PARTICLE SWARM RECUPERATE WITH MATURE DIRECTOR AND CONFRONTATIONS FOR MULTISWARM ESCALATION

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Abstract

In genuine each and every organism ages has a limited life span. Aging is a important factor for maintaining diversity. In common essence the aging leader becomes weak and leaves opportunities to other individual to challenge for the leadership position. This paper revamps the aging leader and challengers (ALC-PSO) by taking its advantages and proposes Aging leader and challengers (ALC-PSO) in multiswarm. The leader that shows the long leading power attract the swarm toward best position. Otherwise, if the leader of the swarm fail to improve the swarm towards better position the new challengers claim for the leadership. This concept ALC-PSO in multiswarm serves as a mechanism for upgrading a suitable leader to lead the swarm and provides the best optimal solution.

Keywords – aging, Aging leader and challengers(ALC), Particle swarm optimization(PSO).

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I. INTRODUCTION

A. Particle Swarm Optimization

PARTICLE Swarm Optimization (PSO) is an optimization technique based on population[27] proposed by Kennedy and Eberhart in [1] and [2].The concept of PSO is to imitate the social interaction behavior of birds flocking and fish schooling. In PSO technique, the term "particles" indicatess population members that are mass-less and volume-less (or with an arbitrarily small mass or volume) and are subject to velocities and accelerations towards a better mode of behavior. During each propagation the particle updates its velocity and position by its learning through the particle's historical best position and by the best position found by the entire swarm so far. The PSO finds its best position by comparing the position of other particles. Comparison done in PSO is of three ways, it may be ***pbest, lbest*** or ***gbest*** .The ***pbest*** is the best solution achieved by the particle so far and *lbest* is the another "best" value that is chased by the particle swarm optimizer as the best value, obtained so far by any particle in the neighbours of the particle[28]. The *gbest* is the globally found best value in the swarm. The PSO algorithm have some updates rules to update its velocity and position when the particle finds its best solution and try to enhance the swarm towards better position. The PSO is simple and proficient algorithm to find global solutions for hard problems. It is one of the most well accepted technique and has been applied in most of the application areas like task assignment [3], power systems [4], [5], and biomedical image registration [6].

Like other population based techniques, convergence speed and global search ability stands as an hindrances in calculating the performance of PSO algorithms. PSO variants have been developed to enhance the performance of PSO. The methods include tuning the control parameters so as to maintain the balance between local search and global search [7]–[8], designing different neighborhood topologies to replace the traditional global topology [9]–[10], hybridizing PSO with auxiliary search techniques [11]–[12], and using multiswarm techniques [13]–[16].PSO still remains a challenge to avoid premature convergence.

Aging is the common act seen in every organism. In the last decade idea of aging has derivated and has raised the attention. In social animal colony, the younger one will replace the old leader and hence create more opportunities for diversity. This paper extends the previous work [17] ALC-PSO in multiswarm to give the optimized solution in more than one population. ALC-PSO sponsor a suitable leader to lead the swarm with lifespan and if it fails then the lifespan of leader is reduced. The lifespan of the leader is elongated in the act of leading the swarm to best position for a longer lifespan. If the leader fails to provide the best solution then new particles come into sight to challenge the leadership. The lifespan is tuned according to leaders leading power. This paper extend this idea in multiswarm and hence provide a more better solution in more than one population. Our proposed algorithm still has simple structure with fast converging features of PSO.

II. BACKGROUND

A. Related work on PSO

Since the original PSO[1], various PSO variants have already been proposed to increase the performance of PSO. There are nearly more then hundred PSO variants which shows the important works on them.

2-D Otsu PSO (TOPSO)−This algorithm is a combination of the PSO and the optimal threshold selecting search that enhances the PSO performance [26] [18].

Adaptive PSO (APSO) − During the running process of the PSO, sometimes number of particles may be inactive, that is, they does not have the ability of local and global searching and do not change their positions a lot, so their velocity is nearly reached to zero. One solution is to replace the current inactive particles with fresh particles in a way that the existing PSO-based relationships among the particles are kept. This is done by APSO method [26][19].

Binary PSO (BPSO) − The difference between PSO and BPSO lies in their defined searching spaces. In the conventional PSO, moving in the space means a change in the value of position coordinates in one or more of existing dimensions. However, in the BPSO moving in the spaces means a change in the probability of the fact that the value of position coordinate is zero or one [26][20].

Constrained optimization via PSO (COPSO) − The COPSO algorithm is applied to constrained single-objective problems. In this algorithm, a technique is employed to investigate the rules and it has an external file, called "Tolerant", to save the particles. Certainly, in this technique some particles are missed through setting the rules. In order to extend the lifetime of these particles, the external file mentioned above will be is utilized and a ring topology structure is selected. In fact, the COPSO is a kind of enhancement in ***lbest*** version of the PSO. Moreover, the external procedure, which maintains swarm diversity and guidance towards good points keeping the self-setting capacity, are utilized [26] [21].

Evolutionary Programming and PSO (EPPSO) − This algorithm is a combination of the PSO and EP. Certainly, the combination of these two algorithms will cause a help for the PSO ability in making a balance between local and global search to the faster convergence of the EP algorithm. On the other hand, the PSO's drawback in lacking diversity among the particles with mutation between elements in the EP is to some extent removed [26] [22].

Genetic binary PSO model (GBPSO) − This algorithm was developed to improve the dynamic conditions and discovery power in the swarm. In the BPSO, bear and death parameters are employed. In other words, according to BPSO principles, the positions and velocities are updated and then, some of the child particles

are added to swarm and some others die and are separated from the swarm. It is worth nothing that in binary state each particle is considered as a chromosome and chain with the size of space dimension [26] [23].

Self-organization PSO (SOPSO) − In this algorithm, addition to particle information and total swarm information, the feedback agent is employed to increase the particle performance. Indeed, the particle, utilizing the feedback information of total swarm, sets and improves its behavior in the next iteration. Generally, this agent will lead in improvements in discovery and citation of the particles. Moreover, it causes an indignation in the variety among the particles. The main objective of this algorithm is to eliminate the premature confluence of the total algorithm [26] [24].

PSO with area extension (AEPSO) − This algorithm was developed for the movement of more robots in an area. It has in fact some changes to the conventional PSO. These changes are with the information increasing from an extended area. In order to get this goal, a series of heuristics are utilized to update the particles velocity. Moreover, some heuristics are employed to eliminate trapping in local optimum and to avoid the problem from being stuck [26] [25].

Preventing premature confluence and fast confluence of PSO where acquired in ALC-PSO. To make still more globally and to provide a better optimal solution we enter into ALC-PSO in multi swarm.

III.EXISTING SYSTEM

The existing concept introduces a ALC-PSO algorithm for solving premature convergence and brings fast converging features of PSO. It is characterized by assigning the leader of the swarm with a growing age and lifespan, and allow the other individual particle to challenge the leadership when the leader becomes aged. The lifespan is tuned according to the leader's leading power. ALC-PSO algorithm proposed in this paper shares a common attribute with the second category of PSO variants, because it also provides a mechanism for particles to learn not only from ***gBest*** but also from other promising particles.

A Leader is maintained in a population and his lifespan is tuned according to the lifespan and the lifespan is adjusted according to the leader's leading power. When the new particle Θ enters the population which contains the lifespan b and performance p. The database compares the particle performance with that of the leader p if the leader performance is said to be the best then the check for the lifespan criteria and then generate the report. If the particle performance is said to be best then generate the challenger and then update the leader then report the solution. ALC-PSO preserves the fast-converging feature of the original PSO and introduces an aging mechanism to prevent premature convergence, once the present leader finds a promising area, particles can quickly converge to the optimal position in that area [17]. The drawback of the existing work is that it requires diversity to a greater extent in multi-objective and dynamic optimization .

IV.PROPOSED WORK

In our proposed system the aging mechanism is adopted on the leaders of multiple population or species instead of on the leader of a single population of particles and introduce a new algorithm which is Multiswarm ALC-PSO. Here the leader of different population is compared to produce a further more efficient best solution and has the faster convergence of PSO features.

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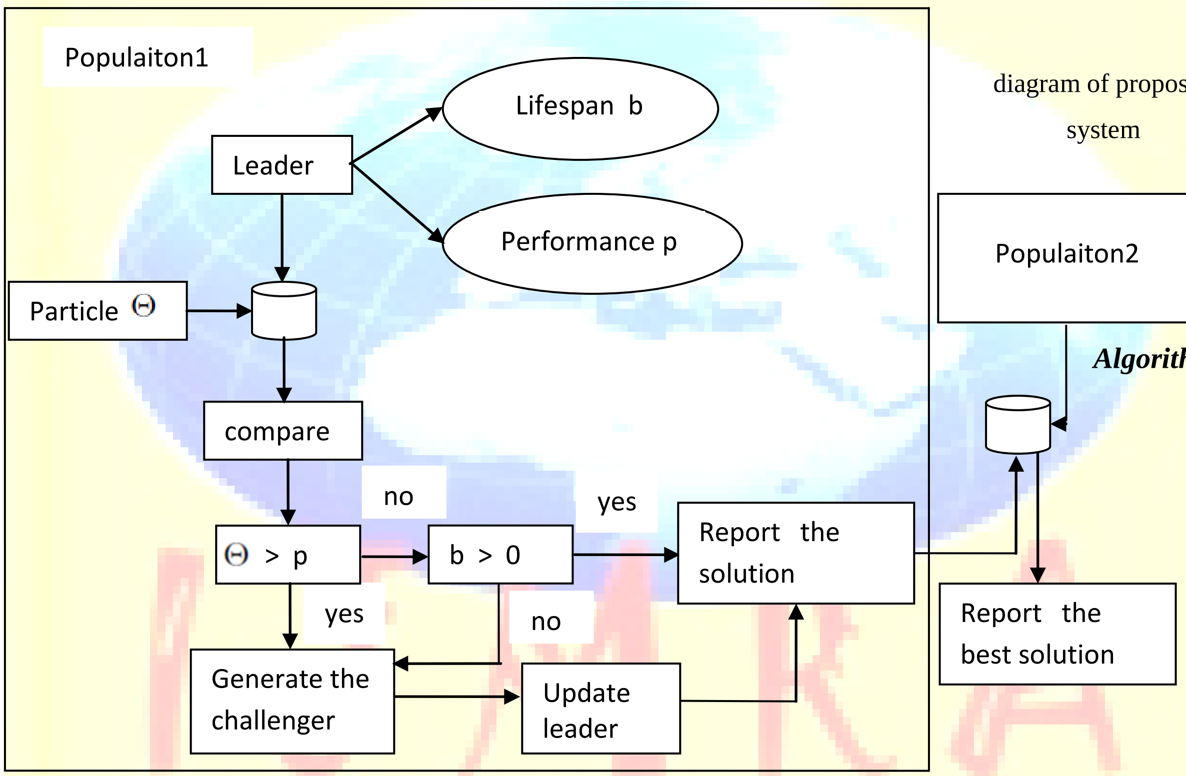

Block diagram of proposed system

Algorithm:

Step1:*Initialization*: The initial positions of all particles are generated randomly within the n-dimensional search space, with velocities initialized to 0. The best particle among the swarm is selected as the Leader. The age of the leader is initialized to zero and the lifespan of the leader is set to an initial value 0.

Step 2 :*Updating leader*: For particle i (i = 1, 2, . . ., M), if the newly generated position is better than Leader then the new generated particle becomes the new Leader of the particular population. The ***Leader*** represents the best solution generated by particles during the leader's lifetime.

Step3: *Lifespan Control*: After the positions of all particles are updated, the leading power of the ***Leader*** to improve the entire swarm is evaluated. The lifespan b is adjusted by a lifespan controller.

Step 4: *Generating a Challenger*: A new particle is generated and is used to challenge the ***Leader*** whose lifespan is exhausted.

Step 5: *Evaluating the Challenger:* The leading power of the newly generated challenger is evaluated. If the challenger has enough leading power, it replaces the old ***Leader*** and becomes the new ***Leader***. Otherwise, the old Leader remains unchanged and will continue to lead the swarm.

Step 6: The best solution found by the population is reported.

Step 7: In the similar way the best solution found by the other population are compared to give the more optimal solution in a multi population.

Lifespan controller

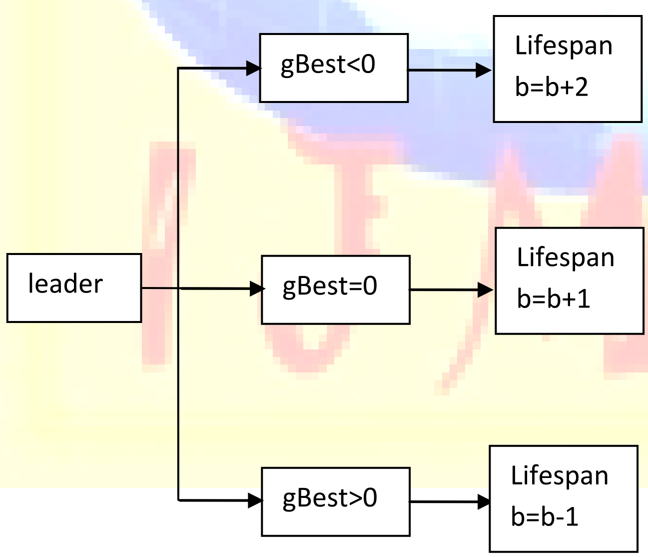

Fig 2. Lifespan controller

Description: The generated leader checks the gBest and has three cases.

Case1: Good leading power(gbest<0)

In this situation the Leader manages to lead the swarm to improve the best solution found by the algorithm. This situation implies that the current Leader is very active to achieves improvements. Therefore the Lifespan b increases by 2.[17]

Case2: Fair leading power(gbest=0)

In this situation although the historically best solution found by the algorithm is not improved, the Leader still manages to lead the swarm to improve the best solution found by the algorithm. This situation implies that the current Leader still has the potential to improve the swarm. Therefore the Lifespan b increases by 1.[17]

Case3: Poor leading power(gbest>0)

In this situation the current leader fails to lead the swarm towards better positions. Therefore the current leader has no potential to improve the swarm . Hence the Lifespan b decreases by 1.[17]

Generation of the challenger

The new challenger is generated when the lifespan of the old leader gets exhausted. The other condition for generating the leader is when the particles performance is said to be greater than the leader's performance and then the leader is updated and then report the solution which is found to be the best solution of the population.

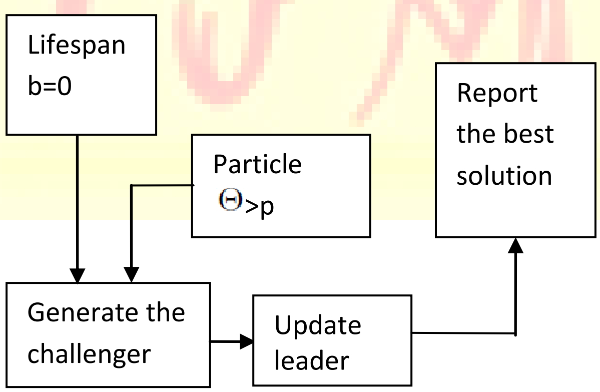

Fig3. Generation of challenger

V.ENVIRONMENT SETUP

This application implementation requires the installation of visual studio 2010(.NET), server management system. The database for the population should be purged often when any leader fail to improve the swarm.

VI. IMPLEMENTATION AND RESULT

The ALC-PSO in multiswarm can be applied in task assignment [3] and for election in a population. This can also be applied in finding the best optimal solution in a swarm. We apply for finding the best product sale in mobile. The features about particular mobile for its best quality is collected and then compared with newer features of the upcoming mobile for its efficiency, speed and quality. If it fails to improve the quality of the mobile then that product will be out of the product sale and when it is found to give the best quality then it will be the first recommended product for product sale. The results were compared with other variants and found to be the effective algorithm. The inputs are the quality of the mobile, efficiency, speed and model of the particle which is compared with the leaders performance and the resulting report of one population is compared with the other population to find the globally optimal solution in multi-swarm. The ALC-PSO in multiswarm sounds good in a multiswarm and the generated results were found to be the best among the PSO variants by evaluating the results of each variants.

Nokia Lumia 520 vs Samsung Galaxy S Duos comparison

	Nokia Lumia 520	Samsung Galaxy S Duos
General		
Alternate names	Lumia 520	GT-S7562
Release date	April 2013	November 2012
Form factor	Bar	Bar
Dimensions (mm)	119,90 x 64,00 x 9,90	121,50 x 63,10 x 10,50
Weight (g)	124,00	120,00

VII.CONCLUSION

A new variant called multiswarm ALC-PSO has been developed. The multiswarm ALC-PSO is characterized by assigning the leader of the swarm with a growing age and a lifespan and then compare the solution found by all the other swarm to obtain the best optimal solution. The lifespan is tuned according to the leader's leading power. We have made an attempt to show that the aging mechanism is helpful to PSO. The proposed multiswarm ALC-PSO manages to prevent premature convergence and keep the fast-converging feature of the original PSO. In future research , it would be interesting to test if the aging mechanism is also helpful for leading the swarm to more complex optimization problems and to decrease the search time for selecting the leader in a swarm.

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