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FIREFLY OPTIMIZATION BASED DESIGN FOR IMPROVING EFFICIENCY OF INDUCTION MOTOR

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ABSTRACT

This paper presents a Firefly Optimization (FFO) based design methodology for improving the efficiency of Induction Motor (IM). Firefly Algorithm, inspired by social flashing behaviour of fireflies, 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 FFO 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, firefly optimization.

Nomenclature

ACO	ant colony optimization
FFO	firefly optimization
f_i	i -th firefly
f_i^j	j -th design variable of i -th firefly
GA	genetic algorithm
$g(x)$	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	light intensity of i -th firefly
"min" & "max"	minimum and maximum limits of the respective variables
nd	number of decision variables
nf	number of fireflies 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.
r_{ij}	Cartesian distance between i -th and j -th fireflies
X	vector of primary design variables
η	a set of limit violated constraints
α	random movement factor
β_o	attractiveness parameter
β_{ij}	attractiveness between i -th and j -th fireflies
γ	absorption factor
w	weight constant of the penalty terms

1. 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

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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 provide a means for finding the minimum or maximum of a chosen objective function of several decision 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 (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) (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.* 2008: 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, firefly optimization (FFO) has been suggested for solving optimization problems (Yang 2008: Yang 2009). It is inspired by the light attenuation over the distance and fireflies' mutual attraction rather than the phenomenon of the fireflies' light flashing. In this approach, each problem solution is represented by a firefly, which tries to move to a greater light source, than its own. It has been applied to a variety of power system problems (Kuldeep Kumar Swarnkar 2012: Sulaiman *et al.* 2012: Chandrasekaran 2012) and found to yield satisfactory results.

The aim of this paper is to develop a FFO 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 five sections. Section 1 provides the introduction, section 2 overviews FFO, section 3 formulates the IM design problem and elucidates the proposed method (PM), section 4 discusses the results and section 5 concludes.

2. FIREFLY OPTIMIZATION

The FFO, a nature-inspired optimization algorithm, is based on the social flashing behaviour of fireflies and similar to other optimization algorithms employing swarm intelligence such as PSO. FFO initially produces a swarm of fireflies located randomly in the problem space. The position of each firefly in the problem space represents a potential solution of the optimization problem. The fitness function takes the position of a firefly as input and produces a single numerical output value denoting how good the potential solution is. The brightness of each firefly depends on the fitness value of that firefly. Each firefly is attracted by the brightness of other fireflies and tries to move towards them. The velocity or the pull of a firefly towards another firefly depends on the attractiveness. The attractiveness depends on the relative distance between the fireflies and is a function of the brightness of the fireflies as well. A brighter firefly far away may not be as attractive as a less bright firefly that is closer. In each iterative step, FFO computes the brightness and the relative attractiveness of each firefly. Depending on these values, the positions of the fireflies are updated. After sufficient amount of iterations, all fireflies converge to the best possible position in the search space. Each i -th firefly is denoted by a vector f_i as (Yang 2008: Yang 2009)

$$f_i = \left[f_i^1, f_i^2 \cdots, f_i^{nd} \right] \quad (1)$$

The search space is limited by the following inequality

$$f^k(min) \le f^k \le f^k(max) \ : \ k = 1, 2, \cdots, nd \quad (2)$$

Initially, the positions of the fireflies are generated from a uniform distribution using the following equation

$$f_i^k = f^k(min) + \left(f^k(max) - f^k(min) \right) \times rand \quad (3)$$

Here, $rand$ is a random number in between 0 and 1, taken from a uniform distribution. Equation (3) generates random values from a uniform distribution within the prescribed range defined by Equation (2). The initial distribution does not significantly affect the performance of the algorithm. Each time the algorithm is executed, the optimization process starts with a different set of initial points. However, in each case, the algorithm searches for the optimum solution. In case of multiple possible sets of solutions, the algorithm may converge on

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different solutions each time. But each of those solutions will be valid as they all will satisfy the requirements.

The light intensity of the i -th firefly, LI_i is given by

$$LI_i = Fitness\,(f_i) \tag{4}$$

The attractiveness (β_{ij}) between the i-th and j-th firefly is given by

$$\beta_{ij} = \beta_o \exp\left(-\gamma\, r_{ij}^2\right) \tag{5}$$

Where r_{ij} is Cartesian distance between i-th and j-th firefly

$$r_{ij} = \left\| f_i - f_j \right\| = \sqrt{\sum_{k=1}^{nd} \left(f_i^k - f_j^k \right)^2} \tag{6}$$

β_o is a constant taken to be 1. γ is another constant whose value is related to the dynamic range of the solution space. The position of firefly is updated in each iterative step. If the light intensity of j-th firefly is larger than the intensity of the i-th firefly, then the i-th firefly moves towards the j-th firefly and its motion at t-th iteration is denoted by the following equation:

$$f_i(t) = f_i(t-1) + \beta_{ij}\left(f_j(t-1) - f_i(t-1)\right) + \alpha\left(rand - 0.5\right) \tag{7}$$

α is a random movement factor, whose value depends on the dynamic range of the solution space. At each iterative step, the intensity and the attractiveness of each firefly is calculated. The intensity of each firefly is compared with all other fireflies and the positions of the fireflies are updated using Equation (7). After a sufficient number of iterations, all the fireflies converge to the same position in the search space and the global optimum is achieved.

3. PROPOSED METHODS

The proposed FFO based solution method for ODIM involves formulation of the problem, representation of fireflies through the chosen design variables and construction of a light intensity function, LI.

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.

$$X = [x_1,\ x_2,\ \cdots,\ x_7] = \begin{bmatrix} \text{Core length to pole pitch} \\ \text{Average value of air gap flux density} \\ \text{Ampere conductor} \\ \text{Length of air gap} \\ \text{Stator current density} \\ \text{Rotor current density} \\ \text{Flux density in the core} \end{bmatrix}^T \tag{8}$$

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

$$\text{Maximize } h(x) = \frac{KW}{KW + P_t} \tag{9}$$

Subject to

$$g(x) \le 0 \Leftrightarrow \left\{ \begin{array}{l} \text{maximum flux density of stator teeth} \le 2 \\ \text{maximum flux density of rotor teeth} \le 2.0 \\ \text{slip at full load} \le 0.05 \\ \text{starting to full load torque ratio} \ge 1.5 \\ \text{stator temperature rise} \le 70 \\ \text{per unit no load current} \le 0.5 \\ \text{power factor} \ge 0.75 \end{array} \right\} \tag{10}$$

$$x_i^{\min} \le x_i \le x_i^{\max} \qquad i = 1,2,\cdots nd \tag{11}$$

$$\text{Where } P_t = P_{nl} + P_{cus} + P_{cur} \tag{12}$$

3.2 Representation of design variables

The firefly, f is represented to denote the chosen primary design variables, defined by Eq. (8), in vector form as:

$$f_i = \left[f_i^1, f_i^2 \cdots, f_i^7\right] = \left[x_1,\ x_2,\ \cdots,\ x_7\right] \tag{13}$$

3.3 Fitness function

The algorithm searches for optimal solution by maximizing a light intensity function LI, which is formulated from the objective function of Eq. (9) and the penalty terms representing the limit violation of the explicit constraints of Eq. (10). The LI function is written as

$$\text{Maximize} \quad LI = \frac{h(x)}{1 + w \sum_{i \in \eta} \left[g_i(x)\right]^2} \tag{14}$$

3.4 Solution process

An initial population of fireflies is obtained by generating random values within their respective limits through Eq. (11). The LI is calculated by considering the values of each firefly and the movements of all fireflies are performed with a view of maximizing the LI till the number of iterations reaches a specified maximum number of iterations. The pseudo code of the PM is as follows.

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Read the IM data
Choose the parameters, nf *,* $Iter^{\max}$*,* α, β_o *and* γ.
Generate the initial swarm of fireflies
Set the iteration counter $t=0$
while (termination requirements are not met) do
  for $i=1:nf$
    Obtain the primary design variables from i *-th firefly.*
    Compute the remaining secondary variables of the design problem.
    Evaluate LI_i *using Eq. 14 respectively*
    for $j=1:nf$
      Obtain the primary design variables from j *-th firefly.*
      Compute the remaining secondary variables of the design problem.
      Evaluate LI_j *using Eq. 14*
      if $LI_i < LI_j$
        Compute r_{ij} *using Eq. (6)*
        Evaluate β_{ij} *using Eq. (5)*
        Move i *-th firefly towards* j *-th firefly through Eq. (7)*
      end-(if)
    end-(j *)*
  end-(i *)*
  Rank the fireflies and find the current best.
end-(while)
Choose the best firefly possessing the largest LI_i *in the population as the optimal solution*

4. NUMERICAL RESULTS

The proposed FFO 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, 6 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 2.67 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 GA, ACO and FFO, 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 for both the IMs and their efficiencies are presented in Table-1 and 2.

Table-1. Comparison of results for Motor-1.

		GA	ACO	PM
Primary design variables X	x_1	1.35114	1.31979	1.36501
	x_2	0.44063	0.42097	0.42688
	x_3	22806.85	23155.24	23181.60
	x_4	0.66918	0.46367	0.58873
	x_5	3.35017	3.64492	3.48672
	x_6	2.10549	2.00461	2.03984
	x_7	1.10444	1.10145	1.10194
Constraints $g(x)$	$g_1 \le 2$	1.736	1.621	1.677
	$g_2 \le 2$	1.733	1.738	1.753
	$g_3 \le 0.05$	0.020	0.021	0.020
	$g_4 \ge 1.5$	4.424	3.427	3.900
	$g_5 \le 70$	46.121	45.728	45.894
	$g_6 \le 0.5$	0.496	0.342	0.430
	$g_7 \ge 0.75$	0.808	0.854	0.827
Objective function $h(x)$	% Efficiency	**86.708**	**86.727**	**86.736**

Table-2. Comparison of results for Motor-2.

		GA	ACO	PM
Primary design variables X	x_1	1.71468	1.19110	1.33580
	x_2	0.34334	0.44126	0.39008
	x_3	27143.81	28217.57	28756.51
	x_4	0.89138	0.89713	0.98477
	x_5	2.69663	2.69634	2.80913
	x_6	2.01937	2.01649	2.02020
	x_7	1.11485	1.10062	1.10010
Constraints $g(x)$	$g_1 \le 2$	1.135	1.487	1.331
	$g_2 \le 2$	1.126	1.528	1.368
	$g_3 \le 0.05$	0.017	0.016	0.016
	$g_4 \ge 1.5$	1.636	1.748	1.598
	$g_5 \le 70$	34.137	46.449	41.805
	$g_6 \le 0.5$	0.278	0.347	0.330
	$g_7 \ge 0.75$	0.807	0.774	0.776
Objective function $h(x)$	% Efficiency	**90.497**	**90.582**	**90.587**

It is observed from these tables that the PM offers an efficiency of 86.736% and 90.587%, 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. (10) 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. (14). The % efficiency enhancements for both the motors are calculated taking a non-optimal efficiency of 79.489% and 83.865% for motor-1 and motor-2 respectively and graphically compared in Figure-1. It is seen from Figure-1 that the %efficiency enhancement of the PM of motor-1 is 9.117%, while for other methods, they are 9.082% and 9.106%. Similarly for motor-2, the PM results in the %efficiency enhancement of 8.015, 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.

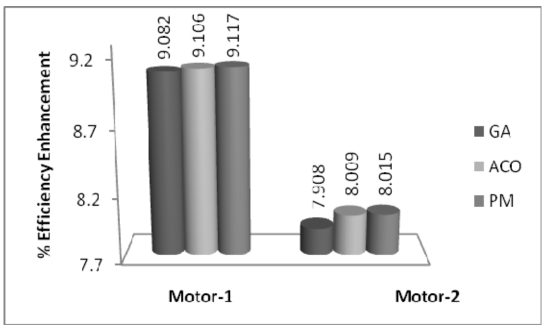

Figure-1. Comparison of % efficiency enhancement.

5. CONCLUSIONS

Indeed the FFO is a powerful population based method for solving complex optimization problems. A new methodology involving FFO 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 FFO and will go a long way in serving as a useful tool in design problems.

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