Design of a Cost Effective Induction Motor Using Gravitational Search Algorithm

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Abstract - *This paper presents a Gravitational Search Algorithm (GSA) based design methodology for reducing the material cost 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.*

Key Words: Induction Motor Design, Gravitational Search Algorithm

Nomenclature

$f(x)$	objective function to be minimized
$g(x)$	a set of inequality constraints
IM	induction motor
$Iter^{\max}$	maximum number of iterations for convergence check
kW	rating of IM
MC	material cost
"min"& "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.
R_{iron}	rate of Iron
R_{copper}	rate of Copper
rand()	is a uniform random number between 0 and 1
W_{iron}^{stator}	stator iron weight
W_{iron}^{rotor}	rotor iron weight
W_{copper}^{stator}	stator copper weight
W_{copper}^{rotor}	rotor conductor weight
X	a vector of primary design variables
η	a set of limit violated constraints
w	weight constant of the penalty terms
Ψ	augmented objective function

1. INTRODUCTION

The Induction motors (IM) are perpetually used in domestic, commercial and various industrial applications as they are characterized by their simplicity, robustness and low cost. They became more attractive and hence captured a leading place in industrial sectors. The climbing raw material cost (MC) has become another influential factor on the design process. In the competitive market, cost optimization of IM through a better design becomes a major concern. The cost of active materials, which comprise the cost of stator-rotor stampings and winding materials, is typically considered as the objective function and minimized through appropriate combination of the design parameters. 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 [1].

In recent decades, in addition to statistical methods [2] and the Monte Carlo technique [3] 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 [4], Lagrangian relaxation method [5], direct and indirect search methods [6] Hooks and Jeeves method [7], Rosenbrock's method [8] Powell's method [9], finite element method [10], sequential unconstrained minimization technique [11] are most cumbersome and time consuming. Besides a few of them requires derivatives and exhibits poor convergence properties due to approximations in derivative calculations.

In order to overcome the drawbacks of classical methods, another class of nature inspired meta-heuristic algorithms such as simulated annealing [12,13], genetic algorithm [14,15], evolutionary algorithm [16], evolutionary strategy [17] and particle swarm optimization [18] 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.

Harmony Search Optimization (HSO) that was conceptualized using musical process of searching for a perfect state of harmony has been suggested for solving optimization problems [19,20]. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques. The HSA does not require initial values for the decision variables and uses a stochastic random search that is based on the harmony memory considering rate (HMCR) and pitch adjusting rate (PAR) so that the derivative information is unnecessary. It requires fewer mathematical computations compared to other meta-heuristic algorithms and can be easily adopted for various types of engineering optimization problems. It has been applied in solving EED problem in [21].

The aim of this paper is to develop a design methodology using GSA for reducing the MC 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. The paper is divided into five sections. Section I presents the introduction, section II overviews GSA, section III explains the IM design problem and suggests the proposed design method (PM), section IV discusses the results and section V concludes.

2. 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:

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right), \quad i=1,2,\ldots,m \tag{1}$$

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:

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

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:

$$F_i^d(t) = \sum_{j=ij\neq i}^{m} rand_j F_{ij}^d(t) \tag{2}$$

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:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{3}$$

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:

$$v_i^d(t+1) = \text{rand}_i\ xv_i^d(t) + a_i^d(t) \tag{4}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{5}$$

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):

$$G(t) = G_o e^{-\alpha \frac{t}{T}} \tag{6}$$

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:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{7}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{m} m_j(t)} \tag{8}$$

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:

$$best(t) = \min_{j\epsilon\{1,\dots,m\}} fit_j(t) \tag{9}$$

$$worst(t) = \max_{j\epsilon\{1,\dots,m\}} fit_j(t) \tag{10}$$

For a maximization problem:

$$best(t) = \max_{j\epsilon\{1,\dots,m\}} fit_j(t) \tag{11}$$

$$worst(t) = \max_{j\epsilon\{1,\dots,m\}} fit_j(t) \tag{12}$$

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_0 is set to100

$\propto$ is set to 20

T =100(total number of iterations)

3. PROPOSED METHOD

The proposed GSA based design method (PM) for ODIM involves formulation of the problem, representation of gravitational force through the chosen design variables and construction of a fitness function, *FIT* .

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.

$$X = [x_1,\ x_2,\ \cdots,\ x_7] = \begin{bmatrix} \text{Core length to pole pitch} \\ \text{Average value of air gap flux density} \\ \text{Ampere conductor} \\ \text{Length of air gap} \\ \text{Stator current density} \\ \text{Rotor current density} \\ \text{Flux density in the core} \end{bmatrix}^T \quad (13)$$

The ODIM problem is formulated by defining an objective function and a set of constraints. The active MC of the motor, determined by computing the motor iron and copper masses and their corresponding market cost, is considered as the objective function.

$$\text{Minimize} \quad f(x) = \left(W_{iron}^{rotor} + W_{iron}^{stator}\right) \times R_{iron} + \left(W_{copper}^{rotor} + W_{copper}^{stator}\right) \times R_{copper} \quad (14)$$

Subject to

$$g(x) \le 0 \Leftrightarrow \begin{Bmatrix} \text{maximum flux density of stator teeth} \le 2 \\ \text{maximum flux density of rotor teeth} \le 2.0 \\ \text{slip at full load} \le 0.05 \\ \text{starting to full load torque ratio} \ge 1.5 \\ \text{stator temperature rise} \le 70 \\ \text{per unit no load current } \le 0.5 \\ \text{power factor } \ge 0.75 \end{Bmatrix} \quad (15)$$

$$x_i^{\min} \le x_i \le x_i^{\max} \qquad i = 1,2,\cdots nd \quad (16)$$

3.2 Representation of Design Variables

The agent, a is represented to denote the chosen primary design variables, defined by Eq. (13), in vector form as:

$$a^i = \left[a_1^i, a_2^i \cdots, a_7^i\right] = [x_1,\ x_2,\ \cdots,\ x_7] \quad (17)$$

3.3 Fitness Function

The algorithm searches for optimal solution by maximizing a fitness function FIT , which is formulated from the objective function of Eq. (18) and the penalty terms representing the limit violation of the explicit constraints of Eq. (19). The fitness function is written as

$$\text{Maximize } FIT = \frac{1}{1+\Psi} \quad (18)$$

Where Ψ the objective function and the penalty terms of limit comprises violated constraints.

$$\Psi = f(x) + w \sum_{i \in \eta} [g_i(x)]^2 \quad (19)$$

4. 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 illustrated through comparing the performances with those of the HSA based design approach. In this regard, the same set of primary design variables, fitness function and design equations, involved in the PM, are used to develop the HSA based design approach. While calculating the cost of the motor, the cost of iron for stampings is considered as Rs.50 per kg and the cost of copper that is used as the winding material for both stator and rotor is considered as Rs. 350 per kg. The cost is calculated from the view point of manufacturers. 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 HSO and GSA and hence the algorithms are run 20 times for each IM and the best ones are presented.

Table 1 Comparison of Results for Motor-1

		HSA	PM
Primary Design Variables x	x_1	0.95849	0.99890
	x_2	0.54685	0.55075
	x_3	16546.29	18205.42
	x_4	0.25621	0.25531
	x_5	4.93176	4.78039
	x_6	7.80947	7.99768
	x_7	1.50055	1.51047
Constraints $g(x)$	$g_1 \leq 2$	1.930	1.930
	$g_2 \leq 2$	1.298	1.298
	$g_3 \leq 0.05$	0.041	0.041
	$g_4 \geq 1.5$	9.332	9.353
	$g_5 \leq 70$	57.135	57.229
	$g_6 \leq 0.5$	0.514	0.520
	$g_7 \geq 0.75$	0.855	0.853
Objective function $h(x)$	MC	**6357.046**	**6349.916**

Table 2 Comparison of Results for Motor-2

		HSA	PM
Primary Design Variables x	x_1	1.91057	1.81060
	x_2	0.65350	0.67948
	x_3	28065.85	23040.18
	x_4	0.25221	0.27659
	x_5	3.58084	3.82883
	x_6	7.85194	7.94654
	x_7	1.61837	1.56126
Constraints $g(x)$	$g_1 \leq 2$	1.854	1.859
	$g_2 \leq 2$	1.656	1.647
	$g_3 \leq 0.05$	0.029	0.028
	$g_4 \geq 1.5$	4.089	4.748
	$g_5 \leq 70$	69.192	66.930
	$g_6 \leq 0.5$	0.500	0.502
	$g_7 \geq 0.75$	0.802	0.810
Objective function $h(x)$	MC	**17475.276**	**17467.905**

The optimal design representing the values of the primary design variables for both the IMs and their MCs are presented in Tables-1 and -2 respectively. It is seen from these tables that the PM offers a MC of Rs. **6349.916** and Rs. **17467.905** which are lower than that of HSA based approach, for motor-1 and -2 respectively. These tables also include the values of the constraints of Eq. (15) 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 fitness function of Eq. (19). It is obvious that the PM offers better MC reduction than the existing approach for both the motors.

5. Conclusion

Indeed the GSA is a powerful population based meta-heuristic 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. The results on two IMs clearly illustrates the ability of the PM to produce the global best design parameters that reduces the MC 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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