Parameter Identification of Induction Motors Using Ant Colony Optimization

Zhenfeng Chen, Yanru Zhong, Jie Li

Abstract—**In this paper, the Ant Colony Optimization (ACO) is introduced and applied to the parameter identification of an induction motor for vector control. The error between the actual stator current output of an induction motor and the stator current output of the model is used as the criterion to correct the model parameters, so as to identify all the parameters of an induction motor. Digital simulations are conducted on speed-varying operation with no load. The ACO is compared with the genetic algorithm (GA) and adaptive genetic algorithm (AGA). Consequently, the ACO is shown to acquire more precise parameter values and need much less computing time than the GA and AGA.**

I. Introduction

IN most applications, ac motors are preferable to dc motors, owing to their simple structure and robust construction. The vector control which achieves a quick torque response has become the standard tool for high-performance control of ac motors because it gives control characteristics similar to separately excited dc motors. The vector control utilizes the motor parameters that vary according to the temperature and nonlinearities caused by skin effect and saturation. Therefore, much effort has been made to identify the induction motor parameters of interest with good accuracy and general practicality [1].

Accurate and reliable parameter identification techniques for induction motors (IMs) are critical for the design and development of high-performance drive systems. In practical application, RLS (Recursive Least Squares) [2], EKF (Extended Kalman Filters) [3], [4] and MRAS (Model Reference Adaptation System) [5] are widely applied to identify the parameters of the induction motor. The EKF, however, retains some inherent disadvantages, such as the influence of noise characteristics, a computational burden and deficiency of the design and tuning criteria. The RLS estimator is one of the most effective methods for online identification, but it requires a torque observer and model approximation owing to linear parameterization for the RLS algorithm, which leads to algorithmic complexities and/or reduction of solution accuracy [1]. The MRAS can identify only one parameter of the induction motor – a rotor time constant or a rotor resistance at the same time.

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Recently, the genetic algorithm (GA) [6-12] and adaptive genetic algorithm (AGA) [13] has been used for parameter identification of induction motor. GA and AGA requires no derivative information of a cost function, and hence, the parameters to be estimated can span all of the values of resistances and inductances in dynamic models of the induction motor. Moreover, if all the parameters of the induction motor are identified with an acceptable accuracy, they can improve the performance even more. Despite the good identification capability of GA and AGA, a serious shortcoming is its considerable long computing time that confines its application only to offline identification. In practice, the time-varying parameters of an operating motor should be compensated dynamically by means of identifying them with signals measured online.

The ant colony optimization (ACO) is a relatively new approach to problem solving that takes inspiration from the social behaviors of ants. These ants deposit pheromone on the ground in order to mark some favorable path that should be followed by other members of the colony. Ant colony optimization exploits a similar mechanism for solving optimization problems. From the early nineties, when the first ant colony optimization algorithm was proposed, ACO attracted the attention of increasing numbers of researchers and many successful applications are now available, such as job shop scheduling, image processing, fault diagnosis, robots and so on. In this paper, the ant colony optimization (ACO) is introduced to identify all the parameters of the induction motor.

The organization of this paper is as follows: Section II starts out with the model of an induction machine. In section III, the ant colony optimization is introduced. This section also introduces the flowchart and the characteristics of ACO. The section IV introduces the principle and implement of parameter identification. In section V, experiments and results will be presented to evaluate the performance of the proposed technique. Finally, some key points of this work are summarized in section VI.

II. Induction Motor Dynamic Model

Dynamic model of an induction motor with rotor flux and stator current, in stationary frame is described as follows:

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases} \tag{1}$$

with

$$x = [i_{sd} \quad i_{sq} \quad \psi_{rd} \quad \psi_{rq}]^T$$

$$y = [i_{sd} \quad i_{sq}]^T$$

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$$u = [u_{sd} \quad u_{sq}]^T$$

$$A = \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s} + \frac{L_m^2}{\sigma L_s L_r \tau_r}\right) & \omega_r & \frac{L_m}{\sigma L_s L_r \tau_r} & \omega_r \frac{L_m}{\sigma L_s L_r} \\ -\omega_r & -\left(\frac{R_s}{\sigma L_s} + \frac{L_m^2}{\sigma L_s L_r \tau_r}\right) & -\omega_r \frac{L_m}{\sigma L_s L_r} & \frac{L_m}{\sigma L_s L_r \tau_r} \\ \frac{L_m}{\tau_r} & 0 & -\frac{1}{\tau_r} & 0 \\ 0 & \frac{L_m}{\tau_r} & 0 & -\frac{1}{\tau_r} \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \qquad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\sigma = 1 - L_{\mathrm{m}}{}^2 / L_{\mathrm{s}} L_{\mathrm{r}}, \tau_{\mathrm{r}} = L_{\mathrm{r}} / R_{\mathrm{r}}.$$

Where R_s and R_r are the stator and rotor resistance; L_s and L_r are the stator and rotor inductance; L_m is the magnetizing inductance; σ is the leakage coefficient; τ_r is the rotor time constant; ω_{r} is the rotor electrical speed; u_{sd} and u_{sq} are the d-axis and q-axis stator voltage; i_{sd} and i_{sq} are the d-axis and q-axis stator current; $\Psi_{\mathrm{r}d}$ and $\Psi_{\mathrm{r}q}$ are the d-axis and q-axis rotor flux.

III. Ant Colony Optimization

The flowchart of the basic ant colony optimization was shown in Fig.1.

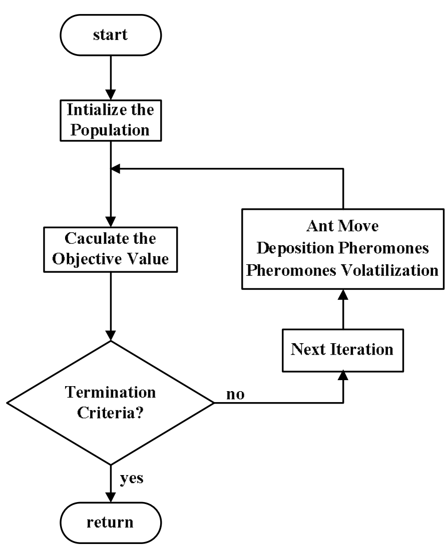

Figure 1. Flowchart of the basic ant colony optimization

The idea of imitating the behavior of ants for finding good solutions to combinatorial optimization problems was initiated by Dorigo. The principle of these methods is based on the way ants search for food and find their way back to the nest. During trips of ants a chemical trail called pheromone is left on the ground. The role of pheromone is to guide the other ants towards the target point. For one ant, the path is chosen according to the quantity of pheromone [14], [15].

While building the solutions, each artificial ant collects pheromone information on the problem characteristics and uses this information to modify the representation of the problem, as seen by the other artificial ants. The larger amount of pheromone is left on a route, the greater is the probability of selecting the route by artificial ants, and vice versa.

The ACO has several characteristics. Firstly the ACO is a system. In nature, the behavior of the single ant is very simple, but the colony of the ant shows very complex behavior in finding food. The single ant of the colony co-operates with each other through the pheromone which is chemical substance they leave on the ground while moving. In this way, the colony of the ant constitutes a system. Secondly, the ant colony is a distributed system. When the ant colony is going to complete one task, each ant does its utmost to work respectively and independently. The task is dependent on the work of each ant, but it is not completed not because of the defect of certain ant. Thirdly, the ant colony is also a self-organization system, so it possesses strong robustness. Finally, it possesses not only positive regeneration but also negative feedback.

IV. Principle and Implement of Parameter Identification

To identify the parameters of an induction motor, the principle and implement of parameter identification are introduced in the section.

A. *Principle of Parameter Identification*

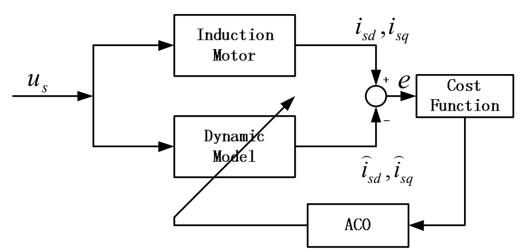

Figure 2. Scheme of parameter identification of induction motor

The Fig.2 provides the scheme of parameter identification of induction motor. The error between the actual stator current output of an induction motor and the stator current output of the model is used as the criterion to correct the model parameters, so as to identify all the parameters of an induction motor. In Fig.2, the output of the induction motor is stator current (i_{sd} and i_{sq}), they are detected by the current Hall sensors and acquired by the transformation of coordinates. The output of the electrical model is $\hat{i}_{sd}$ and $\hat{i}_{sq}$.

Let:

$$L_\sigma = \sigma L_s, \psi'_{rd} = \frac{L_m}{L_r}\psi_{rd} \text{ and } \psi'_{rq} = \frac{L_m}{L_r}\psi_{rq},$$

Equation (1) is changed into:

$$\begin{cases} \dot{x} = A'x + Bu \\ y = Cx \end{cases} \tag{2}$$

where

$$x = [i_{sd} \quad i_{sq} \quad \psi'_{rd} \quad \psi'_{rq}]^T,$$

$$y = [i_{sd} \quad i_{sq}]^T,$$

$$u = [u_{sd} \quad u_{sq}]^T,$$

$$A' = \begin{bmatrix} -\left(\frac{R_s}{L_\sigma} + \frac{L_s - L_\sigma}{L_\sigma \tau_r}\right) & \omega_r & \frac{1}{L_\sigma \tau_r} & \omega_r \frac{1}{L_\sigma} \\ -\omega_r & -\left(\frac{R_s}{L_\sigma} + \frac{L_s - L_\sigma}{L_\sigma \tau_r}\right) & -\omega_r \frac{1}{L_\sigma} & \frac{1}{L_\sigma \tau_r} \\ \frac{L_s - L_\sigma}{\tau_r} & 0 & -\frac{1}{\tau_r} & 0 \\ 0 & \frac{L_s - L_\sigma}{\tau_r} & 0 & -\frac{1}{\tau_r} \end{bmatrix}$$

The matrix B and C are identical with the matrix B and C in equation (1).

In the rotor frame, the stator current and voltage is acquired by the converse as follows:

$$\begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} = \begin{bmatrix} \cos\theta_r & \sin\theta_r \\ -\sin\theta_r & \cos\theta_r \end{bmatrix} \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} u_{sd} \\ u_{sq} \end{bmatrix} = \begin{bmatrix} \cos\theta_r & \sin\theta_r \\ -\sin\theta_r & \cos\theta_r \end{bmatrix} \begin{bmatrix} u_{s\alpha} \\ u_{s\beta} \end{bmatrix} \tag{4}$$

As a matter of convenience, the parameter vector is defined as follows:

$$\lambda = [\lambda_1 \quad \lambda_2 \quad \lambda_3 \quad \lambda_4 \quad \lambda_5] \tag{5}$$

where

$$\lambda_1 = \frac{R_s}{L_\sigma} + \frac{L_s - L_\sigma}{L_\sigma \tau_r}, \quad \lambda_2 = \frac{1}{L_\sigma \tau_r}$$

$$\lambda_3 = \frac{1}{L_\sigma}, \quad \lambda_4 = \frac{L_s - L_\sigma}{\tau_r}, \quad \lambda_5 = \frac{1}{\tau_r}$$

Equations (2), (3) and (4) can be discretized as follows:

$$\begin{cases} i_{sd}(k+1) = i_{sd}(k) + T_s\{-\lambda_1 i_{sd}(k) + \omega_r(k) i_{sq}(k) \\ \qquad + \lambda_2 \psi'_{rd}(k) + \lambda_3[u_{sd}(k) + \omega_r(k)\psi'_{rq}(k)]\} \\ i_{sq}(k+1) = i_{sq}(k) + T_s\{-\lambda_1 i_{sq}(k) - \omega_r(k) i_{sd}(k) \\ \qquad + \lambda_2 \psi'_{rq}(k) + \lambda_3[u_{sd}(k) - \omega_r(k)\psi'_{rd}(k)]\} \\ \psi'_{rd}(k+1) = \psi'_{rd}(k) + T_s[\lambda_4 i_{sd}(k) - \lambda_5 \psi'_{rd}(k)] \\ \psi'_{rq}(k+1) = \psi'_{rq}(k) + T_s[\lambda_4 i_{sq}(k) - \lambda_5 \psi'_{rq}(k)] \end{cases} \tag{6}$$

$$\begin{cases} i_{sd}(k) = i_{s\alpha}(k)\cos\theta_r(k) + i_{s\beta}(k)\sin\theta_r(k) \\ i_{sq}(k) = i_{s\beta}(k)\cos\theta_r(k) - i_{s\alpha}(k)\sin\theta_r(k) \\ u_{sd}(k) = u_{s\alpha}(k)\cos\theta_r(k) + u_{s\beta}(k)\sin\theta_r(k) \\ u_{sq}(k) = u_{s\beta}(k)\cos\theta_r(k) - u_{s\alpha}(k)\sin\theta_r(k) \\ \theta_r(k+1) = \theta_r(k) + T_s\omega_r(k) \end{cases} \tag{7}$$

Suppose $\hat{\lambda} = [\hat{\lambda}_1 \quad \hat{\lambda}_2 \quad \hat{\lambda}_3 \quad \hat{\lambda}_4 \quad \hat{\lambda}_5]$, so the state equation of the electrical model is:

$$\begin{cases} \hat{i}_{sd}(k+1) = i_{sd}(k) + T_s\{-\hat{\lambda}_1 i_{sd}(k) + \omega_r(k) i_{sq}(k) \\ \qquad + \hat{\lambda}_2 \hat{\psi}'_{rd}(k) + \hat{\lambda}_3[u_{sd}(k) + \omega_r(k)\hat{\psi}'_{rq}(k)]\} \\ \hat{i}_{sq}(k+1) = i_{sq}(k) + T_s\{-\hat{\lambda}_1 i_{sq}(k) - \omega_r(k) i_{sd}(k) \\ \qquad + \hat{\lambda}_2 \hat{\psi}'_{rq}(k) + \hat{\lambda}_3[u_{sd}(k) - \omega_r(k)\hat{\psi}'_{rd}(k)]\} \\ \hat{\psi}'_{rd}(k+1) = \hat{\psi}'_{rd}(k) + T_s[\hat{\lambda}_4 i_{sd}(k) - \hat{\lambda}_5 \hat{\psi}'_{rd}(k)] \\ \hat{\psi}'_{rq}(k+1) = \hat{\psi}'_{rq}(k) + T_s[\hat{\lambda}_4 i_{sq}(k) - \hat{\lambda}_5 \hat{\psi}'_{rq}(k)] \end{cases} \tag{8}$$

T_s is the sampling time. According the Fig. 2, the cost function is:

$$H(\hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3, \hat{\lambda}_4, \hat{\lambda}_5) = \sum_{k=1}^{K} \{[i_{sd}(k) - \hat{i}_{sd}(k)]^2 + [i_{sq}(k) - \hat{i}_{sq}(k)]^2\} \tag{9}$$

B. Implement of Parameter Identification Using ACO

According to the actual size of the parameter vector, the maximum and the minimum of each parameter is defined:

$$\lambda_{i\min} \le \lambda_i \le \lambda_{i\max} \quad i = 1, 2, \cdots, 5$$

There are five parameters, thus this problem is changed into five grades strategic decision problem. Each parameter is divided into (N-1) equal parts. This is to say, each grade have N knots, thus there are N×5 knots together. It is shown in Fig. 3.

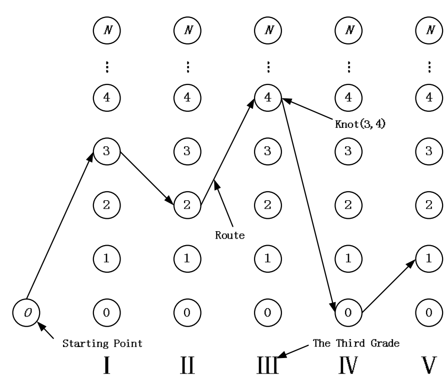

Figure 3. Sketch of knot and route

All the artificial ants move from the first grade to the fifth grade. For example, in Fig. 3, one ant starts from starting point, goes through knot(1,3), knot(2,2), knot(3,4), knot(4,0), and arrives in the end knot(5,1) at last. The moving route of the ant stands for a parameter vector.

As shown in Fig.3, the route stands for:

$$\begin{cases} \lambda_1 = \lambda_{1\min} + \dfrac{\lambda_{1\max} - \lambda_{1\min}}{N} \times 3 \\ \lambda_2 = \lambda_{2\min} + \dfrac{\lambda_{2\max} - \lambda_{2\min}}{N} \times 2 \\ \lambda_3 = \lambda_{3\min} + \dfrac{\lambda_{3\max} - \lambda_{3\min}}{N} \times 4 \\ \lambda_4 = \lambda_{4\min} + \dfrac{\lambda_{4\max} - \lambda_{4\min}}{N} \times 0 \\ \lambda_5 = \lambda_{5\min} + \dfrac{\lambda_{5\max} - \lambda_{5\min}}{N} \times 1 \end{cases} \tag{10}$$

In the construction of a solution, ants select the next knot to be visited through a stochastic mechanism. For ant m, the probability of going to knot (i,j) is given by:

$$P_{ij}^{m}(t) = \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{j=0}^{N}\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} \tag{11}$$

Where the parameters α and β control the relative importance of the pheromone $\tau_{ij}(t)$ versus the heuristic information $\eta_{ij}(t)$. Because the identification parameter is unpredictable, there is:

$$\eta_{ij}(t) = 1 \quad (i = 1 \sim 5, j = 0 \sim N)$$

In this paper, the Ant System is adopted. Its main characteristic is that, at each iteration, the pheromone values are updated by all the m ants that have built a solution in the iteration itself. The pheromone $\tau_{ij}(t)$, associated with the knot i and knot j, is updated as follows:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{m=1}^{M}\Delta\tau_{ij}^{m} \tag{12}$$

Where ρ is the evaporation rate, M is the number of ants, and $\Delta\tau_{ij}$ is the quantity of pheromone laid on knot (i, j) by ant m:

$$\Delta\tau_{ij}^{m} = \begin{cases} Q / P_m, & \text{if ant } m \text{ used knot } (i,j) \text{ in its tour,} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

Where Q is a constant, and $P_m = 10^8 \times H_m$ is the quality of the tour constructed by ant m, H_m is calculated by the cost function (9).

V. EXPERIMENTS AND RESULTS

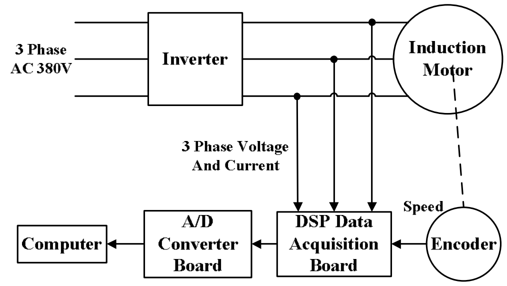

Figure 4. System configuration of parameter identification of induction motor

Fig. 4 shows the system configuration of the parameter identification of the induction motor. The induction motor was controlled by a field orientation control scheme. SVPWM switching frequency is 2 kHz and the sampling time is 500μs. Stator voltages, stator currents and true motor speed were measured by voltage Hall sensors, current Hall sensors and an encoder with 1024 pulse per line respectively in every sampling time. Then the measured data was picked up with a data acquisition card and processed by MATLAB software. The data of the induction motor is shown in Table I.

TABLE I
INDUCTION MOTOR DATA

P_N=1.1kW	R_s=5.27 Ω
U_N=380V	L_s=0.423H
I_N=2.67A	σ=0.125
P=2	R_r=5.07 Ω
f_N=50Hz	L_r=0.421H
n_N=1410r/min	J=0.02kg·m^2

The population and iteration values are 20 and 100 respectively. The five parameters are divided into 99 equal parts. The parameters α and β are 1 and 2 respectively. The evaporation rate ρ is 0.2 and the parameter Q is 100. Let λ_3, λ_4, λ_5 be enlarged 10, 100, and 10 times separately, thus the five parameters are under the same order of magnitude. According to the ranges of the identified parameters, there are five situations shown in Table II. The ranges of the identified parameters were expanded step by step from Case 1 to Case 4, and initial parameters values are randomly selected inside the corresponding upper and lower bounds.

Corresponding to the five cases, the identified results are shown in Table III. The results reveal that the errors are enlarged step by step when the search spaces was expanded especially for λ_5. In order to decrease the error, the range of λ_5 should be relatively adjusted narrow, but the ranges of λ_1, λ_2, λ_3, λ_4 are relatively adjusted wide. This case is no other than the case 5. From Table III, it can be seen that ACO can acquire the accuracy identified parameters. When the ranges of λ are adjusted suitable, the identified results are more accuracy.

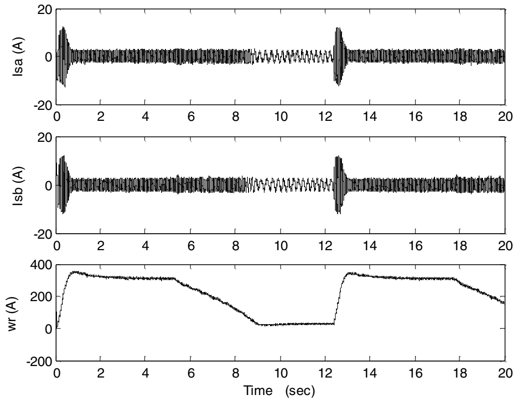

Figure 5. Simulated signals of IM during speed-varying operation with no load

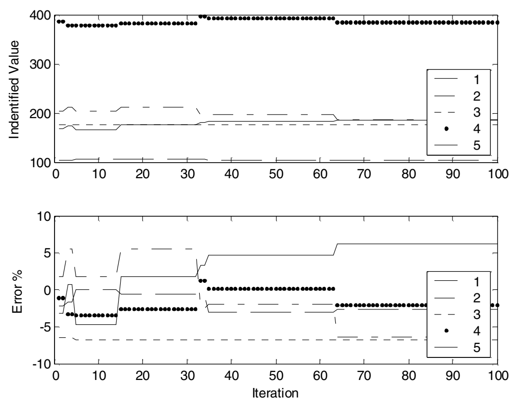

Figure 6. The evolution of identification results and errors versus iteration in Case 5

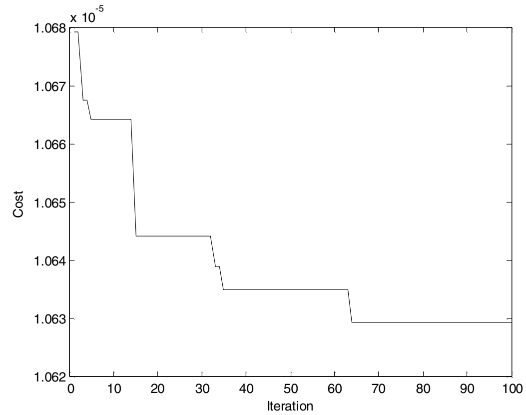

Figure 7. The evolution of cost versus iteration in Case 5

Fig. 5 depicts simulated stator current and rotor speed signals of induction motor during speed-varying operation with no load. Fig. 6 shows the evolution of identification results and errors versus iteration in Case 5. Fig. 7 shows the evolution of cost versus iteration in Case 5. From Fig. 6 and Fig. 7, we can find that when the iteration is about 65, the results are satisfactory.

The comparison of the ACO, AGA and GA is shown in Table IV and the comparison results show that the ACO can yield to more accuracy results than GA and AGA. The computing time of the three algorithms is given in Table V. The CPU times are measured on a Pentium 4 (2.6-GHz) computer with 256MB random-access memory (RAM) under the same experiment condition of Case 5. From the Table V, we can see that the ACO is shown faster computing speed than the GA and AGA.

TABLE II
RANGES OF λ FOR FIVE SITUATIONS

Case	λ_{1min}	λ_{1max}	λ_{2min}	λ_{2max}	$10\lambda_{3min}$	$10\lambda_{3max}$	$100\lambda_{4min}$	$100\lambda_{4max}$	$10\lambda_{5min}$	$10\lambda_{5max}$
Case 1	156	190	179	219	170	206	351	431	95	115
Case 2	139	207	159	239	152	224	311	471	85	125
Case 3	122	224	139	259	134	242	271	511	75	135
Case 4	105	241	119	279	116	260	231	551	65	145
Case 5	122	224	139	259	134	242	271	591	85	125

TABLE III
RESULTS AND ANALYSIS OF PARAMETER IDENTIFICATION OF INDUCTION MOTOR

Para-meter	True	Case 1		Case 2		Case 3		Case 4		Case 5	
		Identified	Error	Identified	Error	Identified	Error	Identified	Error	Identified	Error
λ_1	173.4058	174.8500	0.8328%	179.7000	3.6298%	184.7500	6.5420%	194.5500	12.1935%	184.2500	6.2537%
λ_2	199.7951	197.0000	-1.3990%	203.4000	1.8043%	204.7500	2.4800%	178.3500	-10.7335%	187.0000	-6.4041%
λ_3	18.8761	18.6000	-1.4627%	18.1000	-4.1115%	17.6000	-6.7604%	16.6000	-12.0581%	17.6000	-6.7604%
λ_4	3.9165	3.8910	-0.6511%	3.9140	-0.0638%	3.8675	-1.2511%	4.1255	5.3364%	3.8350	-2.0809%
λ_5	10.5846	10.3050	-2.6416%	9.7900	-7.5071%	11.6000	9.5932%	8.4250	-20.4032%	10.3050	-2.6416%

TABLE IV

COMPARISON OF THREE ALGORITHMS IN CASE 5

Algorithm	λ_1		λ_2		λ_3		λ_4		λ_5	
	Identified	Error	Identified	Error	Identified	Error	Identified	Error	Identified	Error
GA	198.8975	14.7006%	186.8792	−6.4646%	16.8280	−10.8503%	3.7799	−3.4875%	9.6909	−8.4435%
AGA	184.2500	6.2537%	187.0000	−6.4041%	17.6000	−6.7604%	3.8350	−2.0809%	10.3050	−2.6416%
ACO	175.2148	1.0432%	209.9609	5.0881%	17.8000	−5.7009%	4.0036	2.2228%	9.6348	−8.9737%

TABLE V

COMPARISON OF COMPUTING TIME OF ALGORITHMS

Identification algorithms	GA	AGA	ACO
Computing time per trial (CPU)	about 3 sec	about 8 sec	about 1.5 sec

VI. CONCLUSION

In this paper, the ant colony optimization was used to identify the parameters of the induction motor. There were five cases. The obtained identification results of this investigation were reported in Table III. As the search spaces become wide, the identified errors increase. From Tables IV and V, the results reveal that this technique can yield to more accurate model parameters and need less computing time than GA and AGA.

It is worth noting that the ranges of the identified parameters were not adjusted as wide as ±50% of the actual parameter values. In order to acquire more satisfactory results, the relative research is under investigation.

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