

A New Hierarchical Structure for Combining Different Versions of PSO

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ABSTRACT

Particle swarm optimization is a population-based algorithm and used for optimization in a wide range of problems. In this article, a method that is called Hybrid Particle Swarm Optimization or HPSO is proposed. It is composed of some versions of particle swarm optimization algorithms, which have subgroups in their structures. They are DMS-PSO, PS2OS and MCPSO. In fact, a hierarchical structure is used to compose a new version of optimization algorithm and combine the results of other structures of PSO. Proposed structure has been tested on four unimodal and four multimodal test functions. Although the memory usage has no difference with other compared versions, it is much faster in many cases. Also the rank of fitness values, are good and suitable in all test functions. In addition, it is possible to execute it concurrently.

General Terms

Optimization, Evolutionary Algorithms, Swarm Intelligence

Keywords

Particle Swarm Optimization, Hierarchical Structure

1. INTRODUCTION

Kennedy and Eberhart [1] proposed the idea of Particle Swarm Optimization in 1995. They initially wanted to produce some form of computational intelligence by using social relationship that does not need individual ability. Their attempts led to a robust optimization algorithm called Particle Swarm Optimization or PSO algorithm. This algorithm has been inspired from social behavior of animals such as bird's flocking and fish movement. PSO is a population-based algorithm, and this population is consisted of some particles. Although these particles have not enough intelligence separately, they show an excellent intelligence as a whole by following their leader and using their own experience. The implementation of PSO is simple and a few parameters are needed to be valued. However, this algorithm has its own disadvantages such as low speed convergence and trapping in local optimum in some cases, so different versions of this algorithm is suggested. All of them try to improve different aspects of it and cover its weakness. In [2] a dynamic model is introduced that particles are divided into many small groups and each group executes PSO separately. The groups exchange some of their particles randomly to exchange information. It is used for preventing from trapping in local optimums. The same structure is used in [3, 4] however a local search that employs Quasi-Newton method is used in it. In [4] this structure is applied for large-scale optimization. Hanning Chen et al [5] designed hierarchical structure called hierarchical swarm optimization. They try to simulate natural hierarchical systems. Particles are divided into separate groups. Each group executes PSO independently and the best particles of each group are selected as their representative, and make higher level. In this level, the PSO is executed and best

particle is selected as the global best. Ben Nui et al [6, 7] introduced a Master-Slave PSO. Particles are divided into some groups. One of them is master and others are slaves. Slaves groups execute PSO separately. In master group, particles' positions are updated using their own knowledge and slave groups' experiences. Yen and Daneshyari [8] propose a method to exchange information among multiple swarms in particle swarm optimization. This Method is developed to solve problems that have a high number of local optima. [9] proposes a multi-swarm algorithm based on fast particle swarm optimization for dynamic optimization problems. It employs a method to track multiple peaks by preventing overcrowding at a peak and a fast particle swarm optimization algorithm as a local search method. Chen [10] proposes a hierarchical particle swarm optimization. In the suggested algorithm, all particles are arranged in a regular tree structure and move up or down in the tree based on their fitness value. The velocity update of each particle depends on the position of each particle in the tree. A mutation operator is also added into the proposed approach. Bergh and Engelbrecht [11] present a cooperative behavior to improve the performance of the standard algorithm. This is done by using multiple swarms to optimize different components of the solution vector cooperatively. Most of these structures are using different groups in order to improve the quality of PSO.

There are also some surveys that discuss and compare different aspects of PSO [12, 13]. Author in [12] comprises a snapshot of particle swarming from the authors' perspective, including variations in the algorithm, current and ongoing research, applications and open problems. In [13] the history, various methods, and taxonomy of PSO are discussed and its different applications together with an analysis of these applications are evaluated. Sierra and Coello [14] did a comprehensive review of the various Multi-Objective Particle Swarm Optimizers. It includes a classification of the approaches, and the main features of each proposal. In the last part of it, they list some of the topics within this field that are considered as promising areas of future research.

In this research, standard PSO is described in section two. Section three introduces the proposed methodology. Section four and five explain experimental results and conclusions respectively.

2. REVIEW OF STANDARD PSO

PSO is inspired from nature and is based on iteration. It is like many other evolutionary algorithms such as Genetic Algorithms and Ant Colony Optimization, because all of them use an initial random population. Each component of population of the algorithm is called a particle. Each particle is initialized with a random velocity and position. These particles move in an n-dimensional space repeatedly. The dimension of the problem is equal to parameters of function that should be optimized. Each particle not only remembers the best position that has achieved so far but also the global

best position among all other particles. By using these data, the particles set their movements in next iteration. In order to find the optimal solution, in each iteration both the velocity and position of each particle are updated using equations 1 and 2 respectively.

$$v^{new} = w \times v^{old} + \Gamma_1 \times r_1 \times (p^{personalBest} - p^{old}) + \Gamma_2 \times r_2 \times (p^{globalBest} - p^{old}) \quad (1)$$

$$p^{new} = p^{old} + v^{new} \quad (2)$$

Where v is velocity of particle, p is position of particle, r_1 and r_2 are random numbers uniformly distributed between $[0, 1]$, Γ_1 and Γ_2 are learning rates, $p^{personalBest}$ is the best position that a particle has found yet and $p^{globalBest}$ is the best global position. w is inertia weight that causes the particle to continue to its way although it reaches the best position.

According to the equation 1, it is clear that the motion of a particle is influenced by three factors: (i) its best position that the particle has found so far, (ii) Best position that is founded so far by all particles and (iii) The previous path of the particle.

3. A HIERARCHICAL STRUCTURE OF PSO

As it is mentioned, different versions of PSO have been suggested. Their main goal is improving PSO efficiency. In comparison, each version has better results in some cases and functions, and worse results in some others. The main goal is finding an algorithm, which has the best efficiency on all functions as fast as possible. One way to achieve this goal is finding a method to combine efficient algorithms in the best way. The obstacle to do this is the different structures of algorithms, and it is why their combination is not easy. In this research, three different versions of PSO is used and combined. They are selected because not only they have good efficiency but also they have nearly same structure. It makes their combination easier. They are DMS-PSO[2], PS2OS [5] and MCP SO [6]. Table 1 show their average results of 20 times execution of algorithms on some test functions which are introduced in table 2 and 3. Also this structure can be used to combine other versions of PSO.

It is clear in table 1, that each version has better result on some functions. For example, DMS-PSO has the best result on almost all functions except Schwefel, which PS2OS is the best on this function. But Otherwise DMS-PSO is very slow and takes a long time to find optimum. Otherwise PS2OS is very faster and find solution with higher speed and lower time. We can combine their advantages using proposed structure.

In DMS-PSO, velocity update is happened in two steps. At 90% of iterations that form first step, particles are arranged in different groups and their movements are affected by the best position that a particle has ever found; $P^{personalBest}$, and the best position that is found by its neighborhood particles in its group; $P^{localBest}$. Then in 10% of iterations that form second step, particles movements are affected by the global best between all particles; $P^{globalBest}$ instead of local bests. In the first step, a regroup operation is done in some predefined iterations in which some particles move from one subgroup to another one.

In PS2OS, particles are arranged in different groups and their movements are affected by the best position each particle has ever found, the best position its neighborhoods have found and global best position.

MCP SO divides particles into N groups. One group is master and others are slaves. Particle movement in slave groups are affected by the best position each particle found and the best position that found by the other particles in its group. In master group particle movement are affected by previous best position of the master swarm; p_i^M , best global position of the master swarm; p_g^M and previous best position of the slave swarms; p_i^S .

In the proposed method that is a hybrid algorithm and is called HPSO, we use a hierarchical structure and particles are divided into three groups. Each group has some subgroups. Groups have equal number of particles. The first group executes DMS-PSO, the second one executes PS2OS, and the third one executes MCP SO. These algorithms have been chosen because they have good efficiency to some extent and also same structure in creating subgroups. Creating subgroups in all of these algorithms is illustrated in figure 1. In DMS-PSO and PS2OS, particles are affected by local best particles, which are members of predefined subgroups. In MCP SO, both master and slave groups are considered as subgroups. Figure 2 shows the Pseudo Code of this algorithm. They can be executed on separate processor. After each iteration, information is exchanged between the groups. This information is the best position that groups have been founded so far. Each algorithm found its own global best. Then the best one among these three bests is chosen as a global best and all other algorithms use it from now on. If the best positions of each group are named $gBest_{DMS-PSO}$, $gBest_{PS2OS}$ and $gBest_{MCP SO}$, then:

$$gBest_{ALL} = Best(gBest_{DMS-PSO}, gBest_{PS2OS}, gBest_{MCP SO}) \quad (3)$$

The $Best(.)$ function chooses the best one. Update equations in DMS-PSO, PS2OS and MCP SO are changed respectively as equations 4, 5 and 6.

$$v^{new} = w \times v^{old} + \Gamma_1 \times r_1 \times (p^{personalBest} - p^{old}) + \Gamma_2 \times r_2 \times (gBest_{ALL} - p^{old}) \quad (4)$$

$$v^{new} = \chi(v^{old} + \Gamma_1 \times r_1 \times (p^{personalBest} - p^{old}) + \Gamma_2 \times r_2 \times (p^{localBest} - p^{old}) + \Gamma_3 \times r_3 \times (gBest_{ALL} - p^{old}) \quad (5)$$

$$v^{new} = w * v^{old} + \Gamma_1 \times r_1 \times (p_i^M - p^{old}) + \Gamma_2 \times r_2 \times (p_i^S - p^{old}) + \Gamma_3 \times r_3 \times (gBest_{ALL} - p^{old}) \quad (6)$$

4. EXPERIMENTAL RESULTS

HPSO is tested on four unimodal and four multimodal test functions. These functions are shown in table 2 and 3. Table 4 shows parameters values that are needed for different algorithms. In DMS-PSO algorithm, regrouping happens after ten iterations. Population size of particles, the number of iterations, group number and dimension in all algorithms are

100, 10000, 5 and 30 respectively. Each algorithm is executed 20 times and the mean of fitness value are shown in table 5. The best values, standard deviations and execution time are shown in table 6, 7 and 8 respectively. Also figure 3 shows the evolutionary process of proposed structure and other algorithms. In this figure, horizontal axis shows number of iterations and vertical axis shows logarithm of fitness. As it is obvious in table 5 and figures 3 that our algorithm rank is not worse than second in all test functions and in some of them such as Rosenbrock and Griewangk is the best. However, as it

is clear in table 8 the most remarkable point about the results is its time cost. Although the number of particles is constant, execution time is often shorter than other algorithm except standard PSO. We do not consider standard PSO because of its very low efficiency. In Sum of Different Powers and Rosenbrock functions, HPSO algorithm has second and third rank. However, in other functions it is the fastest algorithm. In Rastrigin, Schwefel and Ackley functions, execution speed is about two times faster than others are.

Table 1. The mean of fitness values of 20 times execution on different functions in 30 dimensions

Type	Function Name	Algorithm Name			
		PSO	PS2OS	MCPSO	DMS-PSO
Unimodal	Step	40	10.2	0	0
	Sum of Different Powers	6.68307E+16	61063177863	1.50713E+13	0
	Rosenbrock	2634.983	2051.209	57.12211	5.252174
	Sphere	3920.4	871.2	6.92832E-88	0
Multimodal	Rastrigin	136.1682	80.3533	73.57082	6.56673
	Schwefel	5755.476	3522.819	4394.075	5825.996
	Griewangk	27.15134	4.525284	0.00849	0.00234
	Ackley	7.781164	1.041985	7.8948E-08	2.66454E-15

Table 2: List of functions

Name	Definition	Interval	Global Minimum	Optimal Point
Step	$f(x) = \sum_{i=1}^n [\text{floor}(x_i + 0.5)]^2$	$-100 \leq x_i \leq 100$	0	$x_i=0, i=1, \dots, n$
Sum of Different Powers	$f(x) = \sum_{i=1}^n x_i ^{i+1}$	$-1 \leq x_i \leq 1$	0	$x_i=0, i=1, \dots, n$
Rosenbrock	$f(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	$-2.048 \leq x_i \leq 2.048$	0	$x_i=0, i=1, \dots, n$
Sphere	$f(x) = \sum_{i=1}^n x_i^2$	$-5.12 \leq x_i \leq 5.12$	0	$x_i=1, i=1, \dots, n$
Rastrigin	$f(x) = 10n + \sum_{i=1}^n [x_i^2 - 10 \cos(2\pi x_i)]$	$-5.12 \leq x_i \leq 5.12$	0	$x_i=0, i=1, \dots, n$

Table 3: Continue of List of functions

Name	Definition	Interval	Global Minimum	Optimal Point
Schwefel	$f(x) = \sum_{i=1}^n [-x_i \sin(\sqrt{ x_i })] + 418.9829n$	$-500 \leq x_i \leq 500$	0	$x_i=420.9687$, $i=1,\dots,n$
Griewangk	$f(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}}) + 1$	$-600 \leq x_i \leq 600$	0	$x_i=0$, $i=1,\dots,n$
Ackley	$f(x) = -20 \exp(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}) - \exp(\frac{1}{n} \sum_{i=1}^n \cos(2\pi x_i)) + 20 + e$	$-30 \leq x_i \leq 30$	0	$x_i=0$, $i=1,\dots,n$

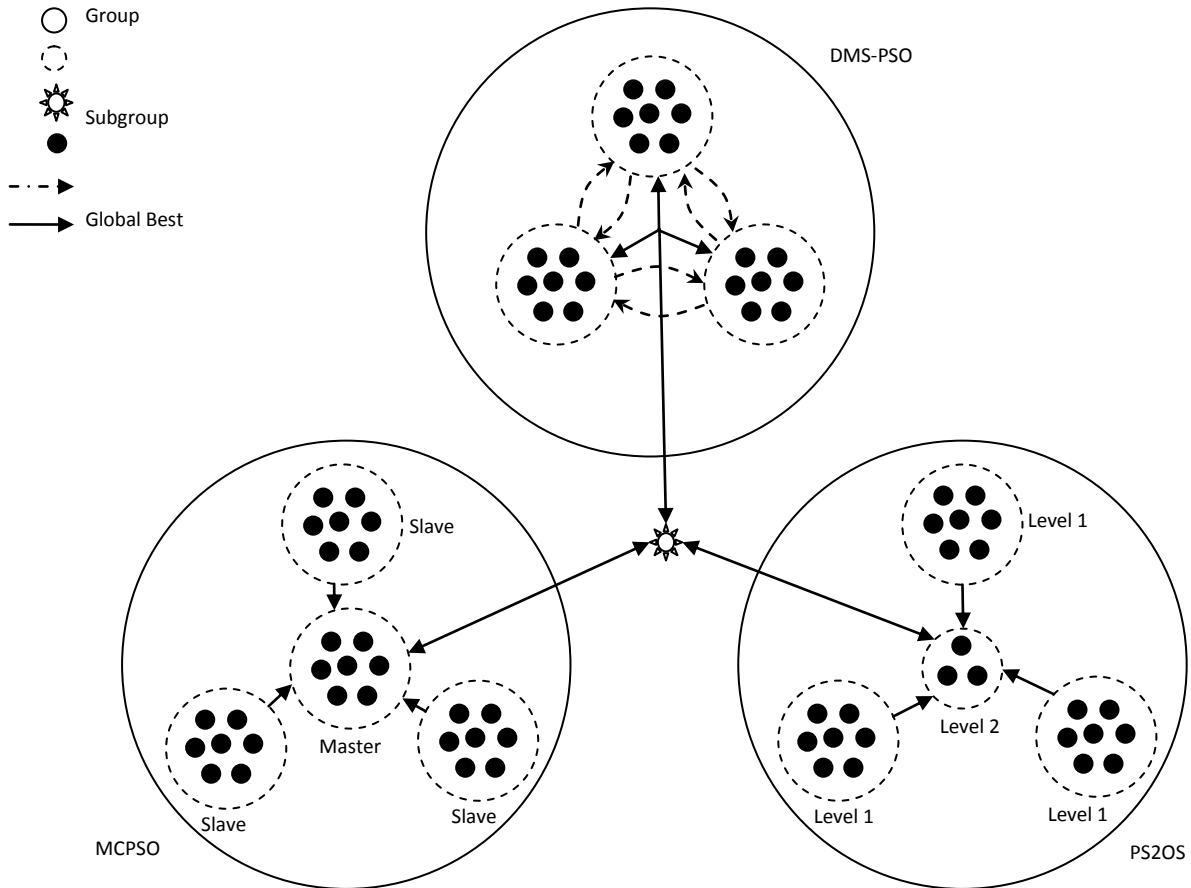


Fig 1: HPSO structure

Algorithm HPSO

Divide population into 3 groups randomly, with equal population in each group

Initialize particles position and velocity

Set globalBest as the best position of particles

Repeat

Do PS2OS, MCP SO and DMS-PSO in parallel using equations 4 to 6

When all process finished update globalBest using equation 3

Until a termination condition is met

Fig 2: Pseudo-code for the HPSO algorithm

Table 4: Different algorithms parameters

	Γ_1	Γ_1	Γ_1	χ
PS2OS	---	---	---	0.4693
MCP SO	2.05	2.05	0.5	---
DMS-PSO	1.3667	1.3667	1.3667	---

Table 5: Fitness value averages

Type	Function Name	Algorithm Name				
		PSO	PS2OS	MCP SO	DMS-PSO	HPSO
Unimodal	Step	40	10.2	0	0	0
	Sum of Different Powers	6.68307E+16	61063177863	1.50713E+13	0	6.0666E-202
	Rosenbrock	2634.983	2051.209	57.12211	5.252174	1.994196
	Sphere	3920.4	871.2	6.92832E-88	0	5.57791E-74
Multimodal	Rastrigin	136.1682	80.3533	73.57082	6.56673	10.24808
	Schwefel	5755.476	3522.819	4394.075	5825.996	3994.704
	Griewangk	27.15134	4.525284	0.00849	0.00234	0.000863
	Ackley	7.781164	1.041985	7.8948E-08	2.66454E-15	5.86198E-15

Table 6: Bets fitness values

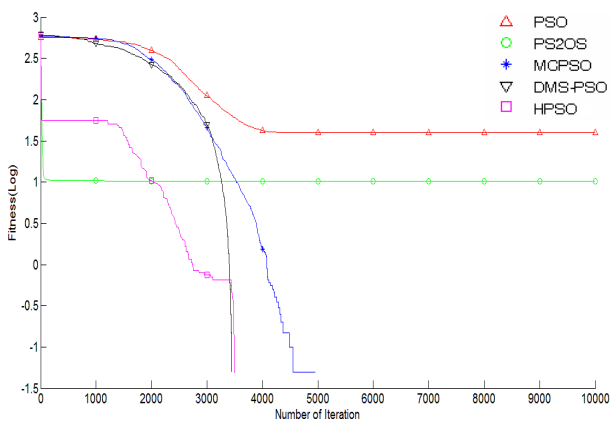
Type	Function Name	Algorithm Name				
		PSO	PS2OS	MCP SO	DMS-PSO	HPSO
Unimodal	Step	0	0	0	0	0
	Sum of Different Powers	1.1101E+11	0	11094.69	0	1.7509E-253
	Rosenbrock	3.074407	2.875E-25	0.806731	0.439654	0.001026
	Sphere	1.41077E-56	0	3.17009E-92	0	3.0032E-156
Multimodal	Rastrigin	63.91875	52.73256	9.984942	2.984877	4.974795
	Schwefel	4059.869	2576.789	3099.119	5596.943	23820.421
	Griewangk	0	0	0	0	0
	Ackley	6.21725E-15	6.21725E-15	7.8948E-08	2.66454E-15	2.66454E-15

Table 7: Standard deviation of fitness values

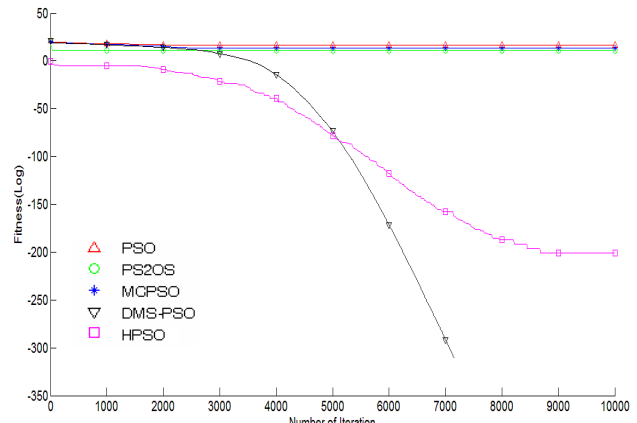
Type	Function Name	Algorithm Name				
		PSO	PS2OS	MCPSO	DMS-PSO	HPSO
Unimodal	Step	50.26247	30.71533	0	0	0
	Sum of Different Powers	2.25161E+17	2.23092E+11	3.6763E+13	0	0
	Rosenbrock	4380.078	4084.7441	54.4867	2.777684	2.568101
	Sphere	3128.413191	1787.665	1.79984E-87	0	1.2786E-142
Multimodal	Rastrigin	43.91864	21.79923	35.44007	2.026243	3.114714
	Schwefel	727.9518	742.4373	689.716	201.5004	812.225
	Griewangk	42.52906	20.22434	0.008932	0.005562	0.002685
	Ackley	8.093677935	3.1937318	2.28128E-07	0	2.27631E-15

Table 8: Mean of 20 times execution of algorithms in second

Type	Function Name	Algorithm Name				
		PSO	PS2OS	MCPSO	DMS-PSO	HPSO
Unimodal	Step	33.96467	951.3122	931.9807	994.7493	680.4106
	Sum of Different Powers	63.88169	2153.533	2096.571	2759.359	2469.466
	Rosenbrock	45.84556	2187.975	2144.549	2469.64	2488.982
	Sphere	34.80072	1179.87	1120.856	1252.537	781.094
Multimodal	Rastrigin	42.7889	1475.199	1545.962	1678.039	719.9123
	Schwefel	56.3996	1470.374	1395.198	1583.201	775.41
	Griewangk	50.42329	2434.045	2360.87	2618.147	2203.812
	Ackley	42.39741	1213.938	1223.791	1305.369	784.7638



(a)



(b)

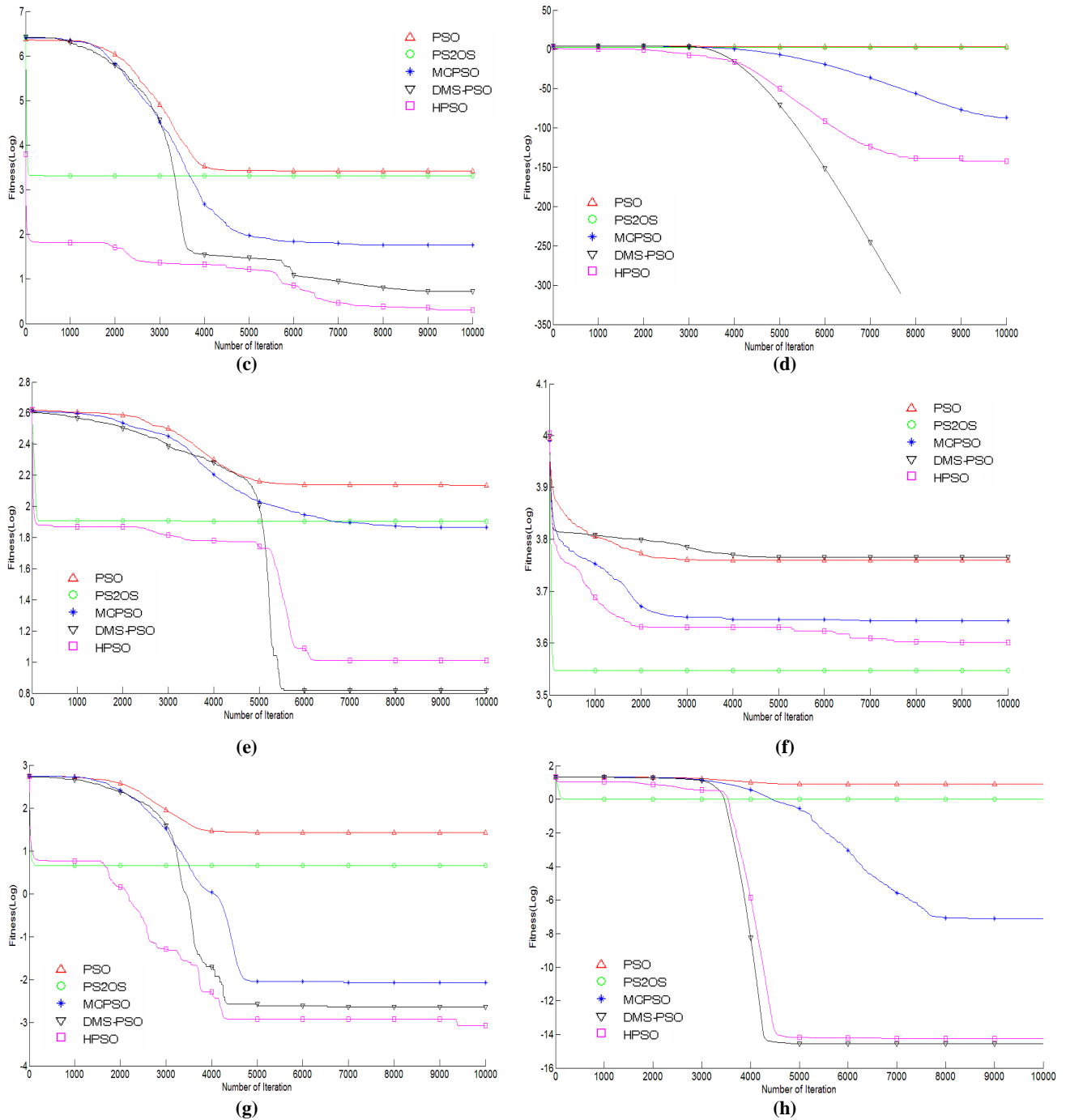


Fig 3: Mean best fitness values in (a)Step (b)Sum of Different Powers (c)Rosenbrock (d)Sphere (e)Rastrigin (f)Schwefel (g)Griewangk (h)Ackley

5. CONCLUSIONS

In this paper, a hybrid PSO that is called HPSO has been proposed. It is composed of three version of PSO i.e. DMS-PSO, PS2OS and MCPSO. In this algorithm, a hierarchical structure is used. Population is divided into three groups and each group executes a different algorithm. Meanwhile, they use the best global best position that each algorithm has ever found. Then it is compared with its components algorithms. They are tested on four unimodal and four multimodal test functions. The performance of HPSO is better in some cases meanwhile its speed is often much better than the algorithms that composed it.

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