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Heuristics for Asynchronous Machine Identification:Genetic Algorithm and Neighbourhood Techniques

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Abstract: The present study describes a comparative study of genetic algorithm and neighbourhood techniques used for off-line identification of three phase asynchronous machine parameters. All the methods are then tested on two distinct machines and the influence of the start time of identification, with reference to the time of startup of machine, is studied. Results show the superiority of genetic algorithm for low values of the start time of identification.

Key words: Asynchronous machine, optimisation, genetic algorithm, neighbourhood techniques

INTRODUCTION

In the few past decades, the important growth in power electronics, control theory and data processing has caused mutation in the field of electrical machines. So, robust, low cost three-phase asynchronous machine has conquered industrial areas traditionally reserved for direct current machine. Simultaneously, asynchronous machine control depends on machine parameters[1]. Although on-line identification appears useful for the enhancement of the performances of control[2]; meanwhile, it is dependent on the initial values of parameters and it is concerned only with some parameters (usually rotor parameters) and for small variations (within 10%)[3]. However, off-line identification is essential for simulation and the correct initialisation of the algorithm of adaptation of parameters. In literature, several methods are advocated for off-line identification of asynchronous machine parameters. These methods are either analytical (determinists)[4-6] or heuristics (approximates)[6-8].

ASYNCHRONOUS MACHINE MODEL

The mathematical model of three-phase asynchronous machine referred to $\alpha\beta$ axes fixed with the stator can be expressed by the following equations[9]:

$$\dot{i}_s = \left[-R_e i_s + \left(I/\tau_r - w_r J\right)\phi_r + V_s\right]/L_e, \quad (1)$$

$$\dot{\phi}_r = \frac{L_s - L_e}{\tau_r} i_s - \left(I/\tau_r - w_r J\right)\phi_r, \quad (2)$$

$$w_r = \left(-f_v w_r + p\left(T_e - T_l - T_d\right)\right)/J_m, \quad (3)$$

$$T_e = p i_s^T J \phi_r, \quad (4)$$

$$T_d = f_d \operatorname{sgn}(w_r), \quad (5)$$

$$V_s = \begin{bmatrix} V_{s\alpha} \\ V_{s\beta} \end{bmatrix}, i_s = \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix}, \phi_r = \begin{bmatrix} \phi_{r\alpha} \\ \phi_{r\beta} \end{bmatrix}, I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

where V_s, i_s, Φ_r represent the stator voltage vector, stator current vector and transformed rotor flux vector, respectively. T_e, T_l, w_r denote the electromagnetic torque, load torque and rotor frequency, respectively. J_m, f_v and f_d denote the rotor inertial moment, viscous friction coefficient and dry friction coefficient, respectively. The equivalent resistance R_e, equivalent inductance L_e and rotor time constant τ_r are related to the machine parameters as shown below:

$$\tau_r = L_r / R_r, R_e = R_s + L_m^2 / L_r^2, L_e = L_s - L_m^2 / L_r \quad (6)$$

where R_s and R_r are the stator resistance and rotor resistance, respectively. L_s, L_r and L_m represent the stator self-inductance, rotor self-inductance and magnetizing inductance, respectively and p is the number of pole pairs. Equations (1-5) are solved by fourth order Runge Kutta method. Since the rotor flux cannot be measured in normal production motors, the behaviour of the system in term of stator current vector and velocity is expressed through the transformed rotor flux vector. Simulation starts with the time of standstill t = 0, where the values of currents, flux, and rotor angular speed are nil. Objective function (generally cost function) is

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computed only upwards the time t_0. The vector of machine parameters to be identified is: $X = [R_e\ L_e\ \tau_r\ L_s\ f_v\ f_d\ J_m]$. The number of simple cage three-phase asynchronous machine parameters is, then, n = 7.

OPTIMISATION TECHNIQUES
GENETIC ALGORITHM (GA)

The main steps of the canonical floating-point-coded genetic algorithm are reported in the following[10]:

- A population of M individuals is randomly generated. Each individual is composed of concatenated sub-strings describing the genotypes. The phenotypes (decision variables) x_i are obtained by decoding the sub-strings.
- All the individuals of the population are evaluated by means of the fitness function f derived from the objective function C, as following:

$$f = 1/(1+C) \tag{7}$$

- The genetic operators are applied:

Selection: Individuals of the old population are selected and put in the new one, according to a rule that favours those with higher fitness. The selection can be stochastic or deterministic.

Crossover: Two randomly selected strings, among those selected in the previous step, are mated. A position along one string is again randomly selected and all the alleles following this position are swapped with those of the second string. This operation takes place with a defined probability p_c.

Mutation: An allele in the strings of the new population is randomly selected, according to a defined probability p_m and its value is complemented according to 1.

- A new population is created. Steps 1 to 3 are repeated until there is no improvement of the best fitness.

NEIGHBOURHOOD TECHNIQUES

The neighbourhood of a solution is defined by means of an elementary transformation. One transformation is considered as elementary (or local) if it does not modify the structure of the solution with which we applies but slightly.

Our neighbourhood system N is based on the following stochastic mechanism of visit:

$$\begin{cases} x'_i = x_i(1-\delta_i) & \text{if} \quad \text{rand} \le 1/3 \\ x'_i = x_i & \text{if} \quad 1/3 < \text{rand} < 2/3, \\ x'_i = x_i(1+\delta_i) & \text{if} \quad \text{rand} \ge 2/3 \end{cases} \qquad i = 1,2,\ldots,n \tag{8}$$

where, δ_i denotes the step size of the movement of the ith parameter, rand is a random number in the range (0, 1).

STOCHASTIC DESCENT (SD)

The principle of stochastic descent consists in generating one solution x', neighbour of the current solution x, according to the neighbourhood system N. If the cost C(x') is better or equal to C(x), then the solution x' is accepted. The procedure finishes when no improvement is observed in the value of objective function.

KANGAROO ALGORITHM (KA)

In the context of one stochastic descent, when objective function was the same value since a long time, the algorithm allows the acceptance of one or more transitions in the current neighbourhood system whatever the value of objective function may be; then, the stochastic descent is restarted[11]. The number of iterations without improvement before a jump is given by the below formula:

$$p_a = \ln(1-\rho) \Big/ \ln\left(1 - \frac{1}{\text{card}(N)}\right), \tag{9}$$

where p_a is the probability of the absence of configurations better than the current one, at the moment of jump.

In practice, the formula (9) is simplified to:

$$p_a \approx 0.7\,\text{card}(N), \tag{10}$$

with: $\text{card}(N)=3^n-1$.

SIMULATED ANNEALING (SA)

Simulated annealing is an extended version of stochastic descent that search more reduced cost configurations by accepting, on a controlled manner, the configurations that degrade the value of objective function[12]. So, at every iteration, a neighbour x' belonging to N(x) of the current configuration x is

randomly generated. If C(x') is better or equal to C(x), then the solution x' is systematically accepted. In the opposite case, x' is accepted with the probability:

$$p(\Delta C, T) = e^{-\frac{\Delta C}{KT}}, \quad (11)$$

where K is known as the Boltzman constant. This lack of aggressiveness that is made possible avoids the entrapment in a local minimum and can provide a globally optimal solution.

The temperature is controlled by a decreasing function that defines the cooling scheme:

$$T(k+1) = \alpha T(k), \quad (12)$$

with α denotes the temperature coefficient.

Generally, authors reproach simulated annealing for having a fixed step length[13]. In order to refine optimisation with the later iterations, the number of iterations at given temperature is chosen linearly increasing from L_{min} to L_{max}.

TABU SEARCH (TS)

Close to one stochastic descent, when examining the neighbourhood of the current solution x, the procedure can escape local optima by executing the least bad movement. In order to eliminate the resulting phenomena of cycling, tabu list is introduced (short term memory of a given size)[14]. The movements whose the attributes are similar to those in the tabu list are forbidden during some number of iterations equal to the list length. The rule of tabu list can be violated if the aspiration criterion is satisfied. We choose the movement sign as attribute: positive for progress, negative for reverse and nil for persistence. The improvement of the objective function is selected as an aspiration criterion.

In the aim to improve the performances of the method, diversification and intensification strategies are introduced; diversification procedure of is included within intensification procedure[15]. The intensification procedure consists in applying the Nelder and Mead method. Diversification procedure is realised by a long term memory based on movement frequency; so, objective function is penalised:

$$C' = C(1+af) \quad (13)$$

with F denotes the frequency of the sign of the movement, a is a weight.

RESULTS

The identification is performed in visual C++ 6 compiler running in 1.7-GH Pentium-based-PC. The sampling frequency is 2 KHz. Voltage signals in the range [-10, 10] V are acquired by means of three resistive voltage dividers, realised with resistors having accuracy equal to 0.1%. Two stator currents are acquired by means of two Hall transducers which generate voltage signals in the range [-5,5] V. DC tachometer generates a voltage proportional to the velocity which, by means of a calibrated resistive voltage divider, is converted into a signal in the range [-10,10] V and, then, acquired.

Table 1: Results of parameter identification of machine-1

	GA	SD	KA	SA	TS
R_s (Ù)	9.355	8.2	9.708	8.2	8.503
L_e (mH)	45.46	39	39	39	46.86
$\hat{o}_r$(ms)	28.59	52.52	24	35.41	47.49
L_s (mH)	254.6	439.9	264	264	424.1
$f_v.10^{-5}$ (Nms)	67	28	37	41	84
$f_d.10^{-5}$ (Nm)	1244	1333	7	1227	379
$J_m.10^{-5}$ (Nms²)	1166	999	999	999	836
C	417.7	323	439.7	393.5	392.5
Time (s)	448	926	800	56	177

Table 2: Results of parameter identification of machine-2

	GA	SD	KA	SA	TS
R_s (Ù)	0.614	0.829	0.829	0.828	0.938
L_e (mH)	4.648	9.088	9.088	9.088	10.22
$\hat{o}_r$(ms)	191.1	214	214	214	214.2
L_s (mH)	93.32	108.1	108.1	108.1	62.21
$f_v.10^{-5}$ (Nms)	28	11	11	133	11
$f_d.10^{-5}$ (Nm)	525	416	416	5514	754
$J_m.10^{-5}$ (Nms²)	238	2073	2073	2073	3655
C	2007	2940	2940	2941	3113
Time (s)	60	596	39	18	41

In order to test optimization techniques, we use two three-phase asynchronous machines:

Machine-1, having the following characteristics: Power rating P = 0.63kw, supply voltage V_s = 380V, nominal angular speed $\dot{U}_r$= 2900rpm, power factor cosϕ_n= 0.737, frequency f = 50Hz, number of poles pairs p = 1. The machine is supplied by a reduced balanced system of sinusoidal voltages V_{seff} = 88 V. The start time of identification t_0 = 0.71 s, load torque T = 0. The preliminary electrical parameters are obtained by classical tests (using DC step supply): R_{ep} = 8.612 Ù, L_{ep} = 39.2 mH, τ_{rp} = 25.7 ms, L_{sp} = 259.2 mH. The step sizes are selected as: δ_1 = 0.005, δ_2 = 0.001, δ_3 = 0.005, δ_4 = 0.001, δ_5 = 0.0001, δ_6 = 0.001, δ_7 = 0.001.

Machine-2, with the characteristics: Power rating P = 5HP, supply voltage V_s = 220 V, nominal angular speed

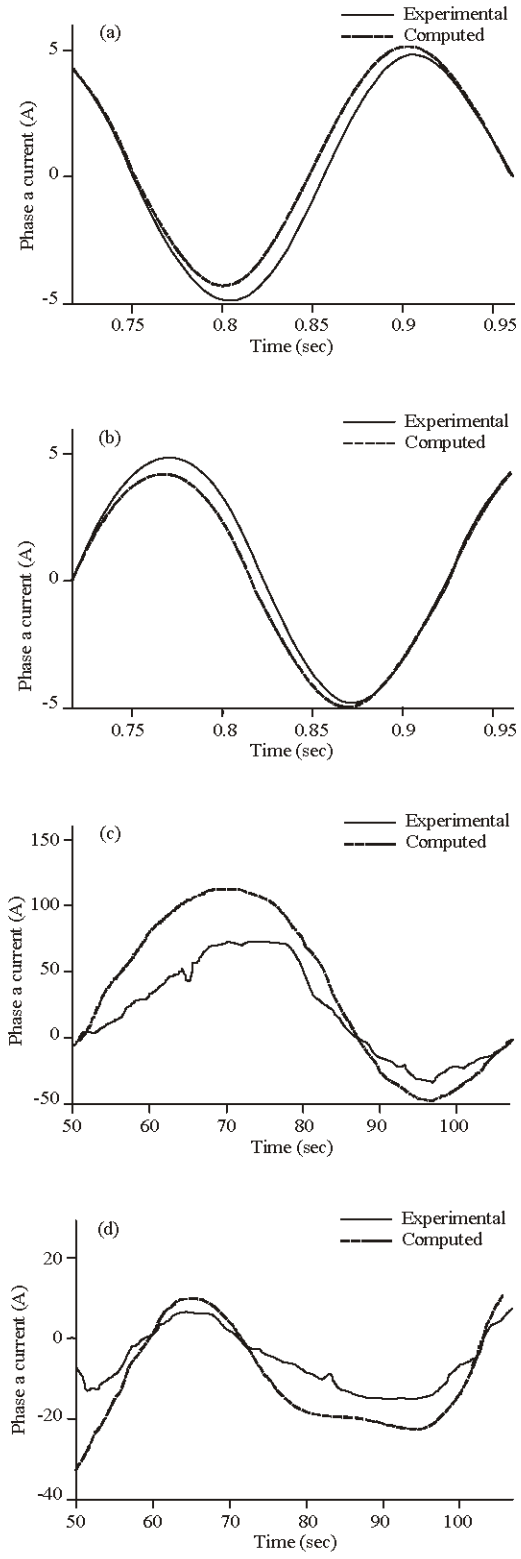

Fig. 1: Machines outputs. a), b) Machine-1 currents resulting from identification using stochastic descent; c), d) Machine-2 currents resulting from genetic algorithm identification.

$\dot{U}_r$ = 1750rpm, frequency f = 60Hz, number of poles pairs p = 2. The machine is supplied by a balanced system of sinusoidal voltages of V_s = 380 V(peak value). The start time t_0 = 0.05 s, load torque T_l = 0. Preliminary electrical parameters are: $R_{ep} = 0.626\,\dot{U}$, L_{ep} = 13.6 mH, τ_{rp} = 321 ms, L_{sp} = 72.1 mH. The step sizes are selected as: $\delta_1 = 0.05$, $\delta_2 = 0.005$, $\delta_3 = 0.001$, $\delta_4 = 0.01$, $\delta_5 = 0.0001$, $\delta_6 = 0.001$, $\delta_7 = 0.001$.

As performance criterion, we choose the weighted absolute cost function:

$$C = \sum_j k_a \left|\left(i_{aj} - i_{saj}\right)\right| + k_b \left|\left(i_{bj} - i_{sbj}\right)\right| + k_w \left|\left(w_j - w_{rj}\right)\right|, \quad (14)$$

where i_{aj}, i_{bj}, $i_{\alpha j}$, $i_{\beta j}$ and w_j denote the measured variables; i_{saj}, i_{sbj}, $i_{s\alpha j}$, $i_{s\beta j}$ and w_{rj} denote the variables obtained by simulation. These quantities are useful for the vector control. Where the weights are chosen as: k_a = 1, k_b = 1 and k_w = 0.5.

The parameters resulting from the application of different methods to parameter identification of machine-1 and machine-2 are reported in Table 1 and 2, respectively.

For machine-1, the best results, those compromise the values of objective function and computation time, are given by simulated annealing and tabu search. Nevertheless, stochastic descent gives the best cost, but execution time is very high. The worst results are given by the genetic algorithm. Electrical parameters obtained by different techniques are close to those given by the DC step supply method.

For machine-2, the best results are given by the genetic algorithm. The worst results are given by the technique of stochastic descent. Electrical parameters obtained by different techniques are far from those given by the DC step supply method. As the results indicate, optimisation techniques give advantages over classical techniques only if the value of the start time of identification t_0 is low. Experimental and simulated results obtained with the parameters resulting from the application of stochastic descent and genetic algorithm are given in Fig. 1. a, b and c, d for machine-1 and machine-2 respectively. Regarding the discrepancy between experimental and computed currents of machine-2, with respect to machine-1, we can conclude that the obtained parameters of machine-1 are more accurate than those of machine-2.

More mature conclusion can be carried out taking into account the fact that asynchronous machine parameters vary according to the test conditions[16]; thereby, overfitting of machine-2 parameters is avoided.

GENETIC ALGORITHM

It has been observed that small populations exhibit large fluctuations in both the average and best fitness[17].

When the size of the population increases, the variability of the results decreases and the choice of crossover and mutation probabilities become significant. High values for crossover and mutation probabilities increase the fluctuation of the average fitness and obstruct the best results to be reproduced. In the other hand, a low crossover probability causes contracted search that can be ineffective. While a high mutation probability produces many mutated strings in the new population which can alter the selection process of the algorithm.

The most effective performance of the genetic algorithm technique seems to be obtained by the stochastic selection, population size M = 100, crossover probability $p_c = 0.9$ and mutation probability $p_m = 0.1$.

When the value of the start time t_o is low, the inrush information allowed by the stator currents and rotor speed (persistent excitation) contributes to the enhancement of the quality of solution, in such a manner that the two offspring resulting from a crossover have not had only inherited old information from their parents but a new information is inserted in the population. From Table 2, it is noticeable that the value of the equivalent inductance L_e resulting from the application of genetic algorithm is clearly distinct from those resulting from the application of neighbourhood techniques. This is due to the diversification effect of the operator of mutation; which causes further increasing the value of the fitness function.

The poor information allowed by a high value of the start time t_0 does not permit genetic algorithm to exhibit good performances. Possible remedy could be the resort to the compact genetic algorithm[18]. In this case, although the low sensitivity to initial estimates is approved, but the value of the fitness function is no longer improved.

STOCHASTIC DESCENT

The algorithm is run ten times, the best results are kept. The performances of the stochastic descent are dependent on the initial parameters of machine.

KANGAROO ALGORITHM

The results obtained from the application of kangaroo algorithm are better than those obtained when reiterated stochastic descents are applied. The jumping mechanism allows kangaroo algorithm to reduce the execution time, with respect to stochastic descent, namely for a low value of the start time t_o.

SIMULATED ANNEALING

The number of configurations necessary to determine the initial temperature is fixed to 30. When a low value is attributed to the temperature coefficient α, premature convergence is observed; while a low number of iterations at given temperature does not allow Markov chains to be irreducible. The parameters of the algorithm that give the best results are the followings: the initial temperature $T_i = 10^5$, final temperature $T_f = 10^{-3}$; limits of the number of iterations at given temperature $L_{max} = 80$ and $L_{min} = 40$ and temperature coefficient $\alpha = 0.9$.

Bearing in mind that simulated annealing is a single-solution based optimisation technique, its transition rule (Equation 11) is stochastic, thus, the information allowed by the stator currents and rotor speed is not guaranteed to be fully exploited by the algorithm. Consequently, the quality of the solution obtained is less good than that given by the genetic algorithm. It is observed that simulated annealing, well known by its lateness, converges faster than the other methods. Furthermore, the algorithm behaviour appears analogous to that of the evolutionary strategy. Thus, one can claim that linearly increasing the number of iterations at given temperature is a fruitful procedure.

RESULT

It is clear that the size of the tabu list can not exceeds 2; elsewhere, all the movements are forbidden.

The performances of the algorithm are not greatly affected by the size and length of the tabu list. Bearing in the mind that the cardinal of the neighbourhood is so large, the number of procedures of diversification before an intensification procedure and, especially, the number of stochastic descents before a procedure of diversification, that exceeds the value of 5 causes execution time to dramatically increasing. To maintain the execution time within reasonable level, a relaxation procedure is adopted. It consists in the restriction of the number of descents before diversification to 100; anywhere the resulting costs, the best element among them is kept. The best results are shown for the list size and length having both the value 2, diversification weight a = 0.1 and the number of diversification procedures before intensification and the descents before diversification within 5.

In its original version, tabu search was designed to escape from limit cycles. Being so, with a fixed list size, tabu search is not well adapted for asynchronous machine identification. However, with a high start time t_0, the untied pattern of machine characteristics make the search less effective; meanwhile, the high nonlinearity

generated by a low value of the start time t_0 seems out of the capacity of the algorithm; which makes the adaptive version its natural alternative. Intensification and diversification strategies contribute to slowing down the algorithm without noticeable improvement of the solution quality.

CONCLUSION

Two classes of optimisation techniques, used for asynchronous machine identification, were described. All the techniques have proven their numerical stability. The choice of the parameters of optimisation techniques is not trivial, but no longer affected by machine parameters. The selection of the start time of identification t_0 is crucial for the performances of different techniques. However, a high value of the time t_0, representing the permanent state of the machine, yields optimisation techniques to exhibit poor performances. However, a low value of the start time t_0, representing the transient regime of the machine, allow global search technique, i.e. genetic algorithm, to give advantage over the basic stochastic descent.

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