible]

IV. Simulation results

Before going to use the genetic algorithm with the experimental data, a simulation study was conducted to fully understand its mechanism. The algorithm was coded as a Matlab script and the data to be processed was simulated via equations (3)-(4) with $\theta_R = [0.127 \quad 0.481 \quad 2.56 \quad 0.163]^T$ and the initial parameter vector was given by $\theta_0 = [0.09 \quad 0.5 \quad 2.0 \quad 0.2]^T$ both in the pu system.

Table 2 present the results obtained at consecutive runs of the algorithm. It is assumed that the measurements of the current and power are contaminated with additive noise that is a white gaussian signal with unit variance and zero mean. Fig. 4 shows the characteristics curves of current and power calculated with θ_R (3) and the equivalent curves obtained with the average value of the estimated vector of Table 2 (2) and with the initial parameter vector (1).

V. Experimental results

In this section the genetic algorithm studied by simulation was evaluated with experimental data collected in the laboratory for a squirrel cage induction motor with the following nominal characteristics: power - 1/3hp, voltage - 380V, current - 0.84A, frequency - 60 Hz and poles - 4. It were collected 21 different measurements of the current

TABLE 2. Parameter optimization with measurement noise

Run #	r_s	x_1	x_2	r_2
1	0.1246	0.4923	2.3744	0.1750
⋮	⋮	⋮	⋮	⋮
6	0.1238	0.4820	2.5111	0.1685
Average	0.1203	0.4856	2.4579	0.1723
Error %	5.50	0.89	3.82	5.38

TABLE 3. Estimated parameters

Run #	r_s	x_1	x_2	r_2
1	0.5672	0.5528	3.9712	0.2647
⋮	⋮	⋮	⋮	⋮
6	0.5461	0.5656	3.9894	0.2698
Average	0.5593	0.5618	3.9896	0.2659

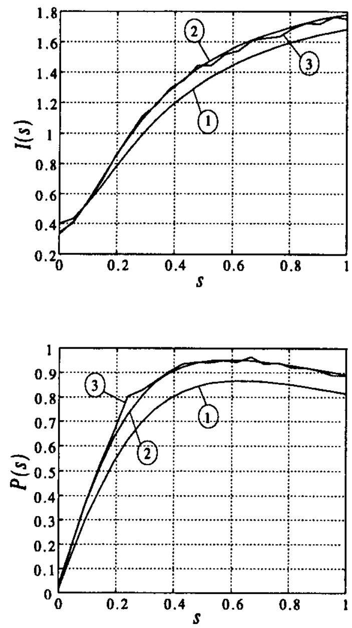

Fig. 4. Simulated p... r (1) Initial parameter vector, (3) Tr... itive noise and (2) Average parameter ... enetic algorithm.

Como assim? Qual critério usado para escolher a função custo (7)?

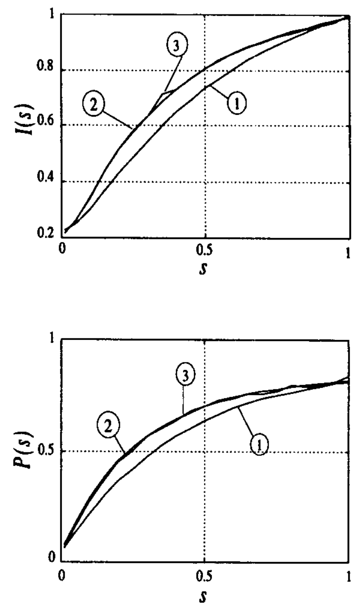

Fig. 5. Plots of $I(s,\theta)$ and $P(s,\theta)$ for (1) Classical tests, (2) Genetic Algorithm and (3) Experimentally collected.

and power as function of the slip which is varied by loading the motor. The size of the initial population was 400 and the algorithm converged after 10 iterations. The the initial parameter vector was $\theta_0 = [0.437 \;\; 0.47 \;\; 3.85 \;\; 0.396]^T$ which was obtained by executing the no-load and locked rotor tests.

Table 3 presents the parameters obtained at consecutive runs of the genetic algorithm. Fig. 5 shows the comparison of the steady-state characteristic curves as calculated: with the parameters of the no-load and locked rotor tests (1), with the parameters of the genetic algorithm (2) and the experimentally collected data (3). Note that the curve calculated with the no-load and locked rotor tests coincide with the experimental curve only at $s = 0$ and $s = 1$. On the other hand the curve calculated with the parameters of the genetic algorithm fits quite well with the experimental data in the entire slip range.

VI. Conclusion

The experimental results were satisfactory and confirmed what was indicated in the simulation studies. The solution of the parameter optimization problem in this case depends of the choice of a fitness function that can handle the experimental data covering the entire slip range. The basic advantage for using a genetic algorithm is its convergence properties when compared to the traditional search techniques has been verified. The proposed method is intended to be used together with the classical tests to improve the quality of the electrical parameter as more measurement data of the steady-state characteristic curves become available in the range of $s \in (0, 1)$.

References

[1] J. Hickiewicz, K. Macek-Kaminska, and P. Wach. Algorithmic methods of induction machines parameters estimation from measured slip-curves. *Arch. Elektrotech.*, 1(72):239–249, 1989.

[2] R. Nolan, P. Pillay, and T. Haque. Application of genetic algorithms to motor parameter determination. In *Conf. Rec. IAS*, pages 47–54, 1994.

[3] J. A. De Kock, F. S. Van der Merwe, and H. J. Vermeulen. Induction motor parameter estimation through an output error technique. *IEEE Trans. Energy Conversion*, 9(1):69–76, March 1994.

[4] A. M. N. Lima, C. B. Jacobina, and E. B. de Souza Filho. Nonlinear parameter estimation of steady-state induction machine models. *IEEE Trans. Ind. Electron.*, 44(3):390–397, June 1997.

[5] D.E. Goldberg. *Genetic algorithms in search optimization and machine learning.* Addison Wesley Publishing Co.- MA - USA, 1989.