Magnetizer Design Based on a Quasi-Oppositional Gravitational Search Algorithm

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Abstract— **The Gravitational Search Algorithm (GSA) is novel metaheuristics approach inspired by the laws of gravitation and motion. In GSA, a set of agents, called masses, searches the design space in order to find the optimal solution by simulation of Newtonian laws of gravity and motion. In this work, a standard and an improved GSA approach based on a quasi-oppositional approach are presented and tested on a magnetic pole design benchmark. Results indicate that the performance of proposed improved GSA on the magnetic pole design is better than the that of classical GSA.**

Index Terms— **Optimization, electromagnetic optimization, gravitational search algorithm, magnetizer design, optimal magnetic pole design.**

I. Introduction

A number of optimization methods have been applied over the years to electromagnetic problems [1], and many successes have been demonstrated for a large class of problems, including multidimensional and nonlinear ones. However, the optimization of non-convex and non-differentiable objective functions is still an open challenge for researchers.

During the last few decades there has been a steady research interest in metaheuristics such as evolutionary algorithms [2] and swarm intelligence [3] which have been shown to be quite robust for many applications.

Recently, a new algorithm called Gravitational Search Algorithm (GSA), which is based on the concepts of the laws of gravitation and motion, has been proposed by Rashedi et al. [4]. This algorithm is based on Newtonian gravity: "Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them".

In this work, we briefly introduce GSA and propose an improved GSA (IGSA) based on a quasi-oppositional approach. Opposition-based learning [5] is a new search strategy, which has been applied to some population-based algorithms to improve their performance [6]-[8]. By adding the quasi-oppositional approach, IGSA increases the probability of escaping from local optimua.

To show the effectiveness of the proposed IGSA, we apply the classical GSA and the proposed IGSA to the design of the pole shape of a magnetizer. The version used here is based on the optimization problem described in [9],[10].

The rest of the paper is organized as follows. Section II briefly introduces the standard GSA and the proposed improved IGSA. In Section III, the case study of the magnetizer design is briefly described. Section IV presents the results and discussions. Finally, the conclusion and future work are summarized in Section V.

II. Fundamentals of the GSA and IGSA Approaches

In GSA, agents are considered as objects and their performance are measured by their masses, with all objects attracting each other by the gravity force, while this force causes a global movement of all objects towards the objects with heavier masses [9].

To describe the GSA, consider a system with N agents (masses) in which the position of the ith agent is represented by:

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

where n is the search space dimension and x_i^d defines the position of the ith agent in the dth dimension. At any time t the force acting between two masses is defined as:

(2)

where $G(t)$ is parameter which is slowly reduced during iterations, M is the mass, r is the distance and ε is a small parameter. It is then assumed that the total force acting on a mass is a randomly weighted sum of the individual forces (2), thus:

$$\mathbf{f}_i(t) = \sum_{j=1, j\neq i}^{N} r_j \cdot \mathbf{f}_{ij}(t) \tag{3}$$

This allows the update of velocities and positions according to:

$$\begin{aligned} \mathbf{v}_i(t+1) &= r_i \cdot \mathbf{v}_i(t) + \mathbf{a}_i(t) \\ \mathbf{x}_i(t+1) &= \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \end{aligned} \tag{4}$$

After this step masses are updated according to:

$$\begin{aligned} m_i(t) &= \frac{f_i(t) - w(t)}{b(t) - w(t)} \\ M_i(t) &= \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \end{aligned} \tag{5}$$

where b and w indicate the best and worst objective function values and f is the objective function. The procedure is then repeated until some convergence criterion is satisfied.

In order to improve the algorithm, we apply the principle of quasi-oppositional based learning (QOBL) [11] in order to utilize opposite numbers to describe the mass (agent) as it was found that the opposite of a random number is likely to be closer to the mass than the original random number.

III. Magnetizer Design

The aim of this design problem is to increase the magnetic flux through a magnetic pole to be designed. In this paper, the geometry of the pole to be designed is described by six design variables ($R_1,\ldots,R_6$) [10]. The required two dimensional magnetic field analysis is carried out using Matlab's PDE toolbox. The objective function (*fobj*) adopted in this minimization problem is given by

$$fobj = \frac{1}{1+mf} \qquad (1)$$

where *mf* is the maximum flux density.

IV. Optimization Results

The following setup is adopted for the GSA and IGSA approaches: G_0 is set to 100, α is set to 20, N is equal to 15, and the maximum of iterations is 50. With this setup, a stopping criterion of 750 objective function evaluations in each run is adopted. In IGSA, the adopted $prob_q$ value was 0.3. Tables I and II show the results over 30 runs, with bold font indicating the best results. It can be observed that the results of IGSA are better than those of GSA. Figs. 1 and 2 presented the best results using GSA and IGSA.

TABLE I
SIMULATION RESULTS OF F IN 30 RUNS

Optimization Method	*fobj*			
	Minimum (Best)	Mean	Maximum (Worst)	StandardD eviation
GSA	0.7005	0.7183	0.7960	3.404E-2
IGSA	**0.6584**	**0.6843**	**0.7958**	4.888E-2

TABLE II
BEST SOLUTIONS FOR MAGNETIZER DESIGN IN 30 RUNS

Design variable	GSA	IGSA
R_1	0.4636	0.4669
R_2	0.2723	0.2518
R_3	0.2632	0.3365
R_4	0.2951	0.3176
R_5	0.2764	0.2636
R_6	0.2712	0.2691
Objective function, *fobj*	0.7005	**0.7680**
Maximum flux density (T)	0.4274	**0.3020**

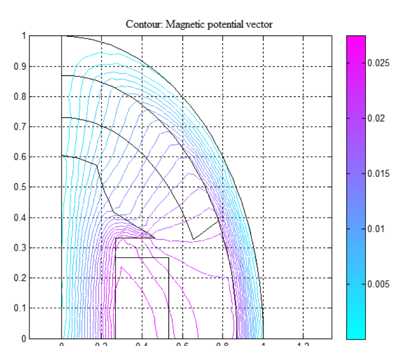

Fig. 1. Geometry of the best magnetizer shape obtained by GSA.

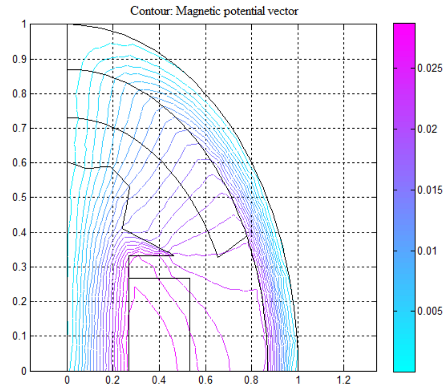

Fig. 2. Geometry of the best magnetizer shape obtained by IGSA.

V. Conclusion

Numerical tests with a magnetic pole design problem show that the proposed IGSA method offers good performance as well as robustness in the solution of the magnetizer design problem. The extended version of the paper will include a detailed description of the algorithm as well as further benchmark results and comparisons with competing metaheuristics.

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