Modified Social-Spider Optimization Algorithm Applied to Electromagnetic Optimization

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Social spider optimization (SSO) is a new nature-inspired algorithm of the swarm intelligence field to global optimization applications, based on the simulation of cooperative behavior of social-spiders. To enhance the performance of the standard SSO, a modified SSO (MSSO) approach based on beta distribution was proposed in this paper. In order to verify the performance of the MSSO, tests using Loney's solenoid benchmark and a brushless DC (Direct Current) motor benchmark are realized to evaluate the effectiveness of the SSO and the proposed MSSO. Simulation results and comparisons with the SSO demonstrated that the performance of the MSSO approach is promising in electromagnetics optimization.

***Index Terms*—Electromagnetic optimization, Metaheuristics, Social-spider optimization.**

I. Introduction

NATURE-INSPIRED ALGORITHMS of the swarm intelligence field perform powerfully and efficiently in solving global optimization problems. Recent research studies [1], [2] in optimization field have led to the development of new approaches that exhibit certain advantages over more traditional techniques in various aspects.

Recently, the social spider optimization (SSO), developed by Cuevas et al. [3], was proposed. SSO is a swarm intelligence method based on the features of cooperative behavior of social-spiders. Being a stochastic search process, SSO is not free from false and/or premature convergence, especially over multimodal fitness landscapes.

The main contribution of this paper is to modify the classical SSO to achieve a better exploration/exploitation trade-off when applied to continuous optimization problems. The proposed modified SSO (MSSO) is based on beta distribution to tune the control parameters. To demonstrate the effectiveness of the proposed MSSO, the Loney's solenoid problem [4], [5] and a brushless DC (Direct Current) motor optimization benchmark [6] are solved.

The remainder of this paper is organized as follows. Section II and III provide the description of the two optimization benchmarks. Section IV covers background information on the SSO and MSSO. Section V presents the results and discussions. Finally, we present concluding remarks on this work in Section VI.

II. Loney's Solenoid Design

Loney's solenoid benchmark problem is a testbed of the rough objective function surface typical of many electromagnetic problems. It is a numerically ill-conditioned problem to find the dimensions called position (l) and size (s) of two coils to generate possibly uniform magnetic field on the segment ($-z_0$, z_0). This is a minimization problem with non-analytical objective function. The box constraints are $0 \le s \le 20\,\text{cm}$ and $0 \le l \le 20\,\text{cm}$. . The upper half plane of the axial cross-section of the system is presented in Fig. 1.

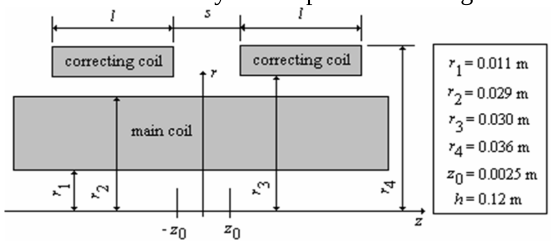

Fig. 1. Axial cross-section of Loney's solenoid (upper half-plane).

III. Brushless DC Motor Benchmark

This optimization problem is characterized by five continuous design variables. As variables are bore stator diameter (D_s), magnetic induction in the air gap (B_e), current density in the conductors (δ), magnetic induction both in the teeth (B_d) and back iron (B_{cs}). In this problem, the efficiency η of the motor is to be maximized (which is equivalent to minimizing the motor losses). Furthermore, the problem is subject to six inequality constraints which are related to technological, and operational and considerations regarding the specific wheel motor. Constraints are handled by a penalty method in the SSO and MSSO approaches.

IV. Description of the SSO and MSSO

In the following sub-sections, the procedures of the SSO and the MSSO are briefly described.

A. The Classical SSO

The steps of the classical SSO algorithm can be summarized as follows [3]:

Step 1: Initialize the male and female spiders in the population;
Step 2: Calculate the radius of mating;
Step 3: Calculate the fitness of each spider;
Step 4: Calculate the weight of every spider in terms of its

fitness;
Step 5: Move female spiders according to the female cooperative operator;
Step 6: Move male spiders according to the male cooperative operator;
Step 7: Perform the mating operation;
Step 8: If the stopping criteria is met, the process is finished; otherwise, go back to *Step 3*.

B. The Proposed Modified SSO (MSSO)

The balance between exploitation and exploration, yet preserving the same population, i.e. individuals who have achieved efficient exploration (female spiders) and individuals that verify extensive exploitation (male spiders) can be found using adaptive operators.

In the proposed MSSO, the control parameters α and β (details in [3]) are adjusted using beta distribution instead to random numbers between [0,1] as in the classical SSO. The use of the beta probability distribution [7] can be useful to preserve diversity, avoids the premature convergence and helps to explore hidden areas in the search space during the optimization process. Moreover, one advantage of beta distribution is that it describes probability densities with various shapes on the interval [0,1].

V. Optimization Results

In the following sub-sections, the results for the two optimization cases are presented.

A. Results for the Loney's Solenoid Design

The following parametric setup was used for tested SSO and MSSO approaches: population size equal to 20 spiders, 30 runs and the stopping criterion is 150 generations. In particular, three different basins of attraction of local minima can be recognized in the domain of f with values of $f > 4\cdot 10^{-8}$ (high level region), $3\cdot 10^{-8} < f < 4\cdot 10^{-8}$ (low level region), and $f < 3\cdot 10^{-8}$ (very low level region – global minimum region).

Table I summarizes the optimization results of SSO and MSSO. A result with boldface means the best values in terms of minimum and mean values in f found in Table I.

As seen from Table I, MSSO outperforms SSO in terms of the mean and minimum objective values in 30 runs. The best result (minimum) using MSSO presented $f = 2.0666\cdot 10^{-8}$ with $s = 11.4704$ cm and $l = 1.4347$ cm. On the other hand, the best f value using SSO was with $s = 11.4351$ cm and $l = 1.4148$ cm.

Table I
Results in Terms of the Objective Function in 30 runs

Optimizer	$f(s, l)\cdot 10^{-8}$			
	Minimum (Best)	Mean	Maximum (Worst)	Standard Deviation
SSO	3.8054	1784.9504	8412.3601	1680.9180
MSSO	**2.0769**	**539.1621**	7430.3010	1232.8103

B. Results for the Brushless DC Motor Design

The following parametric setup was used for tested SSO and MSSO approaches: population size equal to 25 spiders, 30 runs and the stopping criterion is 40 generations.

It can be observed in Table II that the best solution of the MSSO in 30 runs converged to the same solution found by SQP and ACO, which is most probably the global optimum of the problem. The best solution was D_s= 201.2 mm, B_e= 0.6481 T, δ = 2.0437 A/mm^2, B_d = 1.8 T and B_{cs} = 0.8959 T. In this case, the obtained total mass was 15 kg.

Table II
Results using Different Optimizers

Optimizer	η	*OF**
Sequential quadratic programming (SQP) [8]	95.32	90
Genetic algorithm (GA) [9]	95.31	3380
GA and SQP [9]	95.31	1644
Ant colony optimization (ACO) [10]	95.32	1200
Particle swarm optimization (PSO) [10]	94.98	1600
SSO	94.98	1000
The proposed MSSO	**95.32**	**1000**

* *OF*: number of evaluations of the objective function

VI. Conclusion

The computational drawbacks of classical derivative-based numerical methods to solve this optimization problem have forced the researchers all over the world to rely on metaheuristics.

The purpose of this work is to demonstrate the ability of the proposed MSSO to optimize the Loney's solenoid and a brushless DC motor benchmark. Based on preliminary results in Tables I and II, the MSSO offers good performance when compared with the other tested optimization approaches.

Future research may focus on integrating the MSSO with opposition mechanisms [11].

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