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Black Hole Algorithm Optimization Based Design for Improving Efficiency of Three Phase Induction Motor

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ABSTRACT: This paper presents a Black Hole Algorithm Optimization (BHA)based design methodology for improving the efficiency of Induction Motor (IM). Block hole algorithm optimization, inspired by absence of stars in the space identified by integrating Newton's law, is one of the evolutionary computing models for solving multimodal optimization problems. Among the number of design variables of the IM, seven variables are identified as primary design variables and the BHA 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.

KEYWORDS: Induction Motor, Black Hole Algorithm Optimization

NOMENCLATURE

BHA	Black Hole Algorithm Optimization
ACO	Ant Colony Optimization
GA	Genetic Algorithm
s_i	i -th star
s_i^j	j -th design variable of i -th star
$g(x)$	a set of inequality constraints
$h(x)$	Objective function to be optimized
IM	Induction Motor
$Iter^{\max}$	maximum number of iterations for convergence check
kW	Rating of IM
LI_i	fitness of i -th star
"min" & "max"	minimum and maximum limits of the respective variables
nd	number of decision variables
nf	number of stars in the population
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.
X	Vector of primary design variables
η	a set of limit violated constraints

$x_i(t)$ Location of the star at iteration

$X_i(t-1)$ Location of the star at iteration

x_{BH} Location of the black hole in the search space;

$rand$ Random number in the interval [0, 1]

w Weight constant of the penalty terms

G Gravitational constant

M Mass of the black hole

C Velocity of light

I. 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 through the selection of 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'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 2005Kannan et al 2010), genetic algorithm (GA) Satyajit Samaddar et al 2013: Sivaraju et al 2011, evolutionary algorithm Jan Pawel Wieczorek 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 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, Block Hole Algorithms Optimization (BHA) has been suggested for solving optimization problems. It is inspired by The stars are accelerated to move towards black hole as best solutions with random numbers based on current locations in every iterations.. In this approach, each problem solution is represented by a stars, population of stars are randomly created in the search space with the help of objective functions. It has been applied to a variety of power system problems and found to yield satisfactory results.

The aim of this paper is to develop a BHA 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 six sections. Section I provides the introduction, section II overviews BHA, section III formulates the IM design problem and elucidates the proposed method (PM), section IV discusses the results and section V concludes.

II. THE BLACK HOLE PHENOMENA

The concept of black hole was familiarized by John Michell and Pierre Laplace in the century, with the absence of stars in the space identified by integrating Newton's law. On those days the absence of stars in the space is not known as a black hole. Later in the century, an American physicist, John Wheeler who first named the phenomenon that mass collapsing or absence of stars is known as black hole. At the space region, the black hole has a strong gravitational field that even light cannot escape from it once the light enters through it. th 18 th 20

The radius of black hole is mathematically as defined as surface of event horizon also known as Schwarzschild radius [26].

The Schwarzschild radius is mathematically formulated by the equation (1):

$$R = \frac{2GM}{C^2} \qquad (1)$$

Where,

G is the gravitational constant
M is the mass of the black hole
C is the velocity of light

If any particle moves closer to the event horizon or crosses over surface of event horizon that will be absorbed by black hole and swallowed by it. The existence of black hole is distinguished by the effects of surrounding over it, like when light hits the horizon that will be absorbed completely without any reflection and vanish permanently. The schematic view of black hole in the space shown in figure (1)

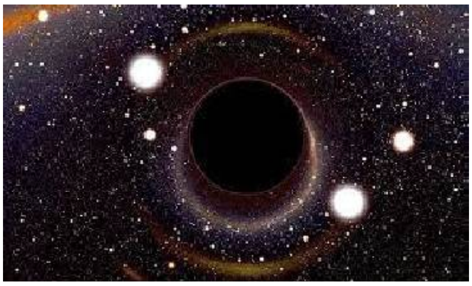

Fig. 1: Black Hole in the Space

2.1 Black Hole Algorithm

The BHA is a recently developed population based metaheuristic algorithm, which is used for optimization problems like genetic algorithm (GA) and particle swarm optimization (PSO) with some similar working mechanism. In BHA, the stars are used as a candidate solutions in a random search space. Where as in Genetic algorithm operators like cross cover, mutation, and reproduction are used for obtaining global best solution. Particle swarm optimization mimics the food foraging behaviour of birds, in which velocity and best positions are used to obtain gbest solutions. In the suggested algorithm, population of stars are randomly created in the search space with the help of objective functions. The candidate of stars are accelerated to move towards black hole as best solutions with random numbers based on current locations in every iterations. The absorbing power of stars is mathematically formulated for initializing of stars with objective functions is as follows:

$$X_i(t+1) = x_i(t) + rand(0,1)(x_{BH} - x_i(t)) \qquad (2)$$

Where

$x_i(t)$ location of the star at iteration ;

$X_i(t-1)$ location of the star at iteration ;

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x_{BH} location of the black hole in the search space;
$rand$ random number in the interval [0, 1].

During the search process towards the black hole, a star can reach the black hole with lower cost, in that occasion the black hole should move to the locations of stars and vice versa. Thereafter, in BHA the black hole will start from its new location and searching will continue towards the new locations. In addition to the above said mechanism, there is a probability that stars will be moving towards the black hole that it may crosses the event of horizon. If the crossing stage happens, at that time stars will be sucked by the black hole, another new star will be created to maintain population size constant. The radius for the event of horizon in black hole algorithm is determined by mathematically as

$$R = \frac{f_{BH}}{\sum_{i=1}^{N} f_i} \qquad (3)$$

Where,

f_{BH} is the fitness for the black hole and f_i is the fitness value for the i^{th} star. N is the number of candidate solutions (stars). The stars will be collapsed, when the distance of stars and black hole is less than the radius R and at randomly new stars will generated in the search space. Based on the above explanation the key steps in the BH algorithm are given in pseudo code as follows:

```
Step1  Initialize a random population of stars at arbitrary locations in the search space. Step2 Calculate the fitness
       value of every star as a candidate of solution.
Step2  Select the best star with lower cost as the fitness value.
Step3  Modify the position of every star according to Eq. (2).
Step4  if star reaches a position with lower cost than the black hole, then interchange their locations.
Step5  When star crosses the event horizon of the black hole, create a new star randomly in search space.
Step6  Distance between black hole and star is less than the R, generate a new star in search space.
Step7  Stop criterion with global best solution.
```

III. PROPOSED METHOD

The proposed BHA based solution method for ODIM involves formulation of the problem, representation of stars through the chosen design variables and stars are accelerated to move towards black hole 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.

$$X = [x_1,\ x_2,\ \cdots,\ x_7] = \begin{bmatrix} \text{Core length to pole pitch} \\ \text{Average value of air gap flux density} \\ \text{Ampere conductor} \\ \text{Length of air gap} \\ \text{Stator current density} \\ \text{Rotor current density} \\ \text{Flux density in the core} \end{bmatrix}^T \qquad (4)$$

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

$$h(x) = \frac{KW}{KW + P_t} \quad (5)$$

Subject to

$$g(x) \le 0 \Leftrightarrow \left\{ \begin{array}{l} \text{maximum flux density of stator teeth} \le 2 \\ \text{maximum flux density of rotor teeth} \le 2.0 \\ \text{slip at full load} \le 0.05 \\ \text{starting to full load torque ratio} \ge 1.5 \\ \text{stator temperature rise} \le 70 \\ \text{per unit no load current} \le 0.5 \end{array} \right\} \quad (6)$$

$$x_i^{\min} \le x_i \le x_i^{\max} \quad i = 1,2,\cdots nd \qquad (7)$$

Where

$$P_t = P_{nl} + P_{cus} + P_{cur} \qquad (8)$$

3.2 Representation of Design Variables

The star s ,is represented to denote the chosen primary design variables, defined by Eq. (4), in vector form as:

$$s_i = \left[s_i^1, s_i^2 \cdots, s_i^7 \right] = [x_1,\ x_2,\ \cdots,\ x_7] \quad (9)$$

3.3 Fitness Function

The algorithm searches for optimal solution by maximizing a fitness of stars LI, which is formulated from the objective function of Eq. (5) and the penalty terms representing the limit violation of the explicit constraints of Eq. (6). The LI function is written as

Maximize $$LI = \frac{h(x)}{1 + w \sum_{i \in \eta} [g_i(x)]^2} \qquad (10)$$

IV. NUMERICAL RESULTS

The proposed BHA method (PM) 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 GA and ACO based design approaches. In this regard, the same set of primary design variables, fitness function and design equations, involved in the PM, are used to develop the GA and ACO based design approaches. 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 GA, ACO and BHA, and hence the algorithms are run 20 times and the best ones are presented. The optimal design representing the values of the primary design variables for both the IMs and their efficiencies are presented in Table-1 and 2 respectively.

Table 1 Comparison of Results for Motor-1

		GA	ACO	PM
Primary Design Variables x	x_1	1.35114	1.31979	1.27631
	x_2	0.44063	0.42097	0.44608
	x_3	22806.85	23155.24	22865.20
	x_4	0.66918	0.46367	0.51578
	x_5	3.35017	3.64492	3.93688
	x_6	2.10549	2.00461	2.00381
	x_7	1.10444	1.10145	1.11679
Constraints $g(x)$	$g_1 \leq 2$	1.736	1.621	1.729
	$g_2 \leq 2$	1.733	1.738	1.856
	$g_3 \leq 0.05$	0.020	0.021	0.020
	$g_4 \geq 1.5$	4.424	3.427	3.855
	$g_5 \leq 70$	46.121	45.728	48.868
	$g_6 \leq 0.5$	0.496	0.342	0.496
	$g_7 \geq 0.75$	0.808	0.854	0.798
Objective function $h(x)$	% Efficiency	**86.708**	**86.727**	**86.753**

Table 2 Comparison of Results for Motor-2

		GA	ACO	PM
Primary Design Variables x	x_1	1.71468	1.19110	1.67666
	x_2	0.34334	0.44126	0.38535
	x_3	27143.81	28217.57	22855.40
	x_4	0.89138	0.89713	0.75880
	x_5	2.69663	2.69634	2.84081
	x_6	2.01937	2.01649	1.00505
	x_7	1.11485	1.10062	1.11540
Constraints $g(x)$	$g_1 \leq 2$	1.135	1.487	1.282
	$g_2 \leq 2$	1.126	1.528	1.655
	$g_3 \leq 0.05$	0.017	0.016	0.011
	$g_4 \geq 1.5$	1.636	1.748	1.712
	$g_5 \leq 70$	34.137	46.449	34.275
	$g_6 \leq 0.5$	0.278	0.347	0.349
	$g_7 \geq 0.75$	0.807	0.774	0.719
Objective function $h(x)$	% Efficiency	**90.497**	**90.582**	**90.777**

It is observed from these tables that the PM offers an efficiency of **86.753%** and **90.777**%, which are higher than those of GA and ACO based approaches, for motor-1 and -2 respectively. These tables also include the values of the constraints of Eq. (6) 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 light intensity function of Eq. (10). The % efficiency enhancements for both the motors are calculated taking a non-optimal efficiency of 79.489% and 83.865% respectively and graphically compared in Fig. 2. It is seen from Fig. 2 that the %efficiency enhancement of the PM of motor-1 is 9.217%, while for other methods, they are 9.082% and 9.106% . Similarly for motor-2, the PM results in the %efficiency enhancement of 8.035%, while for other methods, they are 7.908% and 8.009%. It is obvious that the PM offers better %efficiency enhancement than those of the existing approaches for both the motors.

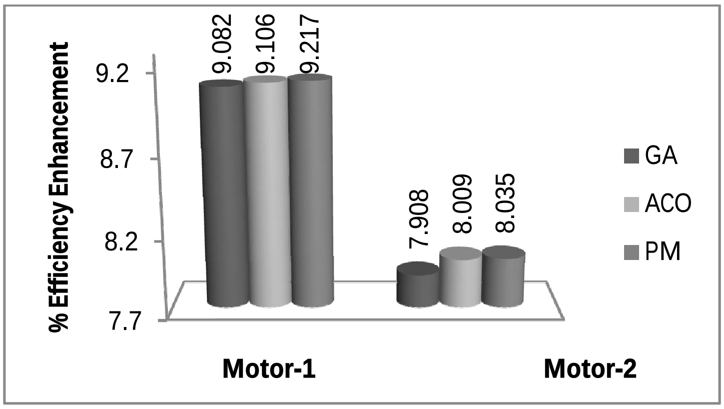

Fig. 2 Comparison of %Efficiency Enhancement

V. CONCLUSION

Indeed the BHA is a powerful population based method for solving complex optimization problems. A new methodology involving BHA 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 improves the efficiency of the motor has been projected. It has been chartered that the new approach fosters the continued use of BHA and will go a long way in serving as a useful tool in design problems.

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