Comparative Study of Heuristic Optimization Techniques (HOTs) for Energy Efficient Induction Motor Design

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Abstract: Three-phase induction motors are widely used in domestic, commercial and industrial applications. On an average, the energy consumed by an induction motor during its life cycle is 60–100 times the initial cost of the motor. Even a small percentage of efficiency increase will result in a significant energy conservation and economic impact. A comparative study of heuristic optimization techniques (HOTs) has been carried out for energy efficient induction motor design (EEIMD) problem considering the active power loss effect to ensure the minimum manufacturing and annual power loss costs. The objective of this paper is to minimize the total manufacturing and annual power loss costs. In this paper, various HOTs such as genetic algorithm (GA), particle swarm optimization (PSO), and exchange market algorithm (EMA) have been applied to obtain EEIMD solutions. The proposed algorithms have been applied on designing the two sample motors. In comparison with the solution quality and execution time obtained by the HOTs, the EMA seems to be a promising technique to solve EEIMD problems.

Index Terms **- Energy efficient motor, evolutionary algorithm, genetic algorithm, heuristic optimization techniques.**

NOMENCLATURE

M_{isc}, M_{ist}	core and tooth iron masses in stator (Kg)
M_{irc}, M_{irtb}, M_{irtt}	core, tooth bodies and tooth tips iron masses in rotor (Kg)
M_b, M_{er}, M_{sc}	bars, end rings and stator conductor copper masses (Kg)
p_{isc}, p_{ist}	specific iron loss of stator core and tooth (W/Kg)
P_{isc}, P_{ist}	core and teeth iron power loss in stator (W)
P_b, P_{er}, P_{sc}	bars, end rings and stator conductors copper power losses (W)
P_f, P_s	friction and stray power losses (W)
K_{sr}, K_{ss}	rotor and stator slot copper insulating factors
δ_r	rotor current densities (A/mm^2)
p	number of poles
T	motor running time per year (hr)
α	annual rate of interest and depreciation
η	full-load efficiency
W	rated power (W)
K_{er}	end ring non-uniformity current distribution factor
W_c, W_i	copper and iron specific masses (Kg/m^3)
ρ_s, ρ_r	stator and rotor copper resistivities (Ω.m)
K_i	iron insulation factor
K_j	end ring to bar current density ratio
f	supply frequency (Hz)
N_r, N_s	rotor and stator number of slots
c_c, c_i	specific copper and iron material costs (Rs/Kg)
c_e	specific energy loss cost (Rs/Wh)
c_p	specific power loss cost (Rs/W)
d_{rc}	rotor core depth (m)
d_{rs}	rotor slot opening depth (m)
w_{rs}	rotor slot opening width (m)
D_i	rotor inner diameter (m)
D_o	stator outer diameter (m)
D_r	rotor diameter (m)
L	gross iron length (m)
L_i	active iron length (m)
m	number of particles in the swarm
N	number of dimensions in a particle
K	pointer of iterations (generations)
Vi, n k	velocity of particle i at iteration k
W	weighting factor
C 1, C2	acceleration factor
rand j	random number between 0 and 1

$X_{i,n}^{k}$	current position of particle i at iteration k
$pbest_i$	personal best of particle i
gbest	global best of the group
W_{max}	final weight factor
W_{min}	initial weight factor
Iter	current iteration number
$Iter_{max}$	maximum iteration number
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
$g_{1,max}$, $g_{2,max}$	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

Improving the efficiency of three-phase squirrel cage induction motors, which are the most energy consuming electric machines in the world, saves much energy. The efficiency can be raised by optimizing the induction motor design. The following two different, partially conflicting approaches are considered for the optimal design of three-phase induction motor (IM) as follows:

- From the manufacture's viewpoint, an optimal design has minimum production cost including the active and construction materials and the manufacturing cost [1-5].
- From the consumer's viewpoint, an optimal designed motor has the lowest annual cost, including the initial capital cost, interest rate, energy losses cost, yearly operation time, etc [4-6].

The optimal design of a three-phase cage IM for minimum annual cost, using evolutionary optimization techniques, is an appropriate approach to the motor design. With this approach, any desired requirements may be easily expressed in the optimization problem formulation. The optimal design parameters of the motor can be obtained by solving a constrained nonlinear optimization problem. The problem consists of an objective function which is optimized (minimized or maximized) with a set of constraints.

Stochastic searching algorithms such as GA [7], evolutionary algorithm [8], neural networks [9], fuzzy logic [10], PSO [11, 12], Adaptive PSO [13], bacterial foraging algorithm (BFA) and Adaptive BFA [14] have been used to solve the IM design problems. Though heuristic algorithms such as GA have been employed to solve IM design problems, recent research has indentified some deficiencies in GA performance [15]. The premature convergence of GA degrades its performance and reduces its search capability that leads to a higher probability toward obtaining local minimum.

A new evolutionary algorithm called exchange market algorithm (EMA) was proposed by Naser Ghorbani and Ebrahim Babaei in 2014 [16]. The EMA is inspired by intelligent dealings of shareholders. The exchange market changes between normal and oscillatory market conditions. These characteristics are introduced in EMA. The two searcher and absorbent operators are used in normal and oscillatory market conditions respectively. As each iteration uses double exploitation and exploration property, EMA is one of the most efficient heuristic search algorithms. Currently, EMA is applied successfully in various areas of power system problems such as economic dispatch and reactive power dispatch [17].

This paper presents the application of GA, PSO and EMA to solve the EEIMD problems. The effectiveness and robustness of the HOTs have been verified by the simulations conducted on two sample induction motors design. The results confirm the effectiveness and robustness of the EMA algorithm through a comprehensive statistical analysis.

The main contributions of this paper can be summarized as follows:

- The EMA algorithm is proposed as a new optimization tool for the EEIMD problems.
- Experiments are carried out to compare EMA with the other HOTs.

This paper is structured as follows. The EEIMD problem is introduced in Section 2. Section 3 presents the overview of HOTs in brief. The implementation of the HOTs to EEIMD is described in Section 4. The computational results are analyzed in Section 5, and the conclusion is provided in Section 6.

II. PROBLEM FORMULATION

A. Definition

If ‘F’ is the objective function, which depends on the design variables vector X= (X_1, X_2, ..., X_N), the corresponding constrained IM design optimization problem can be written as:

$$\begin{cases} \text{Min} \quad \mathbf{F(X)} \\ \text{Subject to } \mathbf{G(X)} \le 0 \end{cases} \tag{1}$$

B. Design variables

The nine design variables are used in formulating the objective and constraint functions of the IM design problem.

C. Constraints

The six important motor performance indices are chosen as design constraints.

D. Objective function

In this study, the annual cost of IM is considered as the objective function. The annual cost of the motor is the summation of annual cost of the motor manufactured iron and copper materials, the annual cost of a fictitious active power source required to cover the total active power loss of the motor and the annual cost of energy needed by that fictitious source. The expression of different cost functions, in terms of the design variables are summarized as follows:

(i) Annual active material cost

Annual iron material cost,

$$C_i = \alpha c_i (M_{isc} + M_{ist} + M_{irc} + M_{irtt} + M_{irtb}) \tag{2}$$

Annual copper material cost,

$$C_c = \alpha c_c (M_{sc} + M_b + M_{er}) \tag{3}$$

Annual active material cost is given by

$$C_m = C_i + C_c \tag{4}$$

(ii) Annual active power loss cost

Annual iron loss cost,

$$C_{ip} = \alpha c_p (P_{isc} + P_{ist}) \tag{5}$$

Annual copper loss cost

$$C_{cp} = \alpha c_p (P_{sc} + P_b + P_{er}) \tag{6}$$

Annual friction and windage loss cost,

$$C_{fp} = \alpha c_p P_f \tag{7}$$

The stray loss is assumed to reduce the efficiency by 0.5%, so that

$$C_{sp} = \alpha c_p P_s \tag{8}$$

The total annual active power loss cost is thus

$$C_p = C_{ip} + C_{cp} + C_{fp} + C_{sp} \tag{9}$$

(iii) Annual energy loss cost

$$C_e = \frac{c_e T C_p}{\alpha c_p} \tag{10}$$

The objective function is given by

$$F(X) = C_m + C_p + C_e \tag{11}$$

III. Overview of HOTs

A. GA

Genetic algorithm (GA) is a search algorithm based on the behavior of natural selection and genetics. GA's operate on a population of potential solutions applying the principle of survival of the fittest to produce better solution. At each generation, a new set is created by the process of selecting individuals according to their fitness in the problem domain and breeding them by crossover and mutation operators. This process leads to the evolution of populations of individuals that are better than the individuals [6]. It consists of a population of bit strings transformed by three genetic operators: selection, crossover and mutation. Each string (called chromosome) represents a possible solution to the problem being optimized and each bit (or group of bits) represents a value for some variable of the problem (gene). These solutions are classified by an evaluation function to better solutions. Each solution is evaluated by the fitness function to produce a value. The pair of chromosome and fitness represents an individual. The selection operator creates a new population (or generation) by selecting individuals from the previous population. Crossover is the main genetic operator and consists of swapping the chromosome between individuals. Crossover is being controlled by a crossover probability [7]. This probability should have a larger value. The last operator is mutation and consists of changing a random part of the string representing the individual.

B. PSO

Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart, is one of the heuristic optimization algorithms. A simple PSO maintains a swarm of particles that represent the potential solutions to the problem on hand. The simple PSO consists of a swarm of particles moving in the D-dimensional space of possible problem solutions. Each particle embeds the relevant information regarding the D decision variables and is associated with a fitness that provides an indication of its performance in the objective space. Each particle i has a position $X_i = [X_{i,1}, X_{i,2} \ldots X_{i,D}]$ and a flight velocity $V_i = [V_{i,1}, V_{i,2} \ldots V_{i,D}]$. Moreover, a swarm contains each particle i own best position $pbest_i = (pbest_{i,1}, pbest_{i,2}, \ldots, pbest_{i,D})$ found so far and a global best particle position $gbest = (gbest_i, gbest_i, \ldots, gbest_D)$ found among all the particles in the swarm so far.

In essence, the trajectory of each particle is updated according to its own flying experience as well as to that of the best particle in the swarm. The standard PSO algorithm can be described as

$$V_{i,d}^{k+1} = W \times V_{i,d}^{k} + C_1 \times rand_1 \times (pbest_{i,d}^{k} - X_{i,d}^{k}) + C_2 \times rand_2 \times (gbest_{d}^{k} - X_{i,d}^{k})$$

$$X_{i,d}^{k+1} = X_{i,d}^{k} + V_{i,d}^{k+1}$$

$$i = 1, 2 \ldots, n; \; d = 1, 2 \ldots, D$$

The time varying weighting function is given by

$$W = W_{max} - (W_{max} - W_{min}) \times Iter / Iter_{max}$$

C. EMA

EMA is a new population-based meta-heuristic algorithm proposed by Ghorbani and Babaei [16]. 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.

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.

i) 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.

ii) 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.

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

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

iii) 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.

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

$$2\times r_2\times\left(pop_{i,1}^{group\,(1)}-pop_k^{group\,(3)}\right)$$

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

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

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.

i) 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.

ii) 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 is constant. The share values of the individuals can be updated as

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

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

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

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

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

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 value which is given as follows.

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

where n_{t2} is the total share value of t^{th} member after employing share variations.

IV. Implement of HOTs to EEIMD Problem

The different steps of HOTs for solving EEIMD problem are described in the Fig. 1.

V. Simulations and Comparisons

To evaluate the performance of the proposed EMA in solving the EEIMD problem, computational simulations are conducted on designing two sample motors. Moreover, to further verify the effectiveness of the proposed algorithm, the other HOTs (GA and PSO) are employed for comparisons. For rational comparison, same values are chosen for similar parameters as used in the compared HOTs. Specifically, for the two sample motors, the population size is set to 20 and the maximum number of iterations is set to 100. The HOTs are implemented using MATLAB 7.1 on a core i3 processor with 2.40 GHz and 4 GB RAM, and is replicated for 20 independent runs. The specifications of the sample motors are given in Appendix. The annual active material cost, and annual active material, annual power loss and annual energy loss costs are considered in Case 1 and 2 respectively.

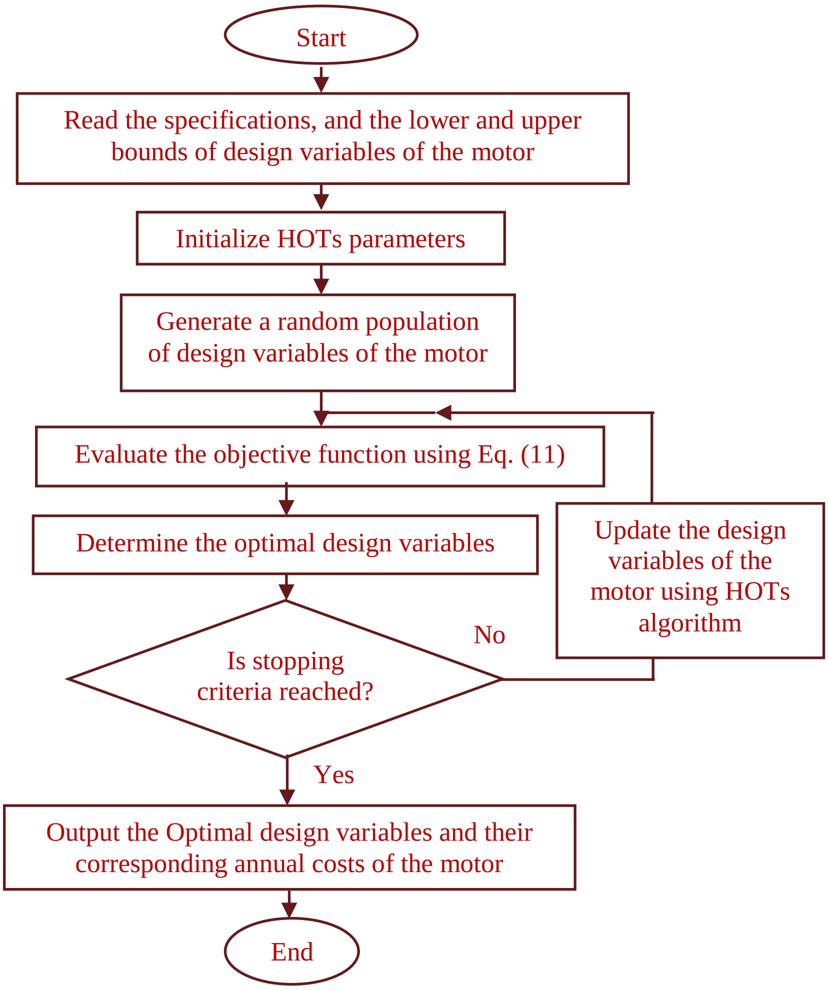

Fig. 1. Flowchart of HOTs based EEIMD problem

Table 1. Comparison of results of HOTS for 5 HP motor

Variables/ indices/cost	Conventional method	Case 1			Case 2		
		GA	PSO	EMA	GA	PSO	EMA
Independent variables							
Stator bore diameter (mm)	150	145	145.7	147.5	138	137	136
Average air gap flux density (Wb/m^2)	0.46	0.476	0.456	0.474	0.427	0.435	0.454
Stator current density (A/mm^2)	4	4.2	4.02	4.5	3.54	3.65	3.8
Air gap length (mm)	0.43	0.41	0.39	0.45	0.35	0.33	0.32
Stator slot depth (mm)	24.15	22.8	22.74	22.55	28	27.8	25.46
Stator slot width (mm)	6.92	7.2	7.15	7.3	7.6	7.8	7.92
Stator core depth (mm)	24.94	26.6	26.4	26.35	29.5	29.7	31.4
Rotor slot depth (mm)	10	10	12	9	13.6	11	12.7
Rotor slot width (mm)	5	4.6	5	4.7	6	6	4
Dependent Variables							
Gross iron length (mm)	89	92.6	95.8	94.6	11.4	112.7	116.72
Rotor current density (A/mm^2)	7.74	7.6	7.4	7.36	6.1	6.4	5.8
Performance index							
Maximum to full-load torque ratio	2.21	2.57	2.7	2.66	3.3	2.6	2.4
Starting to full-load torque ratio	1.27	1.6	1.37	1.5	1.23	1.15	1.04
Starting to full-load current ratio	4.15	4.92	4.68	4.78	4.1	4.2	3.92
Full-load efficiency	81.57	82.32	83.47	82.7	86.15	85.77	86.23
Full-load power factor	0.86	0.82	0.84	0.88	0.88	0.89	0.89
Maximum temperature rise	52	50.68	49.68	51.54	46.6	46.7	46.58
Annual Cost							
Material cost (Rs)	487.1	460.42	499.43	448.8	564.19	517.02	469. 75
Power loss cost (Rs)	981.02	912.56	890.01	874.16	847.28	844.56	823.43
Energy loss cost (Rs)	5115.24	4758.3	4640.8	4590.28	4418	4403.79	4275.36
Total cost (Rs)	6583.36	6131.28	6030.2	5912.87	5829.5	5765.37	5568.54

Table 2. Performances of HOTs for 5 HP motor in the 20 trials

Compared item	Case 1			Case 2		
	GA	PSO	EMA	GA	PSO	EMA
Maximum cost (Rs)	6423.63	6217.36	6000.56	6116.2	5940.29	5770.64
Minimum cost (Rs)	6131.28	6030.2	5912.87	5829.5	5765.37	5568.54
Mean cost (Rs)	6293.2	6134.8	5970.38	5949.8	5803.1	5569.32
Standard deviation of cost (Rs)	81.2	61.61	40.52	86.8	65.45	39.7
CPU time (sec)	3.2	2.72	2.64	3.3	2.88	2.73

Table 3. Comparison of results of HOTS for 10 HP motor

Variables/ indices/cost	Conventional method	Case 1			Case 2		
		GA	PSO	EMA	GA	PSO	EMA
Independent variables							
Stator bore diameter (mm)	165	163	164	162.64	139	136	132.8
Average air gap flux density (Wb/m^2)	0.45	0.465	0.466	0.462	0.445	0.45	0.438
Stator current density (A/mm^2)	4	4.04	4.17	4.16	3.9	4.02	3.8
Air gap length (mm)	0.35	0.388	0.38	0.378	0.33	0.37	0.34
Stator slot depth (mm)	25	26.84	26.9	26.6	27.88	27.3	25.76
Stator slot width (mm)	7	7.5	7.4	7.35	6.5	6.6	6.4
Stator core depth (mm)	26	27.5	26.7	26.4	27.89	22	25.32
Rotor slot depth (mm)	13	13	10	10	14	12.8	13.67
Rotor slot width (mm)	4	3.8	5	4.68	5	6.8	5
Dependent Variables							
Gross iron length (mm)	133.2	122	130.2	136	189.8	186.6	216.4
Rotor current density (A/mm^2)	5.13	6.07	6.36	6.19	4.6	4.84	4.04
Performance index							
Maximum to full-load torque ratio	2.5	2.8	2.73	2.38	3.04	2.06	2.43
Starting to full-load torque ratio	0.975	1.25	1.28	1.15	1.01	1.02	0.98
Starting to full-load current ratio	3.6	4.8	4.92	4.84	4.6	4.7	3.26
Full-load efficiency	85.5	85.45	85.08	85.72	86.3	85.62	86.74
Full-load power factor	0.9	0.92	0.92	0.929	0.92	0.91	0.92
Maximum temperature rise	60	61.2	60.08	57.43	55.53	56	53.54
Annual Cost							
Material cost (Rs)	815.19	752.5	757.2	732.6	940.19	820.91	966.69
Power loss cost (Rs)	1533.55	1524.32	1523	1498.33	1461.4	1476.7	1408.94
Energy loss cost (Rs)	7996.47	7948.33	7940	7822.56	7620.2	7700	7460.36
Total cost (Rs)	10345.21	10225.1	10220	10053.49	10022	9997.6	9835.99

Table 4. Performances of HOTs for 10 HP motor in the 20 trials

Compared item	Case 1			Case 2		
	GA	PSO	EMA	GA	PSO	EMA
Maximum cost (Rs)	10499.46	10413.23	10236.79	10299.65	10161.12	10023.67
Minimum cost (Rs)	10225	10220	10053.5	10022	9997.6	9835.99
Mean cost (Rs)	10338	10319	10148.37	10154	10060	9928.46
Standard deviation of cost (Rs)	87.67	55.76	38.6	84.23	50.6	40.67
CPU time (sec)	3.42	2.68	2.46	3.5	2.87	2.57

The results of the sample motors obtained using the proposed EMA technique are given in Tables 1 and 3 and compared with the results obtained using GA, PSO and conventional design methods. It can be seen that the proposed EMA method gives the minimum annual cost. When the total annual cost of the motor (Case 2) is chosen as objective function, the average flux density and the stator current density are appreciably reduced. Accordingly, the proposed optimal designed motors have better efficiency, lower starting current and lower temperature rise than the optimal designed motor by minimizing the annual material cost only (Case 1). The nature of convergence characteristics of the GA, PSO and EMA algorithms are shown in Fig. 2. It is clear from the Fig. 2 that the proposed EMA algorithm can avoid the short coming of premature convergence and can obtain better solution quality.

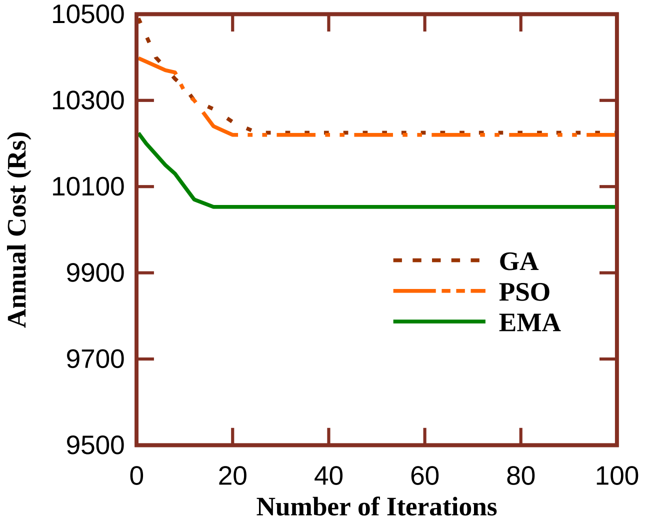

Fig 2. Convergence chracteristics of the compared HOTs for case 1(Motor 2)

Tables 2and 4 summarize the performances of the GA and PSO approaches are obtained in 20 runs. The results show that the proposed EMA algorithm gives less annual cost and takes less CPU time than the other HOTs.

VI. Conclusions

This paper compares three different heuristic optimization techniques (HOTs) viz., genetic algorithm, particle swarm optimization and exchange market algorithm to solve energy efficient induction motor design problems considering the annual power loss cost. A comparative analysis has been done for different HOTs with respect to the total minimum cost, solution quality and convergence criteria. The effectiveness of these techniques have been demonstrated and validated on two sample motors design viz., 5 HP and 10 HP motors. The results achieved are quite encouraging and indicate viability of the proposed technique to deal with other machine design and power system optimization problems. On comparison of all the three HOTs, the operation of EMA is found to be easier and its application is more flexible with respect to its solution quality and convergence criteria.

Appendix

Specification of Test Motors

Specifications	Motor1	Motor 2
Capacity	5 HP	10 HP
Voltage	400 V	415 V
Current	7.8 A	13.68 A
Frequency	50 Hz	50 Hz
No. of Poles	4	4
Power factor	0.8	0.87
Efficiency	83 %	87 %

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