Enhanced Invasive Weed Optimization Algorithm Applied to Electromagnetic Optimization

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Abstract— **In recent years there has been extensive research on bio-inspired optimization algorithms. Invasive weed optimization (IWO) was recently proposed as a simple but powerful metaheuristic algorithm for real-parameter optimization. This paper proposes an enhanced IWO algorithm (EIWO), which combines the conventional IWO technique with a strategy using exponential distribution and opposition-based learning. Loney's solenoid benchmark problem is used to examine the effectiveness of the conventional IWO and the proposed EIWO algorithms. Simulation results and comparisons with EIWO demonstrate that the performance of the IWO approach is promising for electromagnetic design optimization.**

Index Terms— **Optimization, electromagnetic optimization, Loney's solenoid, invasive weed optimization.**

I. INTRODUCTION

A typical case study of the numerically ill-conditioned inverse problems in the electromagnetic field is Loney's solenoid benchmark problem [1],[2]. The computational drawbacks of classical derivative-based numerical methods to solve this optimization problem have forced researchers to rely on metaheuristics, since deterministic approaches are very likely to get trapped in a local optimum.

On the other hand, over the past decades, there has been continuos improvement in metaheuristics for tackling optimization problems. The invasive weed optimization (IWO) is a very recent metaheuristic algorithm proposed in [3] which is inspired by the phenomenon of colonization of invasive weeds in nature. However, it was pointed out that IWO usually suffers from premature convergence and tuning of its control parameters in order to avoid convergence to local optima.

In order to improve the global performance of conventional IWO, in this paper, a strategy based on exponential distribution and opposition-based learning is combined with the standard IWO (EIWO). To evaluate the efficiency of EIWO, both algorithms are applied to Loney's solenoid benchmark problem.

II. FUNDAMENTALS OF THE IWO AND EIWO

As described in [3], the IWO algorithm is an adaptive algorithm for function optimization based on the metaphor of natural biological evolution of weed colonizing opportunity spaces. IWO is capable of solving multi-dimensional, linear and nonlinear optimization problems with appreciable efficiency. In the following sub-sections, the IWO is first described and then the fundamentals of the proposed EIWO are provided.

A. IWO

The detailed steps of the IWO may be summarized as follows [3]-[5]:

Step 1 (Initialization): A finite number of weeds are initialized randomly with uniform distribution in the search space. This initial population of each generation is $X=\{x_1, x_2, \ldots x_m\}$.

Step 2 (Reproduction): Each member of the population is allowed to produce seeds within a specified region centered at its own position. The number of seeds produced by x_i, $i=\{1, 2,\ldots, m\}$, depends on its relative fitness in the population with respect to the best and worst fitness. The number of seeds produced by any weed varies linearly from *min_seed* to *max_seed* with *min_seed* for a weed with worst fitness and *max_seed* for a weed with best fitness in the population.

Step 3 (Spatial dispersal): The generated seeds are randomly scattered with a normal distribution over the search space. The mean of distribution is equal to the location of parent plant, but standard deviation σ is applied to decrease over the generations in the following manner. If $\sigma_{\max}$ and $\sigma_{\min}$ are the maximum and minimum standard deviations, then the standard deviation in a particular generation (or iteration given by *iter*) is given by

$$\sigma_{iter} = \sigma_{\min} + \left(\frac{iter_{\max} - iter}{iter_{\max}}\right)^{nmi} \cdot \left(\sigma_{\max} - \sigma_{\min}\right) \qquad (1)$$

where *nmi* represents the non-linear modulation index. This step ensures that the probability of dropping a seed in a distant area decreases nonlinearly so that the algorithm gradually moves from exploration to exploitation with increasing generations.

Step 4 (Competitive exclusion): In competitive exclusion, there is a kind of competition between plants to limit the maximum number of plants in the population.

Step 5 (Termination condition): The whole process continues until the maximum number of iterations has been reached, and we hope that the weed with the best fitness is the closest one to the optimal solution.

B. The proposed EIWO

The conventional IWO presents certain drawbacks usually related to the possibility of premature convergence to a local optima. To overcome this difficulty, in this paper we propose a variant, implemented in Matlab, called EIWO, which uses an exponential distribution and opposition-based learning.

The exponential family is a practically convenient and widely used unified family of distributions on finite dimensional Euclidean spaces parametrized by a finite dimensional parameter vector. Specialized to the case of the real line, the exponential family contains as special cases most of the continuous distributions used for practical modeling, such as the normal, Poisson, binomial, exponential and gamma [6]. The exponential distribution is often used to model the insurance risks. However, in recent years, researchers have proposed the use of distributions in metaheuristics design such as Evolutionary Programming [7],[8] and Particle Swarm Optimization [9]. In the EIWO algorithm, the exponential distribution is used in *Step 3 (Spatial dispersal)* of the conventional IWO instead of the Gaussian distribution.

Furthermore, opposition-based learning (OBL), originally introduced in [10],[11], has proven to be an effective method to improve metaheuristics for some optimization problems (e.g. [12]-[14]). The concept of OBL is general enough that it can be utilized in a wide range of learning and optimization fields to make these algorithms faster. The main idea behind OBL is the simultaneous consideration of an estimate and its corresponding opposite estimate in order to achieve a better approximation for the current candidate solution.

By adding the OBL approach, EIWO increases the probability of escaping from the local optimum enhancing the exploration ability. In the EIWO procedure, the OBL is applied after the *Step 4 (Competitive exclusion)* of the conventional IWO with an application probability set to 0.1 (10%).

III. LONEY'S SOLENOID DESIGN

Loney's solenoid design problem, shown in Fig. 1, consists in determining the position and size of two coils to generate a uniform magnetic flux density within a given interval on the axis of a main solenoid.

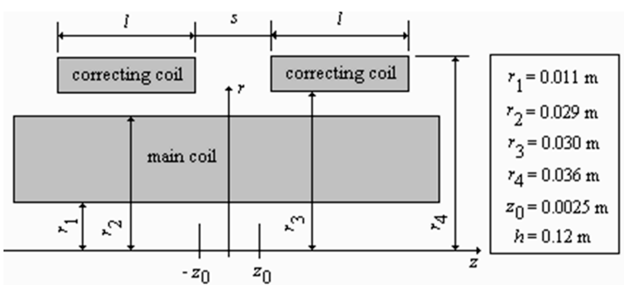

Fig. 1. Axial cross-section of Loney's solenoid (upper half-plane).

We used the following parameter setup for IWO and EIWO: the number of independent runs is 100, the initial number of plants is 10, the minimum (*min_seed*) and maximum (*max_seed*) number of plants are 1 and 30, respectively; the maximum number of iterations is equal to 300, and stopping criterion is set to 9,000 objective functions evaluations in each run. The initial (σ_{max}) and final (σ_{min}) values of standard deviations are 1 and 0.1, respectively.

The objective function F has a global minimum region with $F < 3\cdot10^{-8}$ [2]. Table I summarizes the optimization results of IWO and EIWO. Boldface indicates the best value found in Table I. As seen from Table I, on all benchmark test functions, EIWO outperforms IWO clearly. The best result (minimum) using EIWO presented $F = 2.0643\cdot10^{-8}$ with s = 11.4919 cm and l = 1.4469 cm. On the other hand, the best F using IWO was with s = 11.8447 cm and l = 1.6680 cm.

TABLE I
RESULTS IN TERMS OF THE OBJECTIVE FUNCTION IN 100 RUNS

Approach	$F(s, l)\cdot10^{-8}$			
	Maximum (Worst)	Mean	Minimum (Best)	StandardD eviation
IWO	206.9186	9.1236	2.1236	25.4916
EIWO	5.1317	**4.2187**	**2.0643**	4.7701

IV. CONCLUSION

The purpose of this work is to demonstrate the ability of the proposed EIWO to optimize Loney's solenoid benchmark problem. It is clear from the optimization results obtained that the proposed EIWO algorithm offers good performance and is free from the shortcoming of premature convergence exhibited by the conventional IWO algorithm. The extended paper will provide more algorithmic details, further benchmark results and comparisons with competing metaheuristics.

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