Effective Identification of Induction Motor Parameters Based on Fewer Measurements

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***Abstract*—This paper applies genetic algorithms (GAs) to the problem of parameter identification for field orientation control (FOC) induction motors. Kron's two-axis dynamic model in per-unit system is given, and the model's parameters are estimated by a GA using the motor's dynamic response to a direct on line start. Results with different levels of measurement noise are presented for the model both in the per-unit system and in actual values. For comparison, the results of a simple random search (SRS) method under the same condition are also given. The results show that the parameter identification accuracy, the convergence speed and the practicality of the algorithm have been improved significantly by use of the model in the per-unit system. The results also show that fewer measurements are required to identify the induction motor parameters accurately.**

***Index Terms*—Genetic algorithms (GAs), induction motors, modeling, parameter estimation, simulation.**

I. Introduction

THE FIELD orientation control (FOC, also referred to as vector control) of induction motors is increasingly employed when high dynamic performance of the speed control system is required. The method is based on measuring or estimating of the magnitude and position of the rotor flux, and can be classified as direct and indirect. The direct method measures the flux by means of search coils or Hall sensors that are inserted into the stator slots. This degrades the motor's main advantages of mechanical simplicity and ease of maintenance. The indirect method combines a slip calculation with a rotor position or speed measurement, with an on-line model of the machine to calculate the rotor flux position.

The calculation of the slip depends heavily on the mathematical model of the induction motor and its parameters, especially those of the rotor. These parameters are normally those of the equivalent circuit corresponding to the steady operating state and determined traditionally by standard tests. At different machine operating points, the parameter values may vary because of the temperature and the nonlinearities caused by skin effect and saturation. As a result the performance of FOC will degrade if the controller parameters do not match the motor parameters. Therefore, parameter identification for the induction motor's dynamic model is necessary to achieve high performance vector control. It is thus a significant advantage to have an easy and robust way to identify the parameters with good accuracy, high efficiency and general practicality.

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Observed stimulus–response data are used to identify the parameters, and a criterion of the response data is used as an objective function to be minimized. Typically an objective function is a function of the squared predictive errors. In recent years the automated identification of motor parameters has been the subject of much work. The extended Kalman filter (EKF) has been employed to identify parameters and/or states of induction motors [1]–[5]. Among them, Kim *et al.* [3] regarded the state speed as a parameter and Atkinson *et al.* [4] defined the rotor resistance as a state variable. Lin and Su used the recursive least square (RLS) estimator to determine the rotor time-constant, the rotor inertia constant, the damping constant and the disturbed load torque of the induction motor [6]. Two identifiers have been introduced, one for identifying the leakage inductance and the other for compensating the parameter mismatch of the magnetizing inductance and the rotor time-constant by Noguchi *et al.* [7]. Other parameter identification techniques have also been employed [8]–[12]. The conventional techniques applied to electric machines require the measurement of full state variables and probing signals to excite dynamic modes of the machine for the identification purpose, and/or involve a number of experiments to determine a set of parameters. Therefore they are restricted to a limited number of applications. Evolutionary computation techniques provide a more powerful means to resolve the problem. Ma and Wu employed evolutionary programming to identify the parameters of a synchronous generator connected in a two-machine system [13]. GAs have been used most recently for motor parameter identification [14] and [15]. Among them, Pillay *et al.* [14] determined the parameters from the name-plate data for subsequent study of transients, testing four different versions of the GA; Alonge *et al.* [15] estimated the electrical and mechanical parameters of the motor's model.

This paper is to provide a solution based on a GA to obtain the best possible set of parameter values for the improved model of a FOC induction motor, by means of minimizing the errors between the model's simulated dynamic performances and the actual ones. A few measurement variables are involved in a simple process of parameter identification. As an example, start-up performance is used in this study, which can ensure the accuracy of the parameters identified in a noisy environment. Section II describes the computation procedure of the GA used for parameter identification. The improved model in the per-unit system is presented in Section III, which aims to improve the parameter identification accuracy, the efficiency and the practicality of the GA. A simple random search (SRS) is also employed for the parameter identification to provide results for comparison with those of the GA. In Section IV, the improved model both in actual values and in per-unit system is employed, and the two methods, the GA and the SRS, are applied to them under the same condition. Some typical simulation results are described.

II. Identification of Dynamic Model Parameters Using GAs

Suppose that the parameter identification problem can be described as

$$DX = f(\theta, X, V) \tag{1}$$

where

X state variable vector;
V stimulus, i.e., the input vector from the supply;
θ parameter variable vector to be identified;
D differential operator (d/dt).

Let

$$p = [p_1 \quad p_2 \quad \dots \quad p_l]^T \tag{2}$$

be the parameter variable matrix and

$$p_i = [p_{i1} \quad p_{i2} \quad \dots \quad p_{im}] \quad i = 1, 2, \dots, l \tag{3}$$

the parameter vector, where l is the number of the individuals in a generation, and m is the number of the parameters to be identified.

$$Y(t_k) = CX(t_k) + w(t_k) \tag{4}$$

is the measured performance vector which is contaminated by the measurement noise $w(t_k)$ and k is the sequence number of the series measurement sample and t_k is the measuring time instant corresponding to the kth measurement. The whole measurement is supposed to start at $t_k = 0$ and end at $t_k = T_N$; T_N is the time span of the series measurement sample. w is the measurement noise vector, and C is coefficient matrix depending on which measurements of performance are used.

The measurement vector $Y(t_k)$ can be alternatively expressed as

$$Y(t_k) = [y_1(t_k) \quad y_2(t_k) \quad \dots \quad y_M(t_k)]^T \tag{5}$$

where the measurement $y_i(t_k)$ $(i = 1, 2, \dots, M)$ can be either a state variable or a nonstate variable which includes the measurement noise. M is the number of the variables to be measured. Let g stand for the sequence number of generations; the application of the GA to parameter identification can be described as follows.

1) An initial population of parameters, $\hat{p}^{(0)} = \left\{\hat{p}_i^{(0)} | i = 1, 2, \dots, l\right\}$ is formed with randomly selected individuals. Each individual parameter vector is constrained by the following condition:

$$p_{\mathtt{min}j} \le \hat{p}_{ij}^{(g)} \le p_{\mathtt{max}j} \quad j = 1, 2, \dots, m \tag{6}$$

where $p_{\mathtt{min}j}$ and $p_{\mathtt{max}j}$ are the limits of the jth element of the parameter vector $\hat{p}_i^{(g)}$ given by *a priori* knowledge. $\hat{p}_{ij}^{(g)}$ denotes the estimation of the jth element of the ith individual in the gth generation of the parameter. The process starts with $g := 0$.

2) Each individual $\hat{p}_i^{(g)}$ is used to calculate the state variable $\hat{X}(t_k)$ and the general performance $\hat{Y}(t_k)$ corresponding to the measurement defined by (4)

$$\begin{cases} D\hat{X}(t_k) = f\left(\hat{p}_i^{(g)}, \hat{X}(t_k), V(t_k)\right) \\ \hat{Y}(t_k) = C\hat{X}(t_k) \end{cases} \tag{7}$$

and the error vector

$$E\left(\hat{p}_i^{(g)}, t_k\right) = Y(t_k) - \hat{Y}(t_k) \tag{8}$$

where $Y(t_k)$ stands for the measured performance vector, $\hat{Y}(t_k)$ the simulated one and E the expectation operator. Then we get the fitness of $\hat{p}_i^{(g)}$

$$h\left(\hat{p}_i^{(g)}\right) = \sum_{t_k=0}^{T_N} E\left(\hat{p}_i^{(g)}, t_k\right)^T \Lambda E\left(\hat{p}_i^{(g)}, t_k\right) \tag{9}$$

where Λ is a unit matrix and t_k is the discrete computing time which is the same as the measurement sampling time.

3) A new generation, $\hat{p}^{(g+1)}$, with the same individual number of $\hat{p}^{(g)}$, is formed by means of reproduction, crossover, and mutation based on the the previous $\hat{p}^{(g)}$.

4) The process will stop if the minimum $h\left(\hat{p}_i^{(g)}\right) \le \varepsilon$ or $g = MG$, and $\theta = \hat{p}_i^{(g)}$, corresponding to the minimum $h\left(\hat{p}_i^{(g)}\right)$, where ε is a very small real and MG is a big integer representing the maximum generation number. Otherwise, $g := g + 1$, the process is repeated from step 2.

III. Induction Motor Model in the Per-Unit System

It can be seen from the procedure described in the Section VI that the GAs need neither to differentiate the objective function, nor to have a good initial estimate, which is significantly different from the conventional optimization methods, however, it does need good limits (initial ranges) expressed by (6), which is similar to the requirement of a random search method. The initial ranges must be large enough to contain the global optimum. However if made too large, the GA might not be able to find the global optimum at the required parameter identification accuracy and in a reasonable period of time; the convergence will be slow and the efficiency poor. Moreover, any wildly inaccurate parameters may cause the machine model (an integral part of the identification procedure) to produce ridiculous results or generate run time errors. To limit the parameter initial ranges in a self consistent way will contribute to the application of the GA to parameter identification problems.

The GA uses a comparison of a set of measured values with corresponding simulated data. In practice the measurement, be it one or three stator phase currents and/or the rotor speed, will be contaminated by noise. Any change which makes the method less sensitive to the measured variables and the measurement noise will clearly be of benefit, making the parameter identification more robust. The central theme of this paper is that the use of the per-unit system achieves both of these objectives: keeping the initial parameter ranges reasonable and minimizing the effect of the measurement noise and the measured variables.

The per-unit system has many advantages over actual value notation. In per-unit system, the values of the machine parameters fall into well defined ranges, so that the initial ranges of the parameter variables required by (6) can be easily defined and limited. All responses of the machine model in per-unit system are of the same order of magnitude. This will contribute to the accuracy of the parameter estimate. It will also give the objective function natural weighting factors, which reduces the GAs sensitivity to the measured variables.

Let U_n be the rated voltage applied to a stator phase winding of the induction motor, I_n the rated current flowed into the winding, f_1 stand for the supply frequency, U_b, I_b, ω_b, R_b, L_b, S_b and T_b the base values, respectively, of the voltage, current, electrical angular speed, resistance, inductance, power and torque, then choose

$$\begin{cases} U_b = U_n, \quad I_b = I_n, \quad \omega_b = \omega_1 = 2\pi f_1 \\ R_b = \frac{U_b}{I_b}, \quad L_b = \frac{U_b}{\omega_b I_b}, \quad S_b = m_{ph} U_b I_b, \quad T_b = \frac{q P_b}{\omega_b} \end{cases} \tag{10}$$

where ω_1 is the synchronous angular speed; q denotes the number of the pole pairs; m_{ph} denotes the number of stator winding phases and $m_{ph} = 3$. The dynamic model, which is normally employed by speed control applications, can be expressed in per-unit values

$$\begin{bmatrix} v_{ds} \\ v_{qs} \\ v_{dr} \\ v_{qr} \end{bmatrix} = \begin{bmatrix} R_s + \frac{L_s D}{\omega_1} & 0 & \frac{L_m D}{\omega_1} & 0 \\ 0 & R_s + \frac{L_s D}{\omega_1} & 0 & \frac{L_m D}{\omega_1} \\ \frac{L_m D}{\omega_1} & L_m \omega_r & R_r + \frac{L_r D}{\omega_1} & L_r \omega_r \\ -L_m \omega_r & \frac{L_m D}{\omega_1} & -L_r \omega_r & R_r + \frac{L_r D}{\omega_1} \end{bmatrix} \times \begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \end{bmatrix} \tag{11}$$

$$T_e = \frac{1}{3} L_m q (i_{ds} i_{qr} - i_{qs} i_{dr}) \tag{12}$$

$$\left(\frac{\omega_1}{q}\right)^2 \left(\frac{J}{P_b}\right) \frac{\partial \omega_r}{\partial t} = -T_e + T_r - \left(\frac{\omega_1}{q}\right) \left(\frac{B}{T_b}\right) \omega_r \tag{13}$$

where

- v_{ds} d-axis stator voltage;
- v_{qs} q-axis stator voltage;
- v_{dr} d-axis rotor voltage;
- v_{qr} q-axis rotor voltage;
- i_{ds} d-axis stator current;
- i_{qs} q-axis stator current;
- i_{dr} d-axis rotor current;
- i_{qr} q-axis rotor current;
- R_s stator resistance per phase;
- R_r rotor resistance per phase referred to stator;
- L_s stator self inductance per phase;
- L_r rotor self inductance per phase referred to stator;
- L_m magnetizing inductance per phase;
- ω_r rotor electrical angular speed;
- D differential operator d/dt;
- T_e electrical torque;
- T_r load toque;
- B damping coefficient;
- J inertia moment.

Among them, ω_r is positive for operation as a generator and negative when motoring, B and J are actual values, all the others are per-unit values.

With manipulation of (11)–(13) inclusive and $v_{dr} = 0$, $v_{qr} = 0$, together with the assumption that the stator self inductance L_s is identical to the rotor self inductance L_r, we have the state equation as follows:

$$\begin{aligned} Di_{ds} =& \sigma\left(-R_s L_r i_{ds} + L_m^2 i_{qs} \omega_r + L_m R_r i_{dr} \right. \\ & \left. + L_m L_r i_{qr} \omega_r\right) + \sigma L_r v_{ds} \\ Di_{qs} =& \sigma\left(-L_m^2 i_{ds} \omega_r - R_s L_r i_{qs} - L_m L_r i_{dr} \omega_r \right. \\ & \left. + L_m R_r i_{qr}\right) + \sigma L_r v_{qs} \\ Di_{dr} =& \sigma\left(R_s L_m i_{ds} - L_r L_m i_{qs} \omega_r - L_r R_r i_{dr} \right. \\ & \left. + L_r^2 i_{qr} \omega_r\right) - \sigma L_m v_{ds} \\ Di_{qr} =& \sigma\left(L_r L_m i_{ds} \omega_r + R_s L_m i_{qs} + L_r^2 i_{dr} \omega_r \right. \\ & \left. - L_r R_r i_{qr}\right) - \sigma L_m v_{qs} \\ D\omega_r =& \left(\frac{P_b}{J}\right) \left(\frac{q}{\omega_1}\right)^2 \left[\frac{1}{3} L_m (-i_{ds} i_{qr} + i_{qs} i_{dr}) + T_r\right] \\ & - \frac{B}{J} \omega_r \end{aligned} \tag{14}$$

where $\sigma = \omega_1 / (L_s L_r - L_m^2)$. The state (14) is a nonlinear differential equation, for the solution of which the fourth-order Runge–Kutta method has been employed. Let

$$X = [\, i_{ds} \quad i_{qs} \quad i_{dr} \quad i_{qr} \quad \omega_r \,]^T \tag{15}$$

$$V = [\, v_{ds} \quad v_{qs} \,]^T \tag{16}$$

$$\theta = [\, R_s \quad R_r \quad L_r \quad L_m \,]^T \tag{17}$$

then the (14) can be interpreted as

$$DX = f(\theta, X, V) \tag{18}$$

which is exactly the same as (1) so that the GA procedure described in Section IV can be employed to estimate the parameters of the induction motor's dynamic model in per-unit system.

IV. Implementation of the GA and Its Simulation Results

The GA has been employed off-line to identify the parameters of the induction motor's dynamic model both in actual values and in per-unit system, based on a no-load, direct-on-line start. Two different measurement vectors have been used, respectively,

$$Y_1(t_k) = [\, i_{as}(t_k) \quad i_{bs}(t_k) \quad i_{cs}(t_k) \quad \omega_r(t_k) \,]^T \tag{19}$$

and

$$Y_2(t_k) = [\, i_{as}(t_k) \quad \omega_r(t_k) \,]^T \tag{20}$$

TABLE I
MEASUREMENT NOISE VARIANCE σ^2

	i_{as}	i_{bs}	i_{cs}	ω_r
case 1	0.0001	0.0001	0.0001	0.0001
case 2	0.005	0.005	0.005	0.005
case 3	0.01	0.01	0.01	0.01
case 4	0.05	0.05	0.05	0.05
case 5	0.10	0.10	0.10	0.10

the corresponding coefficient matrices C_1 and C_2 for (7) are, respectively,

$$C_1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} & 0 & 0 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{21}$$

and

$$C_2 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{22}$$

so that the calculated performance corresponding to the measurement $Y_1(t_k)$ and $Y_2(t_k)$ will be

$$\hat{Y}_1(t_k) = C_1 X(t_k) \tag{23}$$

and

$$\hat{Y}_2(t_k) = C_2 X(t_k) \tag{24}$$

where

i_{as} current of stator winding A;
i_{bs} current of stator winding B;
i_{cs} current of stator winding C.

The parameter identification was undertaken for five cases of different levels of measurement noise $w(t)$. The measurement noise is taken to be Gaussian random variable $\mathcal{N}(\mu, \sigma^2)$ where μ is the mean (set to zero) and σ^2 is the variance of the noise. The noise variances for the five cases are listed in Table I. The ranges of the identified parameters are assumed to be $\pm 50\%$ of the real values that are determined from the traditional tests. For the GA, the maximum generation number is $MG = 2000$ for the model in actual values and $MG = 1000$ for the model in per-unit system, the number of individuals in a generation l is set to 50. A simple random search method (SRS) has also been employed under the same condition for the purpose of comparison with the GA. The number of the test points for the SRS is $MG \times l$ giving the SRS a similar computation time to the GA. The period for the simulation and the test is set to 0.3 s, that is, $T_N = 0.3$ s. The error E, the maximum error ME, and the fitness F are, respectively, defined as

$$E_i(\%) = \frac{\theta_i - \hat{\theta}_i}{\theta_i} \times 100\% \quad i = 1, 2, 3, 4 \tag{25}$$

$$ME(\%) = \text{Maximum}\{E_1, E_2, \ldots, E_4\} \tag{26}$$

$$F = \sum_{t_k=0}^{T_N} \sum_{j=1}^{M} (y_j(t_k) - \hat{y}_j(t_k))^2 \tag{27}$$

TABLE II
IDENTIFIED PARAMETERS OF THE MODEL IN ACTUAL VALUE (USING GA, BASED ON $l = 50$, $MG = 2000$, AND Y_1)

(Using GA, based on $l = 50$, $MG = 2000$ and Y_1)						
	$R_s(\Omega)$	$R_r(\Omega)$	$L_r(H)$	$L_m(H)$	ME	FG
RV	5.85	5.87	0.252	0.2346	0.00	
case 1	5.8499	5.8691	0.2519	0.2345	0.04	1673
case 2	5.8324	5.8221	0.2478	0.2304	1.79	1997
case 3	5.8117	5.7707	0.2437	0.2263	3.54	1994
case 4	5.8679	5.4496	0.2167	0.1994	15.00	1310
case 5	5.8439	5.1672	0.1940	0.1767	24.68	1899

TABLE III
IDENTIFIED PARAMETERS OF THE MODEL IN PER-UNIT SYSTEM (USING GA, BASED ON $l = 50$, $MG = 1000$, AND Y_1)

(Using GA, based on $l = 50$, $MG = 1000$ and Y_1)						
	R_s	R_r	L_r	L_m	ME	F
RV	0.08775	0.08805	1.18522	1.10553	0.00	0.00
case 1	0.08775	0.08804	1.18610	1.10640	0.08	0.00
case 2	0.08783	0.08820	1.18526	1.10557	0.17	0.05
case 3	0.08792	0.08839	1.18512	1.10545	0.39	0.22
case 4	0.08863	0.08964	1.18561	1.10596	1.18	5.40
case 5	0.08959	0.09131	1.18603	1.10647	3.70	21.60

TABLE IV
IDENTIFIED PARAMETERS OF THE MODEL IN PER-UNIT SYSTEM (USING SRS WITH TEST POINTS $MG \times l$ AND MEASUREMENT Y_1)

(Using SRS with test points $MG \times l$ and measurement Y_1)						
	R_s	R_r	L_r	L_m	ME	F
case 1	0.09044	0.08436	1.21691	1.14384	4.19	4.08
case 2	0.08788	0.09176	1.21992	1.13975	4.21	1.12
case 3	0.08682	0.09107	1.22794	1.14379	3.60	2.11
case 4	0.08718	0.08922	1.18988	1.10493	1.33	7.41
case 5	0.08817	0.09105	1.10494	1.02766	7.04	25.33

TABLE V
IDENTIFIED PARAMETERS OF THE MODEL IN PER-UNIT SYSTEM (USING GA, BASED ON $l = 50$, $MG = 1000$, AND Y_2)

(Using GA, based on $l = 50$, $MG = 1000$ and Y_2)					
	R_s	R_r	L_r	L_m	ME
case 1	0.08777	0.08808	1.18515	1.10547	0.03
case 2	0.08779	0.08819	1.18524	1.10542	0.16
case 3	0.08782	0.08832	1.18547	1.10553	0.31
case 4	0.08810	0.08942	1.18652	1.10556	1.56
case 5	0.08858	0.09090	1.18474	1.10264	3.24

TABLE VI
IDENTIFIED PARAMETERS OF THE MODEL IN ACTUAL VALUE (USING GA, BASED ON $l = 50$, $MG = 1000$, AND Y_2)

(Using GA, based on $l = 50$, $MG = 1000$ and Y_2)					
	$R_s(\Omega)$	$R_r(\Omega)$	$L_r(H)$	$L_m(H)$	ME
case 1	5.8546	5.8790	0.2526	0.2352	0.26
case 2	5.8299	5.8868	0.2539	0.2364	0.77
case 3	5.8592	6.2380	0.2894	0.2716	15.77
case 4	5.6853	5.5938	0.2289	0.2114	9.89
case 5	5.4838	5.1423	0.1932	0.1759	25.02

where $\hat{\theta}_i$ stands for the identified parameter, and θ_i its real value. $y_j(t_k)$ stands for the performance measured, $\hat{y}_j(t_k)$ the corresponding performance simulated by the parameter $\hat{\theta}$. The lower the fitness, the better the performance of the algorithm.

Tables II–VI give the results of the parameter identification of the induction motor's model both in actual values and in per-unit system, using the GA and the SRS, based upon the measurement Y_1 or Y_2, $MG = 2000$ or $MG = 1000$. The results in-

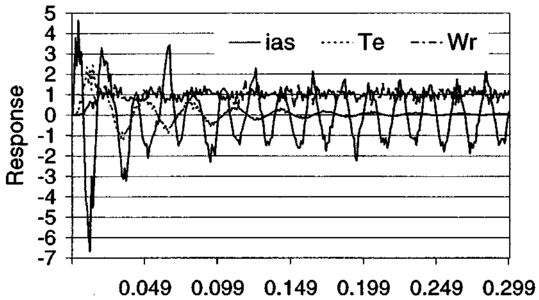

Fig. 1. Induction motor output with noise $\sigma^2 = 0.2$.

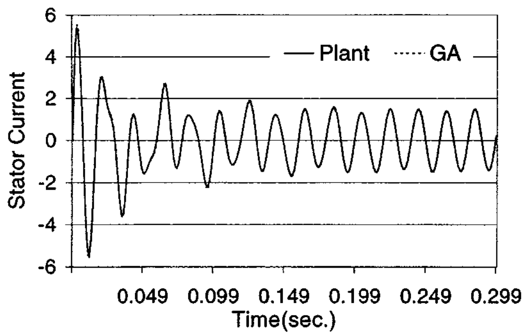

Fig. 2. Stator current start-up response.

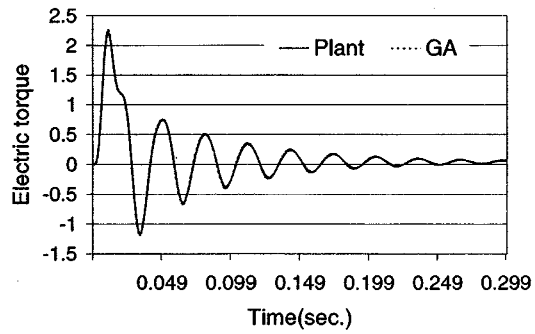

Fig. 3. Electrical torque start-up response.

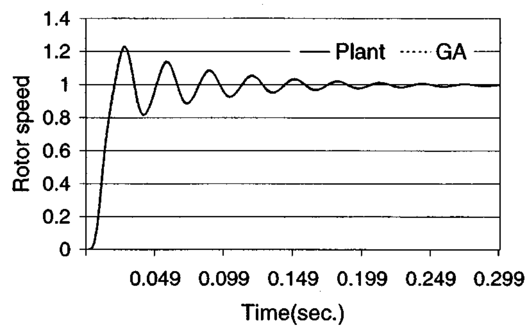

Fig. 4. Rotor speed start-up response.

clude identified parameters, their maximum error and fitness. In Table II, FG is the generation number at which the GA found the identified parameters. RV stands for the real values of the parameters in Tables II and III.

Comparing the results from Tables II–VI, some useful conclusions can be reached.

1) In Tables II and III, the maximum errors are lower and the fitness better for the parameter identification of the machine model in per-unit system calculated in less time (half maximum generation number), which means that the efficiency of parameter identification of the model in per-unit using the GA has been improved significantly, especially for those cases with greater measurement noise. The convergence speed of the algorithm has been increased two times at least.
2) The measurement is $Y_1 = [i_{as}\ i_{bs}\ i_{cs}\ \omega_r]^T$ in Table III and $Y_2 = [i_{as}\ \omega_r]^T$ in Table V. The maximum errors in both tables are almost equal to each other. This means the effective parameter identification can be achieved based on the model in per-unit system and two measurements.
3) The GA estimated the parameters with better accuracy and fitness than that of the SRS shown in Table IV; the GA is a powerful and robust method to identify parameters.

Fig. 1 illustrates the start-up performances of stator current i_{as}, electrical torque T_e, and rotor speed ω_r which are contaminated, respectively, by noise. Figs. 2–4 show the responses which are produced with the real parameters and the identified parameters obtained in case 5 using the GA and the measurement $Y_2 = [i_{as}\ \omega_r]^T$. All the responses and the parameters are in per-unit system. The errors between the response of the induction motor with the real parameters and the GA identified parameters are very small.

V. Conclusion

The paper applied the GA to the parameter identification of the FOC induction motor's dynamic model. The solutions of the problem depends on the mathematical model and its measured data. The improved model in per-unit system has been presented, and the model's parameters have been identified with five different levels of noise and two different measurements, resulting in good accuracy, high efficiency and general practicality as expected. It would be of great interest in practice if fewer measurements could be used in the parameter identification process. The results of the extensive computer simulation studies show that the parameter identification of the FOC induction motor's model in per-unit system using the GA is a powerful and robust technique which can be used in a real environment where there exists measurement noise and the number of measurements is limited.

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