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Tuning Exploitation and Exploration for Flower Pollination Algorithm: A Case Study on Function Optimization Problem

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ABSTRACT

Nature has exposed various progression to the researchers around the world. For solving diverse types of problems, many nature inspired algorithms are used. Swarm Intelligence (SI) Algorithms generally evolve from the biological behavior of nature. These algorithms use Probabilistic search methods which is used to resemble the behavior of biological entities. Flower Pollination Algorithm is one of them. Flower pollination can take place either in two ways: Global Pollination and Local Pollination. This paper has experimented with different mix of global and local operations to discover their optimal proportion for different uni-modal and multi-modal problems and with different search space size.

General Terms:

Algorithms, Artificial Intelligence, Genetic Algorithm, Optimization

Keywords

Meta-heuristics Algorithm, Flower Pollination Algorithm, Bioinformatics, Swarm Intelligence

1. INTRODUCTION

Optimization Problems are becoming more and more complex as they are becoming difficult to solve, even in hyper-polynomial time variants. Nature inspired optimization algorithms provide great results in comparison to other optimization algorithms [1] [2] [3]. Flower Pollination Algorithm is inspired by the pollination process of flowers. Pollination is the act of transferring pollen grains from the male anther of a flower to the female stigma [5]. The goal of every living organism, including plants, is to create offspring for the next generation. One of the ways that plants can produce offspring is by making seeds. Seeds contain the genetic information to produce a new plant [?].

The performance of the Flower Pollination Algorithm in terms of different probability values for exploitations and explorations is compared in this paper. This paper has designed a comparative study to identify with which probability value Flower Pollination Algorithm can attain the best optimized result for different uni-modal and multi-modal problem variants.

The rest of this paper is organized as follows. Section 2 describes the Flower Pollination Algorithm. Section 3 provides details of the simulation and analysis of this algorithm having different values of probability on the benchmarking problems, parameter settings of the algorithms and compares their results. Finally, section 4 draws the outcomes of this paper with a few comments and suggestions on future research.

2. FLOWER POLLINATION ALGORITHM

2.1 Characteristics of Flower Pollination

Flowers are the agents that plants use to make their seeds. Seeds can only be produced when pollen is transferred between flowers of the same species. A species is defined a population of individuals capable of interbreeding freely with one another but because of geographic, reproductive, or other barriers, they do not interbreed with members of other species.

Flowers must rely on vectors to move pollen. These vectors can include wind, water, birds, insects, butterflies, bats, and other animals that visit flowers. Animals or insects that transfer pollen from plant to plant "pollinators" [?]. Pollinators can be very diverse. It is estimated that there are at least of two hundred thousand varieties of pollinator exist in nature.

Pollination is usually the unintended consequence of an animal's activity on a flower. The pollinator is often eating or collecting pollen for its protein and other nutritional characteristics or it is sipping nectar from the flower when pollen grains attach themselves to the animal's body. When the animal visits another flower for the same reason, pollen can fall off onto the flower's stigma and may result in successful reproduction of the flower.

Pollen must be transferred from a flower's stamen to the stigma to initialize the pollination process. When pollination occurs in the same plant then it is called self-pollination and when pollen from a plant is transferred to a different plant then that process is known as cross-pollination.

There are two types of pollination — Biotic Pollination process and Abiotic Pollination process [?] [8] [9]. In Biotic pollination, pollen is carried to the stigma by insects and animals and in Abiotic pollination, pollination occurs via wind or diffusion in water [?]. Biotic, cross-pollination may be happened in long distance. Bees, bats, birds and flies are mostly used as pollinators which are able to fly a long distance. So, these pollinators are considered as the carrier of the global pollination [?] [5].

Xin-She Yang describes this flower constancy and pollinator behavior in the pollination process into the following four rules:

(1) Biotic and cross-pollination is considered as global pollination process with pollen-carrying pollinators performing Lévy flights.
(2) Abiotic and self-pollination are considered as local pollination.
(3) Flower constancy can be considered as the reproduction probability is proportional to the similarity of two flowers involved.

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(4) Local pollination and global pollination is controlled by a switch probability $p \in$ [0,1]. Besides the physical proximity and other factors like wind and water, local pollination can have a significant fraction p in the overall pollination process.

2.2 Global Pollination and Local Pollination

The two key steps in flower pollination algorithm are: Global Pollination Process and Local Pollination Process [**?**]. In global pollination process, flower pollens are carried by pollinators so they may travel over a long distance because pollinators can often fly and move in longer range. This global pollination can be represented mathematically as

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(x_i^t - g_*) \tag{1}$$

Here x_i^t is the pollen i or solution vector x_i at iteration t, and g^* is the current best solution found among all solutions at the current iteration. Here λ is a scaling factor to control the step size. Hence, parameter $L(\lambda)$ is also the step size which corresponds to the strength of the pollination [**?**] [**?**] [**?**]. Since pollinators can be travelled over a long distance with different distance steps. Here, Lévy flight can be used to mirror this travelling characteristic. Assuming $L > 0$ from a Lévy distribution

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

Here, $\Gamma(\lambda)$ is the standard gamma function and Lévy distribution is valid for long steps $S > 0$. Therefore, Rule 2 and Rule 3 which are basically for the local pollination can be represented like

$$x_i^{t+1} = x_i^t + \epsilon(x_j^t + x_k^t) \tag{3}$$

Here, x_j^t and x_k^t are pollen from different flowers of the same plant species. The equation narrates flower constancy in limited neighborhoods [**?**]. Assuming in mathematically if x_j^t and x_k^t comes from the same species or selected from the same population, this equivalently becomes a local random walk if a graph can be drawn ϵ from a uniform distribution in [0,1]. The pseudo code of the flower pollination algorithm is given below.

2.3 Pseudo Code of Flower Pollination Algorithm

In reality every plant can have multiple flowers and each flower patch can release millions and billions of pollen gametes. However, to eliminate the complexity, Xin-She Yang assumed that each plant has only one flower and each flower only produce one gamete.So there is no necessity to distinguish between a pollen gamete or a flower or a plant.

For the simplicity one pollen gamete is characterised by x_i. The most fittest solution is g_*

In Algorithm 1 we have described the Flower Pollination Algorithm in details.

Algorithm 1 Flower Pollination Algorithm

```
Objective min or max f(x), x = (x_1, x_2 ..., x_d)^t
Initialize a population of n flowers/pollen gametes with random solutions
Find the best solution g_* in the initial population
Define a switch probability p ∈ [0,1]
while (t < MaxGeneration))
    for i = 1 : n (all n flowers in the population)
      if (rand < p)
         Draw a (d-dimensional) step vector L which obeys a Lévy distribution
         Global pollination via x_i^{t+1} = x_i^t + L(g_* - x_i^t)
      else
         Draw ε from a uniform distribution in [0,1]
         Randomly choose j and k among all the solutions
         Local pollination via x_i^{t+1} = x_i^t + ε(x_j^t - x_k^t)
      end if
      Evaluate new solutions
      if new solutions are better, update them in the population
    end for
    Find the current best solution g_*
end while
```

3. SIMULATION AND ANALYSIS

3.1 Benchmark Functions

To evaluate that this procedure truly provides better result than the standard algorithm, we will be taking help from benchmark functions. A set of four benchmark functions suit consisting of uni-modal, multi-modal, high dimensional, low dimensional optimization functions is used by this paper and has tested whether the results have been improved or not.

A uni-modal function has only one local optimum whereas multi-modal has multiple local optima.

The search process must be able to avoid getting trapped at regions around local minima to reach global minima in multi-modal functions.

The analytical form each function, along with their names and bounds of search space of the functions are shown in Table 1.

For all the functions the global minimum value f_{min} is 0.0. The benchmark functions that we will be using are shown in Table 1 as follows:

3.2 Parameter Settings

The Algorithm is tested with 100 independent runs on each of the test functions listed in Table 1. The swarm size (i.e., no. of candidate solutions) is set to 25. The number of generations is set to 1000, 1500 and 2000 for D = 10, 30 and 50 respectively for each run. We have used probability value p as 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.9 in the simulation.

3.3 Experimental Results

For any swarm intelligence algorithm, there should be a coordination between the degrees of explorations and exploitations with which the swarm members search across the search space.

Too much exploitation may cause the algorithm to be captured around the locally optimal points, which makes it difficult or even impossible to find the global optimum. On the other hand, too much exploration slows down the convergence speed and compromise the overall search performance.

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Table 1. : Benchmark functions used in the experimental studies. Here, D: Dimensionality of the Function, S: Search Space, C: Function Characteristics with Values — U: Uni-modal and M: Multi-modal.For all the function $f_{min} = 0.0$

Function No	***Function Name***	***D***	***C***	***S***	***Function Definition***
f_1	Rastrigin	10,30,50	M	$[-15, 15]^D$	$f_1(x) = 10d + \sum_{i=1}^{d}(x_i^2 - 10cos(2\pi x_i))$
f_2	Sphere	10,30,50	U	$[-5.12, 5.12]^D$	$f_2(x) = \sum_{i=1}^{d} x_i^2$
f_3	Zakharov	10,30,50	U	$[-5, 10]^D$	$f_3(x) = \sum_{i=1}^{d} {x_i}^2 + (\sum_{i=1}^{d} 0.5ix_i)^2 + (\sum_{i=1}^{d} 0.5ix_i)^4$
f_4	Michalewicz	10,30,50	M	$[0, \pi]^D$	$f_4(x) = -\sum_{i=1}^{d} \sin(x_i)sin^{2m}(\frac{ix_i^2}{\pi})$

Flower Pollination Algorithm controls the degrees of explorations and exploitations with a switch probability p. In FPA the global and local pollination technique is used to balance between explorations and exploitations.

In global pollination, the Lévy distribution is applied to generate new solutions; while in local pollination new solutions are generated using randomly selected local solutions. The Lévy distribution has the capability to generate new solutions with bigger mutation step size. Thus the algorithm is more likely to escape from the locally optimal points.

For simulation, four benchmark functions have been used in this experiment. Among them Sphere Function and Zakharov Function are uni-modal and Rastrigin Function and Michalewicz Function are multi-modal. In Table 2 and Table 3 , it can be seen that the solution quality (mean value) is much better for Probability values lower for the uni-modal function and higher for the multi-modal function. Also the probability decreases inversely with the dimension can be observed by the values of this tables.

In this paper, the values of minimum mean with reference to probability in different dimensions for the four functions is plotted to gather some knowledge in which values of p the functions gives the best result.

For uni-modal functions,

Figure 1 shows that the value of f_{min} increases with the increase of probability.So it may be expected that the best result may be obtain from probability value 0.1.

Figure 2 shows that the value of f_{min} decreases with the increase of probability upto it reaches a neighbouring area of probability 0.5 for dimension 10 and dimention 30.But for dimension 50 the value of f_{min} increases with probability.So the best result may be obtained from probability value 0.5 for dimension 10 and dimension 30 and for dimension 50 the value of p may be 0.1 to 0.4 to obtain the best result can be expected.

For multi-modal functions,

Figure 3 shows that the value of f_{min} decreases with the increase of probability upto it reaches a neighbouring area of probability 0.5. After that it starts increasing again with the probability. So the best result may be obtain from probability value 0.5.

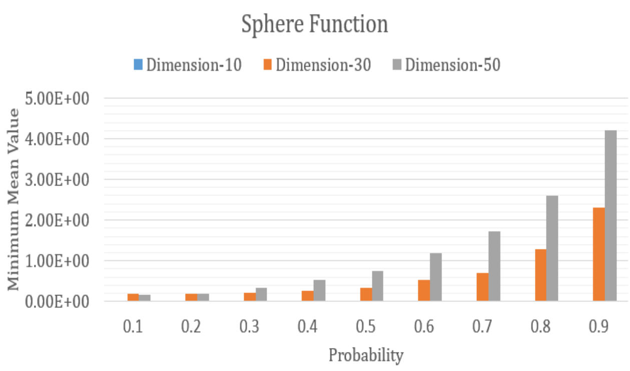

Fig. 1: Sphere Function

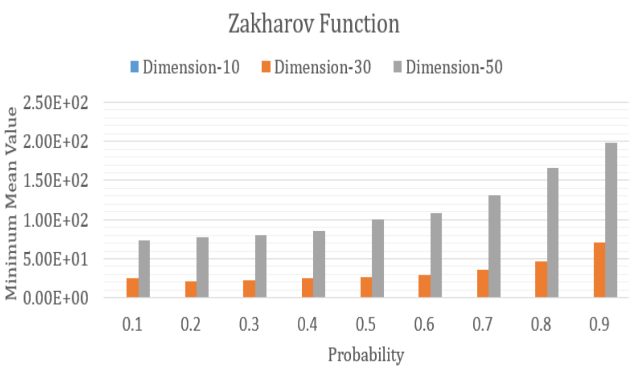

Fig. 2: Zakharov Function

Figure 4 shows that the value of f_{min} decreases with the increase of probability upto 0.5.After that it starts increasing again. So the best result may be obtain from probability value 0.5 can be expected.

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Table 2. : Comparison of Probability p used in FPA on four standard benchmark functions. Algorithms are run 100 different times on each of the functions. The best result for each probability with each dimensionality is marked with boldface font.

Function Number	***Function Name***	***Probability***	***Dimension***	***Best***	***Worst***	***Mean***	***Median***	***SD***
1	Rastrigin	0.1	10	1.75E+01	6.21E+01	3.20E+01	3.14E+01	7.86E+00
		0.2		1.16E+01	4.89E+01	2.60E+01	2.56E+01	6.69E+00
		0.3		1.34E+01	3.47E+01	2.25E+01	2.18E+01	5.11E+00
		0.4		9.36E+00	3.34E+01	2.03E+01	1.95E+01	4.95E+00
		0.5		1.00E+01	3.46E+01	2.03E+01	1.91E+01	5.23E+00
		0.6		9.62E+00	3.15E+01	**2.01E+01**	2.01E+01	5.09E+00
		0.7		1.18E+01	3.05E+01	2.03E+01	1.95E+01	4.44E+00
		0.8		1.12E+01	3.52E+01	2.37E+01	2.31E+01	4.95E+00
		0.9		2.27E+01	5.56E+01	3.81E+01	3.76E+01	6.49E+00
		0.1	30	1.04E+02	2.27E+02	1.60E+02	1.61E+02	2.34E+01
		0.2		8.58E+01	1.86E+02	1.35E+02	1.36E+02	2.20E+01
		0.3		6.66E+01	2.05E+02	1.27E+02	1.29E+02	2.46E+01
		0.4		7.84E+01	1.72E+02	1.21E+02	1.20E+02	2.02E+01
		0.5		7.16E+01	1.72E+02	**1.17E+02**	1.16E+02	1.91E+01
		0.6		8.02E+01	1.95E+02	1.20E+02	1.19E+02	2.06E+01
		0.7		7.79E+01	1.88E+02	1.22E+02	1.22E+02	1.94E+01
		0.8		9.51E+01	2.07E+02	1.39E+02	1.38E+02	1.95E+01
		0.9		1.56E+02	2.57E+02	1.94E+02	1.90E+02	1.90E+01
		0.1	50	1.64E+02	3.50E+02	2.59E+02	2.57E+02	3.80E+01
		0.2		1.47E+02	3.19E+02	2.30E+02	2.30E+02	3.26E+01
		0.3		1.34E+02	3.09E+02	2.15E+02	2.14E+02	3.32E+01
		0.4		1.38E+02	2.65E+02	2.06E+02	2.07E+02	2.73E+01
		0.5		9.23E+01	2.82E+02	2.08E+02	2.09E+02	3.06E+01
		0.6		1.51E+02	2.83E+02	**2.05E+02**	2.01E+02	2.87E+01
		0.7		1.36E+02	2.80E+02	2.12E+02	2.09E+02	2.67E+01
		0.8		1.76E+02	3.11E+02	2.37E+02	2.37E+02	2.82E+01
		0.9		2.45E+02	3.79E+02	3.08E+02	3.07E+02	2.73E+01
2	Sphere	0.1	10	2.45E-04	1.30E-02	2.57E-03	2.13E-03	1.75E-03
		0.2		3.29E-05	8.31E-04	1.68E-04	1.33E-04	1.35E-04
		0.3		4.14E-06	1.08E-04	2.12E-05	1.64E-05	1.76E-05
		0.4		1.02E-06	6.47E-05	6.98E-06	4.30E-06	9.67E-06
		0.5		1.55E-07	1.31E-05	**2.47E-06**	1.72E-06	2.12E-06
		0.6		2.53E-07	1.63E-05	2.68E-06	1.95E-06	2.73E-06
		0.7		7.02E-07	4.65E-05	9.02E-06	6.35E-06	8.13E-06
		0.8		1.44E-05	5.81E-04	1.46E-04	1.18E-04	1.09E-04
		0.9		1.99E-03	2.84E-02	1.08E-02	9.21E-03	5.87E-03
		0.1	30	6.30E-02	4.22E-01	1.97E-01	1.78E-01	8.21E-02
		0.2		5.63E-02	6.90E-01	**1.93E-01**	1.78E-01	1.06E-01
		0.3		3.07E-02	6.09E-01	2.15E-01	2.00E-01	1.10E-01
		0.4		4.60E-02	8.45E-01	2.72E-01	2.23E-01	1.63E-01
		0.5		6.76E-02	1.37E+00	3.38E-01	2.85E-01	2.21E-01
		0.6		1.47E-01	1.75E+00	5.37E-01	4.97E-01	2.90E-01
		0.7		1.17E-01	1.81E+00	6.96E-01	5.91E-01	3.63E-01
		0.8		3.73E-01	3.07E+00	1.29E+00	1.14E+00	6.36E-01
		0.9		6.50E-01	4.73E+00	2.31E+00	2.17E+00	8.02E-01
		0.1	50	6.29E-02	3.97E-01	**1.54E-01**	1.47E-01	5.47E-02
		0.2		7.85E-02	4.45E-01	1.93E-01	1.79E-01	6.99E-02
		0.3		7.78E-02	9.25E-01	3.41E-01	3.03E-01	1.72E-01
		0.4		1.72E-01	1.44E+00	5.29E-01	4.81E-01	2.42E-01
		0.5		2.22E-01	1.70E+00	7.41E-01	6.54E-01	3.18E-01
		0.6		3.94E-01	5.60E+00	1.18E+00	1.05E+00	6.54E-01
		0.7		5.44E-01	3.94E+00	1.73E+00	1.74E+00	6.87E-01
		0.8		9.84E-01	6.40E+00	2.61E+00	2.36E+00	9.47E-01
		0.9		1.82E+00	7.60E+00	4.21E+00	4.04E+00	1.34E+00

Table 3. : Comparison of Probability p used in FPA on four standard benchmark functions. Algorithms are run 100 different times on each of the functions. The best result for each probability with each dimensionality is marked with boldface font.

Function Number	*Function Name*	*Probability*	*Dimension*	*Best*	*Worst*	*Mean*	*Median*	*SD*
3	Zakharov	0.1	10	1.49E-02	5.35E-01	8.21E-02	6.60E-02	6.88E-02
		0.2		1.06E-04	1.29E-02	3.05E-03	2.21E-03	2.37E-03
		0.3		1.86E-05	2.05E-03	2.78E-04	1.98E-04	2.79E-04
		0.4		1.27E-06	2.83E-04	4.78E-05	3.71E-05	4.10E-05
		0.5		1.83E-06	9.27E-05	**1.66E-05**	1.26E-05	1.49E-05
		0.6		1.91E-06	1.47E-04	1.91E-05	1.30E-05	2.16E-05
		0.7		3.24E-06	2.47E-04	6.65E-05	5.48E-05	4.89E-05
		0.8		5.27E-05	4.52E-03	9.56E-04	7.51E-04	7.48E-04
		0.9		1.80E-02	3.38E-01	8.49E-02	7.11E-02	5.71E-02
		0.1	30	8.95E+00	5.30E+01	2.47E+01	2.30E+01	9.01E+00
		0.2		6.06E+00	5.92E+01	**2.14E+01**	1.95E+01	9.57E+00
		0.3		5.42E+00	6.99E+01	2.32E+01	2.09E+01	1.13E+01
		0.4		6.27E+00	7.58E+01	2.45E+01	2.08E+01	1.39E+01
		0.5		8.79E+00	6.76E+01	2.69E+01	2.52E+01	1.12E+01
		0.6		1.15E+01	6.71E+01	2.92E+01	2.64E+01	1.26E+01
		0.7		1.27E+01	9.35E+01	3.53E+01	3.24E+01	1.52E+01
		0.8		1.60E+01	1.22E+02	4.70E+01	4.09E+01	2.14E+01
		0.9		2.43E+01	1.46E+02	7.01E+01	6.63E+01	2.68E+01
		0.1	50	3.64E+01	1.73E+02	**7.36E+01**	7.01E+01	2.16E+01
		0.2		3.14E+01	1.50E+02	7.73E+01	7.55E+01	2.54E+01
		0.3		2.15E+01	1.91E+02	8.01E+01	7.91E+01	2.91E+01
		0.4		4.03E+01	1.79E+02	8.58E+01	8.64E+01	2.88E+01
		0.5		3.86E+01	2.62E+02	1.00E+02	9.36E+01	3.53E+01
		0.6		5.63E+01	2.24E+02	1.09E+02	9.73E+01	3.82E+01
		0.7		7.15E+01	2.71E+02	1.31E+02	1.22E+02	4.29E+01
		0.8		6.42E+01	4.40E+02	1.66E+02	1.56E+02	6.36E+01
		0.9		8.63E+01	3.97E+02	1.98E+02	1.77E+02	6.84E+01
4	Michalewicz	0.1	10	-8.61E+00	-6.69E+00	-7.48E+00	-7.46E+00	3.76E-01
		0.2		-8.41E+00	-6.48E+00	-7.55E+00	-7.48E+00	4.25E-01
		0.3		-8.55E+00	-6.76E+00	**-7.56E+00**	-7.59E+00	3.70E-01
		0.4		-8.76E+00	-6.48E+00	-7.51E+00	-7.49E+00	4.11E-01
		0.5		-8.64E+00	-6.65E+00	-7.55E+00	-7.46E+00	3.87E-01
		0.6		-8.26E+00	-6.56E+00	-7.41E+00	-7.36E+00	3.51E-01
		0.7		-8.38E+00	-6.29E+00	-7.20E+00	-7.15E+00	4.12E-01
		0.8		-7.97E+00	-6.15E+00	-7.01E+00	-7.07E+00	4.06E-01
		0.9		-7.29E+00	-5.92E+00	-6.46E+00	-6.40E+00	3.34E-01
		0.1	30	-1.88E+01	-1.42E+01	-1.59E+01	-1.57E+01	8.88E-01
		0.2		-1.82E+01	-1.43E+01	**-1.59E+01**	-1.58E+01	8.46E-01
		0.3		-1.89E+01	-1.40E+01	-1.59E+01	-1.57E+01	9.68E-01
		0.4		-1.77E+01	-1.37E+01	-1.57E+01	-1.57E+01	8.65E-01
		0.5		-1.87E+01	-1.36E+01	-1.57E+01	-1.56E+01	1.05E+00
		0.6		-1.83E+01	-1.35E+01	-1.56E+01	-1.55E+01	1.00E+00
		0.7		-1.84E+01	-1.35E+01	-1.52E+01	-1.51E+01	8.75E-01
		0.8		-1.70E+01	-1.28E+01	-1.45E+01	-1.44E+01	7.82E-01
		0.9		-1.55E+01	-1.18E+01	-1.33E+01	-1.33E+01	6.92E-01
		0.1	50	-2.67E+01	-1.91E+01	-2.10E+01	-2.09E+01	1.33E+00
		0.2		-2.65E+01	-1.87E+01	-2.13E+01	-2.10E+01	1.75E+00
		0.3		-2.82E+01	-1.86E+01	-2.16E+01	-2.16E+01	1.56E+00
		0.4		-2.58E+01	-1.86E+01	-2.19E+01	-2.19E+01	1.64E+00
		0.5		-2.94E+01	-1.87E+01	-2.19E+01	-2.15E+01	2.04E+00
		0.6		-2.69E+01	-1.77E+01	**-2.20E+01**	-2.17E+01	1.65E+00
		0.7		-2.60E+01	-1.85E+01	-2.11E+01	-2.09E+01	1.54E+00
		0.8		-2.37E+01	-1.78E+01	-2.06E+01	-2.05E+01	1.16E+00
		0.9		-2.25E+01	-1.69E+01	-1.92E+01	-1.92E+01	1.11E+00

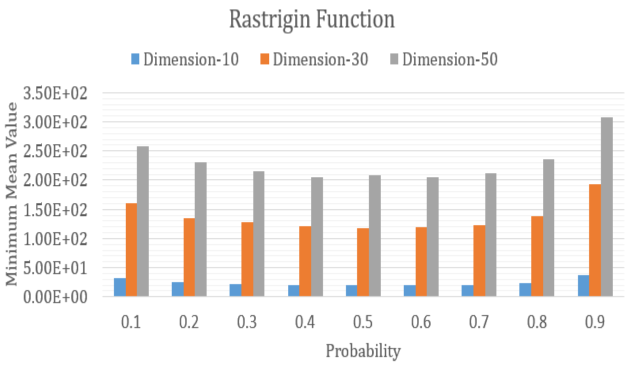

Fig. 3: Rastrigin Function

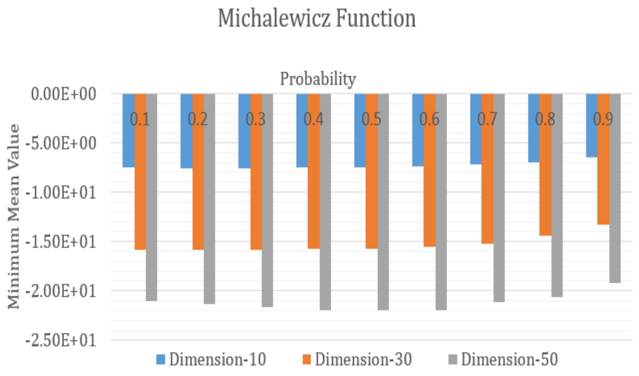

Fig. 4: Michalewicz Function

4. CONCLUSION

This paper presents a comparative study between different values of the switch probability p in flower pollination algorithm. This algorithm uses swarm intelligence to find the global optimum value of the continuous optimization problems. Numerical results on the standard benchmark problems for Flower Pollination algorithms demonstrate the effectiveness and competitiveness of the algorithms based on the value of p. There has been a few research works that try to improve the performance of the Flower Pollination Algorithm. In future the plan is to compare with those algorithms with the Flower Pollination Algorithm with modified switch probability with a conjecture to obtain better results.

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