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MULTIOBJECTIVE DESIGN OF INDUCTION MOTOR USING ARTIFICIAL INTELLIGENCE TECHNIQUE

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ABSTRACT

This paper presents an Ant Colony Optimization (ACO) based design methodology for improving the Efficiency (Eff) besides reducing the Temperature Rise (TR) of Induction Motor (IM). 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 developed methodology is applied in solving two IM design problems and the results are presented with a view of exhibiting the superiority of the developed algorithm.

Keywords: Induction Motor, Ant Colony Optimization (ACO).

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. 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 $^{\circ}C$ 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, (Ramarathnam*et al*. 1971), Lagrangian relaxation method (Gyeorye Lee *et al*. 2013), direct and indirect search methods (Nagrial*et al*. 1979), Hooks and Jeeves method (Faiz*et al*. 2001), Rosenbrock'smethod (Bharadwaj*et al*. 1979-a), Powell's method (Ramarathnam*et al*. 1973), finite element method (Parkin*et al*. 1993) and sequential unconstrained minimization technique (Bharadwaj*et 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 (Bhuvaneswari*et al*. 2005;Kannan*et al*. 2010), genetic algorithm (GA) (SatyajitSamaddar*et al*. 2013;Prakash*et al*. 2014-a), evolutionary algorithm (Jan PawelWieczorek*et al*. 1998), evolutionary strategy (Kim MK *et al*. 1998), particle swarm optimization (PSO) (Thanga Raj *et al*. 2008;Sakthivel*et al*. 2011) and harmony search optimization (Prakash*et 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*.

$$P_{ij}^{k} = \begin{cases} \dfrac{\left(\tau_{ij}(t)\right)^{\mu}\left(\eta_{ij}\right)^{\delta}}{\sum\limits_{m\in J_i^k}\left(\tau_{im}(t)\right)^{\mu}\left(\eta_{im}\right)^{\delta}} & if\ \ j \in J_i^k \\ 0 & otherwise \end{cases} \qquad (1)$$

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:

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

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:

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

where

$\Delta\tau_{ij}(t) = \sum\limits_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$, represents the distance of the globally best tour from the beginning of the trial (4)

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

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).
7. 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 involves large number of design variables. Many of these variables fortunately have a little influence either on the objective function or on the specified constraints. However, to ease the curse of high dimensionality, the following seven variables are identified as primary design variables (Prakash*et al.* 2014-b).

$$X = [x_1,\ x_2,\ \cdots,\ x_7] = \begin{bmatrix} \text{Core length to pole pitch} \\ \text{Average value of air gap flux density} \\ \text{Ampere conductor} \\ \text{Length of air gap} \\ \text{Stator current density} \\ \text{Rotor current density} \\ \text{Flux density in the core} \end{bmatrix}^T \quad (6)$$

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

$$\text{Minimise} \quad f(x) = \omega\left(\frac{1}{Eff}\right) + (1-\omega)\,TR \quad (7)$$

Subject to

$$g(x) \le 0 \Leftrightarrow \begin{Bmatrix} \text{maximum flux density of stator teeth} \le 2 \\ \text{maximum flux density of rotor teeth} \le 2.0 \\ \text{slip at full load} \le 0.05 \\ \text{starting to full load torque ratio} \ge 1.5 \\ \text{stator temperature rise} \le 70 \\ \text{per unit no load current } \le 0.5 \\ \text{power factor } \ge 0.75 \end{Bmatrix} \quad (8)$$

$$x_i^{\min} \le x_i \le x_i^{\max} \quad i = 1,2,\cdots nd \quad (9)$$

Where

$$Eff = \frac{KW}{KW + P_t} \quad (10)$$

$$TR = 0.03 \times \frac{P_{st}}{A_{coolt}} \quad (11)$$

$$P_t = P_{nl} + P_{cus} + P_{cur} \quad (12)$$

$$P_{st} = P_{cus} + P_{it} + P_{ic} \quad (13)$$

$$A_{coolt} = [(1+0.1v) \times (\pi D(L \times 2.5) + 2\pi(D+50) \times 0.04)] + (\pi D_O\ L) \quad (14)$$

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:

$$Ant^{Path} = [a_1, a_2 \cdots, a_7] \leftarrow [x_1,\ x_2,\ \cdots,\ x_7] \quad (15)$$

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

$$\Psi = f(x) + \lambda \sum_{i \in \Phi} [g_i(x)]^2 \quad (16)$$

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.

Initially the designs are obtained by optimizing the individual objectives of efficiency and temperature rise by setting the w values as 1 and 0 respectively, and presented in Table-1 for both the motors. It is clear from the Table that the PM is able to obtain better efficiency when $w=1$ and lower temperature rise when $w=0$ than that of the GA approach. However, it is to be noted that the other performance value of efficiency for the case with $w=0$ and temperature rise for the case with $w=1$ are inferior, as the respective function is omitted in the optimization process.

Table-1. Comparison of performances by individual objectives.

w	Motor	Performance	GA	PM
1	1	Eff	86.708	86.727
		TR	46.121	45.728
	2	Eff	90.497	90.582
		TR	34.137	33.449
0	1	Eff	83.439	83.432
		TR	10.772	10.741
	2	Eff	87.980	87.984
		TR	10.040	9.958

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 $g(x)$	$g_1 \le 2$	1.313	1.027
	$g_2 \le 2$	0.886	0.749
	$g_3 \le 0.05$	0.032	0.029
	$g_4 \ge 1.5$	9.044	11.808
	$g_5 \le 70$	28.288	24.454
	$g_6 \le 0.5$	0.289	0.493
	$g_7 \ge 0.75$	0.932	0.866
Performances	Eff	**84.431**	**84.276**
	TR	**28.288**	**24.454**

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 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.

Tables 2 and 3 also contain the values of the constraints of Eq. (8) 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. (8) to lie within the respective limit, as the constraints are added as penalty terms in the fitness function of Eq. (16).

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

		GA	PM
Primary design variables X	x_1	1.65033	1.85576
	x_2	0.39569	0.39759
	x_3	13326.72	13325.83
	x_4	0.52086	0.53655
	x_5	3.25569	3.46173
	x_6	6.77276	6.86975
	x_7	1.27144	1.27976
Constraints $g(x)$	$g_1 \leq 2$	1.200	1.142
	$g_2 \leq 2$	0.946	0.891
	$g_3 \leq 0.05$	0.025	0.026
	$g_4 \geq 1.5$	10.242	9.799
	$g_5 \leq 70$	29.601	27.809
	$g_6 \leq 0.5$	0.354	0.340
	$g_7 \geq 0.75$	0.902	0.906
Performances	Eff	**87.773**	**87.774**
	TR	**29.601**	**27.809**

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 the efficiency and reduces the temperature rise. The results on two IMs clearly demonstrate the ability of the PM to produce the universal best design parameters that maximises the efficiency and reduces the temperature rise 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.

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NOMENCLATURE

$f(x)$	objective function to be optimized
GA	genetic algorithm
$g(x)$	a set of inequality constraints
IM	induction motor
A_{coolt}	total cooling area in m^2
L	Stator core length in m
v	Peripheral speed m/s
D	Stator core diameter in m
ACO	ant colony optimization
Eff	efficiency
$Iter^{max}$	maximum number of iterations for convergence check
J_i^k	the set of nodes that remain to be visited by ant-k positioned on node-i

kW rating of IM
P_{cus} stator copper losses in W

L_k the length of the tour between edges i and j.
P_{st} total stator loss in W
P_{it} iron loss in tooth in W
P_{ic} iron loss in core in W

"min" and "max" minimum and maximum limits of the respective variables
nd number of decision variables
ODIM optimal design of IM
PM proposed method
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 an 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

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