Novel Efficiency Estimation Technique for In-Service Motor Using Exchange Market Algorithm

V.P. Sakthivel

Assistant Professor
Department of Electrical and Electronics Engineering
Government College of Engineering, Dharmapuri – 636704, India.

Abstract : This article presents a new evolutionary optimization approach named Exchange Market Algorithm (EMA), which is based on the intelligent behavior of shareholders in the share market, for the in-field efficiency determination of three-phase cage induction motor (EDIM). The proposed method exploits the measuring data of stator voltage, stator current, power factor, input power, stator resistance and rotor speed of the in-field three-phase induction motor. The EMA algorithm is employed to estimate the motor equivalent circuit parameters by minimizing the error between the measured and estimated data instead of using no-load and locked rotor tests. Then, the efficiency of the in-field induction motor is estimated by using modified equivalent circuit model which cogitates stray load losses. Since EMA algorithm expends double exploration and exploitation characteristics in each iteration, it affords high solution quality and fast computational time. The proposed algorithm is implemented and tested on 5 HP motor. The results ratify the potential and effectiveness of the proposed algorithm compared to torque cage method, equivalent circuit method (ECM) and Particle Swarm Optimization (PSO) method.

***IndexTerms* - Efficiency estimation; Evolutionary algorithm; Exchange Market Algorithm; Induction motor; Modified equivalent circuit model.**

NOMENCLATURE

r_1	stator resistance (Ω)
x_1	stator leakage reactance (Ω)
r_2	rotor resistance referred to stator (Ω)
x_2	rotor leakage reactance referred to stator (Ω)
r_m	core loss resistance (Ω)
x_m	magnetizing reactance (Ω)
r_{st}	stray loss resistance (Ω)
S	slip
V_1	stator voltage (V)
I_1	stator current (A)
I_2	rotor current (A)
I_m	magnetizing current (A)
pf	power factor
P_{in}	input power (W)
P_{out}	output power (W)
P_{fw}	friction and windage losses (W)
η	efficiency of the motor
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 group
r_1 and r_2 random numbers	
n_k	n^{th} member of the third group
$pop_k^{group\,(3)}$	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, l is a
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

I. INTRODUCTION

Induction motor efficiency determination empowers the energy savings in industry. Owing to the uninterrupted characteristic of industrial process, traditional methods defined in IEEE Std-112 cannot be used. Nonintrusive motor efficiency estimation methods have to be developed for in-situ motor testing. The least intrusive categories of induction motor efficiency estimation methods are equivalent circuit-based methods. Over the years, many efficiency estimation methods have been developed based on induction motor equivalent circuit. The IEEE Std-112 F method is the typical equivalent circuit method [1]. Although this method is expected to be quite accurate, the required no-load, variable voltage, removed – rotor, and reverse rotation tests make it impossible to be used in in-situ testing. Subsequently, the standard 112-F method is modified by eliminating the variable voltage test [2]. However, a no-load test and a full load test both under rated voltage are still required. In [3], the authors surveyed over twenty methods for evaluating the efficiency of induction motors and proposed least intrusive methods for efficiency estimation. Shaft torque measurement is the most direct method for efficiency determination, by using the ratio of motor output power to the input power. However, all methods utilizing dynamometer measurement are not practical in the field [4]. A new method [5] for the identification of induction motor equivalent circuit parameters using the single-phase test instead of the locked-rotor test was proposed. However, the no load test remains a major problem especially when the motor cannot operate at no-load since its shaft is permanently connected to its load.

The no-load and locked rotor tests are used for estimating the parameters of equivalent circuit model. The no-load test is conducted at normal no load voltage and the locked rotor test is performed by locking the rotor mechanically, and applying reduced voltage and frequency. Since no-load and locked rotor tests are highly intrusive, evolutionary algorithms are used for equivalent circuit parameter estimation by minimizing the error between the measured and estimated data.

Genetic algorithm (GA) [6] [7], adaptive GA [8] evolutionary algorithm (EA) [9], PSO [10] Bacterial Foraging algorithm [11] have also been used for parameter identification and efficiency estimation. Thus, the evolutionary algorithms provide non-intrusive method to determine efficiency which requires input values of the motor.

However, some of these heuristic methods may have poor performance on different set of problems. Some algorithms perform local exploitation at the mature stage of the search and global exploratory search at the early stages of the evolutionary process.

Few of the aforementioned methods have excellent global search capabilities but, they have some imitations in their local search ability. Some of the techniques have premature convergence. To overcome premature convergence and speed up the search process a more powerful heuristic algorithm is needed.

Recently, a newly developed meta-heuristic algorithm, exchange market algorithm (EMA) has been proposed [12]. The algorithm imitates the human behavior of shareholders in exchange market and provides better solution quality and convergence speed than the other evolutionary algorithms.

In this research work, a non-intrusive method for in-field efficient estimation of three-phase induction motor based on the EMA is proposed. The better optimum solutions with lower computation burden can be found in EMA compared to the PSO search technique. To justify the effectiveness of the proposed method, the proposed EMA approach is tested on a 5 HP motor.

II. PROBLEM FORMULATION

EDIM is formulated as an optimization problem. The proposed efficiency estimation method incorporates the loss segregation method, the equivalent circuit method and the EMA, as a technique for solving nonlinear equation. An equivalent stray-load resistor is added in serious with the rotor circuit as shown in Fig. 1. The aim is to reach a parameter set, which yields minimal squared error when compared to the measured data.

The stray load resistance is given by

$$r_{st} = \frac{0.018 r_2 (1 - S_{fl})}{S_{fl}} \tag{1}$$

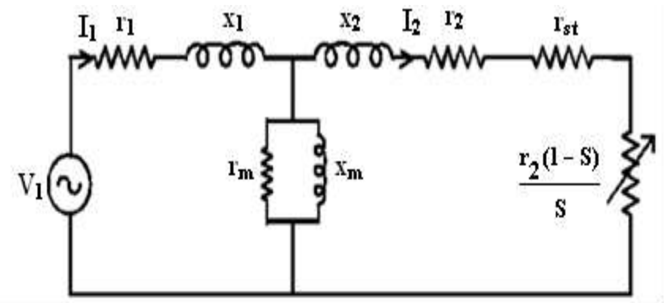

Fig. 1. Modified equivalent circuits of an induction motor

The admittance of each branch of the equivalent circuit can be calculated as follows:

$$\overline{Y_2} = \frac{1}{r_2/S + r_{st} + jx_2} \tag{2}$$

$$\overline{Y_1} = \frac{1.0}{r_1 + jx_1} \tag{3}$$

The stator, rotor and magnetizing currents, power factor, input and output powers and efficiency of the motor can be calculated using the following equations.

$$I_{1e} = |\bar{I}1| = \left|\frac{\overline{V_1 Y_1 (Y_2 + Y_m)}}{\overline{Y_1 + Y_2 + Y_m}}\right| \tag{4}$$

$$I_{2e} = \left|\frac{\overline{V_1 Y_1 Y_2}}{\overline{Y_1 + Y_2 + Y_m}}\right| \tag{5}$$

$$I_{me} = \left|\frac{\overline{V_1 Y_1}}{\overline{r_m (Y_1 + Y_2 + Y_m)}}\right|. \tag{6}$$

$$pf_e = \frac{\Re(\overline{I_1})}{I_{1e}} \tag{7}$$

$$P_{in\,e} = 3\left(I_{1e}^2 r_1 + I_{2e}^2\left(\frac{r_2}{S} + r_{st}\right) + I_{me}^2 r_m\right) \tag{8}$$

$$P_{out\,e} = 3I_{2e}^2 r_2 \frac{1-S}{S} - P_{fw} \tag{9}$$

$$\eta_e(\%) = \frac{P_{out\,e}}{P_{in\,e}} \times 100 \tag{10}$$

The objective function is written as:

$$F(X) = \left[\frac{I_{1c} - I_{1m}}{I_{1m}}\right]^2 + \left[\frac{P_{inc} - P_{inm}}{P_{inm}}\right]^2 + \left[\frac{pf_c - pf_m}{pf_m}\right]^2 \tag{11}$$

III. EXCHANGE MARKET ALGORITHM

EMA is a new population-based meta-heuristic algorithm proposed by Ghorbani and Babaei [12]. The algorithm imitates the human behavior of stock market in which shareholders trade shares under balanced and oscillated market situations. This algorithm uses two searcher and absorbent operators in normal and oscillation modes respectively. In EMA, optimum solution is regarded as one that is searched out by a shareholder population. Each individual of this population is called a shareholder. The individuals of searcher group and absorbent group are responsible for improving the exploration and exploitation abilities of the algorithm.

3.1. Exchange Market in Normal Mode

In normal condition of the exchange market, the shareholders try to maximize their profit using elite shareholders experience. In the population, each shareholder is ranked according to the fitness function.

3.1.1. Shareholders with High Ranks

These shareholders do not change their shares without performing any risk and trade to maintain their ranks. This group of shareholders composes 10 – 30% of the population.

3.1.2. Shareholders with Average Ranks

This group of shareholders composes 20–50% of the population. The members of this group use the experiences of elite stockbrokers and take the least possible risk in changing their shares.

$$pop_{j}^{group\,(2)} = r \times pop_{1,i}^{group\,(1)} + (1-r) \times pop_{2,i}^{group\,(1)} \tag{12}$$

$$i = 1,2,3,\ldots n_i \quad \text{and} \quad j = 1,2,3,\ldots. n_j$$

3.1.3.Shareholders with Weak Ranks

This group of shareholders composes 20–50% of the population. The members of this group utilize the differences of share values of elite and medium shareholders with their share values. The population of this group is given in the following equation.

$$S_k = 2 \times r_1 \times \left(pop_{i,1}^{group\,(1)} - pop_{k}^{group\,(3)}\right) + 2 \times r_2 \times \left(pop_{i,1}^{group\,(1)} - pop_{k}^{group\,(3)}\right) \tag{13}$$

$$pop_{k}^{group\,(3)\,new} = r \times pop_{k}^{group\,(3)} + 0.8 \times S_k \tag{14}$$

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

3.2. Exchange Market in Oscillation Mode

In this mode, the shareholders perform intelligent risks according to their own rank among other members to gain the maximum possible profit. The shareholders can be divided into three different groups based on their performances.

3.2.1. Shareholders with High Ranks

This group allocates 10-30% of the market population known as elite members, which do not participate in the market exchange.

3.2.2. Shareholders with Medium Ranks

The market share of the second group is changed in such a way that the whole share values of the group are constant. The share values of the individuals can be updated as

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \tag{15}$$

$$\mu = \frac{t_{pop}}{n_{pop}} \tag{16}$$

$$n_{t1} = \sum_{y=1}^{n} (S_{ty}) \quad y = 1,2,3,\ldots,n \tag{17}$$

$$\eta_1 = \eta_{t1} \times g_1 \tag{18}$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{Iter_{max}} \times k \tag{19}$$

In order to maintain the shares remain constant, each shareholder randomly sells some of the shares equal to the shares purchased. Hence, each shareholder reduces the share values which are given as follows.

$$\Delta n_{t,2} = n_{t,2} - \delta \tag{20}$$

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

3.3. Shareholders with Weak Ranks

The shareholders can either purchase or sell the shares. Hence, the total share value is variable. The share values of the individuals can be updated as

$$\Delta n_{t,3} = 4 \times r_s \times \mu \times \eta_2 \tag{21}$$

$$r_s = 0.5 - \text{rand} \tag{22}$$

$$\eta_1 = \eta_{t1} \times g_1 \tag{23}$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{Iter_{max}} \times k \tag{24}$$

IV. EMA APPLIED TO EDIM PROBLEM

The different steps of EMA for solving EDIM problem are described below.

Step 1. Input data for market operation

The total shareholders in the market (m), shares (n), lower and upper limits of each shares (equivalent circuit parameters), maximum iteration number, risk factors (g1 and g2) and EMA constants are initialized.

Step 2. Initialization of shareholders

Since the decision variables for EDIM problems are equivalent circuit parameters of in-field induction motor, they are used to form the shares of shareholders. The i[th] shareholder for n equivalent circuit parameters is represented as

$$x_i = \left[x_{i1,}\ x_{i2,} ..., x_{im}\right] \tag{25}$$

Each share of the shareholder matrix is initialized using a uniform probability distribution function in the range (0 – 1) and located between the maximum and minimum limits of the equivalent circuit parameters.

The shareholder can be represented below:

$$x_{ij} = x_{jmin} + rand \times \left(x_{jmax} - x_{jmin}\right) \tag{26}$$

Step 3. Evaluation of shareholders' cost

The shareholders cost is evaluated by using Eq. (11)

Step 4. Ranking and allocation of shareholders

The shareholders are sorted in ascending order and are divided into three different groups. The 30%, 40% and 30% of population are allocated for elite, medium and weak shareholders respectively.

Step 5. Updating the shares of medium and weak shareholders in normal market condition

The share values of medium and weak ranking shareholders are updated using Eqs. (12) and (13) respectively.

Step 6. Reevaluation, ranking and allocation of shareholders

The medium and weak shareholders' costs are reevaluated using Eq. (11). Subsequently, the shareholders are repositioned and separated into three different groups.

Step 7. Updating the shares of medium and weak shareholders in oscillated market condition

The share values of medium and weak ranking shareholders in oscillated market situation are updated using Eqs.(15) and (21) respectively.

Step 8. Stopping Criteria

If the maximum iteration number is reached, then the EMA is terminated and the optimal equivalent circuit parameters are obtained. Otherwise, the procedure is repeated from Step 3.

The flowchart of EMA based EDIM problem is depicted in Fig. 2

V. RESULTS AND DISCUSSIONS

In this article, to evaluate the effectiveness of the recently developed EMA algorithm, it is implemented to solve EDIM problem considering modified equivalent circuit model. MATLAB 7.1 Software is used to simulate EDIM problems and tested on 2 GHz Pentium IV, 1 GB RAM personal computer. The shareholders (population size) and the maximum iteration number are taken as 20 and 100 respectively.

The results of the torque gauge method are depicted in Table 1. The two methods of experiments are conducted on a 5 HP motor whose specifications is given in Appendix and the simulation results of the proposed method are compared with ECM and PSO.

Table 1.
Load test data of three-phase induction motor

Motor Load	I_1 (A)	P_{in} (w)	pf	Efficiency (%)
25%	6.4	1600	0.63	57.2
50%	8.5	2500	0.74	67.05
75%	10.6	3300	0.78	77.01
100%	12.5	4100	0.82	63.81

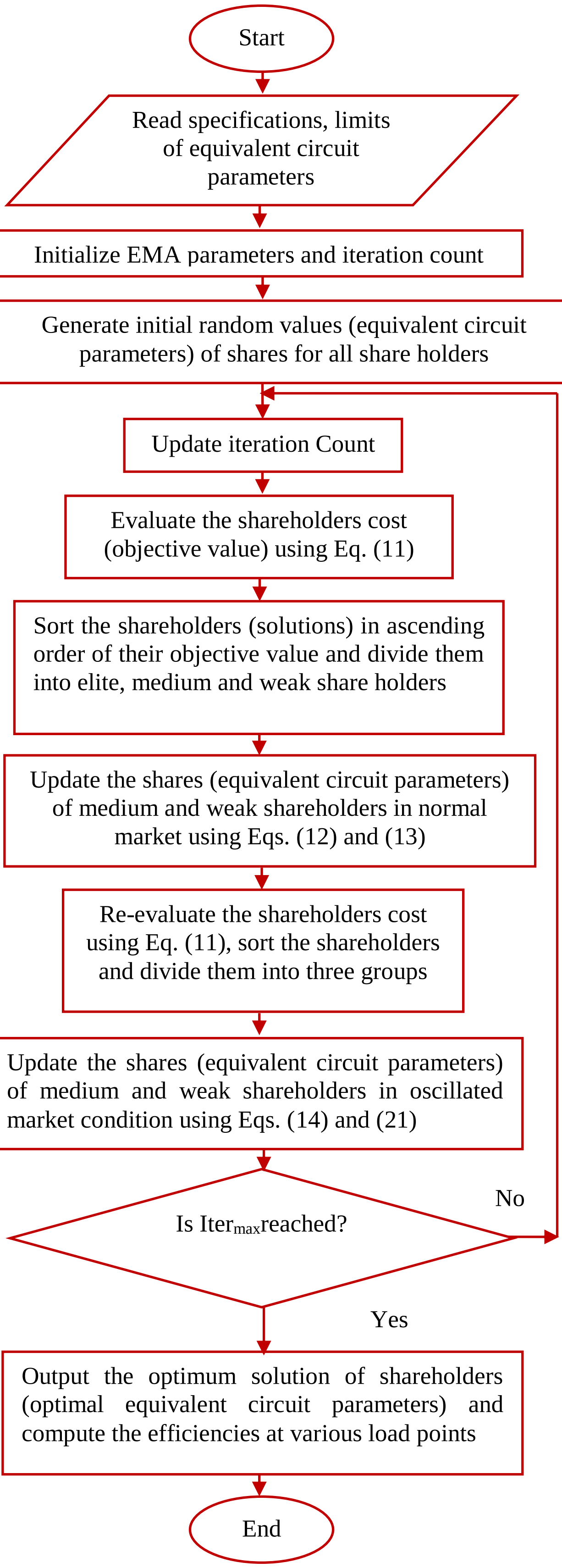

Fig. 2. Flowchart of EMA based EDIM problem

Test Case 1: Initially, full load experimental data is considered for equivalent circuit parameter estimation.
Test Case 2: Secondly, each load experimental data is considered for equivalent circuit parameter estimation.

5.1. Test Case 1

In this test case, only full load experimental data are used for motor parameter determination. The equivalent circuit parameters, X_1, R_2, X_m, and R_m are randomly generated by EMA method. Then these values are used to compute the stator line current, power factor, input power, output power, and the corresponding efficiencies at different load points. The calculated values are compared with the measured experimental data. The error is the difference in the percentage efficiency obtained from MOEAs and the measured data at each load point.

The comparative results for test case 1 are summarized in Table 2. Figs. 3 and 4 show the errors and efficiencies obtained by various approaches for this test case respectively. The results show that the error produced by EMA is less when compared with PSO which emphasizing its better solution quality. Moreover, it is observed from Table II that average simulation time of the proposed EMA approach is significantly less than that of PSO.

Table 2
Comparison of ECM, PSO and EMA results for test case 1

Motor Load	ECM		PSO		EMA	
	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)
25%	73.57	16.37	66.08	8.88	64.12	6.92
50%	82.56	15.51	76.24	9.1	59.28	-5.77
75%	84.25	7.24	69.98	-7.03	72.21	-4.81
100%	82.65	18.84	58.32	-5.49	61.08	-2.73
CPU Time (sec)	-		5.23		4.78	

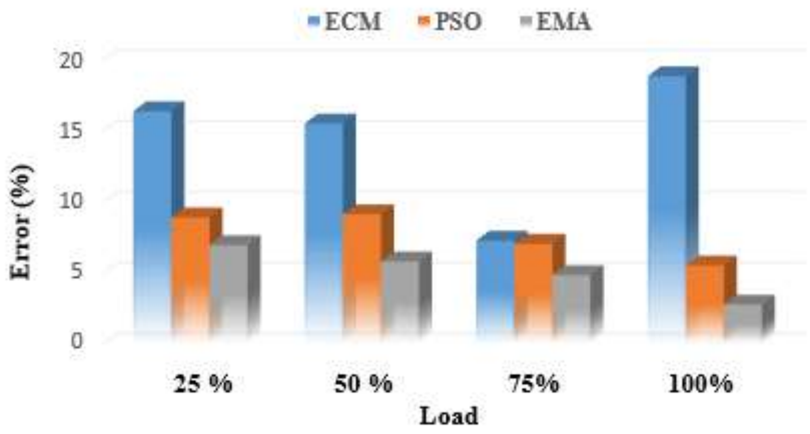

Fig. 3. Magnitude of errors in percentage efficiency for test case 1

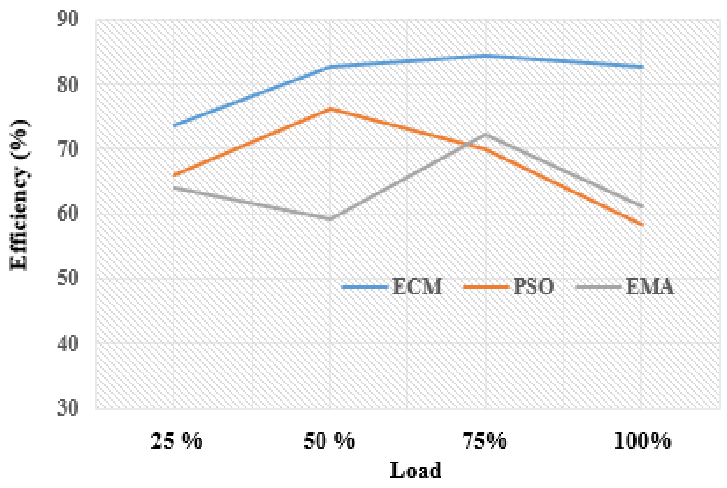

Fig.4. Comparison of various methods for test case 1

5.2. Test Case 2

In this test case, each load point experimental data is used for motor parameter and efficiency determination. The comparison of PSO and EMA based EDIM problem for test case 2 is summarized in Table 3, and shown in Figs. 5 and 6.

It can be observed from Table 3 and Figs. that the proposed technique provides significantly better results in comparison with the PSO technique. Hence, it may be concluded that the PSO optimization is computationally better organized than the PSO approach in terms of quality of solution. Furthermore, heuristic algorithms using test case 2 provides better results than the test case1.

Table 3
Comparison of ECM, PSO and EMA results for test case 2

Motor Load	ECM		PSO		EMA	
	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)
25%	73.57	16.37	65.51	8.31	49.77	-5.43
50%	82.56	15.51	58.43	-8.62	71.77	4.72
75%	84.25	7.24	69.58	-7.43	71.40	-3.61
100%	82.65	18.84	59.44	-4.37	60.60	-1.21
CPU Time (sec)	-		6.62		5.34	

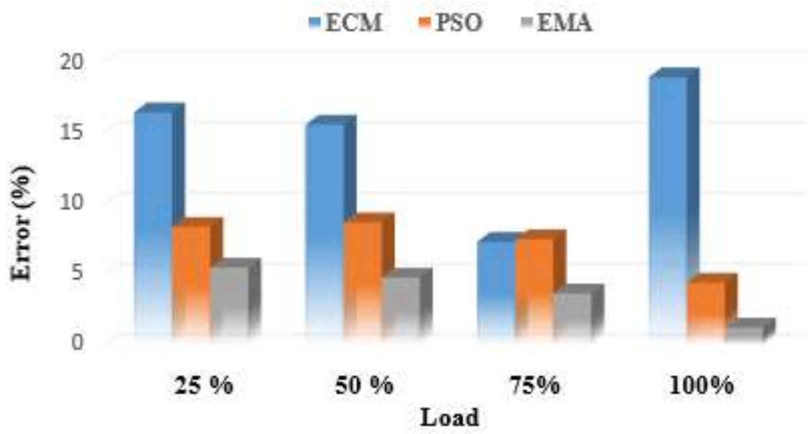

Fig. 5. Magnitude of errors in percentage efficiency for test case 1

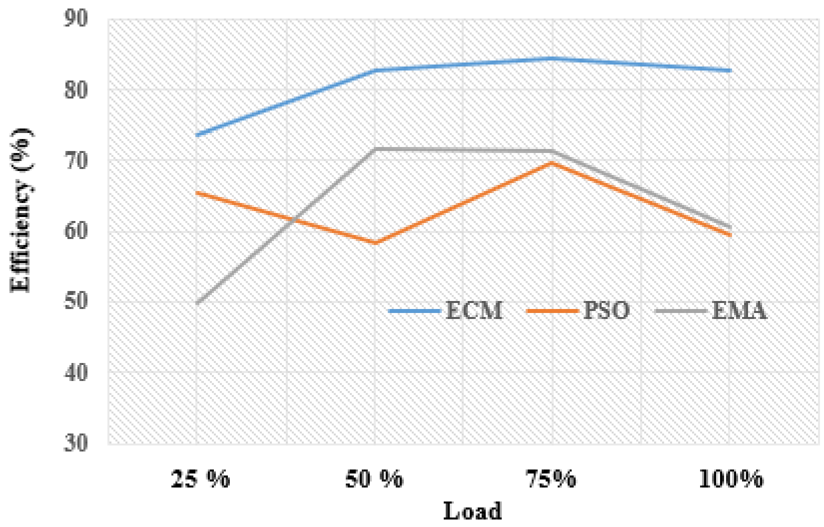

Fig.6. Comparison of various methods for test case 2

VI. Conclusion

In this work, an efficient and abstemiously new algorithm named EMA is proposed to solve the EDIM problem using modified equivalent circuit model. The proposed method encompasses the equivalent circuit method, the segregated losses method and EMA algorithm. Two test cases are employed to determine the in-field efficiency of 5 HP motor to exhibit the applicability of the EMA method. Simulation results expose that the EMA method has superior aspects, improvements over PSO algorithm in terms of better solution quality and less computational efforts. Though the proposed algorithm is employed to solve EDIM problems in the current study, it seems from its distinctive feature that EMA has the potential to solve many other optimization problems in the field of electrical machine design and power systems.

Appendix
Specifications of 5 HP motor

Specifications	Value
Capacity	5 HP
Voltage	230 V
Current	12.5 A
Speed	1450 rpm

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