Application of Intelligent Search Techniques to Identify Single-Phase Induction Motor's Parameters

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Abstract: - This paper presents an intelligent approach to identify parameters of single-phase induction motors. Because of the complication of space-phasor equations describing its dynamic behaviors, the parameters of single-phase induction motors could be roughly estimated via conventional tests based on the steady-state analysis. Therefore, they may cause inaccurate estimation. In this paper, some efficient intelligent search techniques, i.e. (i) Genetic Algorithm (GA), (ii) Particle Swarm Optimization (PSO), and Adaptive Tabu Search (ATS), are employed to demonstrate the intelligent identification. The effectiveness of the proposed approach is assured when comparing with the conventional parameter tests.

Key-Words: - parameter identification, genetic algorithm, particle swarm optimization, adaptive tabu search, space-phasor equation

1 Introduction

To characterize the performance of single-phase induction motors, steady-state analysis has become a powerful tool over half a century [1],[2]. It is satisfactory to describe steady-state behaviors of single-phase induction motors to perform simple control. However, nowadays, a very accurate torque-speed control of single-phase induction motors by using the space-phasor theory, called vector control, is increasingly required by industries [3],[4]. Therefore, accurate parameter identification of single-phase induction motors is challenged. Many methods of parameter identification, for example [5],[6],[7], have been proposed. However, there is no strong evidence to verify their use in industries.

This paper introduces an alternative approach to identify parameters of single-phase induction motors based on intelligent search techniques. The space-phasor model is employed to represent single-phase induction motors' behaviors. Parameters appeared in complex space-phasor models can be adjusted and improved by using a simple tuning scheme proposed in this paper. Three efficient intelligent search techniques, i.e. Genetic Algorithm (GA) [8], Particle Swarm Optimization (PSO) [9], and Adaptive Tabu Search (ATS) [10], are employed to perform the proposed identification approach. Moreover, comparisons among results from conventional identification method and those from intelligent identification approach are examined and discussed.

This paper consists of five sections. Section 2 provides modelling of a single-phase induction motor. Intelligent parameter identification is described in Section 3. The results of experiment and simulation are provided in Section 4, while conclusions are given in Section 5.

2 Modelling of Induction Motor

Single-phase induction motors can be characterized by several different models. The space-phasor approach [2],[4] is the method used in this paper. With this model, motor currents, torque and speed can be observable. The space-phasor model is very complicated and needs more space for explanation. However, in this paper only a brief description is presented as follows.

Figure 1 describes winding alignment of a single-phase induction motor consisting of main and auxiliary windings with their induced voltages and currents. As shown in the figure, a stationary reference frame which is along the axis of the main stator winding is defined and used for mathematical analysis throughout this paper. It is essential to inform that all quantities especially on the rotor need to be transferred to the stator axis.

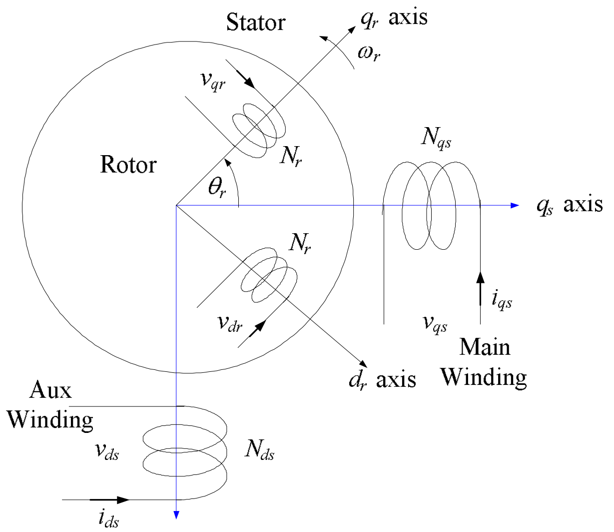

Fig. 1 Winding alignment of a single-phase induction motor.

By using appropriate transform matrix, all state variables can be transformed into the stator direct axis as shown in (1).

$$\frac{d}{dt}[i]=[A][i]+[B][v] \tag{1}$$

…, where $[A]=[D]^{-1}[E]$, $[B]=[D]^{-1}$,

$[i]=\left[i_{qs}\;\; i_{ds}\;\; i'_{qr}\;\; i'_{dr}\right]^T$,

$[v]=\left[v_{qs}\;\; v_{ds}\;\; v'_{qr}\;\; v'_{dr}\right]^T$,

$$[E]=\begin{bmatrix} -R_{qs} & 0 & \omega_r L_{mqs}\sin\theta_r & \omega_r L_{mqs}\cos\theta_r \\ 0 & -R'_{ds} & -\omega_r L_{mqs}\cos\theta_r & \omega_r L_{mqs}\sin\theta_r \\ \omega_r L_{mqs}\sin\theta_r & -\omega_r L_{mqs}\cos\theta_r & -R'_r & 0 \\ \omega_r L_{mqs}\cos\theta_r & \omega_r L_{mqs}\sin\theta_r & 0 & -R'_r \end{bmatrix},$$

$$[D]=\begin{bmatrix} L'_{lqs}+L_{mqs} & 0 & L_{mqs}\cos\theta_r & -L_{mqs}\sin\theta_r \\ 0 & \left(L'_{lds}+L_{mqs}\right) & L_{mqs}\sin\theta_r & L_{mqs}\cos\theta_r \\ L_{mqs}\cos\theta_r & L_{mqs}\sin\theta_r & \left(L'_{lr}+L_{mqs}\right) & 0 \\ -L_{mqs}\sin\theta_r & L_{mqs}\cos\theta_r & 0 & \left(L'_{lr}+L_{mqs}\right) \end{bmatrix}$$

…, where R_{qs} is stator resistance of the main winding, R_{ds} is stator resistance of auxiliary winding, L_{ls} is leakage inductance of the main winding, L_{ls} is leakage inductance of the auxiliary winding, L_{mqs} is mutual inductance on the stator q-axis, R_r is rotor resistance, and L_{lr} is leakage inductance of the rotor q-axis.

As can be seen, the two mechanical quantities, the rotor speed ω_r and the rotor position θ_r, cause the need for additional two equations which can be obtained from Newton's second law of motion as shown in (2). All above equations can be combined as stated in (3), where J_m is motor's moment of inertia and B_m is damping coefficient.

$$\begin{bmatrix} \frac{d\omega_r}{dt} \\ \frac{d\theta_r}{dt} \end{bmatrix}=\begin{bmatrix} -\frac{B_m}{J_m} & 0 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} \omega_r \\ \theta_r \end{bmatrix}+\begin{bmatrix} \frac{P}{2J_m} \\ 0 \end{bmatrix}\left[T_e-T_L\right] \tag{2}$$

$$\begin{bmatrix} \frac{d[i]_{4x1}}{dt} \\ \frac{d\omega_r}{dt} \\ \frac{d\theta_r}{dt} \end{bmatrix}=\begin{bmatrix} [A]_{4x4} & \cdots & 0 & \cdots \\ \vdots & & -\frac{B_m}{J_m} & 0 \\ 0 & & 1 & 0 \\ \vdots & & & \end{bmatrix}\begin{bmatrix} [i]_{4x1} \\ \omega_r \\ \theta_r \end{bmatrix}+\begin{bmatrix} [B]_{4x4} & \cdots & 0 & \cdots \\ \vdots & & \frac{P}{2J_m} & 0 \\ 0 & & & \\ \vdots & & 0 & 0 \end{bmatrix}\begin{bmatrix} [v]_{4x1} \\ T_e-T_L \\ 0 \end{bmatrix} \tag{3}$$

3 Intelligent Parameter Identification

Traditionally, the no-load test, the locked-rotor test, and retardation test are all together used as the conventional method to identify single-phase induction motor's parameters. Based on the steady state model, such the conventional method cannot be used to estimate parameters, accurately and precisely. In this paper, some intelligent search techniques are used to identify such parameters.

The use of artificial intelligent search technique to identify single-phase induction motor's parameters can be represented by the block diagram in Figure 2. The speed response of a tested single-phase induction motor is firstly measured. The selected intelligent search technique is employed to generate a set of initial random parameters. During the search process, the cost function, J, the sum of squared error (SSE) between the measured speed (y) and the simulated speed (y^*) as stated in (4), is fed back to the AI search engine block. J is minimized to find the appropriate parameters that give the simulated response from the space-phasor model best fitting close to the measured response. Selected intelligent search techniques used in this work, i.e. (i) Genetic Algorithm (GA), (ii) Particle Swarm Optimization (PSO), and Adaptive Tabu Search (ATS), are summarized.

$$J = \sum_{i=1}^{N} \left(y_i - y_i^* \right)^2 \tag{4}$$

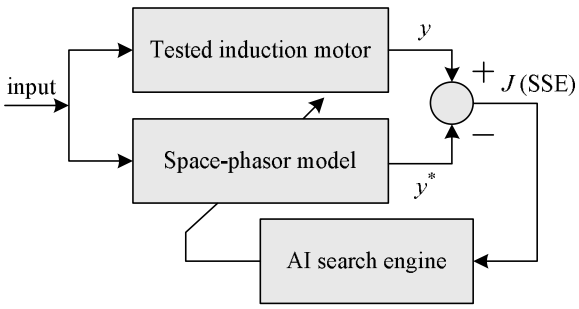

Fig. 2 Intelligent parameter identification.

3.1 Genetic Algorithm (GA)

The GA [8] is a stochastic search technique based on two natural processes, i.e. selection and genetic operation. The search process of the GA is similar to the nature evolution of biological creatures in which successive generations of organisms are given birth and raised until they themselves are able to breed. The GA algorithm is summarized as follows.

(1) Randomly initialize populations or chromosomes and set them as a search space.
(2) Evaluate the fitness value of each chromosome via the objective function.
(3) Select some chromosomes giving better fitness value to be parents.
(4) Reproduce new generation (offspring) by genetic operations, i.e. crossover and mutation.
(5) Compute the fitness value of each new chromosome via the objective function.
(6) If the termination criteria are met, stop the search process. The optimum solution found is the best chromosome in a search space, otherwise replace old chromosomes by new ones and go back to (2).

3.2 Particle Swarm Optimization (PSO)

Inspired by the sociological behavior associated with birds flocking, the PSO was proposed [9] as a simple model of lives' group. In the original concept, particles fly through the solution space with two factors, i.e. the best position of each particle (personal best), and the group's best position (global best). Based on the notion of particle flying, the PSO algorithm updates a particle by moving towards the particle's past personal best and the best particle that has been found. In addition, the particle's velocity is an important key used to define the direction of particle's motion. The motion's direction of all particles will be improved correspondingly to that of the best particle. The PSO has a powerful performance in finding global optimum. The PSO algorithm is briefly described as follows.

(1) Initialize particle swarm and set it as a search/solution space.
(2) Evaluate the fitness value of each particle via the objective function.
(3) Investigate and improve the personal best and the global best.
(4) Improve each particle's velocity.
(5) If the termination criteria are met, stop the search process. The optimum solution found is the best particle in a group, otherwise improve all particles and go back to (2).

3.3 Adaptive Tabu Search (ATS)

The ATS [10] is also a stochastic search technique based on iterative neighborhood search approach for solving combinatorial and nonlinear problems. The Tabu list is used to record a history of solution movement for leading a new direction that can escape a local minimum trap. In addition, the ATS method has two additional mechanisms, namely back-tracking and adaptive search radius, to enhance its convergence. The ATS algorithm is summarized as follows.

(1) Initialize a search space.
(2) Randomly select an initial solution x_o from the search space. Let x_o be a current local minimum.

(3) Randomly generate N solutions around x_o within a certain radius R. Store the N solutions, called neighborhood, in a set X.
(4) Evaluate a cost function of each member in X. Set x_1 as a member that gives the minimum cost in X.
(5) If $x_1 < x_0$, put x_0 into the Tabu list and set $x_0 = x_1$, otherwise, store x_1 in the Tabu list instead.
(6) Activate the back-tracking mechanism, when solution cycling occurs.
(7) If the termination criteria are met, stop the search process. x_0 is the best solution, otherwise activate the adaptive search radius mechanism, when a current solution x_0 is relatively close to a local minimum to refine searching accuracy, and go back to (2).

4 Results and Discussions

To perform the effectiveness of the proposed intelligent identification, a 0.5-hp, 220-V, 50-Hz, 4-poles, single-phase, squirrel-cage induction motor is used for test as shown in Figure 3. With the conventional method, no-load, locked-rotor, and retardation tests, the parameters of the single-phase induction motor can be obtained as shown in Table. 1.

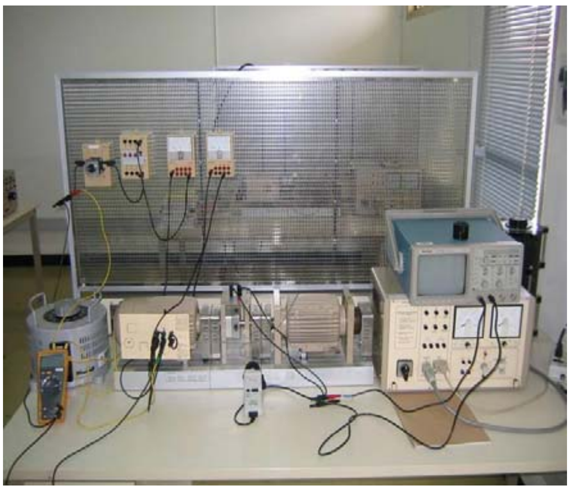

Fig. 3 Experimental set up.

For intelligent identification, the GA, the PSO, and the ATS are used, respectively. In this work, parameter settings for these three intelligent methods are as follows: GA-{number of population = 50, crossover probability = 70%, and mutation probability = 4.7%}; PSO-{number of particle = 20, and maximum velocity = 15}; ATS-{number of neighborhood = 40, search radius R = 10% of the search space, activate back-tracking mechanism when solution cycling = 5, and invoke adaptive search radius mechanism using $R = 0.8*R$ when number of solution cycling = 20, 40, 60, 80}. The parameters of the single-phase induction motor obtained from conventional method are used to perform search spaces for these three intelligent methods as follows: $R_{qs} \in [2, 8]$, $R_r \in [20, 30]$, $R_{ds} \in [4, 10]$, $L_{lqs} \in [0.0005, 0.05]$, $L_{lr} \in [0.0005, 0.01]$, $L_{lds} \in [0.1, 1]$, $L_{mqs} \in [2, 20]$, $J_m \in [0, 0.01]$, and $B_m \in [0, 0.01]$. In this work, the termination criteria for three intelligent methods are set as follows: (i) maximum number of iteration/generation = 100, (ii) maximum sum of squared error allowance (SSE_{max}) = 3.600×10^4.

Table 1 also shows the parameters obtained by three intelligent search techniques. As parameters listed in Table 1, although some parameters obtained from intelligent search techniques met the bound of their correspondingly search spaces, it has no necessary to extend such the search spaces. This is because the termination criteria are satisfied and the search spaces formed from the conventional-based parameters should not be extended more so. From four sets of parameters in Table 1, the rotor speed, the stator current, and the motor torque can be simulated and depicted through the space-phasor model as illustrated in Section 2. The effectiveness and the accuracy of each method are revealed when comparing with the experimental results as shown in Figure 4-7. In addition, the sums of squared error of each method are reported in the value of SSE in the figure.

Table 1. Comparison among obtained parameters

Parameters	Conventional	AI Search Techniques		
		GA	PSO	ATS
$R_{qs}(\Omega)$	5.27	4.00	2.00	2.00
$R_r(\Omega)$	25.91	28.07	28.35	28.35
$R_{ds}(\Omega)$	6.07	8.00	4.00	4.00
L_{lqs}(H)	0.002	0.01	0.0005	0.0006
L_{lr}(H)	0.002	0.001	0.0005	0.0006
L_{lds}(H)	0.603	0.57	0.70	0.70
L_{mqs}(H)	15.86	10.00	20.00	19.98
$J_m(N.m.s^2/rad)$	0.008	0.01	0.01	0.009
$B_m(N.m.s/rad)$	0.003	0.00	0.001	0.0009

5 Conclusions

An intelligent approach to identify parameters of single-phase induction motors has been proposed in this paper. Based on the steady-state analysis, the parameters of induction motors could be roughly estimated by conventional methods. In this paper, efficient intelligent search techniques, i.e. GA, PSO, and ATS, have been employed to identify single-phase induction motors' parameters. As results, the responses simulated by using the parameters obtained from the selected intelligent search techniques give very much better wave-shape than those obtained from the conventional method. The responses obtained from the use of the GA, the PSO, and the ATS are relatively close to the experimental ones. It can be concluded that the effectiveness of the proposed intelligent identification approach has been confirmed.

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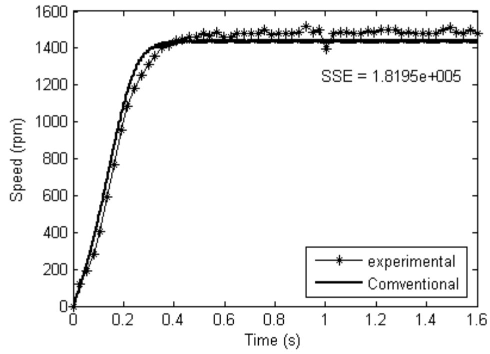
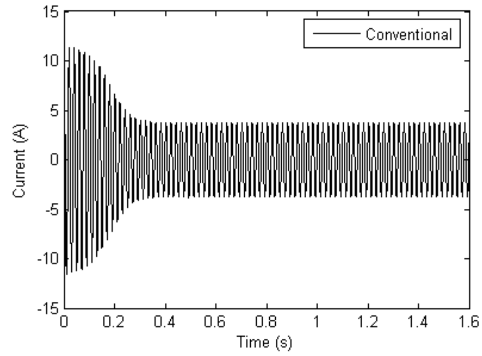
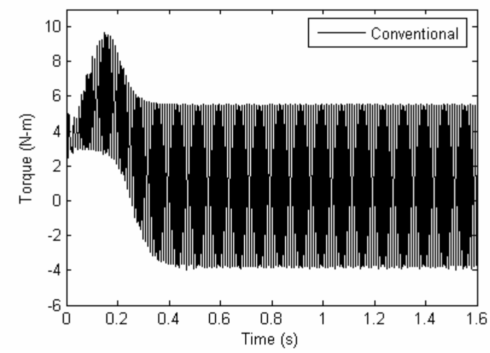


(a) Speed responses

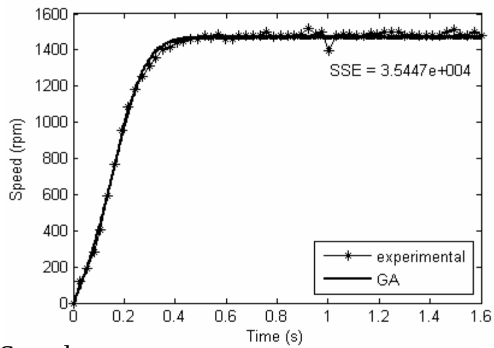


(b) Current response

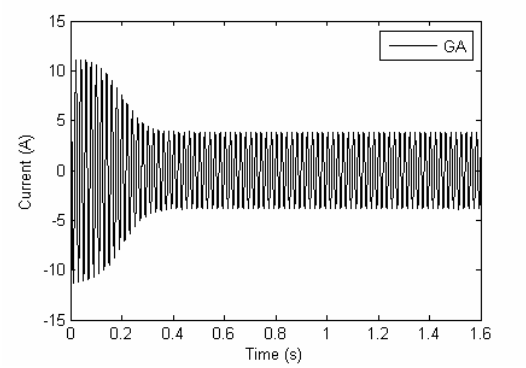


(c) Torque response

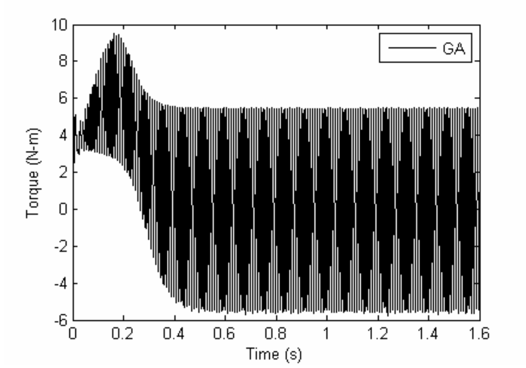
Fig. 4 Responses of experiment and simulation from conventional method.



(a) Speed responses

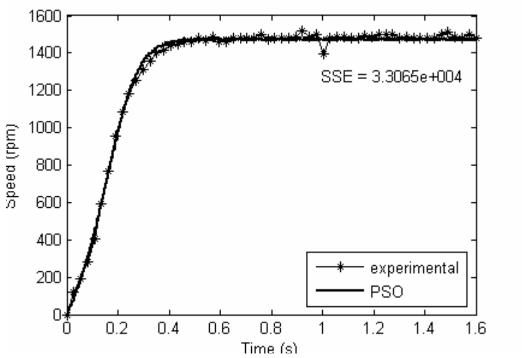


(b) Current response

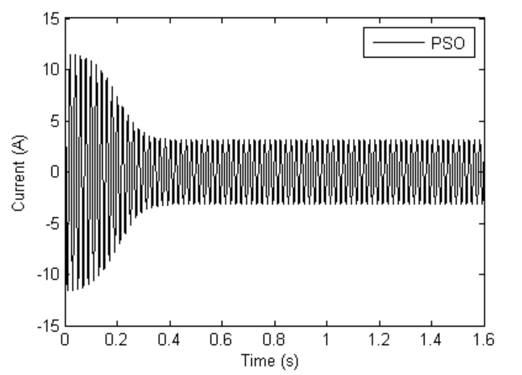


(c) Torque response

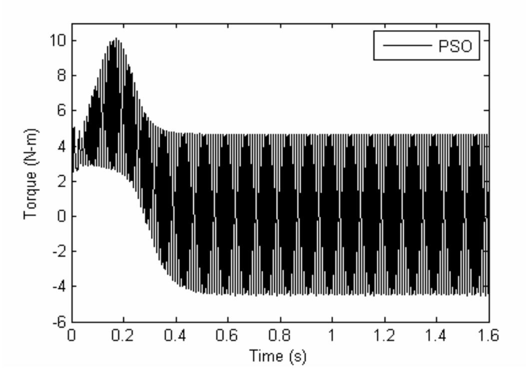
Fig. 5 Responses of experiment and simulation from GA-based method.



(a) Speed responses

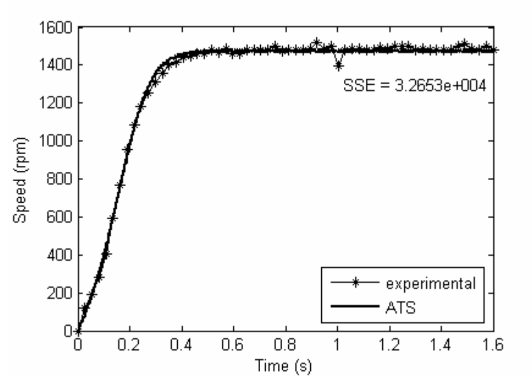


(b) Current response

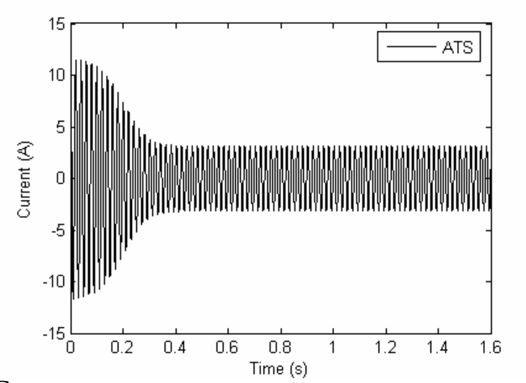


(c) Torque response

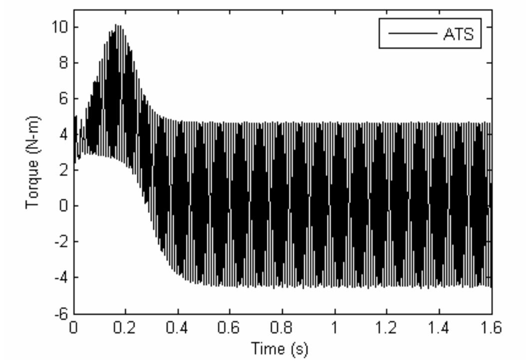
Fig. 6 Responses of experiment and simulation from PSO-based method.



(a) Speed responses



(b) Current response



(c) Torque response

Fig. 7 Responses of experiment and simulation from ATS-based method.