Adaptive Particle Swarm Optimization for the Design of Three-Phase Induction Motor Considering the Active Power Loss Effect

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Abstract—The paper presents an effective evolutionary method to the optimum design of three-phase induction motor using adaptive particle swarm optimization (APSO) technique. To avoid premature convergence of the classical PSO algorithm, the parameters such as inertia weight factor and acceleration factors are made adaptive on the basis of objective functions of the current and best solutions. The optimization algorithm considers the annual cost of the motor including the power loss cost as objective function and six important motor performance indices as inequality constraints. These functions are expressed in terms of motor design variables. The APSO integrates penalty parameter-less constraint handling strategy for handling the constraints. The potential of the proposed approach has been tested on two sample motors, and the results are compared with genetic algorithm, classical PSO and conventional design methods. It is observed that the proposed method is superior in terms of solution quality, robustness and computational efficiency.

Index Terms— Adaptive particle swarm optimization, genetic algorithm, Induction motor, optimal design, particle swarm optimization.

I. INTRODUCTION

Minimal energy consumption of three-phase induction motors is one of the important factors for energy savings because of the number of three-phase induction motors in-service are more. Due to the massive fabrication and usage of the induction motor, its manufacturer and operating cost should be minimized. The objective of the optimal design of induction motor is usually to minimize either the initial cost of the machine or its life time cost including the cost of loss energy. The initial (manufacturer) cost minimization is the primary interest of the motor manufacturer but may not be benefit to the users. Because the manufacturer cost is a small portion of the total power loss cost of the motor during its life time. Therefore, active power loss effect should also be included in the design of induction motor. This objective is

the main consideration for the motor user as the life time cost is reduced and also results to the admirable goal of global energy conservation.

The optimization of induction motor design has been approached as a multi variable nonlinear programming problem using various conventional local optimization methods [1-10]. However, the occurrence of undesired local minima was pointed out in several works [2-4].

For satisfactory handling of induction motor design optimization problems, efficient approaches are still required. The methods that qualify are evolutionary algorithm [11], GA [12], neural network [13], fully logic [14] and particle swarm optimization [15]. These heuristic approaches suffer from the problem of premature convergence. Though GA-based approaches perform well for complex optimization problems, recent research has identified certain deficiencies [16], particularly for problems in which variables are highly correlated. In such cases, the GA crossover and mutation operators do not generate individuals with better fitness of offspring as the chromosomes in the population pool have some structure towards the end of the search. Premature convergence degrades the performance of GA and increases possibility of convergence to a local optimum solution.

The PSO, first introduced by Kennedy and Eberhart [17] is a flexible, robust, population based stochastic search/optimization algorithm with inherent parallelism. In recent years this method has gained popularity over its competitors and is increasingly gaining acceptance for solving many power system problems [18-20], due to its simplicity, superior convergence characteristics and high solution quality. However, the performance of the classical PSO greatly depends on its parameters and it often suffers from the problem of being trapped in local optima [21-23].

To overcome the above problems, adaptive PSO parameters are employed in this paper for solving the induction motor design optimization problem considering the active power loss effect. Finally, the APSO algorithm is tested on two sample motors and compared with the classical PSO and the conventional design methods [24-25]. The objectives of this paper are as follows:

- 1) To optimize the design variables of the induction motor, its total annual cost is chosen as objective function. The total annual cost is considered to be summation of
 - i. annual cost of the motor manufactured iron and copper materials,

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- ii. annual cost of a fictitious active power source required to cover the total active power loss of the motor and
- iii. annual cost of energy needed by that fictitious source.
- 2) To avoid premature convergence, the inertia weight factor and the acceleration factors are made adaptive.
- 3) To handle the constraints effectively, the penalty parameter-less approach is used.

II. FORMULATION OF AN INDUCTION MOTOR DESIGN PROBLEM

The problem in the induction motor design is to select an appropriate combination of the design variables which minimize the annual cost of the motor. The design problem would have been much complicated while using too many variables. Therefore the design variables selection is important in the motor design optimization. The design has some constraints to guarantee the some motor performance indices. The design optimization problem can be formulated as a general nonlinear programming problem of the standard form:

Find $X(x_1, x_2, \dots, x_n)$ such that $J(X)$ is a minimum
Subject to
 $g_j(X) \geq 0 \quad j = 1, 2, \dots, m$
and
 $x_{Li} \leq x_i \leq x_{Ui} \quad i = 1, 2, \dots, n$

where $X(x_1, x_2, \dots, x_n)$ is the set of independent design variables with their lower and upper limits as x_{Li} and x_{Ui} , for all 'n' variables. $J(X)$ is the objective function to be optimized and $g_j(X)$ are the constraints imposed on the design.

A. Variables

The following variables ($X_1, \dots, X_9$) are considered.

- x_1 = stator bore diameter
- x_2 = average air gap flux density
- x_3 = stator current density
- x_4 = air gap length
- x_5 = stator slot depth
- x_6 = stator slot width
- x_7 = stator core depth
- x_8 = rotor slot depth
- x_9 = rotor slot width

The remaining parameters can be expressed in terms of these variables or may be treated as fixed for a particular design.

B. Constraints

The constraints ($g_1, \dots, g_6$) imposed into induction motor design in this paper are as follows.

- g_1 = maximum to full-load torque ratio
- g_2 = starting to full-load torque ratio
- g_3 = starting to full-load current ratio
- g_4 = full-load efficiency
- g_5 = full-load power factor
- g_6 = maximum temperature rise

Apart from these constraints, the lower and upper limits of the design variables are included. The expression of the constraint functions is as follows:

(i). Maximum to full-load torque ratio

$$g_1 = \frac{S_{fl} \left[\left(R_{th} + \frac{R_2}{S_{fl}} \right)^2 + (X_{th} + X_2)^2 \right]}{2R_2 \left[R_{th} + \sqrt{R_{th}^2 + (X_{th} + X_2)^2} \right]} \quad (1)$$

(ii). Starting to full-load torque ratio

$$g_2 = \frac{S_{fl} \left[\left(R_{th} + \frac{R_2}{S_{fl}} \right)^2 + (X_{th} + X_2)^2 \right]}{(R_{th} + R_2)^2 + (X_{th} + X_2)^2} \quad (2)$$

(iii). Starting to full-load current ratio

$$g_3 = \sqrt{\frac{g_2}{S_{fl}}} \quad (3)$$

(iv). Full load power factor

$$g_4 = \cos \left[\tan^{-1} \left(\frac{X_{th} + X_2}{R_{th} + \frac{R_2}{S_{fl}}} \right) \right] \quad (4)$$

(v). Full load efficiency

$$g_5 = \frac{W}{W + P_t} \quad (5)$$

Where, $P_t = P_{isc} + P_{ist} + P_{sc} + P_b + P_{er} + P_f$

(vi). Maximum temperature rise

$$g_6 = \frac{P_{is} + \frac{LP_{sc}}{L_o}}{\frac{\pi D_o L}{C_{sco}} + \frac{\pi x_1 L}{C_{sci}} + \frac{\pi (D_o - x_1)(2 + n_v)}{4C_{scv}}} \quad (6)$$

$$\text{where, } V_{th} = \frac{V_{ph} X_m}{X_1 + X_m}, \quad R_{th} = \frac{R_1 X_m}{X_1 + X_m}, \quad X_{th} = \frac{X_1 X_m}{X_1 + X_m}$$

The equivalent circuit parameters R_1, R_2, X_1, X_2 and X_m can be found in terms of the design variables [24, 25].

C. Objective function

To have an optimal induction motor which is acceptable to both the manufacturer and the user, the minimization of the annual cost of the motor is considered as objective function while designing the motor using optimization algorithms. The expression of the objective function, in terms of the motor design variables are as follows:

(i) Annual active material cost

Annual iron material cost,

$$C_i = \alpha c_i (M_{isc} + M_{ist} + M_{irc} + M_{irtt} + M_{irtb}) \quad (7)$$

Where,

$$\begin{aligned} M_{isc} &= 0.88\pi \times W_i K_i L x_7 (x_1 + 2x_5 + x_7) \\ M_{ist} &= 0.88\pi \times W_i K_i L x_5 (\pi (x_1 + x_5) - N_s x_6) \\ M_{irc} &= 0.88\pi \times W_i K_i L d_{rc} (D_r - 2x_8 - d_{rc}) \\ M_{irtt} &= 0.88W_i K_i L d_{rs} (\pi (D_r - d_{rs}) - N_r x_9) \\ M_{irtb} &= 0.88W_i K_i L (x_8 - d_{rs}) (\pi (D_r - x_8 - d_{rs}) - N_r x_9) \end{aligned}$$

Annual copper material cost,

$$C_c = \alpha c_c (M_{sc} + M_b + M_{er}) \quad (8)$$

Where,

$$\begin{aligned} M_{sc} &= W_c K_{ss} x_5 x_6 N_s \left[0.0635 + 0.472 \left(\frac{x_1}{p} \right) + L \right] \\ M_b &= 1.02W_c K_{sr} L x_9 N_r (x_8 - d_{rs}) \\ M_{er} &= 1.9W_c K_{sr} x_1 x_9 N_r \frac{(x_8 - d_{rs})}{K_j p} \end{aligned}$$

Annual active material cost is given by

$$C_m = C_i + C_c \quad (9)$$

(ii) Annual active power loss cost

Annual iron loss cost,

$$C_{ip} = \alpha c_p (P_{isc} + P_{ist}) \quad (10)$$

Where,

$$\begin{aligned} P_{isc} &= p_{isc} M_{isc} \\ P_{ist} &= p_{ist} M_{ist} \end{aligned}$$

Where, p_{isc} and p_{ist} are the specific iron loss corresponding to B_{sc} and B_{st} respectively.

B_{sc} and B_{st} are given as follows

$$\begin{aligned} B_{sc} &= \frac{\pi x_1 x_2}{1.76K_i x_7 p} \\ B_{st} &= \frac{1.5x_1 x_2}{0.88K_i \left[x_1 + \frac{2x_5}{3} - \frac{N_s x_6}{\pi} \right]} \end{aligned}$$

Annual copper loss cost

$$C_{cp} = \alpha c_p (P_{sc} + P_b + P_{er}) \quad (11)$$

Where,

$$\begin{aligned} P_{sc} &= \frac{x_3^2 \rho_s M_{sc}}{W_c} \\ P_b &= \frac{\delta_r^2 \rho_r M_b}{W_c} \\ P_{er} &= \frac{(\delta_r K_j)^2 \rho_r K_{er} M_{er}}{W_c} \end{aligned}$$

Annual friction and windage loss cost,

$$C_{fp} = \alpha c_p P_f \quad (12)$$

$$\text{Where, } P_f = 661x_1^3 L \left(\frac{f}{p} \right)^2$$

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

$$C_{sp} = \alpha c_p P_s \quad (13)$$

Where,

$$P_s = \frac{0.005 \times W}{\eta}$$

The total annual active power loss cost is thus

$$C_p = C_{ip} + C_{cp} + C_{fp} + C_{sp} \quad (14)$$

(iii) Annual energy loss cost

$$C_e = \frac{c_e T C_p}{\alpha c_p} \quad (15)$$

The objective function is given by

$$J(X) = C_m + C_p + C_e \quad (16)$$

III. PARTICLE SWARM OPTIMIZATION

PSO is a well known optimization method proposed by Kennedy and Eberhart [17]. It is motivated by social behavior of organisms such as fish schooling and bird flocking. In PSO, potential solutions called particles fly around in a multi-dimensional problem space. Population of particles is called swarm. Each particle in a swarm flies in the search space towards the optimum solution based on its own experience, experience of nearby particles and global best position among particles in the swarm.

A. Advantages of PSO

- PSO is easy to implement, and only few parameters have to be adjusted.
- Unlike the GA, PSO has no evolution operators such as crossover and mutation.
- In GAs, chromosomes share information so that the whole population moves like one group, but in PSO, only global best particle (gbest) gives out information to the others. It is more robust than GAs.
- PSO can be more efficient than GAs; that is, PSO often finds the solution with fewer objective function evaluations than that required by GAs.
- Unlike GAs and other heuristic algorithms, PSO has the flexibility to control the balance between global and local exploration of the search space.

B. PSO Algorithm

Let X and V denote the particle's position and its corresponding velocity in search space respectively. At iteration K , each particle i has its position defined by $X_i^K = [X_{i,1}, X_{i,2}, \dots, X_{i,N}]$ and a velocity is defined as $V_i^K = [V_{i,1}, V_{i,2}, \dots, V_{i,N}]$ in search space N . Velocity and position of each particle in the next iteration can be calculated as

$$\begin{aligned} V_{i,n}^{k+1} &= W \times V_{i,n}^k + C_1 \times \text{rand}_1 \times (p_{\text{best}_{i,n}} - X_{i,n}^k) + \\ &\quad C_2 \times \text{rand}_2 \times (g_{\text{best}_n} - X_{i,n}^k) \quad (17) \\ &\quad i = 1, 2, \dots, m \\ &\quad n = 1, 2, \dots, N \end{aligned}$$

$$\begin{aligned} X_{i,n}^{k+1} &= X_{i,n}^k + V_{i,n}^{k+1} \text{ if } X_{\min,i,n} \leq X_i^{k+1} \leq X_{\max,i,n} \quad (18) \\ &= X_{\min,i,n} \quad \text{if } X_{i,n}^{k+1} < X_{\min,i,n} \\ &= X_{\max,i,n} \quad \text{if } X_{i,n}^{k+1} > X_{\max,i,n} \end{aligned}$$

The inertia weight W is an important factor for the PSO's convergence. It is used to control the impact of previous history of velocities on the current velocity. A large inertia weight factor facilitates global exploration (i.e., searching of new area) while small weight factor facilitates local exploration. Therefore, it is wise to choose large weight factor for initial iterations and gradually reduce weight factor in successive iterations. This can be done by using

$$W = W_{\max} - (W_{\max} - W_{\min}) \times \text{Iter} / \text{Iter}_{\max} \quad (19)$$

Acceleration constant C_1 called cognitive parameter pulls each particle towards local best position whereas constant C_2 called social parameter pulls the particle towards global best position. The particle position is modified by Eq. (18). The process is repeated until stopping criterion is reached.

IV. ADAPTIVE PARTICLE SWARM OPTIMIZATION

In the classical PSO, the inertia weight factor is made constant for all the particles in a single generation and the acceleration factors are made constant for all the particles in the whole generation. But these factors are very important parameters that move the current position of the particle towards its optimum position. In order to increase the search ability, the algorithm should be modified in which the movement of the swarm should be controlled by the objective function. In the proposed APSO, the particle position is adjusted such that the highly fitted particle moves slowly when compared to the lowly fitted particle. This can be achieved by using adaptive parameter values for each particle according to their objective functions of the current and best solutions.

The adaptive inertia weight factor (AIWF) is obtained as follows:

$$W_i^k = W_{\min} + \frac{J_{\text{pbest}}^{k-1} \times |J_i^{k-1} - J_{\text{pbest}}^{k-1}|}{J_i^{k-1} \times |J_i^{k-1} - J_{\text{best}}^{k-1}|} \quad (20)$$

So, from Eq. (19), it can be seen that the inertia weight for the best particle is set to the minimum value and vice versa.

The adaptive acceleration factors are determined as follows:

$$C_{1,i}^k = \sqrt{\frac{J_i^{k-1}}{J_{\text{pbest}}^{k-1}}} \quad (21)$$

$$C_{2,i}^k = \sqrt{\frac{J_i^{k-1}}{J_{\text{gbest}}^{k-1}}} \quad (22)$$

It is concluded from Eqs. (20) and (21) that C_1 and C_2 values are greater than or equal to one. Higher acceleration factors are obtained for higher objective function and vice versa. Use of Eqs. (19), (20) and (21) in Eq. (17) is expected to provide better optimum solution compared to classical PSO.

V. IMPLEMENTATION OF APSO FOR INDUCTION MOTOR DESIGN PROBLEM

The induction motor design problem with power loss cost consideration is solved using APSO approach. The PSO parameters such as inertia weight and acceleration factors are made highly adaptive to avoid the premature convergence of the algorithm. Then the parameter-less penalty approach is incorporated in the proposed algorithm to handle the constraints effectively.

Fig.1 Computational flowchart of the proposed APSO algorithm

The flow of the APSO is depicted in Fig.1 and is described as follows:

Step 1. Initialization of the swarm: For a population size m , the particles are randomly generated between the minimum and maximum limits of the design variables.

Defining the fitness function: A suitable fitness function should be used for constraints handling based on the current population. In a population, solutions are assigned to fitness so that feasible solutions are emphasized more than infeasible solutions. In this paper, a penalty parameter-less approach is used. This approach uses tournament selection operator where two solutions are chosen from the population and one is selected. The following criteria are used during the selection operator:

- Any feasible solution is preferred to any infeasible solution.
- Among the two feasible solutions, the one having better objective value is preferred.
- Among the two infeasible solutions, the one having smaller constraint violation is preferred.

In this scheme, the objective function value is evaluated for feasible solutions and not for particles with constraint violation. The infeasible solutions are compared based on only their constraint violation values. Motivated by this argument, the following composite fitness function is used.

$$J(X) = \begin{cases} J(X) & \text{if } x \text{ is feasible} \\ J_{\max} + CV(X) & \text{otherwise} \end{cases} \quad (23)$$

Where, $J_{\max}$ is the objective function of the worst feasible solution in the population. $CV(X)$ is the overall constraint violation of solution X . It is calculated as follows:

$$CV(X) = \max(0, g_1(s) - g_1(c)) + \max(0, g_2(s) - g_2(c)) + \max(0, g_3(c) - g_3(s)) + \max(0, g_4(s) - g_4(c)) + \max(0, g_5(s) - g_5(c)) + \max(0, g_6(c) - g_6(s)) \quad (24)$$

where c and s denote the computed and specified constraint values respectively.

Step 2. Initialization of pbest and gbest: The fitness values obtained above for the initial particles of the swarm are set as the initial pbest values of the particles. The best value among all the pbest values is identified as gbest.

Step 3. Evaluation of adaptive inertia weight and acceleration factors: The inertia weight and acceleration factors are computed using Eqs. (20), (21) and (22).

Step 4. Evaluation of velocity: The new velocity for each particle is computed as

$$V_{i,n}^{k+1} = W_i^k \times V_{i,n}^k + C_1^k \times \text{rand}_1 \times (\text{pbest}_{i,n} - X_{i,n}^k) + C_2^k \times \text{rand}_2 \times (\text{gbest}_n - X_{i,n}^k) \quad (25)$$

Step 5. Update the swarm: The particle position is updated using Eq. (18). The values of the fitness function are calculated for the updated positions of the particles. If the new value is better than the previous pbest, the new value is set to pbest. Similarly, gbest value is also updated as the best pbest.

Step 6. Stopping criteria: A stochastic optimization algorithm is usually stopped either based on the tolerance limit or when maximum number of generations are reached. The number of generations is used as the stopping criterion in this paper.

VI. RESULTS AND DISCUSSIONS

In order to verify the efficiency and effectiveness of the proposed APSO, two sample motors are used, whose specifications are given in Appendix B. The results obtained by this method are compared with the GA, classical PSO and conventional design methods [24, 25]. The value of design constants is given in Appendix C.

A. Parameter selection

For PSO method, a population size (m) of 10 is selected, the maximum number of iteration is set to 50, the acceleration constants C_1 and C_2 are both set to 2.0, and the inertia weight (W) is varied linearly from 0.9 to 0.3 over 50 iterations. In the proposed APSO approach, the population size and the maximum number of iteration are the same as those used in PSO approach, and the inertia weight and acceleration factors

are made adaptive using Eqs. (20), (21), and (22).

Fig. 2 Variations of W with iterations for motor 1

Fig. 3 Variations of C_1 with iterations for motor 1

Fig. 4 Variations of C_2 with iterations for motor 1

TABLE I: INDIVIDUAL ANNUAL COMPONENTS OF MOTOR 1

Annual cost components	Conventional approach	Case 1			Case 2		
		GA	PSO	APSO	GA	PSO	APSO
Material							
Iron (Rs)	142.33	141.37	147.16	139.33	166.84	163.12	166.53
Copper (Rs)	344.77	319.05	352.27	299.6	397.35	353.9	319.34
Total (Rs)	487.1	460.42	499.43	438.9	564.19	517.02	485.87
Power loss							
Iron (Rs)	339.27	317.87	328.04	311.6	351.12	344.29	338.07
Copper (Rs)	566.08	522.15	487.91	494.04	422.57	427.53	420.54
Friction and windage (Rs)	43.66	40.82	42.78	42.22	43.29	42.3	41.08
Stray (Rs)	32.01	31.72	31.28	32.28	30.3	30.44	30.54
Total (Rs)	981.02	912.56	890.01	880.14	847.28	844.56	830.23
Energy loss							
Iron (Rs)	1769	1657.5	1710.5	1624.7	1830.8	1795.2	1762.8
Copper (Rs)	2951.7	2722.6	2544.1	2576	2203.4	2229.3	2192.8
Friction and windage (Rs)	227.65	212.83	223.12	220.15	225.75	220.57	214.2
Stray (Rs)	166.89	165.37	163.10	168.34	158.04	158.72	159.22
Total (Rs)	5115.24	4758.3	4640.8	4589.19	4418	4403.79	4329.02
Total annual cost (Rs)	6583.36	6131.28	6030.2	5908.23	5829.5	5765.37	5645.12

TABLE II: OPTIMUM DESIGN RESULTS OF MOTOR 1 FOR DIFFERENT APPROACHES

Variables/ indices	Conventional approach	Case 1			Case 2		
		GA	PSO	APSO	GA	PSO	APSO
Independent variables							
Stator bore diameter (mm)	150	145	145.7	146	138	137	135
Average air gap flux density (Wb/m ²)	0.46	0.476	0.456	0.463	0.427	0.435	0.44
Stator current density (A/mm ²)	4	4.2	4.02	4.7	3.54	3.65	3.9
Air gap length (mm)	0.43	0.41	0.39	0.46	0.35	0.33	0.302
Stator slot depth (mm)	24.15	22.8	22.74	21.55	28	27.8	26.38
Stator slot width (mm)	6.92	7.2	7.15	7.13	7.6	7.8	7.84
Stator core depth (mm)	24.94	26.6	26.4	26.32	29.5	29.7	30.8
Rotor slot depth (mm)	10	10	12	8.8	13.6	11	13.2
Rotor slot width (mm)	5	4.6	5	5	6	6	4
Dependent Variables							
Gross iron length (mm)	89	92.6	95.8	93.8	11.4	112.7	115.5
Rotor current density (A/mm ²)	7.74	7.6	7.4	7.24	6.1	6.4	5.9
Performance index							
Maximum to full-load torque ratio	2.21	2.57	2.7	2.64	3.3	2.6	2.2
Starting to full-load torque ratio	1.27	1.6	1.37	1.48	1.23	1.15	1.15
Starting to full-load current ratio	4.15	4.92	4.68	4.8	4.1	4.2	3.8
Full-load efficiency	81.57	82.32	83.47	81.8	86.15	85.77	85.71
Full-load power factor	0.86	0.82	0.84	0.87	0.88	0.89	0.89
Maximum temperature rise	52	50.68	49.68	51.87	46.6	46.7	46.74

TABLE III: INDIVIDUAL ANNUAL COMPONENTS OF MOTOR 2

Annual cost components	Conventional approach	Case 1			Case 2		
		GA	PSO	APSO	GA	PSO	APSO
Material							
Iron (Rs)	246.87	238.5	237.4	236.9	253.04	245.3	257.44
Copper (Rs)	568.32	514.0	519.8	507.3	687.15	575.61	718.38
Total (Rs)	815.19	752.5	757.2	744.2	940.19	820.91	975.82
Power loss							
Iron (Rs)	633.16	631.48	611.1	607.8	624.99	610.42	591.51
Copper (Rs)	752.79	745.63	767.41	759.78	702.2	732.23	719.42
Friction and windage (Rs)	86.51	86.1	83.03	82.55	73.69	73.08	70.565
Stray (Rs)	61.09	61.11	61.37	61.08	60.5	60.98	60.26
Total (Rs)	1533.55	1524.32	1523	1511.21	1461.4	1476.7	1441.75
Energy loss							
Iron (Rs)	3301.5	3292.8	3186.4	3169.2	3258.9	3182.9	3084.3
Copper (Rs)	3925.3	3887.9	4001.5	3962.3	3661.5	3818	3751.3
Friction and windage (Rs)	451.08	448.98	432.95	430.44	384.27	381	367.95
Stray (Rs)	318.59	318.65	320	318.5	315.5	318	314.24
Total (Rs)	7996.47	7948.33	7940	7880.44	7620.2	7700	7517.79
Total annual cost (Rs)	10345.21	10225.1	10220	10135.85	10022	9997.6	9935.36

TABLE IV: OPTIMUM DESIGN RESULTS OF MOTOR 2 FOR DIFFERENT APPROACHES

Variables/ indices	Conventional approach	Case 1			Case 2		
		GA	PSO	APSO	GA	PSO	APSO
Independent variables							
Stator bore diameter (mm)	165	163	164	162	139	136	131.6
Average air gap flux density (Wb/m ²)	0.45	0.465	0.466	0.463	0.445	0.45	0.44
Stator current density (A/mm ²)	4	4.04	4.17	4.05	3.9	4.02	3.81
Air gap length (mm)	0.35	0.388	0.38	0.384	0.33	0.37	0.33
Stator slot depth (mm)	25	26.84	26.9	26.5	27.88	27.3	24.5
Stator slot width (mm)	7	7.5	7.4	7.3	6.5	6.6	6.3
Stator core depth (mm)	26	27.5	26.7	26.2	27.89	22	27.5
Rotor slot depth (mm)	13	13	10	10	14	12.8	14
Rotor slot width (mm)	4	3.8	5	4.65	5	6.8	5
Dependent Variables							
Gross iron length (mm)	133.2	122	130.2	134	189.8	186.6	214.1
Rotor current density (A/mm ²)	5.13	6.07	6.36	6.28	4.6	4.84	4.08
Performance index							
Maximum to full-load torque ratio	2.5	2.8	2.73	2.43	3.04	2.06	2.52
Starting to full-load torque ratio	0.975	1.25	1.28	1.1	1.01	1.02	0.88
Starting to full-load current ratio	3.6	4.8	4.92	3.89	4.6	4.7	3.11
Full-load efficiency	85.5	85.45	85.08	85.65	86.3	85.62	86.65
Full-load power factor	0.9	0.92	0.92	0.917	0.92	0.91	0.92
Maximum temperature rise	60	61.2	60.08	58.72	55.53	56	51.38

TABLE V: COMPARISON OF DIFFERENT METHODS FOR MOTOR 1 (20-TRIALS)

Compared item	Case 1			Case 2		
	GA	PSO	APSO	GA	PSO	APSO
Maximum cost (Rs)	6423.63	6217.36	6055.12	6116.2	5940.29	5779.77
Minimum cost (Rs)	6131.28	6030.2	5908.23	5829.5	5765.37	5645.12
Mean cost (Rs)	6293.2	6134.8	6001.2	5949.8	5803.1	5653.4
Standard deviation of cost (Rs)	81.2	61.61	46.52	86.8	65.45	42.6

TABLE VI: COMPARISON OF DIFFERENT METHODS FOR MOTOR 2 (20-TRIALS)

Compared item	Case 1			Case 2		
	GA	PSO	APSO	GA	PSO	APSO
Maximum cost (Rs)	10499.46	10413.23	10260.74	10299.65	10161.12	10054.59
Minimum cost (Rs)	10225	10220	10135.85	10022	9997.6	9935.36
Mean cost (Rs)	10338	10319	10213	10154	10060	9999.4
Standard deviation of cost (Rs)	87.67	55.76	40.05	84.23	50.6	36.16

TABLE VII: COMPARISON OF COMPUTATION TIME (IN SECONDS) OF VARIOUS METHODS

Methods	Motor 1		Motor 2	
	Case 1	Case 2	Case 1	Case 2
GA	3.2	3.3	3.42	3.5
PSO	2.72	2.88	2.68	2.87
APSO	3.05	3.13	3.28	3.37

The variation of inertia weight and acceleration factors with the number of iterations for the sample motor 1 has been shown in Figs. 2, 3 and 4. From the figures it is obvious that, W varies between 1 and 0.3, and the C_1 and C_2 values are large at the starting and it reaches unity as the problem converges.

B. Case study

To demonstrate the effectiveness of the proposed approach, two cases have been considered as follows:

Case 1: The annual active material cost is considered as objective.

Case 2: The total annual cost of the motor is considered as objective.

The optimal annual cost and its individual components of

the sample motors obtained from the various approaches are given in Tables I and III. Tables II and IV give the value of design variables and their performance indices of APSO approach in comparison with those of GA, PSO and conventional approaches.

From the obtained results of Tables I and III, it is obvious that the annual cost of the motors is considerably reduced when designed on the basis of Case 2; instead of Case 1 and the proposed approach provides lower annual cost than the other aforementioned approaches. In Case 2 based design of induction motors, the values of air gap density and stator current density are lower than those of Case 1 based design. These design variables are inversely proportional to the active material cost and the efficiency of the motor, and therefore the active material cost and the efficiency of the motor for Case 2 are higher than the Case 1. The increased active material cost for Case 2 is negligible when compared with the decreased motor loss cost. Due to reduction in the air gap flux density and air gap length of the design, the full load power factor is improved in Case 2. The starting current for Case 2 is lower than that of Case 1, because of the increase in leakage reactance due to decrease in the value of the air gap length. The maximum torque and the starting torque to full

load ratios of Case 2 are adversely affected. However, their values remain within the permissible given limits.

Fig. 5 Convergence Characteristic of different approaches for motor 1

Fig. 6 Convergence Characteristic of different approaches for motor 2

C. Comparison with GA and PSO approaches

(i) Convergence behaviors

The convergence behaviors for the GA, PSO and APSO approaches of the two sample motors are shown in Figs. 5 and 6. It is observed that, the GA and PSO approaches saturate quickly and converge to a local optimum solution. But the APSO approach shows superior performance because the premature convergence is avoided by using the adaptive parameters.

(ii) Solution quality

The minimum, maximum, average and standard deviation costs obtained from 20 trials for GA, PSO and APSO are given in Tables V and VI. It can be seen that the proposed method yields smaller standard deviation of costs and lower annual cost than the other approaches.

(iii) Robustness

To verify the robustness/consistency of three different approaches, many trials with different initial populations are

carried out. The lowest cost for each of the 20 different trials has been plotted in Figs. 7 and 8 from which it can be found

Fig. 7 Best results of different approaches for motor 1

Fig. 8 Best results of different approaches for motor 2

that APSO approach produces lowest annual cost of the motor most consistently as compared to the GA and PSO.

(iv) Computation efficiency

The comparison of computation efficiency for various approaches is given in Table VII. From Table VII, it is clear that the average CPU time of the APSO approach is lesser than those of the GA, but it is more than the PSO method. This is due to the introduction of adaptive parameters in every evolutionary process.

VII. CONCLUSION

The adaptive particle swarm optimization (APSO) approach has been proposed for solving the complex induction motor design problem considering the active power loss effect. In this approach, the parameters such as inertia weight and acceleration factors are made adaptive to avoid the premature convergence of the algorithm. The constraints are handled by a penalty-parameter-less penalty approach. In order to verify the efficiency and effectiveness of the

proposed APSO approach, two sample motors are investigated. The performance of this approach is compared with the GA, classical PSO and conventional design approaches, and it is found that APSO outperforms the other approaches in terms of solution quality, convergence and robustness. Hence, the APSO approach is an efficient tool for finding optimized values of design variables of the induction motor. Further work is in progress to develop the actual motor setup.

APPENDIX A.

LIST OF SYMBOLS

C_i	annual iron material cost (Rs)
C_{ip}	annual iron loss cost (Rs)
C_{cp}	annual copper loss cost (Rs)
C_{fp}	annual friction and windage losses cost (Rs)
C_{sp}	annual stray loss cost (Rs)
C_c	annual copper material cost (Rs)
C_p	annual active power loss cost (Rs)
C_e	annual energy loss cost (Rs)
C_m	annual active material cost (Rs)
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_{fl}	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 ($\Omega \cdot m$)
B_{sc}, B_{st}	Flux density of stator core and teeth (Tesla)
K_i	iron insulation factor
K_j	end ring to bar current density ratio
f	supply frequency (Hz)
V_{ph}	Voltage per phase (V)
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)
L_o	Length of the conductor overhang (m)
R_1, R_2	resistances of stator and rotor (Ω)
X_1, X_2, X_m	stator, rotor and magnetizing reactances (Ω)
V_{th}, R_{th}, X_{th}	Thevenin's equivalent voltage, resistance and reactance
S_{fl}	full-load slip
S_{max}	Slip at which maximum torque occurs
$C_{sco}, C_{sci}, C_{scv}$	cooling coefficients for stator core outer, inner and ventilating ducts
m	number of particles in the swarm
N	number of dimensions in a particle
K	pointer of iterations (generations)
$V_{i,n}^k$	velocity of particle i at iteration k
W	weighting factor
C_j	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
W_{min}	initial weight
$Iter$	current iteration number
$Iter_{max}$	maximum iteration number
W_i^k	inertia weight of i th population at k th iteration
J_i^{k-1}	objective value of i th solution at $(K-1)$ th iteration
J_{pbest}^{k-1}	objective value of $pbest$ solution at $(K-1)$ th iteration
J_{gbest}^{k-1}	objective value of $gbest$ solution upto $(K-1)$ th iteration
$C_{1,i}^k, C_{2,i}^k$	first and second acceleration factors for the i th population at k th iteration respectively

APPENDIX B

SPECIFICATION OF TEST MOTORS

Sample motor 1

Capacity	5 HP
Voltage	400V
Current	7.8A
Frequency	50 Hz
No. of Poles	4
Full load power factor	0.8
Full load efficiency	83%

Sample motor 2

Capacity	10 HP
Voltage	415V
Current	13.68A
Frequency	50Hz

No. of Poles	4
Full load power factor	0.87
Full load efficiency	87%

APPENDIX C

ASSUMED DESIGN CONSTANTS

$\alpha = 0.2$, $W_i = 7600 \text{ Kg/m}^3$, $W_e = 8900 \text{ Kg/m}^3$, $c_i = 35 \text{ Rs/Kg}$,
 $c_c = 250 \text{ Rs/Kg}$, $c_e = 0.002 \text{ Rs/Wh}$, $c_p = 7 \text{ Rs/W}$, $\rho_r = 2.1 \times 10^{-8}$,
 $\rho_s = 2.51 \times 10^{-8}$, $K_i = 0.9$, $K_j = 1$; $T = 3650 \text{ hr}$, $N_s = 36$, $N_r = 30$.

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