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# Gravitational Search Algorithm Optimization Based Design for Improving Starting Torque of Induction Motor

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**ABSTRACT**: Thispaper presents a Gravitational Search Algorithm (GSA) Optimization based design methodology for maximizing the starting torque of Induction Motor (IM). The GSA based design methodology is tailored 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. The optimal design obtained by the proposed methodology fortwo IMs are presented with a view of illustrating the superiority.

**KEYWORDS:** Induction Motor, Gravitational Search Algorithm

### NOMENCLATURE

- *EDi* equivalent decimal value of *ith*sub-string
- h(x) Objective function to be maximized
- *LI* fitness function of *ith*star
- g(x) a set of inequality constraints
- *I ph* phase current, A
- IM induction motor
- *Ir* equivalent rotor current, A
- *Isc* short circuit current per phase, A

"min"& "max" minimum and maximum limits of the respective variables

- *nd* number of decision variables
- ODIM optimal design of IM
- PM proposed method
- PS population size



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- SFL slip at full load, per unit
- *Tst* starting torque, per unit
- *Vph* phase voltage, V
- *w* weight constant of the penalty terms
- *xiith* decision variable

*Z* impedance per phase

### I. INTRODUCTION

Although squirrel-cage induction machines are widely used in the industry for their easy manufacturing and robustness, their applications in electrical transport systems such as subways and trains are limited due to inferior starting torque than those of permanent-magnet motors. In the light of the fact that the resistance of a squirrel-cage motor is fixed and small as compared to its reactance that is very large especially at the start, the frequency of the rotor currents equals the supply frequency, the starting current of the rotor is very large in magnitude and lags by a very large angle, resulting a poor starting torque per ampere. It is roughly 1.5 times the full-load torque, although the starting current is 5 to 7 times the full load current. Hence, such motors are not useful where the motor has to start against heavy loads. Therefore it becomes imperative that the best architecture and the corresponding dimensioning have to be determined in order to maximize the starting torque with respect to several constraints in applications requiring high starting torque such as in traction systems. 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). 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, MehmetCunkas 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's method -Bharadwaj et al 1979-a, Powell's method Ramarathnam et al 1973, finite element method T. S. 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: Sivaraju et al 2011, evolutionary algorithm Jan PawelWieczorek et al 1998), evolutionary strategy Kim MK et al 1998), and particle swarm optimization (PSO),Thanga Raj et al Sakthivel et al 2011, 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



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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.

The focus of this paper is to develop a design methodology using GSA for maximizing the starting torque 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 provides the introduction, section II overviews GSA, section III formulates the IM design problem and elucidates the proposed method (PM), section IV discusses the results and section V concludes

#### **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:

$$X_{i = (x_{i}^{1}, \dots, x_{i}^{d}, \dots, x_{i}^{n}), i = 1, 2, \dots, m}$$
(1)

Where  $x_i^d$  position of the ith ismass in the d<sup>th</sup> 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  $\varepsilon$  is a small constant.

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

$$F_i^d(t) = \sum_{j=ij\neq i}^m \operatorname{rand}_j F_{ij}^d(t)$$
(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:

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



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$$v_i^d(t+1) = \operatorname{rand}_i x v_i^d(t) + a_i^d(t)$$
(5)

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$$
(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):

$$G(t) = G_0 e^{-\alpha \frac{t}{T}}$$
<sup>(7)</sup>

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:

$$m_{i}(t) = \frac{fit_{i}(t) - worst(t)}{best(t) - worst(t)}$$

$$M_{i}(t) = \frac{m_{i}(t)}{\sum_{j=1}^{m} m_{j}(t)}$$
(8)
(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:

$$best(t) = \min_{j \in \{1,\dots,m\}} fit_j(t)$$
(10)

$$worst(t) = \max_{j \in \{1, \dots, m\}} fit_j(t)$$
(11)

For a maximization problem:

$$best(t) = \max_{j \in \{1, \dots, m\}} fit_j(t)$$
(12)

$$worst(t) = \min_{j \in \{1, \dots, m\}} fit_j(t)$$
(13)

#### 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.



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Step 5: Calculation of the total force in different directions.

Step 6: Calculation of acceleration and velocity.

Step 7: Updating agent's 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 GO is set to100

∝is set to 20

T =100(total number of iterations)

### **III. PROPOSED METHOD**

The proposed GSA based solution method for ODIM involves formulation of the problem, representation of agents through the chosen design variables and agents are accelerated to move towards acceleration and velocity as best solutions.

### 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.

	Core length to pole pitch	Т
	Average value of air gap flux density	
	Ampere conductor	(14)
$X = [x_1, x_2, \cdots, x_7] =$	Length of air gap	. ,
	Stator current density	
	Rotor current density	
	Flux density in the core	

The ODIM problem is formulated by defining an objective function and a set of constraints as

Maximize

$$h(x) = T_{st} = \left(\frac{I_{st}}{I_r}\right)^2 \times SFL \quad (15)$$



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Subject to

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

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

Where

$$I_r = 0.85 \times I_{ph} \tag{18}$$

$$Isc = \frac{I_{ph}}{Z}$$
(19)

### 3.2 Representation of Design Variables

The agent a, is represented to denote the chosen primary design variables, defined by Eq. (14), in vector form as:

$$a_i = \begin{bmatrix} a_i^1, a_i^2 \cdots, a_i^7 \end{bmatrix} = \begin{bmatrix} x_1, x_2, \cdots, x_7 \end{bmatrix}$$
(20)

### 3.3 Fitness Function

The algorithm searches for optimal solution by maximizing a fitness of agent LI, which is formulated from the objective function of Eq. (15) and the penalty terms representing the limit violation of the explicit constraints of Eq. (21). The LI function is written as

Maximize 
$$LI = \frac{h(x)}{1 + w \sum_{i \in \eta} \left[g_i(x)\right]^2}$$
(21)

### **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, 6 pole, 50 Hz. The effectiveness of the PM is demonstrated through comparing the performances with that of the BHA 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 BHA 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 guarantee that different executions of the developed design programs converge to the same design due to the stochastic nature of the GSA and BHA, and hence the algorithms are run 20 times for each motor and the best ones are presented. The optimal design representing the values of the primary design variables and their performances are presented for both the motors in Table-1 and 2 respectively.



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Table 1 Comparison of Results for Motor-1

		BHA	PM
Primary Design Variables	<i>x</i> <sub>1</sub>	1.96528	1.14355
	<i>x</i> <sub>2</sub>	0.41167	0.34479
	<i>x</i> <sub>3</sub>	6547.07	5180.21
	$x_4$	0.26089	0.38271
	<i>x</i> <sub>5</sub>	3.63145	4.00325
	<i>x</i> <sub>6</sub>	7.03718	7.96031
	<i>x</i> <sub>7</sub>	1.26820	1.16556
Constraints $g(x)$	$g_1 \leq 2$	1.267	1.087
	$g_2 \leq 2$	0.877	0.726
	$g_3 \le 0.05$	0.031	0.034
	$g_4 \ge 1.5$ $g_5 \le 70$ $g_6 \le 0.5$ $g_7 \ge 0.75$	20.202 25.463 0.497 0.899	21.110 20.330 0.490 0.904
Objective function h(x)	Starting Torque (Per unit)	10.435	10.542

Table 2 Comparison of Results for Motor-2

		BHA	PM
Primary Design Variables	<i>x</i> <sub>1</sub>	1.78348	1.62509
	<i>x</i> <sub>2</sub>	0.56613	0.57020
	<i>x</i> <sub>3</sub>	5578.95	5691.08
	<i>x</i> <sub>4</sub>	0.31653	0.27394
	<i>x</i> <sub>5</sub>	2.87318	2.87779
	<i>x</i> <sub>6</sub>	7.26332	7.75605
	<i>x</i> <sub>7</sub>	1.14394	1.24505
Constraints $g(x)$	$g_1 \leq 2$	1.638	1.698
	$g_2 \leq 2$	1.124	1.183
	$g_3 \le 0.05$	0.020	0.019
	$g_4 \ge 1.5$	30.704	31.474



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	$g_5 \leq 70$	26.552	29.414
	$g_6 \le 0.5$	0.500	0.498
	$g_7 \ge 0.75$	0.886	0.888
Objective function h(x)	Starting Torque (Per unit)	16.218	16.448

It is seen from these tables that the PM offers a starting torque of **10.542** and **16.448** per units, which are higher than that of BHA 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 both the methods bring the constraints such as maximum flux density, slip at full load, starting to full load torque ratio, etc., of to lie within the respective limit, as the constraints are added as penalty terms in the fitness function of Eq. (21).

### **IV. CONCLUSION**

Indeed the GSA is a powerful population based method for solving complex optimization problems. A new methodology involving GSA for solving ODIM problem has been developed and applied on two IM design problems. It determines the optimal values for primary design variables. The ability of the PM to produce the global best design parameters that maximizes the starting torque of the motor has been projected. 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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