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An Efficient Survey on Multi Colony- Particle Swarm Optimization (MC-PSO) Algorithm

T. Geetha[1], B. Sowmiya[2], L. JayaKumar[3], A. Sarang Sukumar[3]

[1]*Assistant Professor,* [2]*Associate Professor, Dept of CSE, Chendu College of Engineering & Technology, Tamilnadu,India*
[3]*Assistant Professor, Christ College of Engineering & Technology,Puducherry,India.*
[3]*Adhoc Lecturer, NIT Calicut.*

Abstract- **The Swarm Intelligence plays a major role in solving complex real world optimization problems. This paper proposes an algorithm namely Multi Colony- Particle Swarm Optimization (MC - PSO) algorithm. MC - PSO algorithm mainly focusing the animal collective behavior, and its movement, as well as the intelligence of the swarm. MC - PSO coordinately and cooperatively work together and they share their information with each other. The convergence speed is also high when compared to PSO algorithm. The performance of MC- PSO algorithm is compared with PSO algorithm.**

Keywords- **optimization; swarm intelligence; particle swarm optimization.**

I. INTRODUCTION

In the recent years, nature inspired computation plays a very major role and it got a great attention in solving complex problems. The most successful one is Swarm Intelligence. Swarm Intelligence (SI) comes under the computational intelligence. Swarm Intelligence focusing the animal collective behavior.SI is particularly applied to insects, but it can also be applied to any other animals that exhibits swarm behavior. SI is a population of boids interacting locally with one another and also with their environment.SI are Meta-Heuristic algorithm because they uses natural metaphor to solve the complex, combinatorial as well as numerical optimization problem to get optimal or near optimal solutions. It is either a local search or global search algorithm. SI includes two algorithms they are Ant Colony Optimization (ACO) and Particle Swarm Optimization algorithm (PSO).SI algorithms are suitable to solve "NP-Hard" problems. The common NP-Hard problems are optimization problem, decision making problems and so on. In the few years ,to solve the optimization problems many researchers are using SI algorithm especially PSO[1][2][3][4][5][6].In this paper we proposed a optimization algorithm known as *Multi Colony- Particle Swarm Optimization (MC - PSO)* algorithm. MC-PSO algorithm follows SI principles and its concepts.

The remainder of this paper organized as follows. Section 2 describes the PSO concept.

In Section 3, describes the MC-PSO concept. Section 4 describes the comparison between PSO and the MC-PSO algorithm. Section 5 describes the experimental result analysis of both PSO and MC-PSO algorithms. In section 6, conclusion is discussed.

II. PARTICLE SWARM OPTIMIZATION ALGORITHM

PSO was introduced by James Kennedy and Rusell Eberhart in the year 1995. PSO is a robust, stochastic optimization technique based on the movement and the intelligence of the swarms. PSO is inspired with social behavior. PSO does not belongs to the survival of the fittest.PSO is initialized with a group of random particles and then it searches for optima by updating generations. In every iteration, each particle is updated by two best values. The first one is the personal best (pbest) that is achieved during the local search and the another best value is the global best (gbest) that is achieved during the global search. After finding the two best values the particle updates its velocity and position. PSO uses its particles for local search and global search. It satisfies the local optimization but it is very complicated to express the robustness because of its iteration ability. In order to reduce the iteration, the operator such as crossover and mutation of Genetic algorithm are combined with PSO to achieve a better solution. PSO converge very fast when compared to other evolutionary algorithms. PSO algorithm having its own memory. The main drawbacks of PSO algorithm are premature convergence problem and it falls under the local search [2][6].

III. MULTI COLONY - PARTICLE SWARM OPTIMIZATION

(MC – PSO) Algorithm

The Multi Colony - Particle Swarm Optimization (MC-PSO) algorithm following the principle and it utilizes the concept of PSO algorithm. MC - PSO is a robust (it performs excellent in an unusual condition also), stochastic (selection is based on the random objective function) optimization technique based on the movement and the intelligence of swarms.

MC-PSO algorithm follows the five basic principles of the swarm intelligence and it utilizes the concept of PSO algorithm. The five basic principles are *Proximity* principle (population should be able to carry out simple space and time computation), *Quality* principle (population should respond to the quality factors *pbest* and *gbest*), *Diverse Response* principle (allocation of responses between pbest and gbest should ensure the diversity of responses), *Stability* principle (the population should not change its behavioral mode every time when the environment changes) and *Adaptability* principle (the population should adapt the changes when gbest changes).

MC - PSO is initialized by a group of random particles. Consider each particle as a bird. After initialization the particles are sorted in a descending order. Then the sorted particles are placed into the different colonies (i.e. the entire swarm or community is divided into several colonies).

Intra-Swarm-Communication is described as follows: The community consists of set of colonies. Each colony performs a local search and it finally gives one best solution. Within each colony, the individual birds having their own ideas they share their ideas with each other.

Inter-Swarm-Communication is described as follows**:** This can be evolved through a process of iterations. After a defined number of iterations, the information obtained is passed among the colonies and the knowledge among each colony is shared. These colonies coordinately and cooperatively work together and it provides the optimal solution.

With these intra and inter-birds communication mechanisms, the birds can jump out from local optima and it quickly fly through the neighborhood of the possible global optimum. Therefore a balance between local search and global search is attained. Through this, MC - PSO overcome the problem of *Premature Convergence* in the PSO algorithm.

In [2] James Kennedy and Rusell Eberhart did not include any inertia weight and constriction factor they proposed PSO algorithm without any performance improvement factors. In order to improve the performance of the PSO algorithm, some authors include inertia weight factor [16, 17, 18, 19, 20 and 21] and few of them include constriction factor [20, 22 and 23]. The proposed methodology includes constriction factor concept. By including the constriction factor the performance of the algorithm is improved.

The process is initialized with a group of random particles *P*. For S-dimensional problems (*S* variables), a bird *i* is represented as

$$X_i = (x_{i1}, x_{i2}, x_{is}).$$

Then the birds are sorted in a descending order according to their fitness. Then the entire community is divided into m colonies, each containing n birds (i.e. P = m × n). In this process, the first bird goes to the first colony, the second bird goes to the second colony, bird m goes to the mth colony, and the bird m+1 goes back to the first colony. Within each colony, the birds with the best and the worst fitness are represented as x_b and x_g , and the bird with the global fitness is represented as X_g. Then, a process similar to PSO is applied to improve only the bird with the worst fitness not for all birds in each iteration. In each iteration, the communication is formulated as

$$\text{Velocity}, V = \chi * V + c_1 \times \text{rand}() \times (x_b - \text{current position}) + c_2 \times \text{rand}() \times (x_g - \text{current position}) \text{---------------------------} \quad (1)$$

$$\text{current position} = \text{current position} + \text{Velocity} - - - - - - - - - - - - - (2)$$

Where

- V is the velocity,
- χ is the performance improvement factor,
- x_b is the best position found so far by the particle in the colony,
- x_g is the best position found so far by the multi-colony community.
- c_1 is the social learning rate between the particles within each colony,
- c_2 is the social learning rate between different colonies,
- rand() is a random number between 0 and 1.
-

The term $c_1 \times \text{rand}() \times (x_b - \text{current position})$ describes the cooperation between individuals of the same colony and the term $c_2 \times \text{rand}() \times (x_g - \text{current position})$ describes the cooperation between different colonies in the community.

Then the position of the bird with the worst fitness is represented as follows

$$\text{Change in bird position}, D_i = \text{rand}() \times (x_b - x_w) \text{--} (3)$$

$$\text{New position}, x_w = \text{current position } x_w + D_i - - - - - - - - - - - - - - - - (4)$$

where $D_{\max} \geq D_i \geq -D_{\max}$,where $D_{\max}$ is the maximum allowed change in a bird's position.

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If this process produces a better solution, it replaces the worst bird, else the calculations in this equation are repeated but with respect to the global best bird (x_g replaces x_b). If no updation is possible then a new solution is randomly generated to replace that bird.

A. Pseudocode of Multi Colony - Particle Swarm Optimization (MC - PSO) Algorithm

Begin;

Initialization:

Generate random population of P solutions(i particles);

For each individual i ϵ P;

Fitness Evaluation:

Calculate fitness (i);

Sorting:

Sort the population P in descending order of their fitness;

Divide the entire community P into m Colonies (Community);

Intra Colony Communication:

For each colony;

Determine the best and worst particles;

Improve the worst particle by using equations 3 and 4;

Repeat for a specific number of iterations;

Self- attraction within the colony is achieved by equation 1 in the 2nd term;

End;

Inter Colony Communication:

Combine the evolved colonies;

Sorting: Sort the population P in descending order of their fitness;

Cooperation between different colonies is achieved by equation 1 in the 3rd term;

Termination:

Check if termination = true;

End;

B. Advantages of MC - PSO Algorithm over PSO Algorithm

- It solves premature convergence and local search problem in PSO.
- It is a two way information sharing mechanism. i.e. both pbest and gbest gives the information to others.

IV. COMPARISON BETWEEN PSO AND MC - PSO ALGORITHM

This section describes the common features and the advantages and the disadvantages of both PSO and the MC - PSO algorithm. Table 1 shows the common features and the advantages and the disadvantages of PSO and the MC - PSO algorithms.

TABLE I
COMPARISON BETWEEN PSO AND MC-PSO ALGORITHMS

S.No	COMPARISON BETWEEN PSO AND MC-PSO ALGORITHMS	
	PSO	**MC-PSO**
1	Based on the social behavior of " Flocking of migrating birds"	Based on the social behavior of " Flocking of migrating birds"
2	Used to solve continues non-linear optimization	Used to solve continues non-linear optimization
3	It use only it particles for local and global search	It use only it particles for local and global search
4	It uses one way information sharing mechanism.	It uses two way information sharing mechanism.
5	*Disadvantages:* -premature convergence -falls under local search	*Advantages:* -solves premature convergence problem -does not fall under local search

V. EXPERIMENTAL RESULTS

In order to compute the performance of the MC - PSO algorithm we taken 10 benchmark functions. The ten benchmark functions are taken here in order to compare the performance of both PSO and MC - PSO algorithm. The source code of both PSO and MC - PSO algorithm was written in matlab programming language. The ten benchmark functions are described in Appendix section7. The Table 2 shows the parameter settings of both PSO and MC - PSO algorithms are described as follows:

TABLE III
PARAMETER SETTINGS

Parameter settings		
Parameter Settings	**PSO Algorithm**	**MC - PSO Algorithm**
Particles	100	100
Dimension	30	30
C1 , C2	2	2
Inertia weight	0.4	0.4
Maximum iterations	30000	30000
Runs	30	30
Colonies		10
No of individuals in the colonies		10

Experimental Result analysis: The experimental results of both PSO and the MC - PSO algorithms are given in table 3.Table 3 shows the 10 benchmark functions and the results of both PSO and MC - PSO algorithm with their mean and standard deviation values. From the results we can easily analysis that the MC - PSO algorithm performs very well when compared to PSO algorithm.

TABLE IIII
EXPERIMENTAL RESULTS OF BOTH PSO AND MC-PSO ALGORITHMS

	EXPERIMENTAL RESULTS OF PSO AND MC-PSO ALGORITHMS			
	PSO		**MC - PSO**	
FUNCTION	**MEAN**	**SD**	**MEAN**	**SD**
SPHERE	0.0024	0.7114	-7.5829e-004	0.0415
RASTRIGIN	0.0027	0.8153	0.0013	0.0703
SINUSOIDAL 1	-5.4903e-006	0.0016	6.3779e-004	0.0349
SINUSOIDAL 2	1.9345e-005 +2.9918e+014i	5.8033e-003 +8.9754e+016i	-8.0330e-004	0.0440
SINUSOIDAL 3	2.8040e+003 - 1.1143e+004i	8.4119e+005 - 3.3429e+006i	0.0016	0.0851
BOHACHEVSKY 1	0.0107	3.2125	4.8812e-004	0.0267
BOHACHEVSKY 2	0.0059	1.7753	5.6352e-004	0.0309
BOHACHEVSKY 3	0.0103	3.0893	7.7009e-004	0.0422
PARSOPOLOUS	1.9882e-004	0.0596	-3.2156e-004	0.0176
MCCORMICK	0.0140	4.2125	-0.0011	0.0579

From the below graph we can easily analyze the results of PSO and MC - PSO algorithms. The graph is plotted for each benchmark function with their mean values for both the algorithms. Lower the mean value indicates the high performance. From the graph we can understand that MC - PSO algorithm performs well in 7 benchmark functions except 3 benchmark functions (Sinusoidal 1, Sinusoidal 2, Sinusoidal 3).

VI. CONCLUSION

In this paper, Multi Colony - Particle Swarm Optimization algorithm was proposed and the concept of MC - PSO was discussed and we proved that the MC - PSO performs very well when compared to PSO algorithm. This MC - PSO algorithm is suitable to solve complex real world optimization problem.

Appendix

This section describes the ten benchmark functions. These functions are classified based on their families, constraints and their modality.

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Table 4 shows the function definition and their search domain and their global minimum values for 10 benchmark functions.

- Bohachevsky1, Bohachevsky2, Bohachevsky3, Sinusoidal 1, Sinusoidal 2, Sinusoidal 3, and parsopolous these seven functions are comes under Constrained Multimodal Trignometric family.
- Sphere/Dejong 1 comes under unconstrained unimodal polynomial family.
- Rastrigin and McCormick come under unconstrained multimodal trigonometric family.

TABLE IVV
Benchmark functions with their function definition, search domain and global minima.

FUNCTION	Benchmark Functions		
	FUNCTION DEFINITION	**SEARCH DOMAIN**	**GLOBAL MINIMA**
SPHERE	$f(x) = \sum_{i=1}^{n} {x_i}^2$	-5.12<=x_i<=5.12	0
RASTRIGIN	$f(x) = 10n + \sum_{i=1}^{n} [{x_i}^2 - 10\mathrm{Cos}[2\pi x_i]]$	-5.12<=x_i<=5.12	0
SINUSOIDAL 1	$\boldsymbol{f(x) = \sum_{i=1}^{n} \mathrm{Sin}[6.5x_i]}$	0<=x_i<=10	-2
SINUSOIDAL 2	$f(x) = \sum_{i=1}^{n} \mathrm{Sin}[20\sqrt{x_i}]$	0<=x_i<=10	-2
SINUSOIDAL 3	$f(x) = \sum_{i=1}^{n} \mathrm{Sin}[10\mathrm{Sin}[x_i] + 10\sqrt{x_i}]$	0<=x_i<=10	-2
BOHACHEVSKY 1	$f(x) = {x_1}^2 + 2{x_2}^2 - 0.3\mathrm{Cos}[3\pi x_1] - 0.4\mathrm{Cos}[4\pi x_2] + 0.7$	-100<=x_i<=100	0
BOHACHEVSKY 2	$f(x) = {x_1}^2 + 2{x_2}^2 - 0.3\mathrm{Cos}[3\pi x_1]\mathrm{Cos}[4\pi x_2] + 0.3$	-100<=x_i<=100	0
BOHACHEVSKY 3	$f(x) = {x_1}^2 + 2{x_2}^2 - 0.3\mathrm{Cos}[3\pi x_1 + 4\pi x_2] + 0.3$	-100<=x_i<=100	0
PARSOPOLOUS	$\boldsymbol{f(x) = [\mathrm{Cos}[x]]^2 + [\mathrm{Sin}[y]]^2}$	-5<=x_i<=5	0
MCCORMICK	$f(x) = \mathrm{Sin}[x_1 + x_2] + (x_1 - x_2)^2 - (\frac{3}{2})x_1 + (\frac{5}{2})x_2 + 1$	-1.5<=x_i<=4	-1.9133

REFERENCES

[1] Dario Bruneo, Marco Scarpa, Andrea Bobbio, Davide Cerotti, Marco Gribaudo, Markovian agent modeling swarm intelligence algorithms in wireless sensor networks.

[2] Hongbo Liu, Ajith Abraham, Maurice Clerc, Chaotic dynamic characteristics in swarm intelligence

[3] Dušan Teodorovic, Swarm intelligence systems for transportation engineering:Principles and applications

[4] Ganesh K.Venayagamoorthy _, LisaL.Grant,SheetalDoctor, Collective robotic search using hybrid techniques: Fuzzy logic and swarm intelligence inspired by nature

[5] J. Izquierdo _, I. Montalvo, R. Pérez, V.S. Fuertes, Forecasting pedestrian evacuation times by using swarm intelligence

[6] S. He, Member, IEEE, Q. H. Wu, IEEE, Senior Member, and J. R. Saunders, Group Search Optimizer: An Optimization Algorithm Inspired by Animal Searching Behavior

[7] M. J. D. Powell, "A Survey of Numerical Methods for Unconstrained Optimization", Society for Industrial and Applied Mathematics,Jan-1970. Website:http://www.jstor.org/stable/2029042

[8] Marcin Molga, Czesław Smutnicki, "Test functions for optimization needs", 2005. Website:http://www.scribd.com/doc/46766287/Test-functions-for-optimization-needs

[9] Jani Ronkkonen , Xiaodong Li, Ville Kyrki, Jouni Lampinen, "A framework for generating tunable test functions for multimodal optimization", soft computing, springer, 2010.

[10] Mohammed Obaid Ali, S. P. Koh,K. H. Chong, David F. w. Yap, "Hybrid Artificial Immune System-Genetic Algorithm optimization based on mathematical test functions", Proceedings of 2010 IEEE Student Conference on Research and Development , Dec, 2010.

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[11] Teng nga sing, Jason Teo and Mohd. Hanafi Ahmad Hijazi, "Empirical testing on 3-parents differential evolution (3PDE) for unconstrained function optimization", IEEE Congress on Evolutionary Computation, 2007.

[12] Neculai Andrei, "An Unconstrained Optimization Test Functions Collection", Advanced Modeling and Optimization, Volume 10, Number 1, 2008.

[13] Multivariate test functions. Website: http://extreme.adorio-research.org/download/mvf/html/node8.html .

[14] General test functions. Website: http://www.it.lut.fi/ip/evo/functions/functions.html

[15] Optimization test functions. Website: http://www.math.ntu.edu.tw/~wwang/cola_lab/test_problems/multiple_opt/multiopt_prob/

[16] James Kennedy' and Russell Eberhart[2], "Particle Swarm Optimization".

[17] XiaohuiHu[1,2], Russell Eberhart [2],"Solving Constrained Non-linear Optimization Problems with Particle Swarm Optimization".

[18] Xiaohui Hu [1, 2] and Russell C. Eberhart[2] , "Adaptive Particle Swarm Optimization: Detection and Response to Dynamic Systems".

[19] YuhuiShiand Russell Eberhart, "A Modified Particle Swarm Optimizer".

[20] Russell C. Eberhart, Yuhui Shi," Particle Swarm Optimization: Development, Applications and Resources".

[21] Xiang Xiao, Ernst R. Dow, Russell Eberhart, Zina Ben Miled, Robert J. Oppelt, "Gene Clustering Using Self-Organizing Maps and Particle Swarm Optimization".

[22] Daniel Bratton, James Kennedy,"Defining a Standard for Particle Swarm Optimization", Proceedings of the 2007 IEEE Swarm Intelligence Symposium (SIS 2007).

[23] Maurice Clerc and James Kennedy,"The Particle Swarm—Explosion, Stability, and Convergence in a Multidimensional Complex Space", IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION, VOL. 6, NO. 1, FEBRUARY 2002.