Multi-group Flower Pollination Algorithm Based on Novel Communication Strategies

Jeng-Shyang Pan[1,2], Jiawen Zhuang[2], Hao Luo[3], Shu-Chuan Chu[1,4]

[1] College of Computer Science and Engineering, Shandong University of Science and Technology, China
[2] School of Information Science and Engineering, Fujian University of Technology, China
[3] School of Aeronautics and Astronautics, Zhejiang University, China
[4] College of Science and Engineering, Flinders University, Australia
jspan@cc.kuas.edu.tw, 1085231304@qq.com, luohao@zju.edu.cn, scchu0803@gmail.com

Abstract

Multi-group Flower Pollination Algorithm (MFPA) based on novel communication strategies was proposed with an eye to the disadvantages of the Flower Pollination Algorithm (FPA), such as tardy convergence rate, inferior search accuracy, and strong local optimum. By introducing a parallel operation to divide the population into some groups, the global search capability of the algorithm was improved. Then three new communication strategies were proposed. Strategy 1 combined high-quality pollens of each group for evolution and replaced the old pollens. Strategy 2 let each group's inferior pollens approaching to the optimal pollen. Strategy 3 was a combination of strategies 1 and 2. Then, experiments on 25 classical test functions show that MFPA based on novel communication strategies has a good global optimization ability, improving the convergence speed and accuracy of the FPA. Thus, we compare MFPA using three strategies with FPA and PSO, its result shows that MFPA is better than FPA and PSO. Finally, we also applied it to two practical problems and achieved a better convergence effect than FPA.

Keywords: Flower pollination algorithm, Parallel algorithm, Communication strategy, Function optimization

1 Introduction

Meta-heuristic algorithm has been widely used in transportation, electric, biology, financial, for successfully solving many optimization problems [1-2]. In [1], several meta-heuristic algorithms and their applications in large-scale optimization problems are introduced. In [2], some important developments and applications of bioinformatics algorithms are described. One category of meta-heuristic algorithms is population-based algorithms. Harmony Search (HS) that is put forward by Geem et al. [3] mimicking the improvisation of music players. Cuckoo Search (CS) is developed by Xin-She Yang and Suash Deb [4]. Particle Swarm Optimization (PSO) mimics bird flocking and it has been applied to nonlinear function optimization and neural network training in [5]. Artificial Bee Colony (ABC) optimization based on the foraging behavior of honey bees has been extended for solving constrained optimization problems [6]. Gray Wolf Optimization is proposed by driving the related individuals to approach the centers of the position of the top three individuals and has also been applied to many areas [7-9]. These algorithms are some typical or relatively new population-based algorithms. As a population-based algorithm, Flower Pollination Algorithm (FPA) is proposed by Yang [10] and has been applied for optimization of truss structures [11] and the layouts of nodes in Wireless Sensor Networks [12]. Differential Evolution (DE) is very effective and efficient population- based method for processing the complex single objective numerical optimization problems [13]. Some promising applications have also been presented [14-15]. DE is also implemented in matrix process by applying the affine transformation concept for tackling the bias trouble in DE [16-17]. FPA's basic thought comes from the simulation of pollination of natural flowers. FPA's merit lies in that it is easy for people to implement in hardware by using some program languages.

Since FPA was proposed in 2012, FPA has been studied and improved by many professionals and scholars, such as hybridized FPA with firefly algorithm proposed by Kalra [18] and tested by various standard benchmark functions. Hybridized FPA with PSO proposed in [19] and is also used to solve constrained optimization problems, binary FPA proposed by Rodrigues for applying to Feature Selection [20], multi-objective FPA presented in [21] and can accurately find the Pareto fronts for a set of test functions. Wang and Zhou improve the FPA based on dimension by dimension update for evaluating strategy

*Corresponding Author: Shu-Chuan Chu; E-mail: scchu0803@gmail.com
DOI: 10.3966/160792642021032202003

on solutions and local neighborhood search strategy [22]. Nabil hybridized standard FPA with clonal selection algorithm (CSA) and is tested by 23 optimization benchmark problems for getting better results [23]. Osama Abdel-Raouf in [24] combine FPA with HS that chaotic HS is used to generate the initial pollens of FPA. FPA with Bee Pollinator was proposed by Wang et. al. by using discard pollen operator and crossover operator to increase the diversity of the population, and elite based mutation operator to enhance local searching [25].

In this paper, for the deficiency of basic FPA with tardy convergence rate, inferior search precision, and strong local optimum [26], MFPA based on novel communication strategies is proposed, the algorithm with 25 test functions is tested. We also apply the algorithm to two practical problems. The experimental results show that the proposed MFPA based on novel communication strategies can obtain a relatively accurate solution, with faster convergence rate and better convergence precision.

The following is the remaining of this article. There is a brief review of FPA and parallel algorithms for swarm intelligence in Section 2. Section 3 presents three communication strategies and MFPA based on novel communication strategies. In Section 4, the experiments of test functions and applications are described. Finally, in Section 5, a shortly conclusion is given.

2 Related Work

In this section, FPA and parallel schemes for some swarm intelligence algorithms will be briefly described.

Pollination could take by abiotic form or biotic form and achieved through self-pollination or cross-pollination [10]. Pollinator transfer the pollen. Honeybees are one of the pollinators, with flower constancy [27]. That is the pollinators are inclined to visit a specific only species and avoid others. FPA as a biological heuristic algorithm idealizes the pollination process's characteristics, obeys some rules [10].

In most population-based algorithms, there are exploration and exploiting [12] to direct the optimization process. FPA as a population-based heuristic algorithm, its local pollination contains abiotic and self-pollination, which indicates the exploiting in the search area, its global pollination contains biotic and cross-pollination, which represents global exploration, the proportion of above two pollination process is controlled by its switch probability. The global pollination of FPA [10] is modeled as follows:

$$x_i^{t+1} = x_i^t + L_{step} \times (x_i^t - x_*) \tag{1}$$

where x_i^t is the ith pollen in the tth iteration, x_* is the best pollen in the current iteration among all pollens. In this paper $L_{step} > 0$ and draw from Levy distribution [10].

$$L_{step} \sim \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi s^{1+\lambda}} \tag{2}$$

where $\Gamma(\lambda)$ is the standard gamma function, and $s \gg s_0 > 0$. FPA's Local pollination for exploiting, is modeled as follows [10].

$$x_i^{t+1} = x_i^t + \varphi_{\text{rand}} \times (x_p^t - x_q^t) \tag{3}$$

where x_p^t and x_q^t are pollens from the identical plant species' diverse flowers, and $\varphi_{\text{rand}} \sim \text{U}[0,1]$. U is uniform distribution. Pseudo-code of FPA shows in Figure 1 [10].

Objective Fitness Function $F(x)$, solution $x = (x_1, x_2 \ldots, x_d)$
Initialize a population of n solution x randomly and switch probability $p \in [0,1]$
Calculate $F(x^t)$, and find the best solution x_* and $t = 1$
While (t < MaxIteration) **do**
  for $i = 1, \ldots, N$ **do**
    If $rand \le p$ **then**
      Global pollination via **(1)**
    else
      Local pollination via **(3)**
    end if
    Calculate $F(x^{t+1})$
    Update them, when new pollens are better.
  end for
    Update the best solution x_*
end while

Figure 1. FPA's pseudo-code

There are so many parallel swarm intelligence algorithms that have been put forward. The parallel PSO (PPSO) proposed by Chang et. al. [28] is tested by several optimization functions using three communication strategies for getting promising results. The parallel ant colony optimization is presented in [29] by Chu et. al. and is applied for solving the TSP with effective and efficient solutions by putting forward seven communication methods to update the pheromone level between groups. The parallel grey wolf optimization is also presented by Pan et. al. in [30] by presenting a communication strategy using current group's better particles to update the next group's worse particles. The cat swarm optimization (CSO) mimics the cat's behavior which improve the PSO by implementing tracing mode and seeking mode [31]. The parallel scheme of the CSO is also presented [32] and the parallel CSO is applied to solve the aircraft schedule recovery problem [33] and wireless sensor network [34].

In this article, new parallel schemes of FPA are presented and three new communication strategies are used in FPA and will be described in detail in the next section.

3 MFPA Based on Novel Communication Strategies

In this section, we will describe MFPA based on novel communication strategies and three new communication strategies.

3.1 Strategy 1: Evolution

The strategy was inspired by the evolution of species in nature and refer to the mutation, crossover and selection operation in Differential Evolution [35]. Strategy 1 has the advantage of making the better pollens into improved, through mutation and crossover, the algorithm may be easy to jump off the local optimum. This strategy collected pollens with good fitness in each group to form a new population to be evolved, and it replaced the original pollen with evolved pollen.

Step 1. For every $R1$ iterations, pollens of each group is strictly sorted by their fitness from worst to best.

Step 2. Combine each group's pollen with the best first quarter fitness into a new population x^t for evolution.

Step 3. Mutate [35] the new population according to the formula (4):

$$v_i^{t+1} = x_{r1}^t + F \times (x_{r2}^t - x_{r3}^t) \quad \textbf{(4)}$$

where v_i^{t+1} is the ith mutated pollen in $(t+1)$th iteration, x_{r1}^t, x_{r2}^t and x_{r3}^t are the different random pollens in the tth generation of the new population. F is an adaptive coefficient of mutation [36], and $F \in [0,2]$. It is calculated by the following formula (5):

$$F = F_0 \times (2^l),\ l = e^{1-\frac{t_{\max}}{t_{\max}+1-t}} \quad \textbf{(5)}$$

where F_0 is mutation constant, t is present iteration, $t_{\max}$ is maximum iteration.

Step 4. According to the formula (6), the test pollen $u_i^{t+1} = (u_{i,1}^{t+1}, u_{i,2}^{t+1}, ..., u_{i,d}^{t+1})$ is obtained by crossover operation [35].

$$u_{i,d}^{t+1} = \begin{cases} v_{i,d}^{t+1}, & if\ \ d = d_{rand}\ or\ \mathrm{rand}(0,1) \le CR \\ x_{i,d}^{t+1}, & otherwise \end{cases} \quad \textbf{(6)}$$

where CR is cross-over probability, $i = 1,...,NP$, NP is population's size, d is the dth dimension of pollen, d_{rand} is a random selected number of sequences $[1,...,D]$, and D is pollen's dimension.

Step 5. If fitness value of the test pollen u_i^{t+1} is better than that of the contemporary pollen x_i^t, $x_i^{t+1} = u_i^{t+1}$, otherwise $x_i^{t+1} = x_i^t$ as Eq. (7).

$$x_{i,}^{t+1} = \begin{cases} u_{i,}^{t+1}, & if\ \ (f(u_{i,}^{t+1}) \le f(x_{i,}^t)) \\ x_{i,}^t, & otherwise \end{cases} \quad \textbf{(7)}$$

Step 6. The old group pollens x^t is replaced one by one by the new evolution pollens x^{t+1}, achieving communication between groups

3.2 Strategy 2: Proximity

This strategy is inspired by the biological nature of PSO [5], that is, the birds move towards the food that is optimal solution. The advantage of strategy 2 is that it could directly act on poor pollens and make them better. The thought of this strategy is to set the pollens with poor fitness in each group to move to the optimal fitness of this group or other groups, and the core formula is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + rand(0,1) \times (xbest_k^t - x_{i,j}^t) \quad \textbf{(8)}$$

where $x_{i,j}^t$ is the ith pollen of the jth group of the tth iteration, $xbest_k^t$ is the best pollen of the kth group of the tth iteration. The difference between $xbest_k^t$ and $x_{i,j}^t$ multiply the $rand(0,1)$ and plus $x_{i,j}^t$ means to move $x_{i,j}^t$ to $xbest_k^t$. The steps are as follows.

Step 1. For every $R2$ iterations, pollens of each group are strictly sorted by their fitness from worst to best.

Step 2. For each group's pollens with the one-half poor pollens, formula (8) is applied to set worse pollens approach to the optimal pollen of other random group. The updated formula is as follows:

$$\begin{aligned} & x_{i,j}^{t+1} = x_{i,j}^t + rand(0,1) \times (xbest_{k1}^t - x_{i,j}^t), \\ & i = [1,...,\frac{1}{2}NP] \end{aligned} \quad \textbf{(9)}$$

where $k1$ is a random integer generated from a sequence $[1,...,GP]$ that is not equal to j. GP is the max number of the group.

Step 3. For each group's pollens with the worse fitness from one-half to three quarter, formula (8) is applied to let worse pollens approach to the optimal pollen of each group. The updated formula is as follows:

$$\begin{aligned} & x_{i,j}^{t+1} = x_{i,j}^t + rand(0,1) \times (xbest_j^t - x_{i,j}^t), \\ & i = [\frac{1}{2}NP,...,\frac{3}{4}NP] \end{aligned} \quad \textbf{(10)}$$

3.3 Strategy 3: Combination of Strategy 1 and Strategy 2

Strategy 1 has the advantage for further improving the better pollen, and the advantage of strategy 2 is that it could directly act on poor pollens and make them better. Strategy 3 could effectively use the advantages of two strategies by combining them. As is shown in Figure 2, for every $R1$ iteration, the communication strategy 1 is used and for every $R2$ iteration, communication strategy 2 is applied.

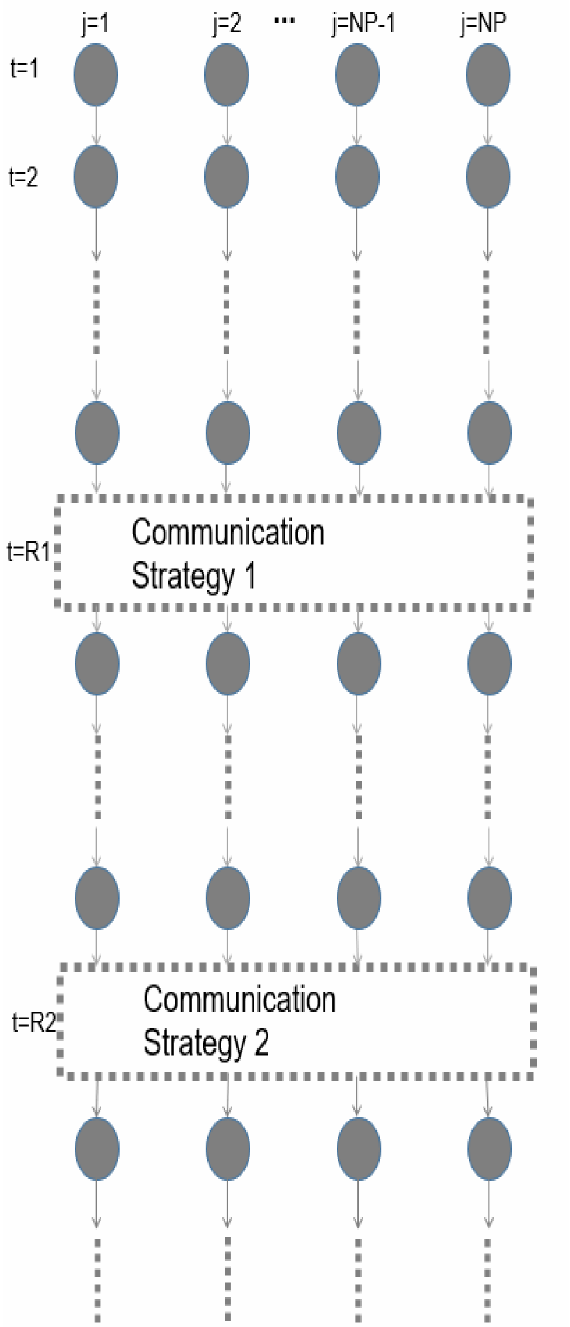

Figure 2. Strategy 3: Combination strategy 1 and strategy 2

3.4 MFPA Based on Novel Communication Strategies

In this section, MFPA based on novel communication strategies will be described. We divide the total population into *GP* group with *POPSIZE* pollens in each group. Firstly, each pollen is initialized randomly, and its fitness value is calculated, the switch probability parameter is initialized, and the parameters of the strategy is initialized. Then for each iteration, each group is updated with the FPA separately, and each group communicates when every strategy's corresponding communication iteration number reached. While meeting the max number of iteration or calculate fitness is just less than the threshold fitness, terminate program. The following is the detailed steps.

1. Initialization: Produce *POPSIZE* pollens $x_{i,j}^{t}$ of the jth group with D dimensions, $i=1,...,NP$, $j=1,...,GP$, where GP is the maximum groups, $POPSIZE$ is the size of pollen, t is the present iteration and $t=1$, initialize switch probability and the parameter of strategy.

2. Evaluation: Calculate $f(x_{i,j}^{t})$ for every pollen. Find every group's best pollen g_* and its fitness. Find the best pollen $TotalBest$ of all group and its fitness.

3. Pollen Update: For every pollen in each group proceed the following steps.

According to switch probability, Global pollination via (1), or Local pollination via (3).

Calculate $f(x_{i,j}^{t+1})$. Update pollen in every group, when new pollens are better. Update the best pollen g_* and its fitness in each group, the best pollen $TotalBest$ of all groups and its fitness.

4. Communication: The following is three communication strategies:

Strategy 1: For every $R1$ iteration, sorts the solution of each group by their fitness from worst to best; combine each group's pollens with the one quarter better fitness into a new population x^{t} for evolution. x^{t} is mutated by (4) and (5), crossed by (6), selected by (7), and finally generate x^{t+1}.

Strategy 2: For every $R2$ iteration, sorts each group's pollens by their fitness from worst to best. (9) and (10) are applied for moving the worse pollens to its group's best pollen or other group's best pollen.

Strategy 3: For every $R1$ iteration, communication strategy 1 is used and for every $R2$ iteration, communication strategy 2 is applied.

5. Termination: Step 2 to 5 are repeated, until threshold fitness is reached, or maximum iteration is achieved. Finally, record best fitness $f\left(TotalBest\right)$ and best pollen $TotalBest$ among pollens.

4 Experiments and Applications

In this section, for meeting test functions' diversity, we utilize first 11 benchmark functions from the CEC2017 test function's basic functions [37], and last 14 benchmark functions from [38], detail result is shown in the Table 1. Next, we select first 6 test functions to compare the rate of convergence of four algorithms, details are shown in the Figure 3. We also compare MFPA with FPA and PSO in 6 test functions that is shown in Figure 4. Finally, we apply the MFPA based on novel communication strategies two practical application problems.

Table 1. Twenty-five test functions in our experiment

No.	Name	Function Expression	Range	Dimension	Iteration
1	Bent Cigar	$f_1(x) = 10^6 \sum_{i=2}^{D} x_i^2 + x_1^2$	±10	30	2000
2	Zakharov	$f_2(x) = (\sum_{i=1}^{D} 0.5x_i)^2 + (\sum_{i=1}^{D} 0.5x_i)^4 + \sum_{i=1}^{D} x_i^2$	[-5, 10]	30	2000
3	Levy	$f_3(x) = (1-w_D)^2[sin^2(2\pi w_D)+1] + \sum_{i=1}^{D-1}(1-\omega_i)^2[1+10sin^2(1+\pi w_i)] + sin^2(\pi w_1)$	±10	30	2000
4	High Conditioned Elliptic	$f_4(x) = \sum_{i=1}^{D} (10^6)^{\frac{i-1}{D-1}} x_i^2$	±100	30	2000
5	Discus	$f_5(x) = 10^6 x_1^2 + \sum_{i=2}^{D} x_i^2$	±100	30	2000
6	Ackley's	$f_6(x) = 20 + e - 20exp(-\frac{1}{5}\sqrt{(1/D)\sum_{i=1}^{D} x_i^2}) - exp(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i))$	±32	30	2000
7	Griewank	$f_7(x) = \sum_{i=1}^{D}\frac{x_i^2}{4000} - \prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}}) + 1$	±600	30	2000
8	Katsuura	$f_8(x) = -\frac{10}{D^2} + \frac{10}{D^2}\prod_{i=1}^{D}(1 + i\sum_{j=1}^{32}\frac{\lvert 2^j x_i - round(2^j x_i)\rvert}{2^j})^{(10/D^{1.2})}$	±100	30	2000
9	HappyCat	$f_9(x) = 0.5 + \lvert \sum_{i=1}^{D} x_i^2 - D \rvert^{1/4} + (0.5\sum_{i=1}^{D} x_i^2 + \sum_{i=1}^{D} x_i)/D$	±100	30	2000
10	HGBat	$f_{10}(x) = 0.5 + \left\lvert (\sum_{i=1}^{D} x_i^2)^2 - (\sum_{i=1}^{D} x_i)^2 \right\rvert^{0.5} + (\frac{1}{2}\sum_{i=1}^{D} x_i^2 + \sum_{i=1}^{D} x_i)\frac{1}{D}$	±100	30	2000
11	Schaffer's F7	$f_{11}(x) = [\frac{1}{D-1}\sum_{i=1}^{D}(\sqrt{s_i}(sin(50s_i^{0.2})+1))]^2, s_i = \sqrt{x_i^2 + x_{i+1}^2}$	±100	30	2000
12	Sum Square	$f_{12}(x) = \sum_{i=1}^{D} ix_i^2$	±10	30	2000
13	Eggholder	$f_{13}(x) = -x_1\sin(\sqrt{\lvert(x_2+47)-x_1\rvert}) - (47+x_2)\sin(\sqrt{\left\lvert 47 + \frac{x_1}{2} + x_2 \right\rvert})$	±512	2	2000
14	Bohachevsky	$f_{14}(x) = 0.7 + x_1^2 + 2x_2^2 - 0.4cos(4\pi x_2) - 0.3cos(3\pi x_1)$	±100	2	2000
15	Sphere	$f_{15}(x) = \sum_{i=1}^{D} x_i^2$	±5.12	30	2000
16	Booth	$f_{16}(x) = (2x_1 + x_2 - 5)^2 + (x_1 + 2x_2 - 7)^2$	±10	2	2000
17	Matyas	$f_{17}(x) = -0.48x_1x_2 + 0.26(x_1^2 + x_2^2)$	±10	2	2000
18	Camels	$f_{18}(x) = x_1x_2 + x_2^2 + 2x_1^2 - 1.05x_1^4 + \frac{x_1^4}{6}$	±5	2	2000
19	Easom	$f_{19}(x) = -cos(x_2)cos(x_1)exp(-(x_2-\pi)^2 - (x_1-\pi)^2)$	±100	2	2000
20	Michalewicz	$f_{20}(x) = -\sum_{i=1}^{D}\sin(x_i)\sin^{2m}(\frac{ix_i^2}{\pi}), m = 10$	[0, π]	10	2000
21	Beale	$f_{21}(x) = (2.625 - x_1 + x_1x_2^3)^2 + (x_1x_2 - x_1 + 1.5)^2 + (x_1x_2^2 - x_1 + 2.25)^2$	±4.5	2	2000
22	Colville	$f_{22}(x) = 10.1((1-x_2)^2 + (1-x_4)^2) + 90(x_4 - x_3^2)^2$ $+100(x_1^2 - x_2)^2 + (1-x_1)^2 + (1-x_3)^2 + 19.8(x_2-1)(x_4-1)$	±10	4	2000
23	Goldstein Price	$f_{23}(x) = [(18 - 36x_1x_2 + 27x_2^2 - 32x_1 + 12x_1^2 + 48x_2)(2x_1 - 3x_2)^2 + 30]$ $\times[1 + (19 + 6x_1x_2 + 3x_2^2 - 14x_1 + 3x_1^2 - 14x_2)(x_1 + x_2 + 1)^2]$	±2	2	2000
24	Hartmann	$f_{24}(x) = -\sum_{i=1}^{4}\alpha_i\exp(-\sum_{j=1}^{3}(x_j - P_{ij})^2 A_{ij})$	[0, 1]	3	2000
25	Powell	$f_{25}(x) = \sum_{i=1}^{d/4}[5(x_{4i} - x_{4i-1})^2 + (10x_{4i-2} + x_{4i-3})^2 + 10(x_{4i} - x_{4i-3})^4 + (x_{4i-2} - 2x_{4i-1})^4]$	[-4, 5]	30	2000

4.1 Experiment with Testing Function

In order to make the following results comparable, for MFPA using strategy 1, MFPA using strategy 2, MFPA using strategy 3, we divide total 160 pollens of above three algorithms into four groups, each group has 40 pollens. As for basic FPA's pollens we set 160 pollens with no divided. The population size of the four algorithms is the same. Then we make the switch probability p of the four algorithms equal to 0. 8. The basic FPA does not adopt communication strategy. From simulations of us, with the mutation constant F_0 equals to 0.5 and crossover constant CR equals to 0.5, MFPA has a pretty good convergence effect. Therefore, the parameter $R1$ equals to 10, of MFPA using strategy 1, that is, communication should be done every 10 iteration, and the mutation constant F_0 equals to 0.5, crossover constant CR equals to 0.5. The parameter $R2$ equals to 20, of MFPA using strategy 2, that is, communication should be done every 20 iterations. As for MFPA using strategy 3, $R1{=}10$, $R2{=}20$, $F_0{=}0.5$, $CR{=}0.5$.

Because of the strong randomness of the meta-heuristic algorithm, we compare and analysis the data after 30 runs of each algorithm, and Table 1 shows that each function of each algorithm iterates 2000 times, so the data obtained is of high reliability.

Table 1 shows that, of the 25 test functions, there are some unimodal functions, such as High Conditioned Elliptic Function, Zakharov Function, and some multimodal functions, such as Levy Function, Ackley's Function. The global search capability of the algorithm could be checked by two kinds of functions that above mentioned. We set the test function with low dimensions, such as 2, 3, 4, and set the test function with high dimensions, such as 30, to compare the optimization ability of the algorithm within different dimensions.

Table 2 shows the test of four algorithms on 25 functions. For enabling the Table 2 shows the information more intuitively, the form like 10/9/6 is used to simply express the mean or std value of algorithm with better effect in 10 functions, and the similar effect in 9 functions, and the worse effect in 6 functions. Note that both MFPA using strategy 3 and MFPA using strategy 2 achieve the best effect on function 22. As it is intuitively shown in Table 3.

Table 2. Result of mean and standard deviation for functions

No.	Function	Type	MFPA using strategy 3	MFPA using strategy 2	MFPA using strategy 1	FPA
1	Bent Cigar	mean	2.71E-20	2.79E-12	5.33E-07	8.91E+01
		std	4.83E-20	3.30E-12	2.91E-07	2.08E+01
2	Zakharov	mean	4.20E-08	3.81E-07	1.21E-05	8.54E-04
		std	5.49E-08	2.99E-07	1.87E-05	2.46E-04
3	Levy	mean	2.09E-02	5.52E-18	3.11E-11	1.41E+00
		std	4.51E-02	4.64E-18	3.29E-11	3.40E-01
4	H. C. E.	mean	2.41E-21	2.52E-12	1.00E-07	1.14E+01
		std	1.87E-21	8.69E-12	3.54E-08	3.21E+00
5	Discus	mean	3.33E-24	8.43E-16	1.25E-10	2.22E-02
		std	2.33E-24	1.19E-15	6.69E-11	6.58E-03
6	Ackley's	mean	3.85E-02	3.85E-02	4.88E-06	1.97E+00
		std	2.11E-01	2.11E-01	1.37E-06	6.08E-01
7	Griewank	mean	0.00E+00	0.00E+00	0.00E+00	0.00E+00
		std	0.00E+00	0.00E+00	0.00E+00	0.00E+00
8	Katsuura	mean	0.00E+00	0.00E+00	0.00E+00	0.00E+00
		std	0.00E+00	0.00E+00	0.00E+00	0.00E+00
9	HappyCat	mean	1.63E-01	1.83E-01	3.76E-01	3.35E-01
		std	2.70E-02	4.48E-02	6.12E-02	4.88E-02
10	HGBat	mean	3.03E-01	2.68E-01	2.72E-01	2.41E-01
		std	9.52E-02	9.16E-02	2.50E-02	2.26E-02
11	Schaffer's F7	mean	2.92E-02	3.83E-02	1.73E-01	3.23E+00
		std	3.42E-02	7.04E-02	3.36E-02	2.25E-01
12	Sum square	mean	1.14E-25	1.02E-18	8.99E-12	1.42E-03
		std	1.45E-25	1.63E-18	6.33E-12	4.03E-04
13	Eggholder	mean	-9.60E+02	-9.60E+02	-9.60E+02	-9.60E+02
		std	5.78E-13	5.78E-13	5.78E-13	5.78E-13
14	Bohachevsky	mean	0.00E+00	0.00E+00	0.00E+00	0.00E+00
		std	0.00E+00	0.00E+00	0.00E+00	0.00E+00
15	Sphere	mean	2.77E-27	2.27E-19	1.86E-13	3.28E-05
		std	2.14E-27	3.01E-19	6.94E-14	7.82E-06

Table 2. Result of mean and standard deviation for functions (continue)

No.	Function	Type	MFPA using strategy 3	MFPA using strategy 2	MFPA using strategy 1	FPA
16	Booth	mean	0.00E+00	0.00E+00	0.00E+00	0.00E+00
		std	0.00E+00	0.00E+00	0.00E+00	0.00E+00
17	Matyas	mean	1.46E-123	9.88E-113	2.73E-70	6.55E-49
		std	3.94E-123	2.79E-112	1.25E-69	1.25E-48
18	Camels	mean	6.19E-134	5.70E-124	5.61E-70	2.69E-46
		std	1.99E-133	1.68E-123	2.54E-69	5.28E-46
19	Easom	mean	-1.00E+00	-1.00E+00	-1.00E+00	-1.00E+00
		std	0.00E+00	0.00E+00	0.00E+00	0.00E+00
20	Michalewicz	mean	-9.58E+00	-9.54E+00	-9.50E+00	-8.33E+00
		std	7.68E-02	9.22E-02	8.68E-02	2.87E-01
21	Beale	mean	0.00E+00	0.00E+00	0.00E+00	0.00E+00
		std	0.00E+00	0.00E+00	0.00E+00	0.00E+00
22	Colville	mean	0.00E+00	0.00E+00	6.80E-32	1.99E-18
		std	0.00E+00	0.00E+00	3.73E-31	3.71E-18
23	Goldstein-Price	mean	3.00E+00	3.00E+00	3.00E+00	3.00E+00
		std	1.59E-15	1.83E-15	1.36E-15	1.68E-15
24	Hartmann	mean	-3.86E+00	-3.86E+00	-3.86E+00	-3.86E+00
		std	2.97E-15	3.05E-15	3.11E-15	3.08E-15
25	Powell	mean	3.66E-05	5.14E-05	8.22E-04	2.35E-06
		std	2.22E-05	3.50E-05	6.21E-04	9.42E-07

Table 3. 25 Test Functions' Simple Expressed Result

type	MFPA using strategy 3	MFPA using strategy 2	MFPA using strategy 1	FPA
Mean	12/9/0	2/9/0	1/9/3	2/9/13
Std	12/7/0	2/7/2	3/7/3	2/7/13

From Table 3, the basic FPA obtain the best effect only in 2 test functions, and others are obtained by MFPA using three novel strategies. Obviously, the proposed algorithm with three communication strategies has the better effect than basic FPA.

From mean value in the Table 3, MFPA using strategy 3 get the best results with the better convergence effect in 12 of the 25 test functions, and the similar convergence effect in 9 functions, and the worse convergence effect in no function. FPA obtain the best convergence effect only in 2 test functions, the similar effect in 9 functions, and the worst effect in 13 functions. It can be seen that MFPA using strategy 3 has the best convergence effect. This algorithm effectively combines the advantages of strategy 1 and strategy 2.

According to the analysis of std value in the Table 3, MFPA using strategy 3 shows that in 12 of the 25 test functions this algorithm has the Least dispersion, has the similar effect in 7 functions, and no function has the maximum dispersion. FPA shows that in 2 of the 25 test functions this algorithm has the Least dispersion, has the similar effect in 7 functions, and 13 of 25 function with the maximum dispersion. It can be seen from the std value that the dispersion degree of FPA is the largest, that is, the randomness of its results is greater than that of the other three algorithms. Among the four algorithms, MFPA using strategy 3 is the one with the smallest dispersion degree and the result is more stable.

In Figure 3, function 1 to 6 is the first 6 function of 25 test functions. The solid line is the convergence curve of MFPA using strategy 3, dashed line is MFPA using strategy 2, dotted line is MFPA using strategy 1, and dash-dot line is FPA. From Figure 3, the rate of convergence of MFPA using three strategies is better than FPA. In 5 functions the rate of convergence is ranked as MFPA using strategy 3 < MFPA using strategy 2 < MFPA using strategy 1 < FPA. Only in function 3, that is Levy function, MFPA using strategy 3 converges quickly at first, but later it is slower than the other two MFPA. Therefore, the rate of convergence MFPA is significantly better than that of FPA.

As is shown in Figure 4, we compare MFPA with FPA and PSO in 6 test functions, the convergence effect of MFPA using three novel strategies is obviously better than that of FPA and PSO. The parameters of the MFPA and FPA are the same as above. As for PSO, inertia weight is equal to 1.0 [39], acceleration coefficients are equal to 2.0 [5].

4.2 Two Application Problems

In this section, we apply MFPA based on novel communication strategies and basic FPA to two application problems [40]: Frequency Modulated (FM) sound synthesis problem and Spread Spectrum Radar (SSR) Polyphase Code Design problem.

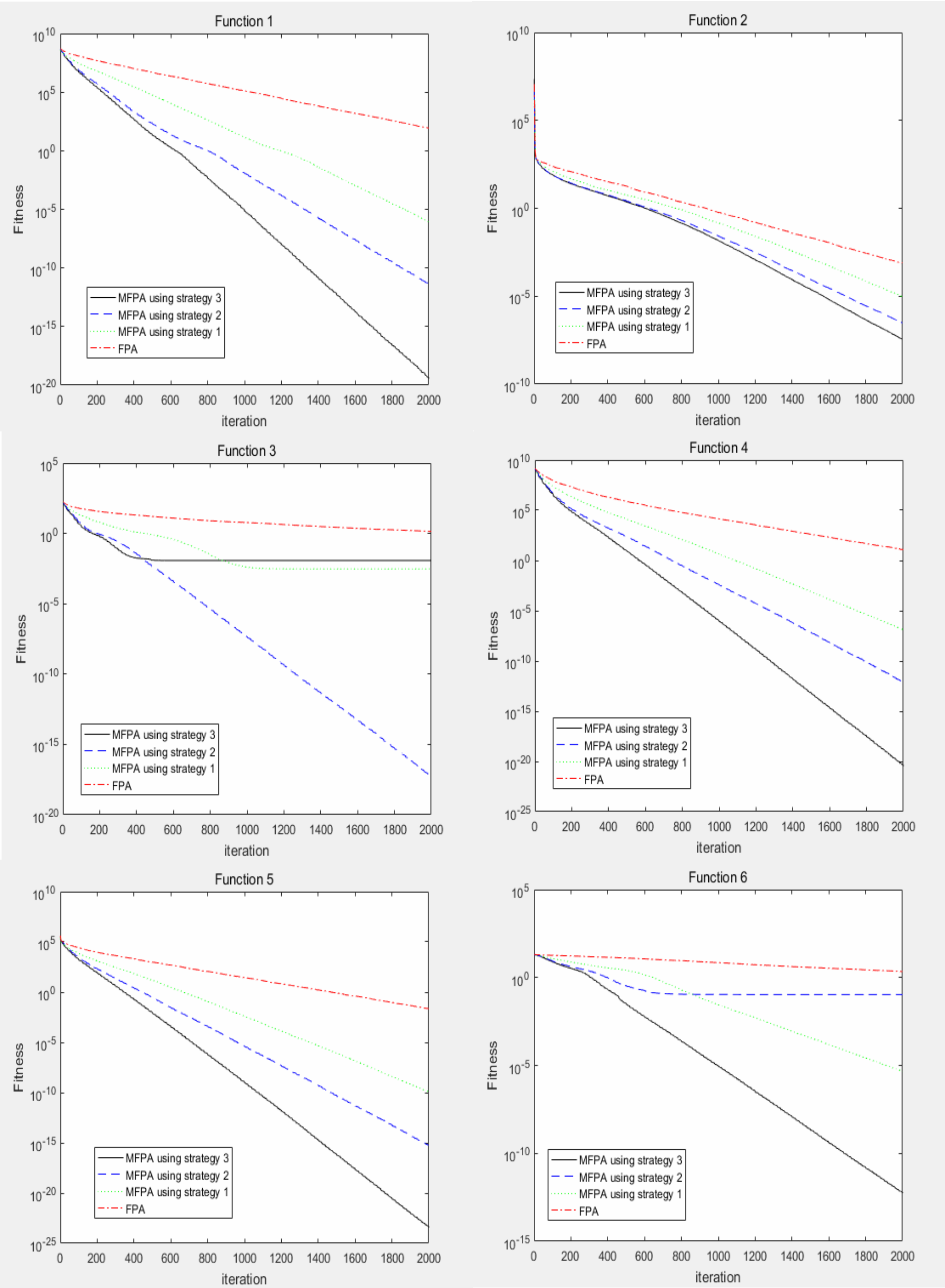

Figure 3. The optimization curves of the first 6 functions

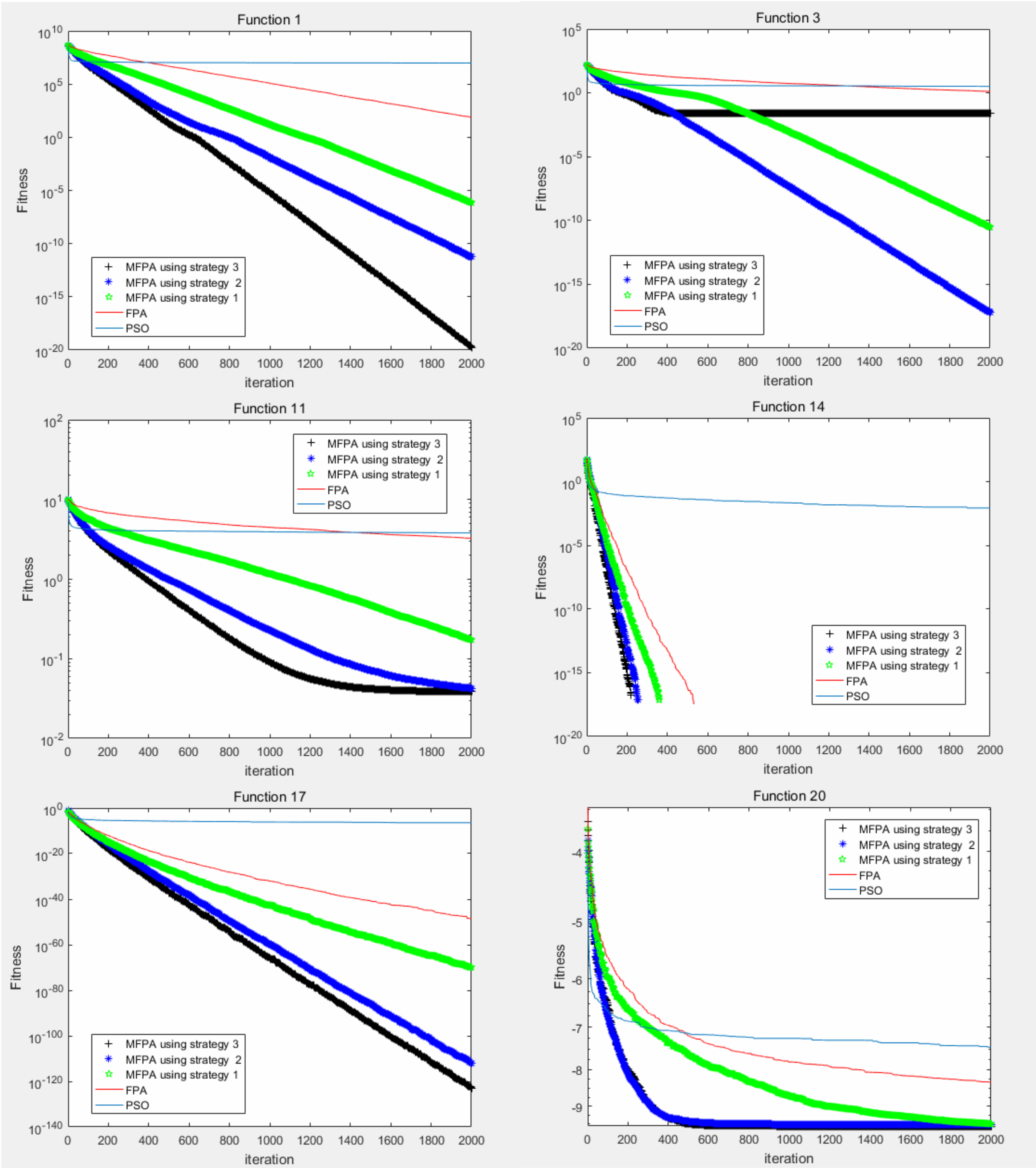

Figure 4. The compared results of algorithms in 6 functions for 30 runs

FM sound synthesis problem [41]: As a significant part in modern music system, this problem aims to optimize its parameter that is X in (11). We only consider the case of 6 dimensions [42-43]. The following formulas are optimized sound wave $z(t)$ and target sound wave $z_0(t)$.

$$z(t) = x_1 \sin(\theta x_2 t + x_3 \sin(\theta x_4 t + x_5 \sin(\theta x_6 t))) \quad \textbf{(11)}$$

$$z_0(t) = \sin(5\theta t - 1.5 \sin(4.8\theta t + 2\sin(4.9\theta t))) \quad \textbf{(12)}$$

where $\theta = 2\pi/100$ and $x_i \in [-6.4, 6.35]$.

The main purpose of FM problem is to make $z(t)$ close to $z_0(t)$, its objective fitness function is as follows, and its global minimum is 0.

$$f(X) = \sum_{t=0}^{T} (z(t) - z_0(t))^2 \quad \textbf{(13)}$$

In experiment we took $T = 150$ and $T = 200$, the results are shown in Figure 5.

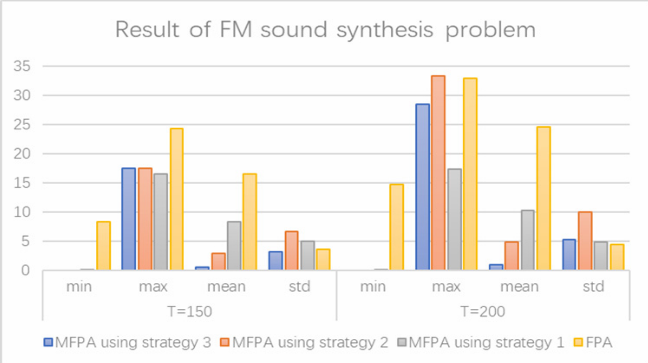

Figure 5. FM sound synthesis problem's result

From the Figure 5, the mean value of MFPA using strategy 3 is the smallest, its convergence effect is the best of four algorithms. The basic FPA has not performed the good effect in mean value, although its std value is pretty good.

SSR Polyphase Code Design problem [41]: While designing radar system with pulse compression, it is necessary to choose the appropriate waveform. Polyphase codes of radar pulse modulation have lower sidelobe in the compressed signal [41]. This is a continuous nonlinear min-max and non-convex problem. It is formally modeled as follows [40]:

$$\min f(v) = \max\{\Phi_1(v), \Phi_2(v), \ldots, \Phi_{2m}(v)\} \quad v \in V, m = 2n-1 \tag{14}$$

$$V = \{(v_1, \ldots, v_n) \in R^n \mid 0 \le v_j \le 2\pi, j = 1, \ldots, n\} \tag{15}$$

$$\Phi_{2i-1}(v) = \sum_{k=i}^{n} cos\left(\sum_{l=|2i-k-1|+1}^{k} v_l\right), i = 1, \ldots, n \tag{16}$$

$$\Phi_{2i}(v) = \sum_{k=i+1}^{n} cos\left(\sum_{l=|2i-k|+1}^{k} v_l\right) + \frac{1}{2}, i = 1, \ldots, n-1 \tag{17}$$

$$\Phi_{m+i}(v) = -\Phi_i(v),\ i = 1, \ldots, m \tag{18}$$

where n is the dimension of v. In this paper, the situation of 19 dimensions and 20 dimensions are implemented, the measured results are shown in Figure 6:

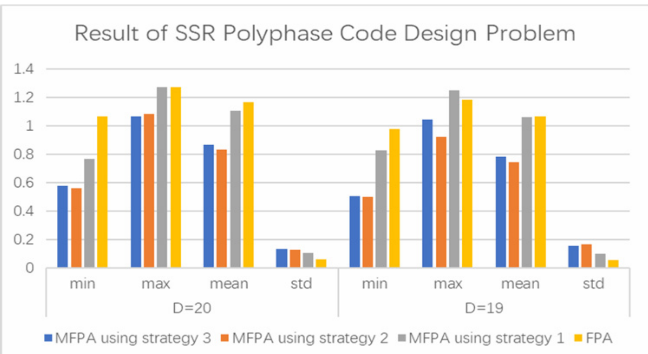

Figure 6. SSR Polyphase Code Design problem's result

From the Figure 6, in SSR Polyphase Code Design problem, the mean fitness of MFPA using strategy 2 is the smallest, so its convergence degree is the best among the four algorithms, while the mean fitness of basic FPA is the largest, so its convergence effect is the worst. Although the standard deviation of FPA is the smallest, its convergence degree is the worst, so the overall effect is still poor compared with the proposed three strategies.

5 Conclusions

In view of FPA's disadvantages of tardy convergence rate, inferior search precision, and strong local optimum, the MFPA based on novel communication strategies is proposed in this paper. In the proposed schemes, the pollen is averagely divided into some groups, and each group runs FPA to update pollens in parallel. When a specific iteration is reached, the proposed communication strategy is applied to individual communication between groups. In the paper, we propose three new communication strategies, and simulation results based on the 25 ordinary test functions and two real world problems demonstrate the proposed parallel strategies for FPA is efficient and effect.

For the future work, MFPA based on novel communication strategies be further improved, such as adding chaotic mapping, discretization, binary, and the proposed strategies can also be further improved by adopting some efficient schemes [44-49]. The algorithm proposed in this paper could also be applied to other fields, such as continuous optimization problem, economic load distribution, wireless sensor networks [50-53] and information security issues [54-56].

Acknowledgements

This paper is partly supported by project 2018Y3001 of Fujian Provincial Department of Science and Technology, Natural Science Foundation of Fujian Province with grant number 2018J01638, the Fundamental Research Funds for the Central Universities (2019QNA4059), Zhejiang Province Basic Public Welfare Research Program (LGG19F020021), Shanghai Automotive Industry Science and Technology Development Foundation (1815).

References

[1] S. Mahdavi, M. E. Shiri, S. Rahnamayan, Metaheuristics in large-scale global continues optimization: A survey, *Information Sciences*, Vol. 295, pp. 407-428, February, 2015.

[2] I. I. Măndoiu, A. Zelikovsky, *Bioinformatics algorithms: techniques and applications*, John Wiley & Sons, 2008.

[3] Z. W. Geem, J. H. Kim, G. V. Loganathan, A New Heuristic Optimization Algorithm: Harmony Search, *Simulation*, Vol. 76, No. 2, pp. 60-68, February, 2001.

[4] X.-S. Yang, S. Deb, Cuckoo search: recent advances and applications, *Neural Computing and Applications*, Vol. 24, No. 1, pp. 169-174, January, 2014.

[5] J. Kennedy, R. C. Eberhart, Particle Swarm Optimization, *Proceedings of the IEEE international conference on neural networks*, Perth, Western Australia, 1995, pp. 1942-1948. DOI: 10.1109/ICNN.1995.488968.

[6] D. Karaboga, B. Basturk, Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems, *International Fuzzy Systems Association World Congress*, Cancun, Mexico, 2007, pp. 789-798.

[7] S. Mirjalili, S. M. Mirjalili, A. Lewis, Grey wolf optimizer, *Advances in engineering software*, Vol. 69, pp. 46-61, March, 2014.

[8] J. S. Pan, P. Hu, S. C. Chu, Novel Parallel Heterogeneous Meta-Heuristic and Its Communication Strategies for the Prediction of Wind Power, *Processes*, Vol. 7, No. 11, Article Number: 845, November, 2019.

[9] P. Hu, J.-S. Pan, S. C. Chu, Q.-W. Chai, T. Liu, Z.-C. Li, New Hybrid Algorithms for Prediction of Daily Load of Power Network, *Applied Sciences*, Vol. 9, No. 21, Article Number: 4514, November, 2019.

[10] X.-S. Yang, Flower Pollination Algorithm for Global Optimization, *International Conference on Unconventional Computing and Natural Computation*, Orléans, France, 2012, pp. 240-249.

[11] G. Bekdaş, S. M. Nigdeli, X.-S. Yang, Sizing optimization of truss structures using flower pollination algorithm, *Applied Soft Computing*, Vol. 37, pp. 322-331, December, 2015.

[12] T.-T. Nguyen, J.-S. Pan, T.-K. Dao, An Improved Flower Pollination Algorithm for Optimizing Layouts of Nodes in Wireless Sensor Network, *IEEE Access*, Vol. 7, pp. 75985-75998, June, 2019.

[13] R. Storn, K. Price, Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces, *Journal of global optimization*, Vol. 11, No. 4, pp. 341-359, December, 1997.

[14] Z. Meng, J.-S. Pan, K.-K. Tseng, PaDE: An enhanced Differential Evolution algorithm with novel control parameter adaptation schemes for numerical optimization, *Knowledge-Based Systems*, Vol. 168, pp. 80-99, March, 2019.

[15] Z. Meng, J. S. Pan, HARD-DE: Hierarchical archive based mutation strategy with depth information of evolution for the enhancement of differential evolution on numerical optimization, *IEEE Access*, Vol. 7, pp. 12832-12854, January, 2019.

[16] Z. Meng, J. S. Pan, H. Xu, QUasi-Affine TRansformation Evolutionary (QUATRE) algorithm: a cooperative swarm based algorithm for global optimization, *Knowledge-Based Systems*, Vol. 109, pp. 104-121, October, 2016.

[17] Z. G. Du, J. S. Pan, S. C. Chu, H.-J. Luo, P. Hu, Quasi-Affine Transformation Evolutionary Algorithm With Communication Schemes for Application of RSSI in Wireless Sensor Networks, *IEEE Access*, Vol. 8, pp. 8583-8594, January, 2020.

[18] S. Kalra, S. Arora, Firefly Algorithm Hybridized with Flower Pollination Algorithm for Multimodal Functions, *Proceedings of the international congress on information and communication technology*, Udaipur, India, 2015, pp. 207-219.

[19] O. Abdel-Raouf, M. Abdel-Baset, I. EI-henawy, A New Hybrid Flower Pollination Algorithm for Solving Constrained Global Optimization Problems, *International Journal of Applied Operational Research*, Vol. 4, No. 2, pp. 1-13, May, 2014.

[20] D. Rodrigues, X.-S. Yang, A. N. de Souza, J. P. Papa, *Binary Flower Pollination Algorithm and Its Application to Feature Selection*, in: X. S. Yang (Eds.), Recent Advances in Swarm Intelligence and Evolutionary Computation. Studies in Computational Intelligence, vol 585, Springer, Cham, 2015, pp. 85-100.

[21] X.-S. Yang, M. Karamanoglu, X. He, Multi-objective Flower Algorithm for Optimization, *Procedia Computer Science*, Vol. 18, pp. 861-868, June, 2013.

[22] R. Wang, Y. Zhou, Flower Pollination Algorithm with Dimension by Dimension Improvement, *Mathematical Problems in Engineering*, Vol. 2014, Article ID 481791, September, 2014. DOI: 10.1155/2014/481791.

[23] E. Nabil, A Modified Flower Pollination Algorithm for Global Optimization, *Expert Systems with Applications*, Vol. 57, pp. 192-203, September, 2016.

[24] O. Abdel-Raouf, I. El-Henawy, M. Abdel-Baset, A Novel Hybrid Flower Pollination Algorithm with Chaotic Harmony Search for Solving Sudoku Puzzles, *International Journal of Modern Education and Computer Science*, Vol. 6, No. 3, pp. 38-44, March, 2014.

[25] R. Wang, Y. Zhou, S. Qiao, K. Huang, Flower Pollination Algorithm with Bee Pollinator for Cluster Analysis, *Information Processing Letters*, Vol. 116, No. 1, pp. 1-14, January, 2016.

[26] W. Li, Z. He, J. Zheng, Z. Hu, Improved Flower Pollination Algorithm and Its Application in User Identification Across Social Networks, *IEEE Access*, Vol. 7, pp. 44359-44371, January, 2019.

[27] L. Chittka, J. D. Thomson, N. M. Waser, Flower Constancy, Insect Psychology, and Plant Evolution, *Naturwissenschaften*, Vol. 86, No. 8, pp. 361-377, August, 1999.

[28] J.-F. Chang, S.-C. Chu, J. F. Roddick, J.-S. Pan, A Parallel Particle Swarm Optimization Algorithm with Communication Strategies, *Journal of Information Science and Engineering*, Vol. 21, No. 4, pp. 809-818, July, 2005.

[29] S.-C. Chu, J. F. Roddick, J.-S. Pan, Ant colony system with communication strategies, *Information Sciences*, Vol. 167, No. 1-4, pp. 63-76, December, 2004.

[30] T.-S. Pan, T.-K. Dao, T.-T. Nguyen, S.-C. Chu, A Communication Strategy for Paralleling Grey Wolf Optimizer, *International Conference on Genetic and Evolutionary Computing*, Yangon, Myanmar, 2015, pp. 253-262.

[31] S.-C. Chu, P.-W. Tsai, J.-S. Pan, Cat Swarm Optimization, *Pacific Rim International Conference on Artificial Intelligence*, Guilin, China, 2006, pp. 854-858.

[32] P.-W. Tsai, J.-S. Pan, S.-M. Chen, B.-Y. Liao, S.-P. Hao, Parallel Cat Swarm Optimization, *2008 international conference on machine learning and cybernetics*, Kunming, China, 2008, pp. 3328-3333.

[33] P.-W. Tsai, J.-S. Pan, S.-M. Chen, B.-Y. Liao, Enhanced parallel cat swarm optimization based on the Taguchi method, *Expert Systems with Applications*, Vol. 39, No. 7, pp. 6309-6319, June, 2012.

[34] L. Kong, J.-S. Pan, P.-W. Tsai, S. Vaclav, J.-H. Ho, A Balanced Power Consumption Algorithm Based on Enhanced Parallel Cat Swarm Optimization for Wireless Sensor Network, *International Journal of Distributed Sensor Networks*, Vol. 11, No. 3, pp. 1-10, March, 2015. DOI: 10.1155/2015/729680.

[35] K. Fleetwood, An Introduction to Differential Evolution, *Proceedings of Mathematics and Statistics of Complex Systems (MASCOS) One Day Symposium*, Brisbane, Australia, 2004, pp. 785-791.

[36] X. F. Yan, J. Yu, F. Qian, Adaptive mutation differential evolution algorithm and its application to estimate soft sensor parameters, *Control Theory & Applications*, Vol. 23, No. 5, pp. 744-748, October, 2006.

[37] N. H. Awad, M. Z. Ali, P. N. Suganthan, J. J. Liang, B. Y. Qu, *Problem Definitions and Evaluation Criteria for the CEC 2017 Special Session and Competition on Single Objective Real-Parameter Numerical Optimization*, October, 2017.

[38] E. P. Adorio, U. P. Diliman, Mvf-multivariate test functions library in c for unconstrained global optimization, *Adorio2005MVFM*, Quezon City, Philippines, 2005.

[39] Y. Shi, R. C. Eberhart, A modified particle swarm optimizer, *1998 IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No.98TH8360)*, Anchorage, Alaska, 1998, pp. 69-73.

[40] H. Wang, S. Rahnamayan, H. Sun, M. G. H. Omran, Gaussian Bare-Bones Differential Evolution, *IEEE Transactions on Cybernetics*, Vol. 43, No. 2, pp. 634-647, April, 2013.

[41] S. Das, P. N. Suganthan, *Problem Definitions and Evaluation Criteria for CEC 2011 Competition on Testing Evolutionary Algorithms on Real World Optimization Problems*, December, 2010.

[42] S. Das, A. Abraham, U. K. Chakraborty, A. Konar, Differential Evolution Using a Neighborhood-Based Mutation Operator, *IEEE Transactions on Evolutionary Computation*, Vol. 13, No. 3, pp. 526-553, June, 2009.

[43] F. Herrera, M. Lozano, Gradual Distributed Real-Coded Genetic Algorithms, *IEEE Transactions on Evolutionary Computation*, Vol. 4, No. 1, pp. 43-63, April, 2000.

[44] J. Wang, Y. Gao, X. Yin, F. Li, H.-J. Kim, An Enhanced PEGASIS Algorithm with Mobile Sink Support for Wireless Sensor Networks, *Wireless Communications and Mobile Computing*, Vol. 2018, Article ID 9472075, December, 2018. DOI: 10.1155/2018/9472075.

[45] J. Wang, Y. Gao, W. Liu, A. K. Sangaiah, H.-J. Kim, An intelligent data gathering schema with data fusion supported for mobile sink in wireless sensor networks, *International Journal of Distributed Sensor Networks*, Vol. 15, No. 3, pp. 1-9, March, 2019.

[46] J.-S. Pan, L. Kong, T.-W. Sung, P.-W. Tsai, V. Snášel, α-Fraction First Strategy for Hierarchical Model in Wireless Sensor Networks, *Journal of Internet Technology*, Vol. 19, No. 6, pp. 1717-1726, November, 2018.

[47] J.-S. Pan, L. Kong, T.-W. Sung, P.-W. Tsai, V. Snášel, A Clustering Scheme for Wireless Sensor Networks Based on Genetic Algorithm and Dominating Set, *Journal of Internet Technology*, Vol. 19, No. 4, pp. 1111-1118, July, 2018.

[48] J.-S. Pan, C.-Y. Lee, A. Sghaier, M. Zeghid, J. Xie, Novel Systolization of Subquadratic Space Complexity Multipliers Based on Toeplitz Matrix-Vector Product Approach, *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, Vol. 27, No. 7, pp. 1614-1622, July, 2019.

[49] X. Yin, K. Zhang, B. Li, A. K. Sangaiah, J. Wang, A task allocation strategy for complex applications in heterogeneous cluster-based wireless sensor networks, *International Journal of Distributed Sensor Networks*, Vol. 14, No. 8, pp. 1-15, August, 2018. DOI: 10.1177/1550147718795355.

[50] J. Wang, C. Ju, Y. Gao, A. K. Sangaiah, G. Kim, A PSO based Energy Efficient Coverage Control Algorithm for Wireless Sensor Networks, *Computers, Materials & Continua*, Vol. 56, No. 3, pp. 433-446, September, 2018.

[51] J. Wang, X. Gu, W. Liu, A. K. Sangaiah, H.-J. Kim, An Empower Hamilton Loop based Data Collection Algorithm with Mobile Agent for WSNs, *Human-centric Computing and Information Sciences*, Vol. 9, Article number: 18, May, 2019.

[52] J. Wang, Y. Gu, K. Wang, A. K. Sangaiah, S.-J. Lim, An Affinity Propagation-Based Self-Adaptive Clustering Method for Wireless Sensor Networks, *Sensors*, Vol. 19, No. 11, Article Number: 2579, June, 2019.

[53] J. Wang, Y. Cao, B. Li, H. Kim, S. Lee, Particle Swarm Optimization based Clustering Algorithm with Mobile Sink for WSNs, *Future Generation Computer Systems*, Vol. 76, pp. 452-457, November, 2017.

[54] T.-Y. Wu, C.-M. Chen, K.-H. Wang, C. Meng, E. K. Wang, A Provably Secure Certificateless Public Key Encryption with Keyword Search, *Journal of the Chinese Institute of Engineers*, Vol. 42, No. 1, pp. 20-28, January, 2019.

[55] C.-M. Chen, K.-H. Wang, K.-H. Yeh, B. Xiang, T.-Y. Wu, Attacks and solutions on a three-party password-based authenticated key exchange protocol for wireless communications, *Journal of Ambient Intelligence and Humanized Computing*, Vol. 10, No. 8, pp. 3133-3142, August, 2019.

[56] C.-M. Chen, Y. Huang, K.-H. Wang, S. Kumari, M.-E. Wu, A secure authenticated and key exchange scheme for fog computing, *Enterprise Information Systems*, January, 2020. DOI: 10.1080/17517575.2020.1712746.

Biographies

Jeng-Shyang Pan received the Ph.D. degree in electrical engineering from the University of Edinburgh, U.K. in 1996. He is currently the Professor in the College of Computer Science and Engineering, Shandong University of Science and Technology. His current research interest includes the information hiding, artificial intelligence and wireless sensor networks.

Jiawen Zhuang is a graduate student in Fujian University of Technology. His research interests include Intelligent Computing, Intelligent Traffic System and Computer Vision.

Hao Luo received the B.S., M.S. and Ph.D. degrees from Harbin Institute of Technology, Harbin, China, in 2002, 2004 and 2008, respectively. From 2014 to 2016, he was a Visiting Scholar at the School of Aerospace, Mechanical and Mechatronic Engineering, the University of Sydney, Australia. Currently, he is an Associate Professor at the School of Aeronautics and Astronautics, Zhejiang University, China, His current research interests include digital signal processing, information security, and image processing.

Shu-Chuan Chu received the Ph.D. degree in 2004 from the Flinders University of South Australia. Currently, She is the Research Fellow with PhD advisor in the College of Computer Science and Engineering of Shandong University of Science and Technology from September 2019. Her research interests are mainly in Swarm Intelligence, Intelligent Computing and Data Mining.