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Parameter Identification of Induction Motor Double-Cage Model Using Exchange Market Algorithm

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Abstract: A newly established method, called the Exchange Market Algorithm (EMA), is provided to identify the parameters of the three-phase induction motor from the manufacturing information. For the suggested technique, input data such as rated output power, beginning torque, breakdown torque, complete load torque, power factor and effectiveness at rated output energy are needed. Using the squared error between the identified and the manufacturing data as the objective function, the parameter identification problem is assigned to an optimization process where the parameters of the double cage model are identified to minimize the defined objective function. The EMA algorithm is used to iteratively minimize the objective function.Two sample engines tested the EMA strategy. The achievement of the EMA algorithm is contrasted with the technique of classical parameter determination (CPD) and other techniques of optimization, including Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Simulation findings show the ability of the suggested method to capture the real values of the machine parameters and the dominance of the outcomes obtained using the EMA over other methods to parameter identification.

Keywords: Double-cage model, Exchange market Algorithm, Manufacturer data, Optimization techniques, Parameter determination.

NOMENCLATURE

V_{ph}	Stator voltage per phase (V)
I_1	Stator current per phase (A)
I_2	Rotor current per phase (A)
R_1	Stator resistance per phase (Ohm)
X_1	Stator leakage reactance per phase (Ohm)
X_m	Magnetizing reactance per phase (Ohm)
R_2	Rotor resistance referred to stator side (Ohm)
X_2	Rotor reactance referred to stator side (Ohm)
R_{21}	Inner cage rotor resistance (Ohm)
R_{22}	outer cage rotor resistance (Ohm)
X_{21}	Inner cage rotor leakage reactance(Ohm)
X_{22}	Outer cage rotor leakage reactance (Ohm)
Y_1	Stator admittance (Mho)
Y_m	Magnetizing admittance (Mho)
Y_{21}	Inner cage rotor admittance (Mho)
Y_{22}	Outer cage rotor admittance (Mho)
Y_{tot}	Total admittance (Mho)
$T_{st}(mf)$	Manufacturer starting torque (Nm)
$T_{max}(mf)$	Manufacturer maximum torque (Nm)
$T_{fl}(mf)$	Manufacturer full-load torque data (Nm)
$T_{max}(d)$	Determined maximum torque (Nm)
$I_{fl}(mf)$	Manufacturer full-load current (A)
$pf_{fl}(mf)$	Manufacturer full-load power factor data
V_{th}	Thevenin's equivalent voltage (V)
R_{th}	Thevenin's equivalent resistance (Ohm)
X_{th}	Thevenin's equivalent reactance (Ohm)
ω_s	Motor's angular velocity (rad /sec)
s	Slip
s_{max}	Slip at which maximum torque occurs
η_{fl}	Full load efficiency (%)
P_{fl}	Rated power (W)
P_{rot}	Rotational losses (W)
$X_{m.f.}$	Manufacturer data of performance characteristic X
X_d	Determined data of performance characteristic X
$\Re$	A function that returns the real part of the given complex number
X_{min}, X_{max}	Minimum and maximum limits of the equivalent circuit parameters
n_i	n^{th} person of the first group
n_j	n^{th} person of the second group
r	random number within [0, 1]
$pop_j^{group(2)}$	j^{th} member of the second group
$pop_{1,i}^{group(1)}$	members of the first group
$pop_{2,i}^{group(1)}$	members of the second groupr_1 and r_2 random numbers
n_k	n^{th} member of the third group

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$pop_k^{group(3)}$	k^{th} member of the third group and
S_k	share variation of the kth member of the third group
Δn_{t1}	share value added randomly to some shares
n_{t1}	total shares of member t
S_{ty}	shares of the t^{th} member
δ	information of exchange market
η_1	risk level for each member of the second group
t_{pop}	number of the t^{th} member in exchange market
n_{pop}	number of the last member in exchange market
μ	constant coefficient for each member
g_1	common market risk amount
$Iter_{max}$	maximum iteration number
$g_{1,max}$, $g_{2,max}$	maximum and minimum values of risk in market respectively
Δn_{t3}	share value added randomly to some shares
r_s	random number between -0.5 and 0.5
g_2	market variable risk in third group

1. INTRODUCTION

The equivalent circuit parameters of three-phase induction motors are usually determined through the trials of no-load, locked-rotor and stator resistance. The parameter values determined by this classical method can reveal significant variations in the entire slip spectrum ranging from 0 to 1.

Using the double-cage model, the performance features of squirrel cage induction devices can be acquired. Deep and narrow rotor bars have the same torque-speed features as double-cage rotor. Single-cage rotors should therefore be modeled as a double-cage model.

The linear parameter identification methods were used to determine the equivalent circuit parameters of a three-phase induction machine.

The problem has also been solved by the sophisticated method for non-linear parameter determination[1]. A study on different techniques of detection of parameters has been discussed [2]. An simple technique for calculating induction motor parameters using IEEE standard 112 techniques has been discussed[3]. To determine the corresponding circuit parameters, no-load, blocked-rotor and overload experiments are performed. In this technique, the mearuring of torque values is not utailized. The standard strategy to determining the equivalent circuit parameters of the induction motor from the accessible information was discussed[4][5]. These methods estimate the parameters of the machine model and then perform the sensitivity analysis with regard to the parameters of the circuit to match the information provided. A fresh parameter determination method for induction motors has been discussed in [6]. In this technique, manufacturer information such as name plate information and motor performance features were used to determine the double cage induction motor parameters. Online techniques for stator resistance and rotor resistance identification of an induction engine were suggested by Vukadinovic et al.[7] and Mehazzem et al.[8] using model reference adaptive system principle and synchronous resonating filtering method. A novel adaptive observer based on Lyapunov is provided concurrently to predict inner fluxes, key loss and rotor resistance of induction motor[9]. A flux observer is extracted from the induction motor model, including the stator core loss resistance, and the observer's stability is demonstrated based on a Lyapunov function.

The developmental algorithm[10], GA[11-15], adaptive GA[16], artificial neural network (ANN)[17][18], PSO[19], IA[20] and differential evolution[21] were used to identify induction engine parameters.

The algorithm for the exchange economy (EMA) was first suggested by Ghorbani and Babaei[22]. It is influenced by the stock market in which shareholders purchase and sell all kinds of stocks under balanced and oscillating market circumstances. This algorithm utilizes two search operators and two absorbents. These operators enable EMA to solve the issues of exploration and exploitation. In this document, the EMA system is used from the manufacturer information to estimate the corresponding circuit parameters of the double-cage induction engine model.

The suggested EMA technique is being tested on two sample engines of distinct dimensions. The parameters acquired by the EMA technique are then used to forecast engine start, breakdown and full-load torques and compare with the respective values provided by the manufacturer.

2. INDUCTION MOTOR MODEL

Figure 1(a) indicates a single induction motor's equivalent circuit. The equivalent circuit is used to define engine

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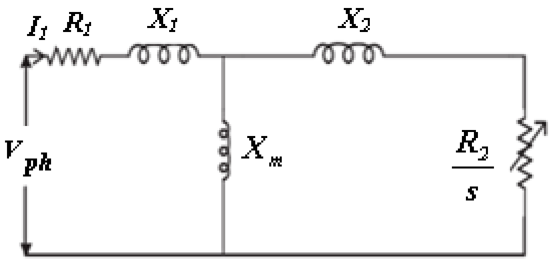
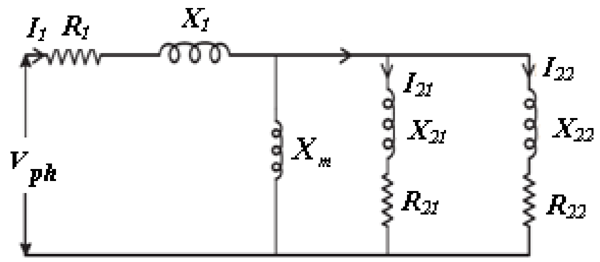
features in the ordinary working region, but gives more mistake when beginning. A double-cage rotor model is used to get better beginning features. The equivalent circuit frequently used for such a model is shown in Figure 1(b). There are seven distinct parameters in this circuit. The internal cage is represented by parameters R_1 and X_1, and the outer cage is represented by R_2 and X_2.

2.1 Single-Cage Model Formulation

The problem formulation utilizes information from the starting torque, peak torque, complete load torque and complete load power factor maker to define stator strength, rotor resistance, stator leakage reaction, rotor leakage reaction, and magnetizing leakage reaction parameters.



(a)



(b)

Figure 1. Equivalent circuit of an induction motor
(a) Single-cage rotor model
(b) Double-cage rotor model

The objective function is defined by Minimize

$$J = f_1^{\,2} + f_2^{\,2} + f_3^{\,2} + f_4^{\,2} \tag{1}$$

where,

$$f_1 = \frac{\dfrac{K_t R_2}{s\left[\left(R_{th} + \dfrac{R_2}{s}\right)^2 + X^2\right]} - T_{fl}(mf)}{T_{fl}(mf)}$$

$$f_2 = \frac{\dfrac{K_t R_2}{\left(R_{th} + R_2\right)^2 + X^2} - T_{lr}(mf)}{T_{lr}(mf)}$$

$$f_3 = \frac{\dfrac{K_t}{2\left[R_{th} + \sqrt{R_{th}^2 + X^2}\right]} - T_{max}(mf)}{T_{max}(mf)}$$

$$f_4 = \frac{\cos\left(\tan^{-1}\left(\dfrac{X}{R_{th} + \dfrac{R_2}{s}}\right)\right) - pf_{fl}(mf)}{pf_{fl}(mf)}$$

$$V_{th} = \frac{V_{ph} X_m}{X_1 + X_m}$$

$$R_{th} = \frac{R_1 X_m}{X_1 + X_m}$$

$$X_{th} = \frac{X_1 X_m}{X_1 + X_m}$$

$$K_t = \frac{3V_{th}^2}{\omega_s}$$

$$X = X_2 + X_{th}$$

The constraints considered for single-cage model parameters determination are

$$X_{i,min} \le X_i \le X_{i,max}$$

$$\frac{T_{max}(d) - T_{max}(mf)}{T_{max}(mf)} \le \pm 0.2$$

$$\frac{P_{fl} - \left(I_{1\,fl}^2 R_1 + I_{2\,fl}^2 R_2 + P_{rot}\right)}{P_{fl}} = \eta_{fl}(mf)$$

2.2 Double-Cage Model Formulation

The issue formulation uses manufacturer information from the starting torque, peak torque, complete load torque, complete load present and complete load power

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factor to define the parameters of the profound bar circuit model.The objective function is defined as Minimize

$$J = f_1^2 + f_2^2 + f_3^2 + f_4^2 + f_5^2 \quad (2)$$

where,

$$f_1 = \frac{\dfrac{k_t |Y_{tot}|^2 \left(R_{21}|Y_{21}|^2 + R_{22}|Y_{22}|^2 \right)}{s|Y_1 + Y_m + Y_{21} + Y_{22}|^2} - T_{fl}(mf)}{T_{fl}(mf)}$$

$$f_2 = \frac{\dfrac{k_t |Y_{tot}|^2 \left(R_{21}|Y_{21}|^2 + R_{22}|Y_{22}|^2 \right)}{|Y_1 + Y_m + Y_{21} + Y_{22}|^2} - T_{lr}(mf)}{T_{lr}(mf)}$$

$$f_3 = \frac{\dfrac{k_t |Y_{tot}|^2 \left(R_{21}|Y_{21}|^2 + R_{22}|Y_{22}|^2 \right)}{s_{max}|Y_1 + Y_m + Y_{21} + Y_{22}|^2} - T_{max}(mf)}{T_{max}(mf)}$$

$$f_4 = \frac{\dfrac{\left(\Re(Y_{21}) + \Re(Y_{22})\right)|Y_1| + R_1|Y_1||Y_m + Y_{21} + Y_{22}|^2}{|Y_m + Y_{21} + Y_{22}||Y_1 + Y_m + Y_{21} + Y_{22}|} - pf_{fl}(mf)}{pf_{fl}(mf)}$$

$$f_5 = \frac{V_{ph}|Y_{tot}| - I_{fl}(mf)}{I_{fl}(mf)}$$

$$Y_1 = \frac{1}{R_1 + jX_1}$$

$$Y_m = \frac{1}{jX_m}$$

$$Y_{21} = \frac{1}{\frac{R_{21}}{s} + jX_1}$$

$$Y_{22} = \frac{1}{\frac{R_{22}}{s} + jX_2}$$

$$K_t = \frac{3V_{ph}^2}{\omega_s}$$

$$Y_{tot} = \frac{|Y_1||Y_m + Y_{21} + Y_{22}|}{|Y_1 + Y_m + Y_{21} + Y_{22}|}$$

The following equations are used as constraints:

$$X_{i,min} \le X_i \le X_{i,max}$$

$$X_{21} > X_{22}$$

$$R_{22} > R_{21}$$

$$\frac{T_{max}(d) - T_{max}(mf)}{T_{max}(mf)} \le \pm 0.2$$

$$\frac{P_{fl} - \left(I_{1fl}^2 R_1 + I_{2fl}^2 R_2 + P_{rot} \right)}{P_{fl}} = \eta_{fl}(mf)$$

3. EXCHANGE MARKET ALGORITHM: A BRIEF OVERVIEW

EMA, first implemented by Ghorbani and Babaei[34], is a flexible, robust, population-based stochastic optimization algorithm with intrinsic parallelism. It is driven by stock market human behavior in which shareholders trade shares in balanced and oscillating market circumstances. This algorithm utilizes two search and absorbent operators in ordinary and oscillation modes respectively. In EMA, optimum solution is considered to be one that a shareholder population is searching for. Each person in this population is called a shareholderThe people of the searcher group and the absorbent group are accountable for enhancing the algorithm's exploration and exploitation capabilities.

3.1 Exchange Market in Normal Mode

The investors attempt to maximize their profit using the expertise of the elite investors in the ordinary situation of the exchange economy. Each shareholder in the population is ranked according to the fitness function.

3.1.1 Shareholders with High Ranks

These shareholders do not alter their stocks without carrying out any danger and trade to preserve their ranks. This group of investors makes up 10-30% of the workforce.

3.1.2 Shareholders with Average Ranks

These shareholders do not change their stocks in order to maintain their ranks without carrying out any risk and trade. This group of investors make up 10-30 percent of the workforce.

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$$pop_j^{group\,(2)} = r \times pop_{1,i}^{group\,(1)} + (1-r) \times pop_{2,i}^{group\,(1)} \tag{3}$$

$i = 1, 2, 3, \dots n_i$ and $j = 1, 2, 3, \dots. n_j$

3.1.3 Shareholders with Weak Ranks

This group of shareholders arranges 20-50 percent of the population. The representatives of this community use the distinctions of elite and medium shareholders ' share values with their share values. This group's population is provided in the following equation.

$$S_k = 2 \times r_1 \times \left(pop_{i,1}^{group\,(1)} - pop_k^{group\,(3)}\right) + 2 \times r_2 \times \left(pop_{i,1}^{group\,(1)} - pop_k^{group\,(3)}\right) \tag{4}$$

$$pop_k^{group\,(3)\,new} = r \times pop_k^{group\,(3)} + 0.8 \times S_k$$

$$k = 1, 2, 3, \dots n_k$$

3.2 Exchange Market in Oscillaion Mode

In this mode, shareholders perform intelligent hazards among other employees according to their own rank in order to obtain the highest possible profit. Shareholders can be split into three distinct organizations depending on their performance.

3.2.1 Shareholders with High Ranks

This group includes 10-30 percent of the market population known as elite participants who do not engage in the stock exchange.

3.2.2 Shareholders with Medium Ranks

The second group's market share is altered in such a manner that the group's entire share values are continuous. Individual share values are updated as

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \tag{5}$$

$$\mu = \frac{t_{pop}}{n_{pop}}$$

$$n_{t1} = \sum_{y=1}^{n} (S_{ty}) \quad y = 1, 2, 3, \dots, n$$

$$\eta_1 = \eta_{t1} \times g_1$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{Iter_{max}} \times k$$

To preserve the stocks, stay continuous, each shareholder randomly sells some of the shares equivalent to the shares bought. Each shareholder therefore decreases the share values provided as follows.

$$\Delta n_{t,2} = n_{t,2} - \delta$$

where $n_{t\,2}$ is the total share value of t^{th} member after employing share variations

3.2.3 Shareholders with Weak Ranks

The shareholders can either buy or sell the stocks. The complete valuation of the share is therefore variable. Individual share values can be updated as

$$\Delta n_{t,3} = 4 \times r_s \times \mu \times \eta_2 \tag{6}$$

$$r_s = 0.5 - \text{rand}$$

$$\eta_1 = \eta_{t1} \times g_1$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{Iter_{max}} \times k$$

4. COMPUTATIONAL FLOWCHART OF THE PROPOSED PARAMETER DETERMINATION METHOD

The computational flow of the suggested BFO algorithm to the problem of parameter determination is shown in Fig. 2.

5. CASE STUDIES

It was applied to parameter determination issues to evaluate the effectiveness of the suggested EMA. The results obtained from the EMA are compared with those of other methods: conventional method of determining parameters (CPD), genetic algorithm (GA) [16] and particle swarm optimization (PSO) [16].

5.1 Test Machines

The suggested technique of determining parameters is applied to two sample engines, one with 5 HP engine and the other with 40 HP engine.

5.2 Numerical Results

The obtained equivalent circuit parameters for single-cage and double-cage models of sample motors using EMA method are given in Tables 1 and 2, and the results are compared with those of CPD, GA[16] and PSO[16]. The effectiveness of the EMA strategy for defining the engine parameters can be assessed by determining the engine's starting torque, breakdown torque and complete load torque and comparing them with the respective

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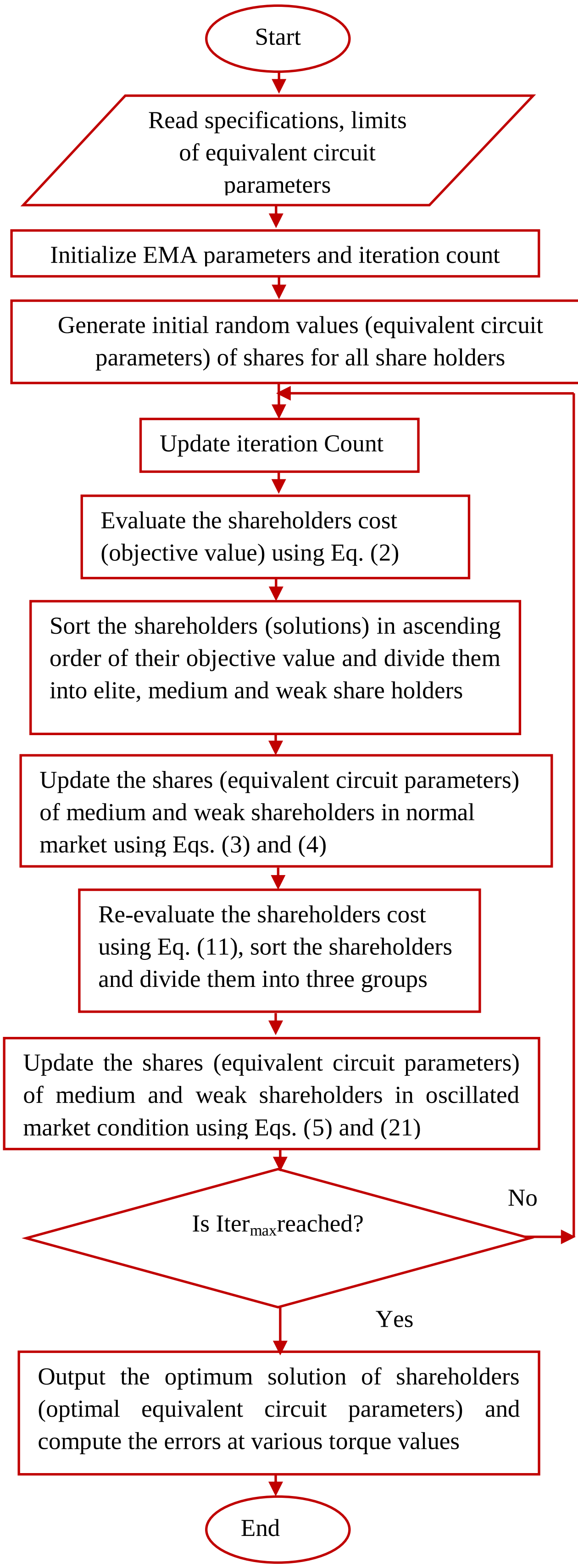

Figure 2. Flowchart of EMA

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Table 1. Summary of single cage model parameters for motors 1 and 2

Parameters	Motor 1				Motor 2			
	CPD	GA	PSO	EMA	CPD	GA	PSO	EMA
R_1(Ohm)	2.67	2.79	1.87	1.88	0.015	0.013	0.023	0.025
R_2(Ohm)	5.274	7.43	5.93	5.96	0.44	0.458	0.45	0.462
X_1, X_2 (Ohm)	14.81	15.8	15.45	15.45	0.576	0.533	0.592	0.585
X_m (Ohm)	409.61	97	284.32	253	11.57	12	12.13	10.70

Table 2. Summary of double cage model parameters for motors 1 and 2

Parameters	Motor 1			Motor 2		
	GA	PSO	EMA	GA	PSO	EMA
R_1(Ohm)	2.39	1.98	2.22	0.0104	0.0235	0.0245
X_1(Ohm)	15.3	11.05	14.01	0.586	0.594	0.666
X_m(Ohm)	103	149.54	226.55	12.7	12.49	14.34
R_{21}(Ohm)	3.32	0.131	0.84	0.597	0.927	0.524
R_{22}(Ohm)	8.52	4.02	4.112	0.444	0.478	0.78
X_{21}(Ohm)	44.6	85.52	90.65	0.704	1.075	0.9
X_{22}(Ohm)	19.5	13.367	10.4	0.635	0.558	0.566

Table 3. Comparison of torque values determined by CPD, GA, PSO and EMA methods with manufacturer data for motor 1

Torque	Manufacturer data	CPD	GA		PSO		EMA	
			Single cage	Double cage	Single cage	Double cage	Single cage	Double cage
T_{st} (Nm)	15	14.25	16.73	16.52	17.6	15.54	15.98	15.45
T_{max}(Nm)	42	36.46	35.98	38.9	40.97	44.1	39.52	42.64
T_{full} (Nm)	25	27.42	20.09	28	22.11	26	26.76	25.8

Table 4. Comparison of errors obtained by CPD, GA, PSO and EMA methods for motor 1

Torque error (%)	CPD	GA		PSO		EMA	
		Single cage	Double cage	Single cage	Double cage	Single cage	Double cage
T_{st}	5	11.53	10.15	17.36	3.6	-6.53	-0.03
T_{max}	13.18	-14.33	-7.38	-2.45	5	5.9	-1.52
T_{full}	-9.66	-19.64	12	-11.56	4	-7.04	-3.2

Table 5. Comparison of torque values determined by CPD, GA, PSO and EMA methods with manufacturer data for motor 2

Torque	Manufacturer data	CPD	GA		PSO		EMA	
			Single cage	Double cage	Single cage	Double cage	Single cage	Double cage
T_{st} (Nm)	260	265.24	258.7	218.85	255.55	222.63	266.55	255.89
T_{max}(Nm)	370	394.71	355.48	410	381.63	364	386.76	382
T_{full} (Nm)	190	178.17	200.99	220	222.78	194.28	182.22	189.49

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Table 6. Comparison of errors obtained by CPD, GA, PSO and EMA methods for motor 2

Torque error (%)	CPD	GA		PSO		EMA	
		Single cage	Double cage	Single cage	Double cage	Single cage	Double cage
T_{st}	-2.01	-0.5	-15.8	-1.7	-14.37	-2.52	1.58
T_{max}	-6.7	-3.92	10.81	3.14	-1.62	-4.53	-3.24
T_{full}	6.22	5.78	15.7	17.25	0.7	4.09	0.268

manufacturer information. Tables 3 and 5 demonstrate the torques calculated from the equivalent circuit parameters of different techniques.
The error in the torque value can be calculated as

$$e(\%) = \frac{X_m - X_d}{X_m} \times 100 \quad (3)$$

For sample engines 1 and 2 respectively, the mistakes found in starting torque, breakdown torque and complete load torque are summarized in Tables 4 and 6. The results of Tables 4 and 6 show that the mistakes in the double-cage model are small. In the single-cage model, the above techniques produce incorrect parameter determination. As seen in Tables, the EMA based double-cage model has provided the better results thus conforming the need to use a more accurate As seen in Tables, the EMA-based double-cage model has delivered better outcomes, thus meeting the need to use a more accurate model in the issue of determining the engine parameter, especially covering a broad variety of speeds.
In this paper, the torque-slip trait is regarded in the objective tasks because it is used to examine a loaded motor's stalling and reacceleration process after a disruption or during the voltage sag situation.

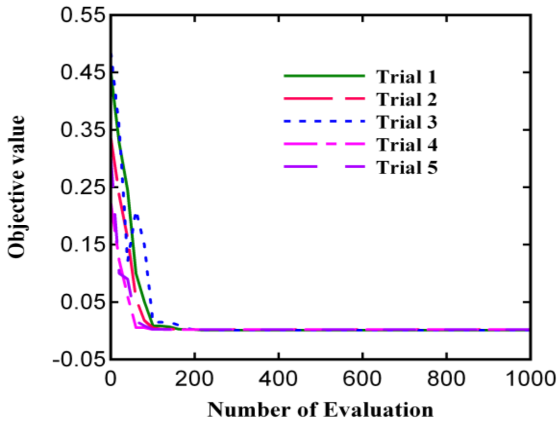

Figure 3. Convergence characteristics of the EMA for different initial group

5.3 Comparative Studies

Figure 3 illustrates the convergence features and demonstrates the effect of random initialization generated by the suggested EMA technique. These provide quick convergence and robustness with regard to the original group of the EMA algorithm.

Table 7. Comparison of standard deviation results between EMA and other methods

Methods	Motor 1		Motor 2	
	Single cage	Double cage	Single cage	Double cage
GA	0.0195	0.0133	0.0013	0.0075
PSO	0.0015	0.0012	0.0021	0.001
EMA	0.002	0.0015	0.00055	0.00045

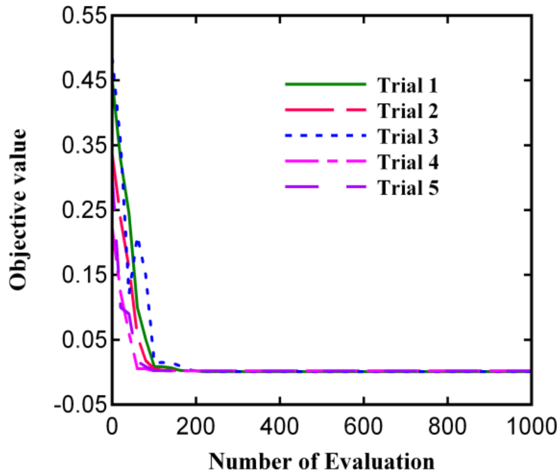

Figure 3. Convergence characteristics of the BFO for different initial group

To statistically compare the outcomes between EMA and various techniques, the standard deviation is given for each model and engine among 20 tests in Table 7. From Table, the robustness and superiority of the suggested EMA technique over the GA and PSO techniques can be observed.

6. CONCLUSION

This article introduces a fresh approach to induction engine double-cage model parameter detection based on the EMA algorithm. The efficiency of the suggested EMA algorithm is proved for 5 and 40 HP engines and is contrasted with the techniques of GA, PSO and conventional parameter determination (CPD).

The following points may be concluded from the results obtained.

- The magnitude of the torque mistakes acquired by the suggested EMA technique was lower than those using the GA, PSO and CPD techniques.
- Double-cage model yielded better outcomes than single-cage model and consequently the induction motor double-cage model is a more accurate model for parameter determination issues.
- The suggested technique is a precious instrument for determining the parameters of the double cage model to be used in the steady state evaluation of the induction motor.
- Overall, the EMA algorithm ensures that it is relatively skilled to solve extremely nonlinear parameter identification problems so that its implementation may also be tried in some other induction motor issues.

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