Enhanced Flower Pollination Approach Applied to Electromagnetic Optimization

Carlos Eduardo Klein[1], Emerson Hochsteiner de Vasconcelos Segundo[2], Viviana Cocco Mariani[2,3] and Leandro dos Santos Coelho[1,3]
[1]*Pontifical Catholic University of Parana, Industrial and Systems Eng. Graduate Program (PPGEPS), Curitiba, PR, Brazil*
[2]*Pontifical Catholic University of Parana, Mechanical Engineering Graduate Program (PPGEM), Curitiba, PR, Brazil*
[3]*Federal University of Parana (UFPR), Department of Electrical Engineering (DEE/PPGEE), Curitiba, PR, Brazil*

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Abstract: It is difficult to use the deterministic mathematical tools such as a gradient method to solve global optimization problems. Flower pollination algorithm (FPA) is a new nature-inspired algorithm of the swarm intelligence field to global optimization applications, based on the characteristics of flowering plants. To enhance the performance of the standard FPA, an enhanced FPA (EFPA) approach based on beta probability distribution was proposed in this paper. In order to verify the performance of the proposed EFPA, five benchmark functions are chosen from the literature as the test suit. Furthermore, tests using Loney's solenoid benchmark, a classical problem in the electromagnetics area, are realized to evaluate the effectiveness of the FPA and the proposed EFPA. Simulation results and comparisons with the FPA demonstrated that the performance of the EFPA approach is promising in electromagnetics optimization.

1 INTRODUCTION

Swarm intelligence is the collective behaviour of a decentralized, self-organized system, and it is able to distribute the functionality of an overall big system among smaller, less-expensive and cooperative agents (Weng et al., 2014). Swarm behavior is one of the main features of many species in the nature. In this context, swarm intelligence originated from the study of colonies or swarms of social organisms (Engelbrecht, 2007).

Nature-inspired algorithms of the swarm intelligence field perform powerfully and efficiently in solving global optimization problems. Recent research studies in optimization field have led to the development of new approaches that exhibit certain advantages over more traditional techniques in various aspects. Inspired by nature, these metaheuristic algorithms have obtained promising performance over continuous domains of optimization problems, such as ant colony (Dorigo and Stützle, 2004), artificial bee colony (Karaboga, 2005), krill heard (Gandomi and Alavi, 2012), bat algorithm (Gandomi and Yang, 2014), cuckoo search algorithm (Coelho et al., 2013), bat algorithm (Yang, 2010), and firefly algorithm (Yang, 2009).

In the nature, many floral traits are related to the pollination and fertilization processes, i.e. floral traits can be adjusted by selection to ensure pollen transfer, the subsequent growth of pollen tubes through the pistil, and finally ovule fertilization (Fernández et al., 2009). Pollination is a process of transfer of pollen from male parts of flower called anther to the female part called stigma of a flower. Pollination of flowers can be inspiration to generate new optimization algorithms. Examples of algorithms based on pollination are presented in Kasinger and Bauer (2006) and Kaur and Singh (2012).

Recently, the flower pollination algorithm (FPA), developed by Xin-She Yang (Yang, 2012), was proposed. FPA is a swarm intelligence method based on the features of flowering plants. Being a stochastic search process, FPA is not free from false and/or premature convergence, especially over multimodal fitness landscapes.

The aim of this paper is to improve the FPA to achieve a better exploration/exploitation trade-off when applied to continuous optimization problems. The proposed enhanced FPA (EFPA) is based on beta probability distribution. To demonstrate the effectiveness of the proposed EFPA framework, a

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set of two benchmark functions and a numerically ill-conditioned inverse problem in the electromagnetic field called Loney's solenoid benchmark problem (Di Barba and Savini, 1995; Ciuprina et al., 2002) are solved. Loney's solenoid benchmark problem is a significant testbed of the rough objective function surface typical of many electromagnetic problems. Such problem are ideally suited for stochastic techniques which escape from local minima. Optimization results and convergence performance are compared with the classical FPA.

The remainder of this paper is organized as follows. Section 2 covers background information on the FPA and EFPA. Section 3 provides the description of the Loney's solenoid benchmark. Section 4 presents the simulation results and discussions. Finally, we present concluding remarks on this work in Section 5.

2 FPA AND EFPA ALGORITHMS

Swarm intelligence is based on self-organized individuals, generally called agents, whose actions and interaction add up to intelligent global behavior. In particular, agents communicate to one another merely by modifying their local environment. These local interactions finally yield to the global self-properties that make a system self-managing.

This section describes the classical FPA and the proposed EFPA, both swarm intelligence approaches. First, the fundamentals of the FPA are introduced, and finally the mechanisms of the proposed EFPA are mentioned.

2.1 FPA

FPA is a swarm intelligence inspired paradigm by the flow pollination process of flowering plants. FPA is useful to solve multimodal continuous optimization problems. For simplicity, we use the following four rules in the FPA, all rules suggest by Yang (2012):

1. Biotic and cross-pollination can be considered as a process of global pollination process, and pollen-carrying pollinators move in a way which obeys Lévy flights (*Rule 1*).
2. For local pollination, abiotic and self-pollination are used (*Rule 2*).
3. Pollinators such as insects can develop flower constancy, which is equivalent to a reproduction probability that is proportional to the similarity of two flowers involved (*Rule 3*).
4. The interaction or switching of local pollination and global pollination can be controlled by a switch probability p in the range [0, 1], with a slight bias towards local pollination (*Rule 4*).

In reality, each plant can have multiple flowers, and each flower patch often release millions and even billions of pollen gametes. However, for simplicity, we assume that each plant only has one flower, and each flower only produce one pollen gamete (Yang, 2012).

In order to formulate updating formulas, we have to convert the aforementioned rules into updating equations. For example, in the global pollination step, flower pollen gametes are carried by pollinators such as insects, and pollen can travel over a long distance because insects can often fly and move in a much longer range (Yang, 2012). Therefore, *Rule 1* and flower constancy can be represented mathematically as:

$$x_i(t+1) = x_i(t) + \gamma \cdot L(\lambda) \cdot [x_i(t) - B] \quad (1)$$

where $x_i(t)$ is the pollen i or solution vector x_i at iteration t, and B is the current best solution found among all solutions at the current generation/iteration. Here γ is a scaling factor to control the step size. In addition, $L(\lambda)$ is the parameter that corresponds to the strength of the pollination, which essentially is also the step size. Since insects may move over a long distance with various distance steps, we can use a Lévy flight to imitate this characteristic efficiently.

The Lévy distribution, named for the French mathematician Paul Lévy (Lévy, 1925), is important in the study of Brownian motion. Lévy stable distribution (Nolan, 2010) is a rich class of probability distributions. It is worthy of noting that the well-known Gaussian and Cauchy distributions are its special cases.

A Lévy flight is a random walk in which the step-lengths have a probability distribution that is heavy-tailed. That is, we draw L>0 from a Lévy distribution:

$$L \sim \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{S^{1+\lambda}}, (S >> S_0 > 0) \quad (2)$$

Here, $\Gamma(\lambda)$ is the standard gamma function, and this distribution is valid for large steps $S > 0$. Then, to model the local pollination, both *Rule 2* and *Rule 3* can be represented as

$$x_i(t+1) = x_i(t) + U \cdot [x_j(t) - x_k(t)] \quad (3)$$

where $x_j(t)$ and $x_k(t)$ are pollen from different flowers of the same plant species. This essentially imitates the flower constancy in a limited neighborhood (Abdel-Raouf et al., 2014).

In order to imitate this, we can effectively use the switch probability like in *Rule 4* or the proximity probability p to switch between common global pollination to intensive local pollination.

The procedure for implementing the FPA can be summarized by the following steps:

Step 1: Initialization of a population of flowers/pollen gametes: Initialize a vectors population (floating-point representation) of flowers/pollen gametes in the n-dimensional problem space using uniform probability distribution function. The counter of generations t is initialized too.

Step 2: Evaluation of population's fitness: Evaluate each flower's fitness value.

Step 3: Determine the best solution in the population: Find the best solution B in the initial population.

Step 4: Apply local or global pollination: Randomly with a switch probability p if a global pollination using Lévy distribution is applied or a local pollination using a uniform probability distribution function. This procedure is applied to all flowers in the population. Update $t = t + 1$;

Step 5: Repeating the evolutionary cycle: Return to *Step 2* until a stopping criterion is met. In this paper, evolutionary process is performed predefined maximum number of generations (adopted as stopping criterion) t_{max} is reached.

2.2 Proposed EFPA

In spite of the prominent merits, sometimes FPA shows the premature convergence and slowing down of convergence as the region of global optimum is approached. In this context, a trade-off between exploration and exploitation actions must be developed. Exploration is the process of visiting entirely new regions of a search space, whilst exploitation is the process of visiting those regions of a search space within the neighborhood of previously visited points.

In the classical FPA, the proximity probability p is constant during the optimization process and p takes values in the range [0, 1]. However, no optimal choice of p was proposed in Yang (2012). This means p is strongly problem-dependent and the user should choose p carefully after some trial and error tests.

In this paper, the proposed EFPA presents three modifications in *Step 4* in relation to the classical FPA using beta probability distribution. The use of the beta probability distribution (Ali, 2007) can be useful to preserve diversity and helps to explore hidden areas in the search space. The modifications are the following:

1. The EFPA incorporates the tuning of p during the evolutionary cycle given by:

$$p = \left[0.5 \cdot (t / t_{\max}) + 0.5\right] \cdot \beta(r, 0.1 \cdot r) \tag{4}$$

where $\beta(r, 0.1 \cdot r)$ is a beta distribution probability, r is a random number generated with uniform distribution in range [0,1], r and $0.1 \cdot r$ are beat distribution parameters (see script *betarnd* in MatLab environment).

2. The EFPA uses beta distribution probability instead of Lévy distribution (see equation (1)) to global pollination given by:

$$x_i(t+1) = x_i(t) + \chi \cdot \beta(r, 0.1 \cdot r) \cdot [x_i(t) - B] \tag{5}$$

where χ is a scale parameter (adopted χ =1.6 in this paper).

3. The EFPA uses beta distribution probability instead of uniform probability distribution (see equation (3)) to local pollination given by:

if $ra > 0.7$ then
$\quad \delta = 1$
else
$\quad \delta = \left[0.5 \cdot (t / t_{\max}) + 0.5\right]$
end
$x_i(t+1) = x_i(t) + \delta \cdot \beta(r, 0.1 \cdot r) \cdot [x_j(t) - x_k(t)]$

where ra is a random number generated with uniform distribution in range [0,1] and δ is a scale parameter.

3 LONEY'S SOLENOID DESIGN

Loney's solenoid design problem is 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.

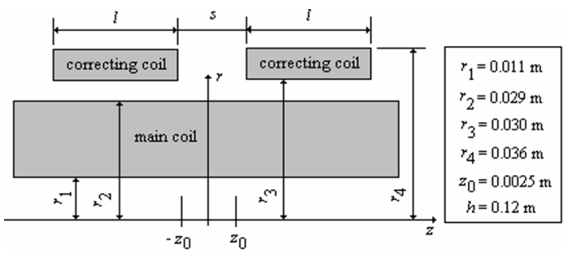

Figure 1: Axial cross-section of Loney's solenoid (upper half-plane).

4 OPTIMIZATION RESULTS

In the following sub-sections, the optimization results are presented and discussed.

4.1 Benchmark Functions Results

The performance of the EFPA and the classical FPA has been analyzed over five benchmarks functions (minimization problems) applied to dimension equal to 10. The optimization methods, EFPA and FPA, were employed using the following parameter settings: population size equal to 50 flowers and the stopping criterion is 2,000 generations.

Fifty independent runs of each algorithm on each problem are taken. The minimum, maximum, mean and the standard deviation of the best objective function values (50 runs) are presented in Tables 1-5. Best entries have been marked in boldface in Tables 1-5. A closed look in Tables 1-5 reveals that the EFPA has the ability to avoid local optima and it presents superior performance when compared with the FPA. However, FPA presents a promising performance in the Griewank case.

Table 1: Results of f_1 (Rastrigin function).

Index	FPA	EFPA
Maximum (Worst)	35.81	8.19×10^{-12}
Mean	19.44	$\mathbf{2.22\times10^{-13}}$
Minimum (Best)	3.98	**0**
Standard Deviation	7.61	1.17×10^{-12}

Table 2: Results of f_2 (Ackley function).

Index	FPA	EFPA
Maximum (Worst)	6.28	8.99×10^{-13}
Mean	3.31	$\mathbf{1.07\times10^{-13}}$
Minimum (Best)	4.93×10^{-12}	$\mathbf{7.99\times10^{-15}}$
Standard Deviation	1.44	1.71×10^{-13}

Table 3: Results of f_3 (Sphere function).

Index	FPA	EFPA
Maximum (Worst)	100	0
Mean	140	**0**
Minimum (Best)	**0**	**0**
Standard Deviation	35.05	0

Table 4: Results of f_4 (Griewank function).

Index	FPA	EFPA
Maximum (Worst)	6.65×10^{-1}	7.40×10^{-3}
Mean	2.19×10^{-1}	$\mathbf{6.57\times10^{-4}}$
Minimum (Best)	3.94×10^{-2}	**0**
Standard Deviation	1.42×10^{-1}	2.05×10^{-3}

Table 5: Results of f_5 (Rosenbrock function).

Index	FPA	EFPA
Maximum (Worst)	408.49	1.29
Mean	31.22	$\mathbf{6.18\times10^{-2}}$
Minimum (Best)	1.86×10^{-2}	$\mathbf{6.15\times10^{-6}}$
Standard Deviation	69.57	1.99×10^{-1}

4.2 Loney's Solenoid Results

We used the following parametric setup for tested FPA and EFPA to optimize the Loney's solenoid benchmark problem (with dimension equal to 2): population size equal to 20 flowers 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 $f>4\cdot10^{-8}$ (high level region), $3\cdot10^{-8} < f < 4\cdot10^{-8}$ (low level region), and $f < 3\cdot10^{-8}$ (very low level region – global minimum region) (Coelho and Alotto, 2007).

Table 6 summarizes the optimization results of FPA and EFPA. A result with boldface means the best values in terms of minimum and mean values in f found in Table 6.

As seen from Table 6, EFPA outperforms FPA clearly. The best result (minimum) using EFPA presented $f = 2.0666\cdot10^{-8}$ with s = 11.6013 cm and l=1.5110 cm. On the other hand, the best f using FPA was with s = 12.3459 cm and l = 2.0691 cm.

Table 6: Results of Loney's solenoid problem.

Approach	$F(s, l)\cdot10^{-8}$			
	Maximum (Worst)	Mean	Minimum (Best)	Standard Deviation
FPA	3.9526	3.4920	2.2524	0.5259
EPFA	3.9952	**3.0206**	**2.0666**	0.6098

5 CONCLUSION

Although during the last years, research on and with swarm intelligence has reached an impressive state, there are still many open problems, and new application areas are continually emerging for the optimization paradigms.

We undertook a comparative study of EFPA with classical FPA over a test-suite comprising 5 well-known numerical benchmarks and the Loney's solenoid problem. Our simulation results indicate that the EFPA remains always better than FPA. In near future, we are planning to compare the EFPA with good performing algorithms available in literature, such differential evolution and covariance matrix adaptation evolution strategy.

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