Australian Journal of Basic and Applied Sciences, 9(11) May 2015, Pages: 59-65

ISSN:1991-8178

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

Ant Colony Optimization based Design for Minimizing Temperature Rise of Induction Motor

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ARTICLE INFO

Article history:
Received 12 March 2015
Accepted 28 April 2015
Available online 5 May 2015

Keywords:
Induction motor design, , Ant colony optimization

ABSTRACT

This paper presents an Ant Colony Optimization (ACO) based design methodology for reducing the temperature rise (TR) of Induction Motor (IM). ACO is inspired from the foraging behavior 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 identified as primary design variables and the ACO based design methodology is tailored to optimize the chosen primary variables with a view to obtain the global best design. The optimal design obtained by the developed methodology for two IMs are presented with a view of exhibiting the superiority.

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To Cite This Article: P.S. Prakash and P. Aravindhababu, Ant Colony Optimization based Design for Minimizing Temperature Rise of Induction Motor. ***Aust. J. Basic & Appl. Sci.,*** *9(11): 59-65, 2015*

Nomenclature:

ACO	ant colony optimization
A_{coolt}	total cooling area
D	stator core diameter, m
D_o	stator core outer diameter, m
FFO	firefly optimization
$f(x)$	objective function to be minimized
GA	Genetic algorithm
$g(x)$	a set of inequality constraints
HSO	Harmony search optimization
IM	induction motor
$Iter^{\max}$	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
L	stator core length, m
L_k	the length of the tour between edges i and j.
"min"& "max"	minimum and maximum limits of the respective variables
nd	number of decision variables
ODIM	optimal design of IM
PSO	particle swarm optimization
PM	proposed method
PS	population size
P_{ij}^k	probability with which ant-k in node-i chooses to move to node- j
P_{st}	total stator loss
P_{cus}	stator copper loss
P_{it}	iron loss in stator tooth

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P_{ic}	iron loss in stator core
Q	an adjustable parameter
TR	temperature rise
v	peripheral velocity.
w	weight parameter
Ψ	augmented cost function
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).
$\Re$	a set of limit violated constraints

INTRODUCTION

Induction motors have been widely used in various industries as actuators or drivers to produce mechanical motions and forces due to their easy manufacturing and robustness. Improving efficiency of IMs is very important as it is estimated that more than around 50% of the world electric energy generated is consumed by electric drives. Recently, IMs are preferred as drives for electric vehicles (EVs) when compared to that of permanent-magnet motors, which have the drawbacks of being costly, field weakening is not easy to increase speed and the problems associated with recycling of permanent magnets. The EVs demand for compactness of IMs and thus the IMs are to be designed with high power density, which makes the magnetic saturation of the rotor-yoke more excessive and the heat generation per unit volume increasing. Besides the losses in the motor rise the body temperature, this should be limited in accordance with the choice of winding insulation material. The insulation life strongly depends on the operating temperature. According to IEEE standard 101, 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 (TR). If the cross-area of ventilation holes are made larger for cooling, the effective magnetic area becomes smaller, which results in the further magnetic saturation. The magnetic saturation causes harmful influence on the fundamental component of the air-gap flux, which increases the magnetizing current and thus produces further TR. Hence, it is obvious that the compactness of IMs makes the TR problem more serious. Therefore it becomes imperative that the best architecture and the corresponding dimensioning have to be determined in order to minimize the TR with respect to several constraints. It is obvious that minimization of TR will indirectly reduces the heat loss and improves the efficiency. The optimal design problem of IM is usually difficult since the design variables contain continuous variables related to the real dimensioning parameters and combinatorial variables associated with architecture characteristics and discrete dimensioning parameters; and their relationship with motor specifications are in general nonlinear (Kentli 2009).

In recent decades, several classical techniques such as nonlinear programming, (Menzies *et al* 1975), Lagrangian relaxation method (Gyeorye Lee *et al* 2013), direct and indirect search methods (Bharadwaj *et al* 1978), Hooks and Jeeves method (Faiz *et al* 2001), Rosenbrock's method (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) have been suggested for IM design problem. Many of these methods are most cumbersome and time consuming and pose difficulty in handling non-linear and discontinuous objectives and constraints. Besides a few of them requires derivatives and exhibits poor convergence properties due to approximations in derivative calculations; and may converge to local solution instead of global ones, when the initial guess is in the neighborhood of a local solution.

In recent years nature inspired metaheuristic optimization algorithms such as simulated annealing (Bhuvaneswari *et al* 2005:), genetic algorithm (GA) (Millie Pant *et al* 2008), evolutionary algorithm (Jan Pawel Wieczorek *et al* 1998), evolutionary strategy (Kim MK *et al* 1998), particle swarm optimization (PSO) (Sakthivel *et al* 2010-a) and bacterial foraging (Sakthivel *et al* 2010-b), differential evolution (Thanga Raj *et al* 2012) have been widely applied in solving the IM design problems with a view of overcoming the drawbacks of classical methods. These algorithms have yielded satisfactory results across a great variety of design 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 focus of this paper is to develop a design methodology using ACO for reducing the TR of IMs with a view of effectively exploring the solution space and obtaining the global best solution. The developed design methodology has been applied in designing two IMs and the performances have been studied.

Ant colony optimization:

ACO, inspired from the foraging behavior of ants, is an optimization technique for solving multimodal optimization problems (Dorigo *et al* 1990). Ants live in colonies and their behavior 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*.

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

Eq. (1) indicates that the state transition rule favors transitions toward nodes connected by shorter edges and with greater amount of pheromone. While constructing its tour, each ant modifies the pheromone by the following local updating rule.

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

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 neighborhood 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

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

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

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).
7. Repeat steps 4-6 till the desired convergence criteria are met.

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Proposed method:

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

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.

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

The ODIM problem is formulated by defining an objective function and a set of constraints. The TR is therefore being considered as the objective function with a view of increasing the motor life.

$$\text{Minimize}\quad f(x)=0.03\times\frac{P_{st}}{A_{coolt}} \quad (7)$$

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

$$A_{coolt}=\begin{bmatrix}(1+0.1v)\times(\pi D(L\times 2.5)+\\ 2\pi(D+50)\times 0.04)\end{bmatrix}+(\pi D_o L) \quad (10)$$

$$P_{st}=P_{cus}+P_{it}+P_{ic} \quad (11)$$

Representation of Design Variables:

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

$$Ant^{Path}=[a_1,a_2\cdots,a_7]\leftarrow[x_1,\ x_2,\ \cdots,\ x_7] \quad (12)$$

Cost Function:

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

$$\Psi=f(x)+w\sum_{i\in\Re}[g_i(x)]^2 \quad (13)$$

Solution Process:

Each ant in the colony initially builds a feasible tour path that denotes a feasible solution. The augmented cost Ψ 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. The flow of the PM is given through the chart of Fig. 1.

Numerical results:

The proposed ACO based method is used to obtain the optimal design of two IMs. The first machine 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 effectiveness of the PM is demonstrated through comparing the performances with those of the GA, HSO and FFO based design approaches. In this regard, the same set of primary design variables, augmented cost function and design equations, involved in the PM, are used to develop the GA, HSO and FFO based design approaches. The software packages are developed in Matlab platform and executed in a 2.67 GHz Intel core-i5 personal computer. There is no guarantee that different executions of the developed design programs converge to the same design due to the stochastic nature of the ACO, GA, HSO and FFO and hence the algorithms are run 20 times for each test case and the best ones are presented. The optimal design representing the values of the primary design variables for both the motors and their TRs are presented in Table-1 and -2 respectively.

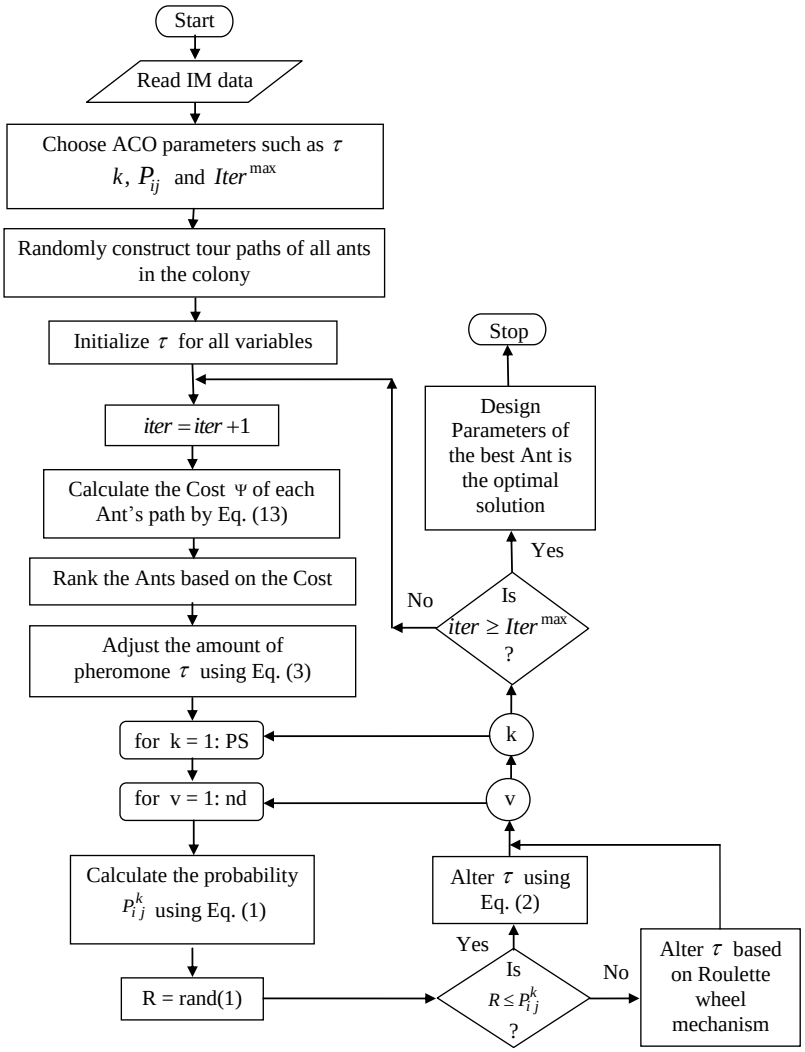

Fig. 1: Flow Chart of the PM.

Table 1: Comparison of Results for Motor-1

		GA	HSO	FFO	PM
Primary Design Variables x	x_1	1.95567	1.92820	1.90886	1.95268
	x_2	0.20073	0.20146	0.20242	0.20192
	x_3	5105.80	5163.72	5022.82	5098.93
	x_4	0.48414	0.38257	0.39798	0.57025
	x_5	3.83728	3.84315	3.61362	3.63509
	x_6	5.29380	6.18515	4.95955	2.24194
	x_7	1.10604	1.10058	1.10987	1.10010
Constraints $g(x)$	$g_1 \le 2$	0.783	0.783	0.601	0.783
	$g_2 \le 2$	0.437	0.434	0.415	0.449
	$g_3 \le 0.05$	0.034	0.042	0.033	0.022
	$g_4 \ge 1.5$	20.859	17.924	18.953	27.467
	$g_5 \le 70$	10.772	10.743	10.912	10.741
	$g_6 \le 0.5$	0.365	0.324	0.340	0.399
	$g_7 \ge 0.75$	0.938	0.949	0.942	0.926
Objective function $h(x)$	Temperature Rise $^{\circ}C$	10.772	10.743	10.912	10.741

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Table 2: Comparison of Results for Motor-2.

		GA	HSO	FFO	PM
Primary Design Variables x	x_1	1.76296	1.99731	1.99723	1.99589
	x_2	0.20243	0.21171	0.21024	0.21086
	x_3	6783.40	5681.03	5672.95	5703.82
	x_4	0.38854	0.48114	0.80807	0.31894
	x_5	2.74932	2.79427	2.78993	2.74932
	x_6	5.39760	5.76785	4.82609	6.88371
	x_7	1.10027	1.10005	1.10155	1.10003
Constraints $g(x)$	$g_1 \le 2$	0.473	0.611	0.500	0.500
	$g_2 \le 2$	0.379	0.434	0.400	0.397
	$g_3 \le 0.05$	0.031	0.028	0.025	0.034
	$g_4 \ge 1.5$	10.374	19.068	16.750	13.852
	$g_5 \le 70$	10.040	10.029	9.967	9.958
	$g_6 \le 0.5$	0.197	0.276	0.357	0.222
	$g_7 \ge 0.75$	0.958	0.949	0.917	0.960
Objective function $h(x)$	Temperature Rise $^\circ C$	10.040	10.029	9.967	9.958

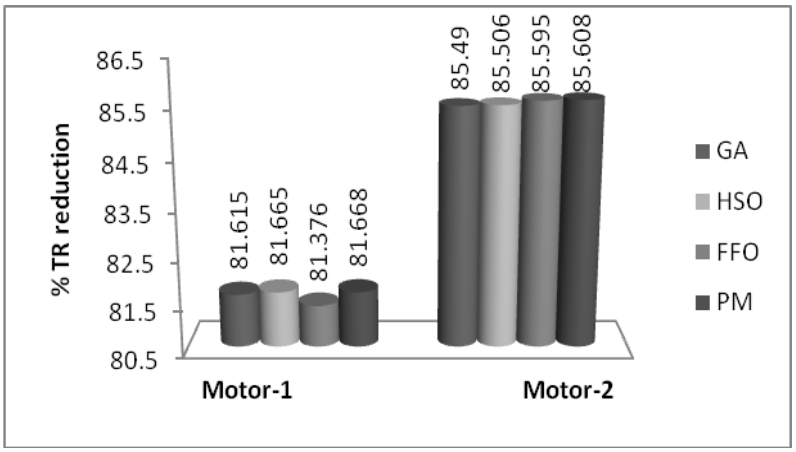

Fig. 2: Comparison of %TR reduction.

It is observed from these tables that the PM offers a TR of $10.741^\circ C$ and $9.958^\circ C$, which are lower than those of GA, HSO and FFO based approaches, for motor-1 and -2 respectively. These tables also include the values of the constraints of Eq. (8) along with their limits. It can also be observed from these tables that all the methods bring the constraints such as maximum flux density, slip at full load, starting to full load torque ratio, etc., to lie within the respective limit, as the constraints are added as penalty terms in the augmented cost function of Eq. (13). The % TR reductions for both the motors are calculated taking a non-optimal TR of $58.592^\circ C$ and $69.192^\circ C$ for motor-1 and motor-2 respectively and graphically compared in Fig. 2.

It is seen from Fig. 2 that the %TR reduction of the PM of motor-1 is 81.668%, while for other methods, they are 81.615%, 81.665% and 81.376% . Similarly for motor-2, the PM results in the %TR reduction of 85.608%, while for other methods, they are 85.49%, 85.506% and 85.595%. It is obvious that the PM offers better %TR reduction than those of the existing approaches for both the motors.

Conclusion:

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 minimizes the TR. The results on two IMs clearly illustrates the ability of the PM to produce the global best design parameters that reduces the TR of the IM. It has been chartered 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 Annamalai University for the facilities offered to carry out this work.

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