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Gravitational Search Algorithm based Design for Minimizing Temperature Rise of Induction Motor

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ABSTRACT: This paper presents a Gravitational Search Algorithm(GSA) based design methodology for reducing the temperature rise of Induction Motor (IM).GSA is based on the physical law of gravity and the law of motion. The gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. GSA a set of agents called masses has been proposed to find the optimum solution by simulation of Newtonian laws of gravity and motion. Among the number of design variables of the IM, seven variables are identified as primary design variables and the GSA 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.

KEYWORDS: Induction Motor Design, Gravitational Search Algorithm

NOMENCLATURE

ACO	ant colony optimization
A_{coolt}	total cooling area
$f(x)$	objective function to be minimized
$g(x)$	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_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
PM	proposed method
P_{st}	total stator loss
P_{cus}	stator copper loss
P_{ic}	iron loss in stator core
P_{it}	iron loss in stator tooth
Q	an adjustable parameter
TR	temperature rise
v	peripheral velocity.
Ψ	augmented cost function
τ_{ij}	the pheromone that is deposited on the edge between nodes i and j

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I.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, which 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 , (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. 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 temperature rise. Hence, it is obvious that the compactness of IMs makes the temperature rise problem more serious. Therefore it becomes imperative that the best architecture and the corresponding dimensioning have to be determined in order to minimize the temperature rise with respect to several constraints. It is obvious that minimization of temperature rise will indirectly reduce the heat loss and improves the efficiency. The resulting mathematical optimization problem 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 neighbourhood 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 a Gravitational Search Algorithm (GSA) that is inspired from the physical law of gravity and the law of motion suggested for solving optimization problems (Rashedi et al2009). The gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. GSA a set of agents called masses has been proposed to find the optimum solution by simulation of Newtonian laws of gravity and motion

The focus of this paper is to develop a design methodology using GSA for reducing the temperature rise 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.

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II. GRAVITATIONAL SEARCH ALGORITHM

2.1 INTRODUCTION

Rashedi et al. proposed one of the newest heuristic algorithms, namely Gravitational Search Algorithm (GSA) in 2009. GSA is based on the physical law of gravity and the law of motion. The gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. GSA a set of agents called masses has been proposed to find the optimum solution by simulation of Newtonian laws of gravity and motion. In the GSA, consider a system with m masses in which position of the i^{th} mass is defined as follows:

$$X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^n), \quad i=1,2,\ldots,m \qquad (1)$$

Where x_i^d is position of the i^{th} mass in the d^{th} dimension and n is dimension of the search space. At the specific time 't' a gravitational force from mass 'j' acts on mass 'i', and is defined as follows:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) x M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \qquad (2)$$

Where M_i is the mass of the object i, M_j is the mass of the object j, G(t) is the gravitational constant at time t, $R_{ij}(t)$ is the Euclidian distance between the two objects i and j, and ε is a small constant.

The total force acting on agent i in the dimension d is calculated as follows:

$$F_i^d(t) = \sum_{j=ij\neq i}^{m} rand_j F_{ij}^d(t) \qquad (3)$$

Where $rand_j$ is a random number in the interval [0,1].

According to the law of motion, the acceleration of the agent i, at time t, in the d^{th} dimension, $a_i^d(t)$ is given as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \qquad (4)$$

Furthermore, the next velocity of an agent is a function of its current velocity added to its current acceleration. Therefore, the next position and the next velocity of an agent can be calculated as follows:

$$v_i^d(t+1) = rand_i \, x v_i^d(t) + a_i^d(t) \qquad (5)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \qquad (6)$$

Where $rand_i$ is a uniform random variable in the interval [0,1].

The gravitational constant, G, is initialized at the beginning and will be decreased with time to control the search accuracy. In other words, G is a function of the initial value (G_o) and time (t):

$$G(t) = G_0 e^{-\alpha\frac{t}{T}} \qquad (7)$$

The masses of the agents are calculated using fitness evaluation. A heavier mass means a more efficient agent. This means that better agents have higher attractions and moves more slowly. Supposing the equality of the gravitational and inertia ma, the values of masses is calculated using the map of fitness. The gravitational and the inertial masses are updating by the following equations:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \qquad (8)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{m} m_j(t)} \qquad (9)$$

Where fit_i (t) represents the fitness value of the agent i at time t, and the best(t) and the worst(t) in the population respectively indicate the strongest and the weakest agent according to their fitness route.

For a minimization problem:

$$best(t) = \min_{j\epsilon\{1,\ldots,m\}} fit_j(t) \qquad (10)$$

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$$worst(t) = \max_{j\epsilon\{1,\ldots,m\}} fit_j(t) \qquad (11)$$

For a maximization problem:

$$best(t) = \max_{j\epsilon\{1,\ldots,m\}} fit_j(t) \qquad (12)$$

$$worst(t) = \min_{j\epsilon\{1,\ldots,m\}} fit_j(t) \qquad (13)$$

5.2.2 ALGORITHM:

The proposed Gravitational Search Algorithm approach for the evaluation of Available Transfer Capability can be summarized as follows:

Step 1: Search space identification.
Step 2: Generate initial population between minimum and maximum values.
Step 3: Fitness evaluation of agents.
Step 4: Update G (t), best (t), worst (t) and M_i (t) for i=1, 2,…, m.
Step 5: Calculation of the total force in different directions.
Step 6: Calculation of acceleration and velocity.
Step 7: Updating agents' position.
Step 8: Repeat step 3 to step 7 until the stop criteria is reached.
Step 9: Stop.

The setup for the proposed algorithm is executed with the following parameters ;

m=50(masses)
G is set using in equation (5.7) where G_O is set to100
$\propto$ is set to 20
T =100(total number of iterations)

III. PROPOSED METHOD

The proposed GSA 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.

$$X = [x_1,\ x_2,\ \cdots,\ x_7] = \begin{bmatrix} \text{Core length to pole pitch} \\ \text{Average value of air gap flux density} \\ \text{Ampere conductor} \\ \text{Length of air gap} \\ \text{Stator current density} \\ \text{Rotor current density} \\ \text{Flux density in the core} \end{bmatrix}^T \qquad (14)$$

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

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$$\text{Minimize } f(x) = 0.03 \times \frac{P_{st}}{A_{coolt}} \quad (15)$$

Subject to

$$g(x) \le 0 \Leftrightarrow \left\{ \begin{array}{l} \text{maximum flux density of stator teeth} \le 2 \\ \text{maximum flux density of rotor teeth} \le 2.0 \\ \text{slip at full load} \le 0.05 \\ \text{starting to full load torque ratio} \ge 1.5 \\ \text{stator temperature rise} \le 70 \\ \text{per unit no load current} \le 0.5 \\ \text{power factor} \ge 0.75 \end{array} \right\} \quad (16)$$

$$x_i^{\min} \le x_i \le x_i^{\max} \quad i = 1,2,\cdots nd \quad (17)$$

Where

$$A_{coolt} = \left[(1+0.1v) \times (\pi D(L \times 2.5) + 2\pi(D+50) \times 0.04)\right] + (\pi D_o L) \quad (18)$$

$$P_{st} = P_{cus} + P_{it} + P_{ic} \quad (19)$$

Cost Function

The algorithm searches for optimal solution by minimizing an augmented cost function Ψ, which is formulated from the objective function of Eq. (15) and the penalty terms representing the limit violation of the explicit constraints of Eq. (16). The augmented cost function is written as

$$\Psi = f(x) + w \sum_{i \in \eta} [g_i(x)]^2 \quad (20)$$

Solution Process

The augmented cost Ψ is calculated by considering the decoded values of the process of each agent. The minimizing the Ψ till the number of iterations reaches a specified maximum number of iterations.

IV. NUMERICAL RESULTS

The proposed GSA 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, 4 pole, 50 Hz. The effectiveness of the PM is demonstrated through comparing the performances with those of the GSA 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 GSA based design approach. The software packages are developed in Matlab platform and executed in a 2.3 GHz Pentium-IV 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 GSA, ACO 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 temperature rises are presented in Table-1 and -2 respectively.

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Table 1 Comparison of Results for Motor-1

		ACO	PM
Primary Design Variables x	x_1	1.95268	1.97831
	x_2	0.20192	0.20102
	x_3	5098.93	5019.07
	x_4	0.57025	0.60457
	x_5	3.63509	3.65513
	x_6	2.24194	2.70718
	x_7	1.10010	1.11306
Constraints $g(x)$	$g_1 \leq 2$	0.783	0.687
	$g_2 \leq 2$	0.449	0.424
	$g_3 \leq 0.05$	0.022	0.024
	$g_4 \geq 1.5$	27.467	23.101
	$g_5 \leq 70$	10.741	10.606
	$g_6 \leq 0.5$	0.399	0.495
	$g_7 \geq 0.75$	0.926	0.924
Objective function $h(x)$	Temperature Rise $^\circ C$	**10.741**	**10.403**

Table 2 Comparison of Results for Motor-2

		ACO	PM
Primary Design Variables x	x_1	1.99589	1.79497
	x_2	0.21086	0.21246
	x_3	5703.82	6850.34
	x_4	0.31894	0.89146
	x_5	2.74932	2.79108
	x_6	6.88371	2.89900
	x_7	1.10003	1.11911
Constraints $g(x)$	$g_1 \leq 2$	0.500	0.654
	$g_2 \leq 2$	0.397	0.454
	$g_3 \leq 0.05$	0.034	0.032
	$g_4 \geq 1.5$	13.852	14.157
	$g_5 \leq 70$	9.958	9.816
	$g_6 \leq 0.5$	0.222	0.394
	$g_7 \geq 0.75$	0.960	0.978
Objective function $h(x)$	Temperature Rise $^\circ C$	**9.958**	**9.810**

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It is observed from these tables that the PM offers a temperature rise of **10.403** $^{\circ}C$ and **9.810** $^{\circ}C$, which are lower than of ACO based approach, for motor-1 and -2 respectively. These tables also include the values of the constraints of Eq. (16) 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. (20).

V. CONCLUSION

Indeed the GSAis a powerful population based algorithm for solving multimodal optimization problems. A new methodology involving GSA for solving ODIM problem has been suggested. It determines the optimal values for primary design variables that minimizes the temperature rise. The results on two IMs clearly illustrates the ability of the PM to produce the global best design parameters that reduces the temperature rise of the IM. It has been chartered that the new approach fosters the continued use of GSA and will go a long way in serving as a useful tool in design problems.

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