An Improved Flower Pollination Algorithm Based on Muti-population Co-evolutionary Strategy to Solve Function Optimization Problems

Meng-Wei Guo, Dong Wei*, Jie-Sheng Wang*, Xiao-Xu Ma

Abstract—**Flower pollination algorithm is an algorithm that simulates the behavior of flower pollination in the biological world. In order to refine the accuracy of the FPA algorithm and effectively improve the convergence speed of the original algorithm FPA, two improved flower pollination algorithms based on clonal operator and bacterial foraging strategy are proposed. Then, based on the synergistic strategy between organisms, the muti-population co-evolutionary flower pollination algorithm (CFPA) was proposed and applied to the proposed two improved FPAs. Finally, this article designs a simulation experiment and uses six typical functions to carry out. According to the experimental data, the improved algorithm proposed in this paper has significantly improved the convergence speed of the algorithm and the optimization accuracy of the experimental results.**

Index Terms—**Flower pollination algorithm, Co-evolutionary, Muti-population, Function optimization**

I. INTRODUCTION

OPTIMIZATION is to select the best element from a series of effective choices for some specific criteria. Optimization is based on the basic principles of nature. It is widely used in industry or scientific research. [1]. The abstract problem is expressed in an intuitive mathematical model, and then the abstracted function is optimized to find the optimal solution of the function, which is the solution to the abstract problem. Algorithm optimization can be used in various practical optimization problems. [2]. However, general function optimization can only be implemented simply in unconstrained low-dimensional optimization. In order to solve all kinds of optimization problems more easily, various algorithms related to simulation biology have appeared. The emergence of biological intelligence algorithm makes the optimization problem can be solved in a very simple form, and then the biological optimization algorithm emerges in an endless stream. Various optimization algorithms are applied to various fields to solve the optimization problems that are difficult to obtain direct results [3-9].

Flower pollination algorithm is an algorithm proposed by Yang to simulate the biological characteristics of flower pollination. [10]. Although this algorithm has fewer parameters, its superiority and convenience are more prominent. At present, it can be known from the experiments of various scholars that FPA has been used to solve various combinatorial optimization problems including economic dispatch problems, knapsack problems, and power dispatch problems. [11], the transformers distribution in low-voltage power grids [12], the power load forecasting based on the multi-objective flower pollination algorithms (MOFPA) [13], the assembly sequence optimization [14], the dynamic multi-objective optimal scheduling thermal system based on the hybrid flower pollination algorithm (HFPA) [15], the solution of the Pareto MOOPF problem [16]. T. T. Nguyen et al. proposed a FPA algorithm that can be globally optimized. Its main strategy is parallelism, and compact technology is mixed in the paper [17]. M. Gao proposed an improved IFPA algorithm [18]. W. Li et al. proposed the OTAFPA algorithm, using two strategies to improve FPA, one strategy is opposite learning, the other is t distribution [19]. P. Kopciewicz et al. proposed the BFPA algorithm [20]. A. Mishra uses the characteristics of genetic algorithm to propose GA-FPA algorithm [21]. As the pollen position changes with the increase of the algorithm cycle, it is not easy for the algorithm to jump out of the local optimal value at the later stage of the cycle, which will affect the global optimization performance of the algorithm and make the accuracy of function optimization very low. This paper proposes a new and improved FPA algorithm based on multi-group co-evolution strategy. The experimental data in the test results show that the improved algorithm has obvious advantages in optimizing functions, which are mainly manifested in the improvement of the convergence speed and the effective improvement of accuracy in function optimization results.

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II. Flower Pollination Algorithm

A. Principle of FPA algorithm

FPA is an optimization algorithm abstracted from the biological characteristics of flower pollination. The main advantages of this algorithm include few setting parameters, easy operation, and convenience for the realization of experimental results. By selecting the parameters p, the dynamic control from local search to global search can be completed. It can also easily realize the balance under the effect of Lévy flight, so it can obtain the better global optimization ability. In the field of nature, the flower fertilization procedure is achieved by allogamy or self-fertilization. During the fertilization process, the movement of pollinator is random or similar. The standard FPA follows the following four rules.

Rule 1: The biological allogamy can be considered as a global fertilization process, and the pollinator's movement is affected by Lévy's flight. The activity of pollinizer is influenced by Levy's flight.

Rule 2: The abiotic self-fertilization is looked upon as a local fertilization procedure.

Rule 3: The propagate probability is regarded as a constant. The extent of simultaneity of two flowers is positively proportional to the chance.

Rule 4: During the transition from local fertilization to global fertilization, the variables $p \in [0,1]$ can be used to control, however, due to other factors, local pollination is slightly biased.

During the global pollination process, the long journey of insects ensures optimal reproduction. Obey the rule (1), the location of flowers is as follows:

$$x_i^{t+1} = x_i^t + \gamma L\left(g* - x_i^t\right) \tag{1}$$

where, x_i^t describes the location of flower i at the t-th iteration. $g*$ is the optimal solution. γ is the step factor. L is the fertilization strength or step length. Operations abstracted from Levi's flight. Lévy distribution is used to obtain L.

$$L \approx \frac{\lambda\Gamma(\lambda)\sin\left(\frac{\gamma\pi}{2}\right)}{\pi}\frac{1}{S^{1+\lambda}} \tag{2}$$

where, λ=1.5 and $\lambda\Gamma$ represents a typical Gamma function. The local pollination can be expressed as follows (according to Rule 2).

$$x_i^{t+1} = x_i^t + \in\left(x_j^t - x_k^t\right) \tag{3}$$

where, x_j^t and x_k^t are pollen come from different inflorescence.

The variable $\in$ is homogeneous distribution between [0,1]. The exchange probability P switches between global and local. In most applications, P=0.8 is more efficient. Therefore, the initial conversion probability P=0.8 is taken in this paper.

B. Pseudo Code of Flower Pollination Algorithm

The pseudo code of FBA based on the above idealized rules can be expressed as follows.

Begin
  Objective function $f(x), x = (x_1, x_2, \ldots x_d)$
  Initialize n pollen gametes using the random strategy
  Find the best solution $g*$ based on the initial population
  Define the transition probability $p \in [0,1]$
  While (gen<maximum iteration number)
    For $i = i : n$ (n pollen gametes in the population)
      If rand $< P$
        Create the d -dimensional vector L in accordance with Levy distribution
        Carry out the global pollination iteration process by using Eq. (1)
      Else
        Produce a uniformly distributed variable $\varepsilon \in [0,1]$
        Carry out the local pollination iteration process by using Eq. (3)
      End if
      Evaluate new solutions and update the population if the solution is better
    End for
    The current optimal solution $g*$
    gen=gen+1
  End while
  Output optimal solution
End

III. Algorithm Simulation and Result Analysis

A. FPA Based on Clonal Selection Algorithm

(1) Modified Flower Pollination Algorithm

The inspiration of the CSA came from the clonal selection theory put forward in 1959 [22]. Based on the clonal selection algorithm, MFPA is proposed to improve the operation and the convergence velocity, and have better capability for solving the nonlinear problems or more complex problems in practice.

The convergence of the solution (antibody) produced by random walks is faster than Lévy flight in local pollination, so the Lévy flight is replaced by the random walk strategy. The random walk is between [0,1]. Before applying the local seach, the principle of incorporating the cloning algorithm is to select the best individual from the original population (Pop) to create a cloned population (ClonesPop) and calculates the affinity (adaptation). The FPA is executed in the cloned population to search the optimal individual. The modified local pollination is realized by leading into step factor γ_2. experimental results show γ_2=3 is suitable for all test cases, and the criteria MAE shown in Eq. (4) is adopted to analyze MFPA.

$$MAE = \frac{\sum_{i=1}^{N}\left|m_i - K_i\right|}{N} \tag{4}$$

where, m_i indicates the average of the best values, k_i is the relevant global optimum, N is the iterative numbers. It is natural to think of adding the number of iterations to the step factor.

$$\gamma = \frac{T-t}{T} \quad (5)$$

where, t represents the current iteration. T is the maximum number of iterations.

At the same time, the optimal individuals are come from the cloned population, the initialized random population in order to form a new population (NewPop) and replace the original population. In order to prevent the local minima, if the optimal value $g*$ has not changed or it is still less than 10e-6 after 100 iterations, a new population is randomly generated to keep finding the optimal solution. This improvement is to enhance the search capability of the algorithm.

(2) Flowchart of MFPA

The flowchart of MFPA is shown in Fig. 1.

B. FPA Based on Bacterial Foraging Algorithm

The bacterial foraging algorithm was put forward by K. M. Passsino. There are three kinds of operations in the bacterial foraging algorithm, which are trending operation, copying operation and migration operation, and find food through these three processes. The improvement of BFA mainly lies in the selection and adjustment of moving step. Therefore, an improved FPA based on bacterial foraging algorithm (BFA-FPA) is proposed. The introduction of the bacterial foraging algorithm into the flower pollination algorithm greatly increases the optimization precision and convergence speed [23]. The algorithm pseudo code is described as follows.

Set cN, reN and edN indicate the number of the moving operations, reproduction operation and migration operation needed to be performed.

Step 1: Initialize the population, use the evaluation function to evaluate each individual in the population and initialize $I = 0$, $k = 0$, $j = 0$.

Step 2: Run the migration operation loop: $I = I + 1$.

Step 3: Run the reproduction operation loop: $k = k + 1$.

Step 4: Run the moving operation loop: $j = j + 1$. Perform the orientation operation on each individual.

Step 5: If $j < cN$, go to Step 4.

Step 6: Carry out the optimization based on the flower pollination algorithm.

Step 7: Perform reproduction operation.

Step 8: If $k < reN$, transfer to Step 3.

Step 9: Migration operation.

Step 10: If $I < edN$, jump to Step 2, otherwise the entire algorithm ends.

IV. Improved FPA Based on Muti-population Co-evolutionary Strategy

For the swarm intelligent optimization algorithms, with the development of the searching process, the individuals will continue to concentrate around the optimal or local optimal particles, which will result in a decline in population diversity. The introduction of the idea of sub populations can improve the population diversity during the iteration optimization process and make the algorithm Depart from the local optimal solution. In the light of the synergistic relationship between organisms, a cooperative strategy of muti-population flower pollination algorithm was brought forward based on the synergistic strategy. In this algorithm, according to a certain rule, the whole population is separated into many small sub-populations, not only can each subpopulation be searched independently, but also realize the collaborative search [19].

In the D -dimensional searching space, the entire population is split into produce K sub-populations. If the number of particles in the sub-population k is N_k, the number of particles in the large population is $N = \sum_{k=1}^{k} N_k$. If the sub-population k is carried out the evolution to reach the t generation, in the sub-population k, the position of the particle i is $x_i^k(t)$, and the global optimal value is recorded as P_g^k, P_g^m is the global optimal value searched by the sub-population m. The sub-population location updating equation participating in the collaborative search can be shown as:

$$X_i^k(t+1) = X_i^k(t) + r_1 * \left(P_g^k - X_i^k(t)\right) + C_1 * r_2 * \left(P_g^m - X_i^k(t)\right) \quad (6)$$

where C_1 is the synergy coefficient, $r_1 \in (0,1)$ and $r_2 \in (0,1)$ are independent random numbers. The sub-populations that are independently searched at the same time are shown in Eq. (1) and (3). In the proposed algorithm, the population is split into many sub-populations, the structure of subpopulations is a ring topology to achieve the purpose of information exchange. In the interior of the sub-population, the all connected topology is used to achieve the purpose of information interaction.

V. Experimental Analysis

Based on the muti-population co-evolutionary strategy, the sub-ideology is introduced into the FPA based on the clonal algorithm and the FPA based on the bacterial foraging algorithm respectively to form MFPAS and BFA-FPAS. The specific settings of the algorithm about the parameters are illustrated in Tab. 1. This section uses six functions to test the performance of the algorithm. Table 2 includes function names, expressions and domain definitions [25-26].

Simulation experiments are carried out by using five optimization algorithms (MFPA, MFPAS, CFPA, BFA-FPA, and BFA-FPAS) with six typical test functions. Each algorithm is run ten times, and the average value of the ten run results is recorded in the table, and the graph of the run results is recorded. The algorithm optimization results are recorded in Table 3, and the experimental graph is shown in Figure 2. The rank sum test was adopted for the statistical test, and the p-value results obtained4 by pinion comparison were appear in Tab. 4. Based on experimental data, the optimization capabilities of the multiple cluster algorithms (CFPA, MFPAS and BFA-FPAS) proposed in this paper are better than the original algorithms (MFPA and BFA-FPA). The searching results are ten times smaller than the other two algorithms. At the same time, the volatility is small and the performance is relatively stable.

TABLE 1 PARAMETER SETTINGS

Algorithm	Parameters Settings
MFPA	population size: N = 20 ; Maximum iterations: T=400 ; Conversion probability $p = 0.8$
MFPAS	population size: N = 20 ; Maximum iterations: T=400 ; Conversion probability $p = 0.8$
BFA-FPA	population size: N = 20 ; Maximum iterations: T=400 ; Conversion probability $p = 0.8$ Number of chemotaxis: cN=50 ; Number of copies: reN=4 ; Number of migrations: edN=4
BFA-FPAS	population size: N = 20 ; Maximum iterations: T=400 ; Conversion probability ; Number of chemotaxis: cN=50 ; Number of copies: reN=4 ; Number of migrations $p = 0.8$ edN=4
CFPA	population size: N = 20 ; Maximum iterations: T=400 ; Conversion probability $p = 0.8$

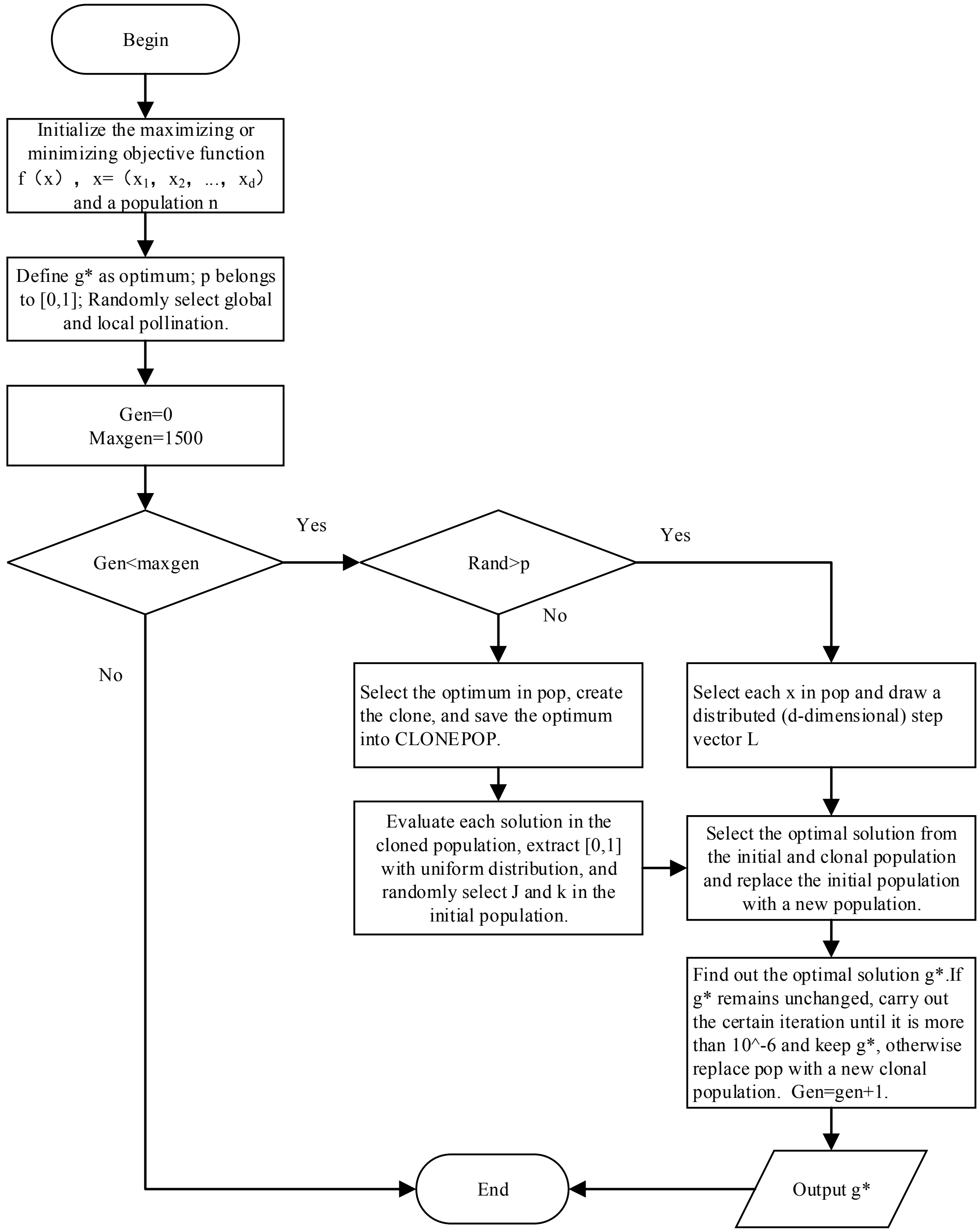


Fig. 1 Flowchart of MFPA.

TABLE 2. SIMULATION TEST FUNCTIONS

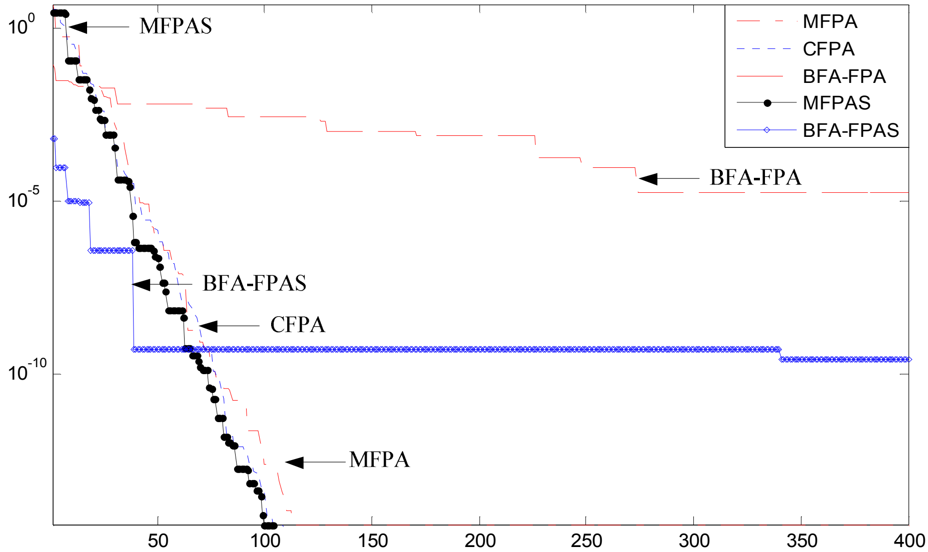
Function	Name	Expression	Scope	Minimum
F_1	Ackley	$f_1(x) = 20 + e - 20e^{\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right)} - e^{\left(\frac{1}{n}\sum_{i=1}^{n}\cos(cx_i)\right)}$	[-32, 32]	0
F_2	Drop-Wave	$f_2(x) = -\frac{1+\cos\left(12\sqrt{x_1^2+x_2^2}\right)}{0.5\left(x_1^2+x_2^2\right)+2}$	[-5.12, 5.12]	-1
F_3	Rotated Hyper-Ellipsoid	$f_3(x) = \sum_{i=1}^{d}\sum_{j=1}^{i} x_j^2$	[−65.536, 5.536]	0
F_4	Quartic	$f_4(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1)$	[-1.28,1.28]	0
F_5	Dixon and Price's	$f_5(x) = (x_1-1)^2 + \sum_{i=2}^{d} i\left(2x_i^2 - x_{i-1}\right)$	[-5, 10]	0
F_6	Zakharov's function	$f_6(x) = \sum_{i=1}^{d} x_i^2 + \left(\frac{1}{2}\sum_{i=1}^{d} ix_i\right)^2 + \left(\frac{1}{2}\sum_{i=1}^{d} ix_i\right)^4$	[-5, 10]	0

From a single function, the optimization function F_1 of CFPA and MFPAS algorithm obtains the minimum value optimal, followed by MFPA algorithm. The five algorithms in this paper can get the best value of function F_2, the variance obtained by the BFA-FPAS algorithm is the smallest; For function F_3, the best solution obtained by the MFPAS algorithm is the best, followed by the optimal value obtained by the CFPA algorithm; Optimize F4 best through MFPAS algorithm, then the value obtained by the CFPA is the second; When optimizing function F_5, MFPAS and CFPA get the best optimization effect; For the function F_6, the CFPA algorithm has the best optimization effect, followed by the MFPAS algorithm.

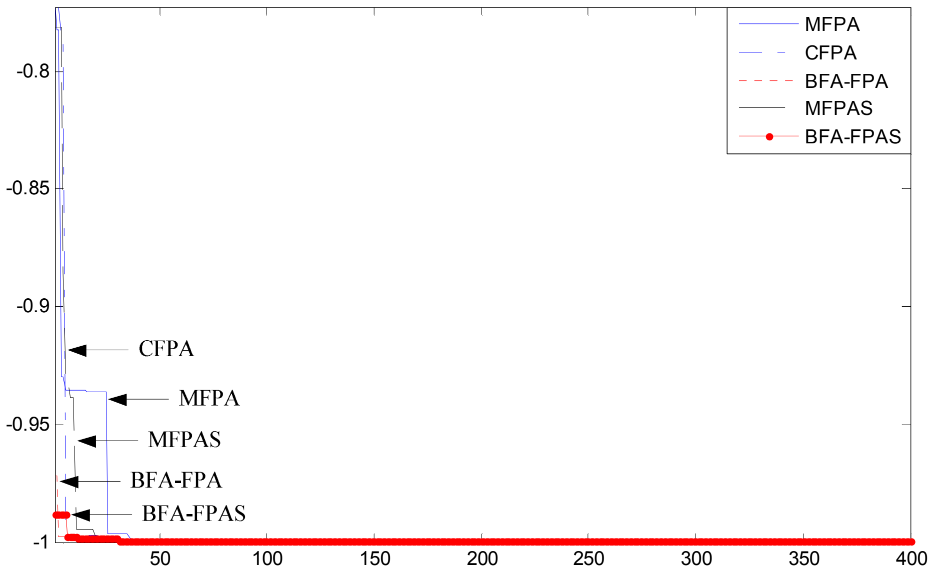
From the comparison results of the six function convergence curves, From the figure, the convergence speed of an overall algorithm is usually faster than the original algorithm. Most of the results of the rank sum test between the two pairs are within 0.05, which shows that these algorithms are significantly different. The optimization ability of multi-population algorithms is more operability and efficiency. For the functions F_1, F_3, and F_5, MFPAS converges faster, BFA-FPAS optimizes F_2 and F_4 to converge faster, CFPA optimized F_6 convergence faster. The overall convergence rate is an increasing trend, only a little delay in the later period. Therefore, it is proved that the multi-population algorithms have better optimization capability by introducing the co-evolutionary strategy.

TABLE 3. SIMULATION RESULTS UNDER FIVE ALGORITHMS

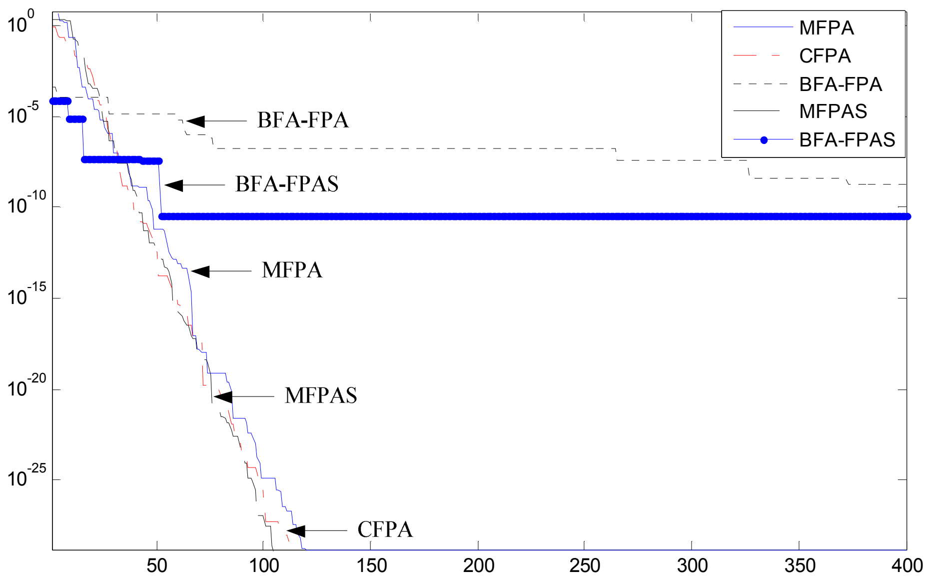
Function	Algorithm	Optimum	Arithmetic mean	Standard Deviation
F_1	MFPA	4.4409e-15	7.5495e-14	2.0607e-13
	CFPA	8.8818e-16	8.8818e-16	0
	BFA -FPA	1.5851e-06	2.7937e-05	3.0192e-05
	MFPAS	8.8818e-16	8.8818e-16	0
	BFA -FPAS	2.7417e-10	2.2474e-09	2.4597e-09
F_2	MFPA	-1	-0.9873	0.0255
	CFPA	-1	-0.9969	0.0268
	BFA -FPA	-1	-0.9996	0.0021
	MFPAS	-1	-0.9966	0.0236
	BFA -FPAS	-1	-1	8.7860e-05
F_3	MFPA	2.3386e-31	1.1749e-26	2.5138e-26
	CFPA	1.0286e-56	3.5375e-52	8.3654e-52
	BFA -FPA	5.9827e-12	1.3856e-09	2.6790e-09
	MFPAS	1.6197e-65	2.0762e-57	4.7241e-57
	BFA -FPAS	1.2481e-11	1.5181e-10	1.6598e-10
F_4	MFPA	2.8592e-04	1.1522e-03	5.5383e-04
	CFPA	2.6010e-06	7.5193e-05	1.0531e-04
	BFA -FPA	3.1405e-05	5.9049e-04	3.2140e-04
	MFPAS	1.1640e-05	5.2210e-04	2.9929e-04
	BFA -FPAS	4.9516e-05	3.2494E-04	3.2357E-04
F_5	MFPA	1.45945e-26	5.6807e-21	1.2915e-20
	CFPA	3.6978e-32	3.6978e-32	5.4738e-48
	BFA -FPA	3.0654e-09	7.5621e-07	1.8409e-06
	MFPAS	3.6978e-32	3.6978e-32	5.4738e-48
	BFA -FPAS	1.9983e-09	5.4699e-08	6.7249E-08
F_6	MFPA	3.1257e-31	5.8827e-27	1.7164e-26
	CFPA	3.1916e-61	1.1112e-55	2.1870e-55
	BFA-FPA	1.4972e-10	4.0588e-08	6.2869e-08
	MFPAS	1.3634e-60	4.7700e-59	3.3354e-59
	BFA -FPAS	1.0620e-11	7.8921e-10	1.3890e-09


MFPA
CFPA
BFA-FPA
MFPAS
BFA-FPAS
MFPAS
BFA-FPA
BFA-FPAS
CFPA
MFPA
10^0
10^{-5}
10^{-10}
50
100
150
200
250
300
350
400

(a) F_1


MFPA
CFPA
BFA-FPA
MFPAS
BFA-FPAS
CFPA
MFPA
MFPAS
BFA-FPA
BFA-FPAS
-0.8
-0.85
-0.9
-0.95
-1
50
100
150
200
250
300
350
400

(b) F_2


MFPA
CFPA
BFA-FPA
MFPAS
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BFA-FPA
BFA-FPAS
MFPA
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CFPA
10^0
10^{-5}
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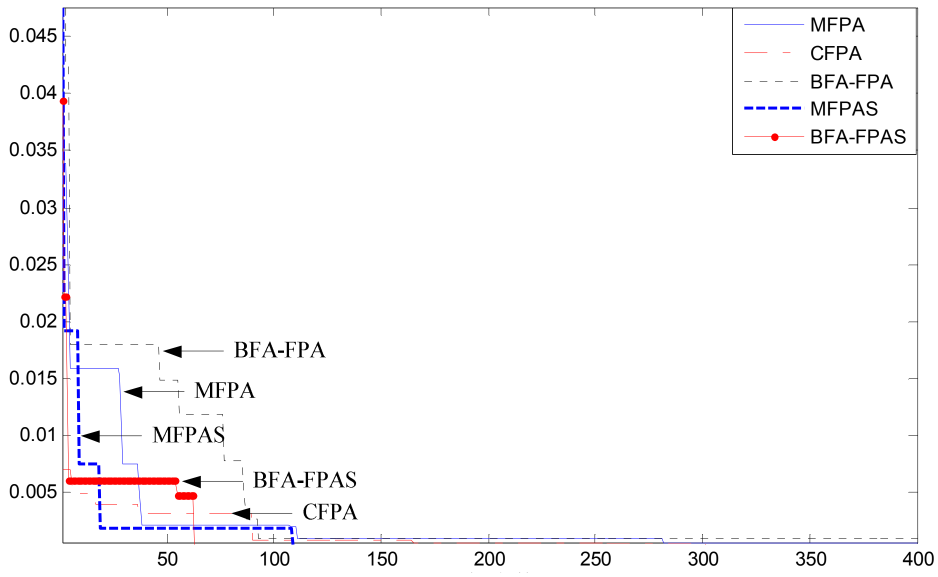
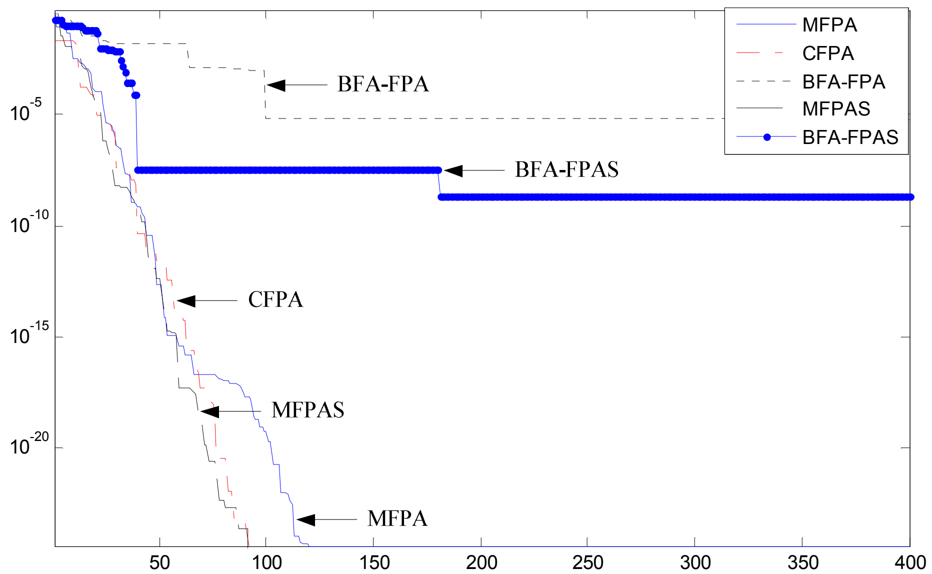
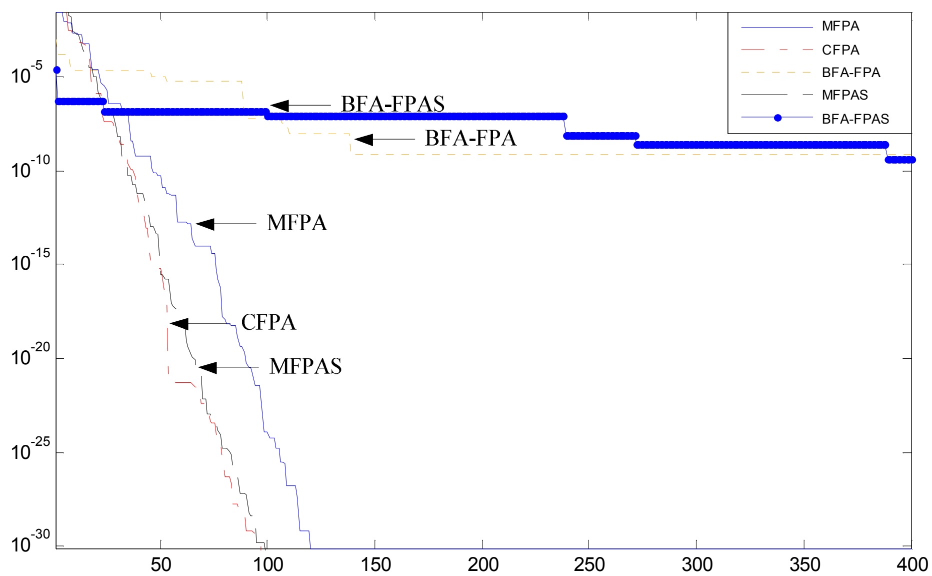
(c) F_3



(d) F_4



(e) F_5



(f) F_6

Fig. 2 Convergence curves under different algorithms.

TABLE 4. RANK SUM TEST RESULT

	F_1	F_2	F_3	F_4	F_5	F_6
MFPA vs CFPA	5.51E-05	0.871	1.83E-04	2.45E-04	6.39E-05	1.83E-04
MFPA vs BFA-FPA	1.63E-04	0.0432	1.83E-04	0.0757	1.83E-04	1.83E-04
MFPA vs MFPAS	5.51E-05	0.3662	1.83E-04	2.11E-02	6.39E-05	1.83E-04
MFPA vs BFA-FPAS	1.62E-04	0.871	1.83E-04	3.60E-03	1.83E-04	1.83E-04
CFPA vs BFA-FPA	6.39E-05	0.0029	1.83E-04	0.0028	6.39E-05	1.83E-04
CFPA vs MFPAS	NaN	0.2055	2.46E-04	2.80E-03	NaN	0.4727
CFPA vs BFA-FPAS	6.34E-05	0.871	1.83E-04	9.10E-03	6.39E-05	1.83E-04
BFA-FPA vs MFPAS	6.39E-05	0.6142	1.83E-04	6.23E-01	6.39E-05	1.83E-04
BFA-FPA vs BFA-FPAS	1.82E-04	0.0432	0.5205	1.04E-01	0.8501	0.0058
MFPAS vs BFA-FPAS	6.34E-05	0.2055	1.83E-04	2.12E-01	6.39E-05	1.83E-04

VI. CONCLUSIONS

This paper mainly studies the flower pollination algorithm and five improved algorithms (MFPA, CFPA, BFA-FPA, MFPAS and BFA-FPAS) are proposed. The performance of the five optimization algorithms is compared by adopting six test functions. According to the simulation results, the muti-population algorithms have a strong searching ability and the performance is also very stable, where the suppression rate can be effectively improved and the accuracy has also increased significantly. It is also proved that the muti-population algorithms (CFPA, MFPAS and BFA-FPAS) can compensate the deficiency of the original algorithms (MFPA and BFA-FPA) in the optimization precision and rate of convergence.

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