

ELEGANT DESIGN STRATEGY FOR MULTI-OBJECTIVE OPTIMIZATION OF INDUCTION MOTORS

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ABSTRACT: This paper presents an Ant colony Based Optimization (ACO) and conventional weight method are combined strategy for improving the Efficiency (Eff), Reducing the Material cost(MC), Improving the Starting torque(ST), Minimize the Temperature Rise (TR) of Induction Motor (IM) solving the multimodal optimization problems. ACO is inspired from the foraging behaviour of ants, and in particular, how ants can find shortest paths between food sources and their nest. It does not require initial values for the decision variables and uses a stochastic random search that is based on the chemical pheromone trail so that the derivative information is unnecessary. Among the number of design variables of the IM, seven variables are branded as primary design variables and the ACO based design strategy is built to optimize the chosen primary variables with a view to obtain the global best design. The elegant design strategy explores the solution space and provides the global best design, while it attempts to offer the best compromised design. The results of two IM design problems are presented with a view of exhibiting the superiority of the developed algorithms.

Key Words: Ant colony based optimization, optimal design of induction motor.

1. INTRODUCTION

Induction motors (IM) are the most widely used in domestic, commercial and various industrial applications. Especially, the squirrel cage IM is characterized by its simplicity, robustness and low cost, making it more attractive and hence captured a leading place in industrial and agricultural sectors. As millions of such motors are in use in various sectors, they consume a considerable percentage of overall produced electrical energy. The ever mounting pressure of oil crisis and the need for energy conservation necessitate designing the IMs with increased levels of efficiency. Motor manufacturers primarily focus their attention on the minimization of production and material cost, whereas users are concerned about the operating cost of the machine over its lifetime. The efficiency of existing motor designs can be improved by addition of active materials or by employing more expensive technology that has an impact on the manufacturing cost. Besides, the rising cost of the raw materials necessitates the design to include minimization of the weight/cost of the motor, which may attempt to increase the loss, leading to partially conflicting objectives.

Another important objective i.e temperature rise is mainly based on the insulation life. According to IEEE

standard 101, (T₂) the expected life of winding insulation is doubled for every 10 °C reduction in operating temperature. Ventilation holes are provided in the rotor-yoke to prevent the temperature rise. It is obvious that minimization of temperature rise will indirectly reduce the heat loss and improves the efficiency. The efficiency of the IM are typically considered in tailoring the objective function and optimized through appropriate combination of the design parameters. The optimal design of IM (ODIM) is so complicated that it is still a combination of art and science. There are many geometrical parameters and their relationships connected with motor specifications, which are in general nonlinear. (Mehmet Cunkas, 2010).

Over the years, in addition to statistical methods (Han and Shapiro 1967) and the Monte Carlo technique (Anderson 1967), several mathematical programming techniques, which provides a means for finding the minimum or maximum of a function of several variables under a prescribed set of constraints, have been applied in solving the IM design problems. These techniques such as nonlinear programming, (Ramarathnamet al. 1971), Lagrangian relaxation method (Gyeorye Lee et al. 2013), direct and indirect search methods (Nagrialet al. 1979), Hooks and Jeeves method (Faizet al. 2001), Rosenbrock's method (Bharadwajet al. 1979-a), Powell's method (Ramarathnamet al. 1973), finite element method (Parkinet al. 1993) and sequential unconstrained minimization technique (Bharadwajet al. 1979-b) are most cumbersome and time consuming. Besides a few of them requires derivatives and exhibits poor convergence properties due to approximations in the derivative calculations.

Apart from the above methods, another class of numerical techniques called evolutionary search algorithms such as simulated annealing (Bhuvaneshwariet al. 2005; Kannanet al. 2010), genetic algorithm (GA) (Satyajit Samaddaret al. 2013; Prakashet al. 2014-a), evolutionary algorithm (Jan Pawel Wiecezoreket al. 1998), evolutionary strategy (Kim MK et al. 1998), particle swarm optimization (PSO) (Thanga Raj et al. 2008; Sakthivelet al. 2011) and harmony search optimization (Prakashet al. 2014-b) have been widely applied in solving the IM design problems. Having in common processes of natural evolution, these algorithms share many similarities; each maintains a population of solutions that are evolved through random alterations and selection. The differences between these procedures lie in the techniques they utilize to encode candidates, the type of alterations they use to create new solutions, and the mechanism they employ for selecting the new parents.

These algorithms have yielded satisfactory results across a great variety of engineering optimization problems.

Recently an Ant Colony Optimization (ACO) that is inspired from the foraging behaviour of ants has been suggested for solving optimization problems (Dorigo *et al.* 1996). In analyzing the behaviours of real ants, it was found that the ants are capable of finding the shortest path from the nest to the food source without using cues. The ACO does not require initial values for the decision variables and uses a stochastic random search that is based on the chemical pheromone trail so that the derivative information is unnecessary. The ACO has been applied to solve the travelling salesman problem (Dorigo *et al.* 1997-a: 1997-b), the quadratic assignment problem (Gambardella *et al.* 2004) and the vehicle routing problem (Bell *et al.* 2004).

The aim of this paper is to develop an ACO based method for optimally designing IMs with a view of effectively exploring the solution space and obtaining the global best solution. The developed methodology has been applied in designing two IMs and the performances have been studied. The paper is divided into five sections. Section 1 provides the introduction, section 2 overviews ACO, section 3 formulates the IM design problem and elucidates the proposed method (PM), section 4 discusses the results and section 5 concludes.

2. ANT COLONY OPTIMIZATION

ACO, inspired from the foraging behaviour of ants, is an optimization technique for solving multimodal optimization problems (Dorigo *et al.* 1990). Ants live in colonies and their behaviour is governed by the goal of colony survival rather than being focused on the survival of individuals. When searching for food, ants initially explore the area surrounding their nest in a random manner. While moving, ants leave a chemical pheromone trail on the ground. When choosing their way, they tend to choose, in probability, paths marked by strong pheromone concentrations. As soon as an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest. During the return trip, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone trails will guide other ants to the food source. Also, they are capable of adapting to changes in the environment, for example, finding a new shortest path once the old one is no longer feasible due to a new obstacle.

Each ant will build a full path, from the beginning to the end state, through the repetitive application of state transition rule. While constructing its tour, an ant also modifies the amount of pheromone on the visited path by applying the local updating rule. Once all ants have terminated their tour, the amount of pheromone on edge is modified again through the global updating rule. In other words, the pheromone-updating rules are designed so that they tend to give more pheromone to paths which should be visited by ants. In the following, the state transition rule, the local updating rule, and the global updating rule are briefly outlined.

The state transition rule used by the ant system, called a random-proportional rule, is given by the following equation that gives the probability with which ant-*k* in node-*i* chooses to move to node-*j*.

$$P_{ij}^k = \begin{cases} \frac{(\tau_{ij}(t))^\mu (\eta_{ij})^\delta}{\sum_{m \in J_i^k} (\tau_{im}(t))^\mu (\eta_{im})^\delta} & \text{if } j \in J_i^k \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Equation (1) indicates that the state transition rule favours transitions toward nodes connected by shorter edges and with greater amount of pheromone. While constructing its tour, each ant modifies the pheromone by the local updating rule. This can be written below:

$$\tau_{ij}(t) \leftarrow (1 - \rho)\tau_{ij}(t) + \rho\tau_o \quad (2)$$

The local updating rule is intended to shuffle the search process. Hence, the desirability of paths can be dynamically changed. The nodes visited earlier by a certain ant can be also explored later by other ants. The search space can be therefore extended. Furthermore, in so doing, ants will make a better use of pheromone information. Without local updating, all ants would search in a narrow neighbourhood of the best previous tour. When tours are completed, the global updating rule is applied to edges belonging to the best ant tour. This rule is intended to provide a greater amount of pheromone to shorter tours, which can be expressed below:

$$\tau_{ij}(t+1) \leftarrow (1 - \sigma)\tau_{ij}(t) + \sigma \Delta\tau_{ij}(t) \quad (3)$$

where

$$\Delta\tau_{ij}(t) = \sum_{k=1}^m \Delta\tau_{ij}^k(t) \quad (4)$$

represents the distance of the globally best tour from the beginning of the trial

$$\Delta\tau_{ij}^k(t) = \begin{cases} Q/L_k & \text{if } (i, j) \in J_i^k \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

This rule is intended to make the search more directed; therefore, the capability of finding the optimal solution can be enhanced through this rule in the problem solving process. The iterative procedure of updating the pheromone in tune with the cost of each ant's tour is continued until the desired conditions are satisfied. The flow of the ACO is summarized below:

1. Choose the ACO parameters such as ant colony size, σ , ρ etc.
2. Randomly generate tour paths for all the ants in the colony to denote decision variables within the respective limits.
3. Initialize the pheromone τ
4. Evaluate the cost of each ant's tour.

5. Perform global update of the pheromone τ using Eq. (3).
 6. Perform local update of the pheromone τ using Eq. (2) based on the probability given by Eq. (1).
- Repeat steps 4-6 till the desired convergence criteria are met.

3. PROPOSED METHOD

The proposed ACO based solution method for ODIM involves formulation of the problem, representation of ants through the chosen design variables and construction of an augmented cost function, Ψ .

3.1 PROBLEM FORMULATION

The ODIM problem is formulated by defining one or more objective functions and a set of constraints, while treating a few of the important design dimensions as decision variables:

$$\text{Minimize } h(x) = [h_1(x), h_2(x), \dots, h_{nobj}(x)] \quad (6)$$

Subject to

$$g(x) \leq 0 \quad (7)$$

$$x_i^{\min} \leq x_i \leq x_i^{\max} \quad i = 1, 2, \dots, ndv$$

$$X = [x_1, x_2, \dots, x_7] = \left[\begin{array}{l} \text{Core length to pole pitch} \\ \text{Average value of air gap flux density} \\ \text{Ampere conductor} \\ \text{Length of air gap} \\ \text{Stator current density} \\ \text{Rotor current density} \\ \text{Flux density in the core} \end{array} \right] \quad (8)$$

Subject to

$$g(x) \leq 0 \Leftrightarrow \left\{ \begin{array}{l} \text{maximum flux density of stator teeth} \leq 2 \\ \text{maximum flux density of rotor teeth} \leq 2.0 \\ \text{slip at full load} \leq 0.05 \\ \text{starting to full load torque ratio} \geq 1.5 \\ \text{stator temperature rise} \leq 70 \\ \text{per unit no load current} \leq 0.5 \\ \text{power factor} \geq 0.75 \end{array} \right. \quad (9)$$

$$x_i^{\min} \leq x_i \leq x_i^{\max} \quad i = 1, 2, \dots, nd \quad (10)$$

The ODIM problem is formulated by defining an objective function and a set of constraints. The chosen problem comprises four objectives of maximizing the efficiency, improving the starting torque, reduce the material cost and minimising the temperature rise. While combining all objective into a single objective, both the terms must be transformed into either maximization or a minimization function. In this paper, the objectives are transformed into minimization function and their relative significance controlled through a weight parameter w .

Objective Function: The objective function $h(x)$ may be either performance oriented or based on some form cost consideration. In this paper, efficiency (Eff), starting torque (ST), active material cost (MC) and temperature rise (TR) are considered as objectives.

$$h(x) = \left\{ \begin{array}{l} h_1(x) = \text{Eff} \\ h_2(x) = \text{ST} \\ h_3(x) = \text{MC} \\ h_4(x) = \text{TR} \end{array} \right. \quad (11)$$

Objective-1: Maximization of Efficiency

$$\text{Maximize } h_1(x) = \text{Eff} = \frac{KW}{KW + P_t} \quad (12)$$

Where

$$P_t = P_{nl} + P_{cus} + P_{cur} \quad (13)$$

Objective-2: Maximization of Starting Torque

$$\text{Maximize } h_2(x) = \text{ST} = \left(\frac{I_{sc}}{I_r} \right)^2 * SFL \quad (14)$$

Where

$$I_r = 0.85 * I_{ph} \quad (15)$$

$$I_{sc} = \frac{V_{ph}}{Z} \quad (16)$$

Objective-3: Minimization of Active Material Cost

Minimize

$$h_3(x) = \text{MC} = \left(W_{iron}^{rotor} + W_{iron}^{stator} \right) * R_{iron} + \left(W_{copper}^{rotor} + W_{copper}^{stator} \right) * R_{copper} \quad (17)$$

Objective-4: Minimization of Temperature Rise

$$\text{Minimize } h_4(x) = \text{TR} = 0.03 * \frac{P_{st}}{A_{coolt}} \quad (18)$$

Where

$$A_{coolt} = [(1+0.1v) * (\pi D(L * 2.5) + 2\pi(D+50) * 0.04)] + (\pi D_o L) \quad (19)$$

$$P_{st} = P_{cus} + P_{it} + P_{ic} \quad (20)$$

The multi-objective optimization problem can be tailored by combining several objectives through weight factors into a single objective so as to optimize the chosen objectives simultaneously. As the IM design problem involves both the minimization and maximization objectives, the maximization functions can be transformed into minimization functions and then blended into a single objective function through weight factors as

$$\text{Minimize } f(x) = \sum_{i=1}^{nobj} w_i f_i \quad (21)$$

Where

$$f_i = \left\{ \begin{array}{l} h_i \quad \text{if } h_i \text{ is a minimization function} \\ \frac{1}{1+h_i} \quad \text{if } h_i \text{ is a maximization function} \end{array} \right. \quad (22)$$

Where the weights w that indicate the relative significance among the chosen objectives, are small positive real values, whose sum is usually set as one.

The transformed objective function can be explicitly written with the chosen objectives of the design

$$f(x,u) = w_1 \times \frac{1}{1+h(1)} + w_2 \times \frac{1}{1+h(2)} + w_3 \times h(3) + w_4 \times h(4) \tag{23}$$

An objective can be removed in the transformed objective function simply by setting the respective weight parameter zero. An objective can be active in the transformed objective function simply by setting the respective weight parameter one. A MTLBO based solution algorithm for multi-objective IM design problem is presented in this section. The method involves representation of design variables and formation of a performance function.

3.2 Representation of design variables

The ant that comprises the tour path is represented to denote the chosen primary design variables, defined by Equation (9), in vector form as:

$$Ant^{Path} = [a_1, a_2, \dots, a_7] \leftarrow [x_1, x_2, \dots, x_7] \tag{24}$$

3.3 Cost function

The algorithm searches for optimal solution by minimizing an augmented cost function Ψ , which is formulated from the objective function of Equation (7) and the penalty terms representing the limit violation of the explicit constraints of Equation (8). The augmented cost function is written as

$$\Psi = f(x) + \lambda \sum_{i \in \Phi} [g_i(x)]^2 \tag{25}$$

3.4 Solution process

Each ant in the colony initially builds a feasible tour path that denotes a feasible solution. The augmented cost is calculated by considering the decoded values of the tour path of each ant. The pheromone values are globally updated using Eq. (3) and then locally through Eq. (2) based on the probability of Eq. (1) with a view of minimizing the Ψ till the number of iterations reaches a specified maximum number of iterations.

4. NUMERICAL RESULTS

The proposed ACO based method is used to obtain the optimal design of two IMs. The first motor under study is rated for 7.5 kW, 400 V, 4 pole, 50 Hz and the second one for 30 kW, 400 V, 6 pole, 50 Hz. The usefulness of the PM is illustrated through comparing the performances with that of the GA based design approach. In this regard, the same set of primary design variables, cost function and design equations, involved in the PM, are used to develop the GA based design approach. The software packages are developed in Matlab platform and executed in a 2.67 GHz Intel core-i5 personal computer. There is no assurance that different executions of the developed design

programs converge to the same design due to the stochastic nature of the GA and ACO and hence the algorithms are run 20 times for each IM and the best ones are presented.

Table-1: Best and worst objective function values

Motor	Eff		ST	
	Best	Worst	Best	Worst
1	86.769	79.967	11.115	0.706
2	90.863	83.948	16.964	0.257
Motor	MC		TR	
	Best	Worst	Best	Worst
1	6345.057	14559.06	10.620	57.293
2	17427.195	44987.47	39.906	67.161

The optimal designs with multiple objectives are presented in Tables 2 and 3 for motor 1 and 2 respectively. The corresponding performances in terms of efficiency, starting torque material cost and temperature rise are also presented in the respective Tables of 2 and 3. It can be observed from these Tables that GA and ACO offer a compromised solution that lies in between the respective best and worst objective function values obtained with individual objectives. The quality of the compromised solutions cannot be estimated as it depends on the weight values assigned to the individual objectives and the range of the each objective function values. It is known that another compromised solution can be obtained by simply changing the weight parameter of each objective.

Table-2. Comparison of results with multiple objectives for Motor-1.

		GA	PM
Primary design variables x	x_1	1.88402	1.80945
	x_2	0.37157	0.31248
	x_3	12163.84	12442.16
	x_4	0.31956	0.81214
	x_5	3.43945	4.78128
	x_6	4.95201	4.07190
	x_7	1.18351	1.14620
Constraints $g(x)$	$g_1 \leq 2$	1.313	1.027
	$g_2 \leq 2$	0.886	0.749
	$g_3 \leq 0.05$	0.032	0.029
	$g_4 \geq 1.5$	9.044	11.808
	$g_5 \leq 70$	28.288	24.454

	$g_6 \leq 0.5$	0.289	0.493
	$g_7 \geq 0.75$	0.932	0.866
Performances	Eff	84.276	84.431
	ST	3.306	3.478
	MC	9047.977	9039.798
	TR	28.288	24.454

Table-3. Comparison of results with multiple objectives for Motor-2.

		GA	PM
Primary design variables x	x_1	1.96496	1.95962
	x_2	0.38338	0.37691
	x_3	15668.38	15515.06
	x_4	0.45094	0.45951
	x_5	3.47195	3.74969
	x_6	5.08892	5.17739
	x_7	1.12812	1.12805
Constraints $g(x)$	$g_1 \leq 2$	1.142	1.142
	$g_2 \leq 2$	0.884	0.884
	$g_3 \leq 0.05$	0.025	0.025
	$g_4 \geq 1.5$	7.556	7.556
	$g_5 \leq 70$	27.581	27.580
	$g_6 \leq 0.5$	0.254	0.254
	$g_7 \geq 0.75$	0.923	0.923
Performances	Eff	88.639	88.641
	ST	2.594	2.596
	MC	25823.199	25823.472
	TR	27.581	27.578

Tables 2 and 3 also contain the values of the constraints of Eq. (9) along with their limits. It can also be observed from these tables that both the methods bring the constraints such as maximum flux density, slip at full load, starting to full load torque ratio, etc., of Eq. (9) to lie within the respective limit, as the constraints are added as penalty terms in the fitness function of Eq. (25).

5. CONCLUSIONS

Indeed the ACO is a powerful population based stochastic algorithm for solving multimodal optimization problems. A new methodology involving ACO for solving ODIM problem has been suggested. It determines the optimal values for primary design variables that maximises efficiency and starting torque also reduces the temperature rise and material cost. The results on two IMs clearly demonstrate the ability of the PM to produce the best design of the IM. It has been demonstrated that the

new approach fosters the continued use of ACO and will go a long way in serving as a useful tool in design problems.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the authorities of Government College of Engineering, Thanjavur for the facilities offered to carry out this work.

NOMENCLATURE

- $f(x)$ objective function to be optimized
- GA genetic algorithm
- $g(x)$ a set of inequality constraints
- IM induction motor
- Eff efficiency
- A_{coolt} total cooling area in m^2
- D stator core diameter in m
- L stator core length in m
- V peripheral speed m/s
- $Iter^{max}$ maximum number of iterations for convergence check
- ACO ant colony optimization
- J_i^k the set of nodes that remain to be visited by ant-k positioned on node-i
- kW rating of IM
- "min" and "max" minimum and maximum limits of the respective variables
- L_k the length of the tour between edges i and j
- nd number of decision variables
- ODIM optimal design of IM
- PM proposed method
- P_{cus} stator copper losses in W
- P_{st} total stator loss in W
- P_{it} iron loss in tooth in W
- P_{ic} iron loss in core in W
- P_t total losses
- P_{nl} no load loss
- P_{cus} stator copper loss.
- P_{cur} rotor copper loss.
- P_{ij}^k probability with which ant-k in node-i chooses to move to node- j
- Q ant adjustable parameter
- w weight values to represent relative significance between objectives
- X vector of primary design variables
- Φ a set of limit violated constraints
- λ weight constant of the penalty terms
- τ_{ij} the pheromone that is deposited on the edge between nodes i and j

- η the inverse of the edge distance,
 μ and δ adjustable parameters that determines the relative importance of pheromone trail and heuristic desirability
 ρ a heuristically defined parameter.
 σ pheromone decay parameter in the range of (0,1).
 Ψ augmented objective function

REFERENCES

Anderson O. W. 1967. Optimum design of electrical machines. IEEE Transactions on Power Apparatus and Systems PAS-86:707-711.

Bell J and McMullen P. 2004. Ant colony optimisation techniques for the vehicle routing problem. Adv Eng Inform. 2004; 18: 41-48.

Bharadwaj.D.G., Venkatesan.K and Saxena.R.B.1979-a. Induction motor design optimization using constrained Rosenbrock method (Hill Algorithm), Comput. Elec. Engg. 6(1): 41-46.

Bharadwaj.D.G, Venkatesan.K.andSaxena.R.B.1979-b. Nonlinear programming approach for optimum cost induction motors-SUMT algorithm, Comput. and Elect. Engg. 6(3): 199-204.

Bhuvanewari.R and Subramanian.S. 2005. Optimization of three phase induction motor design using simulated annealing algorithm. Electric Power Components and Systems. 33: 947-956.

Dorigo. M, Maniezzo.V and Coloni. A. 1996. Ant system: optimisation by a colony of cooperating agents, IEEE Trans. On Systems, Man and Cybernetics, Part B. 26(1): 29-41.

Dorigo and M, Gambardella LM.1997-a. Ant colonies for the traveling salesman problem. Biosystems. 43:73-81.

Dorigo and M, Gambardella LM.1997-b. Ant colony system: a cooperative learning approach to the travelling salesman problem. IEEE Trans EvolutComput. 1(1):53-66.

Faiz.J and Sharifian.M.B.B. 2001. Optimal design of three phase induction motors and their comparison with a typical industrial motor, Comp. and Elect. Eng. 27: 133-144.

Gambardella LM, Taillard E and Dorigo M. 1999. Ant colonies for the quadratic assignment problem. J. Oper Res Soc. 50:167-76.

Gyeorye Lee, Seungjae Min, and Jung-Pyo Hong. 2013. Optimal shape design of rotor slot in squirrel-cage induction motor considering torque characteristics. IEEE Transactions on Magnetics. 49(5): 2197-2200.

Han, G. J. and S. S. Shapiro. 1967. Statistical models in engineering. UK: John Wiley and Sons.

Jan PawelWieczorek, OzdemirGol and ZbigniewMichalewicz. 1998. An evolutionary algorithm for the optimal design of induction motors. IEEE Trans. Magnetic. 34(6): 3882-3887.

Kim MK, Lee CG, Jung HK. (1998). Multiobjective optimal design of three-phase induction motor using improved evolution strategy, IEEE Trans. on Magnetics, 34(5): 2980-2983.

Kannan.R, Subramanian.S and Bhuvanewari.R. 2010. Multiobjective optimal design of three-phase induction motor using simulated annealing technique. International Journal of Engineering Science and Technology. 2(5): 1359-1369.

Mehmet Cunkas. 2010. Intelligent design of induction motors by multiobjective fuzzy genetic algorithm, J.Intell Manuf. 21: 393-402.

Nagrual.M.H and Lawrenson.P.J. 1979. Comparative performance of direct search methods of minimization for designs of electrical machines, Electric machines and Electro mechanics. 3: 315-324.

Parkin.T.S and Preston T.W. 1993. Induction Motor Analysis Using Finite Element, Proc.IEE, The Eighth International Conference on Electrical Machines and Drives.20-24.

Prakash.P.S and Aravindhbabu.P. 2014-a. GA based design for improving starting torque of induction motor, International Journal of Engineering Science and Technology. 6(12): 816-821.

Prakash.P.S and Aravindhbabu.P. 2014-b. Harmony search optimization based design of cost effective induction motor, International Review on Modelling and Simulations. 7(6): 912-917.

Ramarathnam.R and Desai.B.G. 1971. Optimization of polyphase induction motor design- a nonlinear programming approach, IEEE Trans. PAS-90: 570-579.

Ramarathnam R., Desai.B.G. and SubbaRao. V. 1973. A comparative study of minimization techniques for optimization of induction motor design. IEEE Transactions on Power Apparatus and Systems PAS-92 (5): 1448-1454.

Sakthivel.V.P. and Subramanian.S. 2011. Using MPSO Algorithm to Optimize Three-Phase Squirrel Cage Induction Motor Design. Proceedings of ICETECT 2011, 261-267.

SatyajitSamaddar, SurojitSarkar, Subhro Paul, SujaySarkar, Gautam Kumar Panda and Pradip Kumar Saha. 2013. Using genetic algorithm minimizing length of air-gap and losses along with maximizing efficiency for optimization of three phase induction motor, International Journal of Computational Engineering Research. 3(5): 60-66.

Thanga Raj. C., S.P.Srivastava and PramodAgarwal.2008. Optimal design of poly-phase induction motor using improved particle swarm optimization, Proceedings of XXXII National Systems Conference,