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The Combination of a Multiple Demographic Model based on Particle Swarm with Several Solutions for Learning in Dynamic Environment

Seyed Ahad Zolfagharifar[1], FaramarzKaramizadeh[2] , Hamid Parvin[3]
[1]Department of Computer Engineering, Yasouj Branch, Islamic Azad University, Yasouj, Iran
[2]Department of Electrical and Computer Engineering, Shiraz University, Shiraz, Iran
[3]Department of Computer Engineering, Yasouj Branch, Islamic Azad University, Yasouj, Iran
Correspondence: Faramarz Karamizadeh, Department of Electrical and Computer Engineering, Shiraz University,

Abstract: the dynamic environment in which global and local optimization over time replaced. Optimization of particle mass is one of algorithm based on collective intelligence and the behavior of birds in nature.Each evolutionary algorithm has particular advantages and disadvantages. In this paper, a multiple demographic algorithm based on particle swarm to dealing with dynamic environments is used. In this algorithm as the multiple demographic algorithms mQSO of quantum particles and neutral as well as disposal operations and anti-convergence with the difference that in this method has been used in several different ways. Control solution of neutral particles is used to find the worst areas. There is also a clear memory to maintain good solutions. Clustering algorithm was used to maintain diversity while hill climbing search method to improve local search in each cluster is used. Famous problem benchmark peaks moving for the test environment and experimental results show that this method is suitable for dynamic environments.
Keywords: particle swarm optimization, learning model, dynamic environments, benchmark the moving peaks

1. Introduction

In most animal species collective behavior are seen [1]. In early 1900, research on the social behavior of monkeys was conducted [16].It was found that the species of monkey performance and behavior of each member of the group ordered hierarchically from the higher. There is more interesting context that species of animals live together, but not guides. Each member has a self-organizing behavior without the use of a guide that can move in the environment and met their natural needs. Such as birds, fish and flocks of sheep that these animals do not have any knowledge about the general behavior of the entire group or even have any knowledge of the environment they are in which. Instead, members are able to exchange the information with your neighbors move in their environment. This simple interaction between the particles (the group members) creates more complex treatment group. Find a place like particles [2], [17] and [22]. Much research has been done on the social behavior of the particles; some of them are as following:

- Behavior of birds [22]
- Fish group behavior [20], [21] and [24]
- hunting of humpback whales. [25]
- Food-seeking behavior in the wild monkeys [8] and [18]
- Expressions of love and searching for food in shark [26] and [27]

In [12] the behavior of birds was simulated. In this way, a member of the birds as the ringleader of the group will attract other birds. Kennedy and Eberhart first time after simulation of bird’s social behavior provided particle mass by optimization method [11]. Each of the components of this group should follow a simple behavior. This means that each member of the group of mimicking lead to the success of their neighbors [19]. The purpose of this algorithm is that members of the movement and in an optimal point in the search space (eg, food source) collected. This behavior is similar to the hypothesis that in [28] presented.

Particles swarm optimization technique is rooted in the work of Reynolds as a rudimentary simulation of social behavior of birds. In this simple behavior model to find the nearest neighbors (set speed) is implemented. This model birds randomly placed in a search space of the pixel in each iteration, the nearest neighbor particle and particle velocity at the nearest neighbor replaced. This action causes the group to move quickly to an uncertain and changing converge. To solve this problem, a component of madness used as random variations in the group [22].

Reinforcement learning method is learning the proper operation and performs several functions over time, from a limited set of pre-defined actions that can be performed in a random environment. It is assumed that learning model in a random environment of the unknown, in every moment of your operation from the set of actions and with its environment. Environmental action taken in response to an output of a set of defined outputs (it can be limited or unlimited) and with its model and model response of the environment, your decision-making style choices during its next action. It is assumed that a possible correlation between each action of learning model and environment and the relationship between the internal profiles during learning environment is characterized by learning model. For more information about learning model can be [23] presented.

Today, we face engineering affairs issues or issues which should be optimized. In some issues the goal is to reduce cost optimization (minimization) and in others to maximize profit (maximization). Optimization expressed which should be a function of the parameters to values and can minimize or maximize their objective function. Generally, optimization problems can be divided into two main issues, static optimization and dynamic optimization problems. The static optimization problems, optimizing the fixed and does not change, so the optimal tracking is somewhat easy task. The issues are optimized in dynamic nature, the problem will change over time and therefore the optimal tracking algorithm will be difficult to change. Whenever a change in the purpose of optimization, or some variation of the limitations of an optimization problem occurred, it may change its optimum. If this happens it is necessary to adapt the solution to old solution. A standard method for facing this dynamic, dealing with every change as an optimization problem that must first resolved. This method is sometimes impractical, because the solution is a problem from the beginning, no re-use of the information is very time consuming. In the optimization of complex issues, using careful optimization is impossible.So, random search methods used to achieve a near-optimal response.

In fact, this type of algorithms is appropriate responses can be taken in a reasonable timeframe, but there is no guarantee to get the best response.

Among the random search method that evolutionary algorithms are derived from nature have a special place. Given the complexity of many optimization problems with a dynamic development to improve the efficiency of these algorithms to solve dynamic optimization was carried out. The fact is evolutionary algorithms commonly is evolving, are not good candidate for solve optimization problems.Evolutionary algorithms are not able to track the response of an optimization problem with a dynamic nature, therefore, should these algorithms combined with a suitable strategy to the changing environment in accordance with their performance and track answers for issue. One of the main challenges to solve dynamic optimization by evolutionary algorithms with the performance of the algorithm is to maintain diversity. The main problem with standard evolutionary algorithms is that eventually converges to an optimal diversification. When the population evolutionary algorithm converged, loses its ability to adapt to environmental changes.

Review of literature

Hu and Eberhart presented a method based on particle swarm optimization called RPSO for dynamic environments where necessary diversity is lost every time and a random movement of particles is used [7].

Li and Dam have shown [13] that a grid-like structure adjacent to optimize particle called collective FGPSO, presented by Kennedy and Mendez in the dynamic methods [12] is more effective than RPSO.

Li and Yang is a method of optimization multiple demographic particles called FMSO that is capable progress is necessary to maintain diversity algorithm [14].

Liu and et al developed a method called combinatorial optimization CPSO proposed the particle mass and the method was diagnosed after every change in the environment, a further search in the search space performs the necessary diversity algorithm created during development [15].

Hashemi and Meybodi suggested a cellular automata-based particle mass optimization technique called Cellular PSO that in dynamic environments is very efficient. The main idea of this approach utilizes local interactions in CA and dividing the population of particles within cells are cellular automata and each group tries to find a local optimum, which makes finding the global optimum.

In this way a cellular automata with cd cells in D-dimensional environment used so a particle in the search space can be assigned to a cell of the cellular automata. This concept has been used to maintain diversity in the search space, a concept also known as particle density was used for each cell that is a threshold for the maximum number of particles that can be placed in a cell. These causes the particles converging on a cell so only a fraction of the particles can search in one area of the search space to do and the remaining particles doing the search operation in other areas of the search space [5].

Camosi and et al optimized a few particles suitable for dynamic environments have provided a population that is much better than conventional methods. In Camosi and et al created a working group to begin its algorithm. Then each group of children if they are active and their position update rate equations after updating the position and speed, a group checked if the radius of convergence (maximum distance of two particles in a radius group of convergence specified), the group is less than the total radius of convergence and the fitness of the group of the elegance found in the best position among all groups is also less and this group is disabled groups instead of the radius of convergence that is greater than the radius of convergence of the group that has a higher fitness level. Also in the way, two groups are within a radius that each other activities of the group have the fit out are less than the search space [9].

Parvin and et al, believed a new instance of the new hybrid evolutionary algorithms, include the optimization of particle mass, learning automata and Delioj algorithms for dynamic environments offered [29]. Lung and Dumitrescu offered an algorithm called CESO, so that the method of two populations of equal size detected and track moving optimization in dynamic environment. One of these populations is responsible for maintaining diversity in the search space and the population is responsible for finding the global optimum, maintain diversity in the population with the use of evolutionary algorithms based on swarm and difference is optimized for multi-objective work done while the particle swarm is used directly to find a global optimum.One of the main problems in dynamic environments is premature convergence to a local optimum to overcome the problem of population called CESO and CRDE to keep a collection of the best local and global search process and other people who called swarm population, find a global optimum during the entire search process is used, both population and CRDE swarm from their normal behavior and no additional mechanism is not added to their behavior [30],[31].

Multi-team PSO (MPSO) for the first time in [19] and then, in [33] were further examined, this diversity is maintained on two levels. Group is divided into a number of subgroups that are driven to different parts of the search space, and each group has a number of quantum particles can provide diversity in the group. Blackwell and et al Adaptive mQSO algorithm for dynamic environments presented. The algorithm Adaptivem QSOis number of groups from the outset given is not a change in the environment and find new peak number of groups, so that the operator against integration and all groups converged a free group has created and helps to find new local optimization [34].

Yang and Lee proposed PSO algorithm for dynamic environments. CPSO algorithm divides the particles to clusters of particles in each cluster to the cluster's local search. Each particle searches the average particle in best position visited by the cluster. The algorithm used to measure the degree of overlapping particles if the area of the search space was created bustle particles, some particles randomly congestion in the area and they are overlapping, ie more private area of the search space their random migration. To achieve the optimal solution for multi-peak function in dynamic environments using changes in PSO is an evolutionary algorithm. To achieve this, a component-based model that allows the parallel development subpopulations used and for clustering the populations of Ka-average method is used [35].

Lee and et al SPSO method for dynamic environments presented. SPSO algorithm enables the dynamic distribution group that is particles. This cleaning method in [38] presented. SPSO based on the concept of "components" has been designed. Center is a component that called the grain component [39] particle is always the best fit of components. All the seed particles within predefined component placed in the same condition. This algorithm groups instead of convergence to a global optimum will converge to a local optimum, thus expanding several subpopulations in parallel.

Particle swarm algorithm (PSO) (11) with a random group of questions is started. Then find the optimal solution in the problem space by updating the position and velocity of every particle. Every bit as multidimensional (depending on the nature of the problem) with the amount v_i^dv and x_i^drespectively represent the position and velocity of a particle that related to i-th and d-th dimension defined. At each step of the population, each particle is updated according to the best values. The best value, the best solution in terms of competence has been obtained for each particle separately. This value is best for each individual and called$pbest_i$. The best of which was obtained by PSO, the best value ever achieved by all particles in the population, this is the best all-around and called$gbest$. After finding two values $pbest_i$ and , each particle velocity and position to date their new relationship (1) and (2).

$$\boldsymbol{v_i'^d = wv_i^d + n_1 r_1 (x_{pbest_i}^d - x_i^d) + n_2 r_2 (x_{gbest}^d - x_i^d)} \quad (1)$$

$$\boldsymbol{x_i'^d = x_i^d + v_{i'}'^d} \quad (2)$$

$\boldsymbol{x_i'^d}$ and$\boldsymbol{x_i^d}$are the current location and the previous location of the d-th of i- th particle. ^ d) and v_i ^ d -d my current speed and speed previously belonged to the i- th particle. As w∈ (0,1) and is the inertia weight, n_2 and n_1 acceleration coefficient, r_ (2) and r_1 uniformly distributed random numbers in the interval (1, 0), respectively.

As shown in the speed and position of the particles has changed position and speed of the particles updated. **Figure 2shows the particle swarm algorithm pseudo-**code.

Figure 1:Change the position and speed of the particles in the swarm

Algorithm1: Particle Swarm Optimization

1. Generate the initial swarm by randomly generating the position and velocity for each particle
2. Evaluate the fitness of each particle
3. Repeat
4. **for** each particle i **do**
5. Update particle i according to Eqs(1)and (2)
6. **if** $f(\vec{x}_i) < f(\vec{x}_{best_i})$ **then**
7. $\vec{x}_{best_i} \coloneqq \vec{x}_i$
8. **if** $f(\vec{x}_i) < f(\vec{x}_{gbest})$ **then**
9. $\vec{x}_{gbest} \coloneqq \vec{x}_i$
10. end if
11. end if
12. end for
13. until the stop criterion is satisfied

Figure 2: Pseudo code particle swarm algorithm

A special kind of particle swarm algorithm for dynamic environments mQSO algorithm is suggested [32]. In this algorithm, particles are divided into two categories:

1. Neutral particles: particles, particle swarm algorithm standard was neutral for the first time. The task of the rapid convergence of particles of inert particles is considered optimal.
2. Quantum particles: quantum particles [32] as a tool to maintain a certain level of diversity in a given group, the atomic models are affected. Quantum particles are placed in random positions to maintain diversity groups.

MQSO algorithm that particle swarm algorithm based on quantum particles is known in this algorithm are divided into several groups of the population and includes three functional diversity called quantum particle, is repelling and anti-convergence. Operator disposal of a mechanism prevent premature convergence and diversity. Anti-convergence operation between the two groups re-initialized. Anti-convergence operation when all groups are converging, re-initialize the worse group [32]. Pseudo-code related to MQSO algorithm in Figure 3 below shown.

Algorithm2*$mQSO$*: algorithm

```
Randomly initialize the particle in the search space;
While stoppingconditionisnotmet do
foreachswarm s do
Test for exclusion;
if sneedstobeexclude then
Relocate s randomly;
end
else
Move particle according to Eqs (1) and (2);
end
Evaluate each particle position;
Update x_pbest and x_gbest;
end
end
```

Figure 3:pseudo-codealgorithmsmQS

3 Suggested methods

In this section, a new model of particle swarm algorithm for dynamic environment provided that this algorithm is some what similar tom QSO algorithm. The proposed method is similar tom QSO of quantum particles, neutral particles, disposal operator, operator of anti-convergence and quantum radius is used.

For inert particles, the particles are about speed and position relationships (1) and (2). These ties in [32] were brought.

In this way, such as anti-convergence algorithm is used mQSO operator. In order to identify new technique called anti-integration summit. At a time when all parties have been to the summit where they are closed, a group that has less fit again in the search space is randomly as wide as the radius of the smallest circle that encompasses neutral particles is less than the radius of convergence. Anti-convergence is important that the number of groups significantly is less than the optimum number of local, where each group can be found on the convergence of various internal optimization. The summit may be a local optimum is still the future growth of the global optimization therefore a group again allowed to enter the search space and the possibility of finding is the peak of [32].Fixed degree of diversity can be maintained at all times through the disposal operator. In this operation, a group made up of charged and neutral particles. Charged particles repel each other, leading to a mass of charged particles that are spinning around neutral particles. Rapid convergence is to optimize the function of neutral particles and charged particles responsibility to maintain diversity within a group. If the optimum position has changed at least one or more of the particles within the new peak and it is able to find the optimal networks [32].

In this method the population is divided into clusters. Each cluster consists of neutral particles and quantum particles. Clustering method can assign the particles into different areas. The idea is that if the particles to a top local search, then the converged to avoid being caught in a local optimum of a leap for particle used. Mutations in the hill-climbing method create diversity among the particles and thus the particles trapped in local optimum partly avoided. Used clustering, clustering Ka is average. In this way every particle to the center of each cluster is calculated. The center of each cluster in the first stage will be randomly selected. In iteration, it calculates the average per cluster and the cluster is considered as a new center. The standard location for each cluster particles (particles clustering is done based on location). In bars - the average distance between the two particles i and j in a d- dimensional space of the equation (3) is calculated.

$$distance(i,j) = \sqrt{\sum_{i=d}^{D} (x_i^d - x_j^d)^2} \qquad (3)$$

Here it must be stated that the clustering was also made clear to bits stored in memory (that has been more properly express this better). The exchange of information between cluster-only memories tagged with the same population as the original. Each cluster of the main population and cluster corresponds with their population exchanges its memory (the corresponding clusters are clusters with the same label). Pseudo code search method hill climbing with mutations in Figure 4 below. The method detects minute changes in the environment for pseudo-code form (5) action. In pseudo-code form (5) reassess the particles were performed. If in the assessment of the performance for even a bit has changed, then the algorithm recognizes that a change has occurred in the environment. To better explain the clustering approach using the form (6) is used.

Algorithm3: Hillclimbing algorithm

1. Procedure hill climbing;
2. Create a solution (s')
3. Best =s';
4. Loop
5. s = best;
6. $\mathbf{s' = neighbors\ (s)}$
7. Best = select Best (s');
8. IF there is no change in Best solution THEN
9. Jump to new state in state space;
10. Until stop criterion satisfied;
11. End

Figure 4: Pseudo-code search for improved hill climbing

Algorithm4: DetectChange

1. Re-evaluate the global best particle over all ***subswarms***;
2. ***evals*** :=++***evals***;
3. IF The**fitness**of the re-evaluatedposition changes THEN;
4. **ChaneDetectedinenvironment**;
5. End

Figure 5: The pseudo-code for detecting changes in the environment

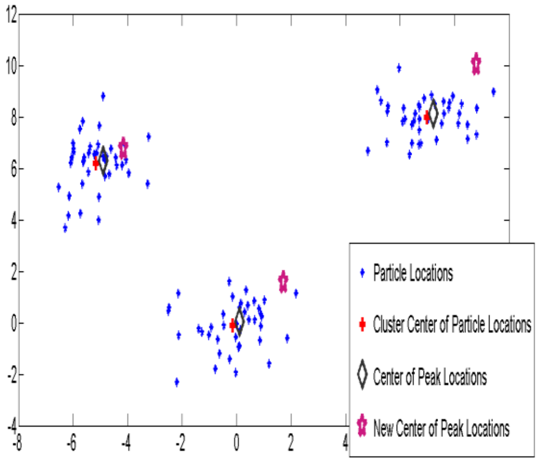
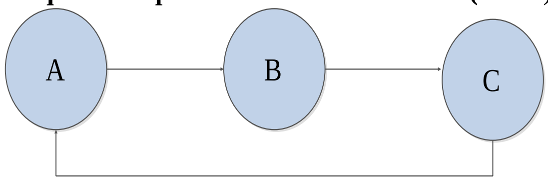


Figure 6: explain the clustering method with a suitable form

In Fig. 6 particles have been divided into three clusters. The particles in each cluster are marked with small blue star. The diamond is shown top center and new center of the summit after a change in the environment has been shown to be a big star. Clustering algorithm, and maintain diversity while also improving local search. The proposed method for controlling operation of neutral particles in multigrain method provided and used to increase performance. Also in the way to keep a clear memory solutions obtained in the past and used to speed up the convergence of the particles. Control function as neutral particles called. The operator can control the neutral particles per cluster worst neutral particles that have little efficacy identify the best particles in explicit memory to replace these particles. The particles as standard particle swarm algorithm update their position and speed in the search space. Idea for operator control of neutral particles so that each particle in each of his move to the new location, if you do not find optimal factor failure to produce the lack of success. In this method, a threshold is used to break the sequence. That is, if the average number of failures of the threshold is greater than the area of the search space as a bad area and the particles were detected in this area are identified as the worst particle group. Figure 7 show a sequence of moving particles in space that have failed.

Figure 7: Themotionsequence of particles with lack of **failure(**defeat) **in the search space**



Figure(8) **shows changesoccurin acyclicalenvironment**.

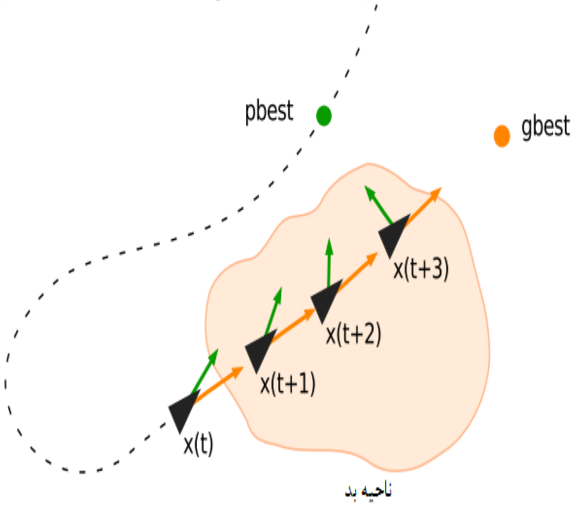


Figure 8: Changes in the environment as cyclic

Figure 9 converging particles to changes in the environment show the proposed method. In this form, it marked with blue dots and circles show on the peaks. Change summit in this form are possible and may be used to optimize a local peak is the new change in a global optimum. Previously mentioned solutions optimized for tracking the national cause peaks particles can be detected well. In Figure 10 it is clear that the peaks are displaced and solutions described in this method may well have detected peaks. Pseudo code proposed in (11) is given. For better description of the proposed method (12) is used. Figure (12) shows that the change in a memory can quickly trace the location of a new peak population of particles into the lead. The memory in the form of a circle is shown. The center of each cluster of the memory box is displayed.

Figure 9:Howtochangethe convergence ofparticlesin theenvironment

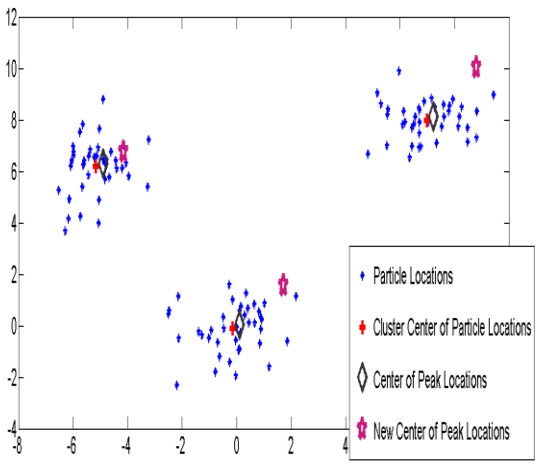
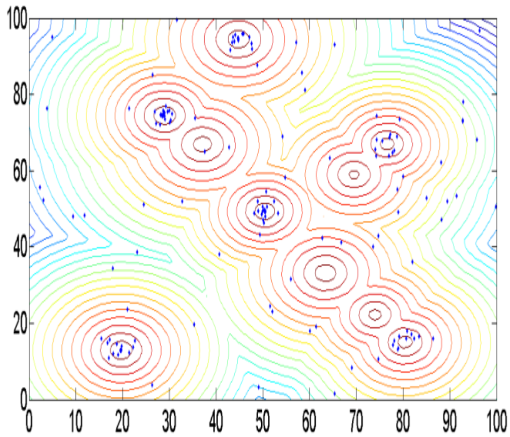


Figure 10: How the convergence of particles after the change of environment



Algorithm5: proposed algorithm

Randomly initialize the particle in the search space;
While ***stoppingconditionisnotmet*** do
foreach*swarms* do
Test for exclusion;
if ***sneedstobeexclude*** then
Relocate ***s*** randomly;
end
else
Move particle according to **Eqs** (1) and (2);
end
Evaluate each particle position;
Update $\vec{\boldsymbol{x}}_{pbest}$ and $\vec{\boldsymbol{x}}_{gbest}$;
end
Insert failure for each particle;
Threshold considered for consecutive failure;
if (average(consecutive failure)>threshold) then
Region is bad;
Memory update in random time;
if (change detected=1) then
local search with improve hill climbing;
Memory retrieval;
end
end
end

Figure 11:Pseudo-codeof theproposed method

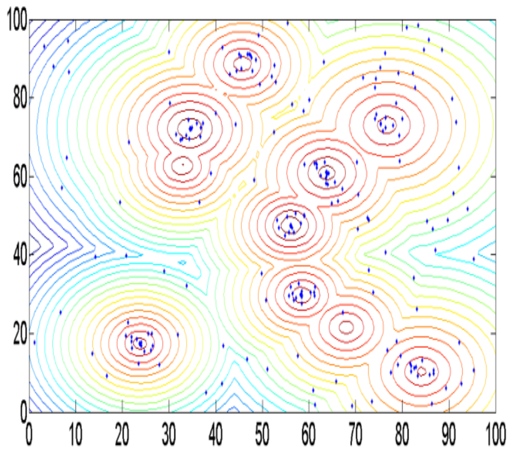
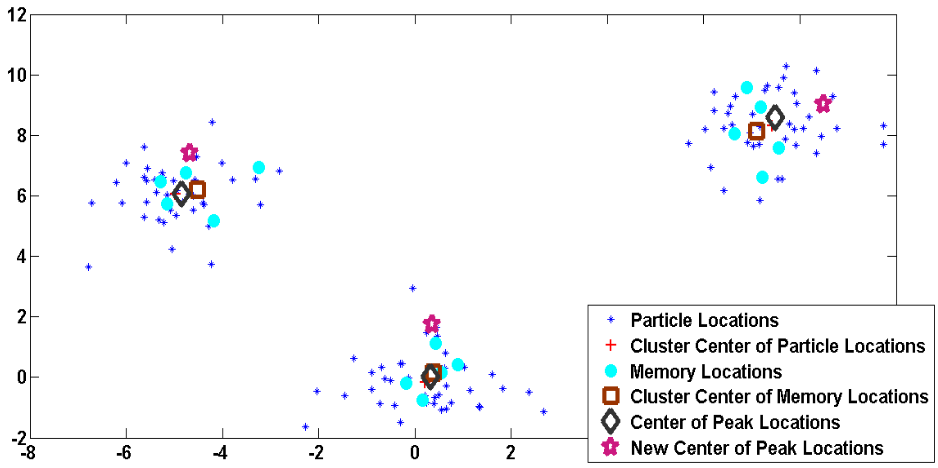


Figure 12 outlines the proposed approach as appropriate



4. Benchmark Moving Peaks

Bronk in [3] suggested a problem of dynamic issue for testing optimization algorithms in dynamic environments and called moving peaks function. Animated peak of m peaks in an n-dimensional space, which is the maximum amount eligible on top of all functions defined by equation (4) is calculated (3).

$$\boldsymbol{F(\vec{x},t) = max(B(\vec{x}), \max_{i=1\dots m} P(\vec{x}, h_i(t), w_i(t), \vec{p}_i(t)))} \quad (4)$$

In equation (4) $B(\vec{x})$ parameter is time-independent that specifies the basis of merit. The peak form is determined by P function. Each m peak vary time, the height (h), width (w) and position (p). After a specified number of occurrences (frequency changes), it change height, width and location of each peaks. The height and width of each peak Gaussian random variable is changed by adding and location of each peak by vector v and fixed-length s (the number of peaks in the frequency changes) moved. The s parameter allows controlling the intensity of a change. Parameter λ, also determined that the peak shift to what extent depends on your previous move. If $\lambda = 0$, any movement is completely random and always in the same direction move to the top. Relationships that cause changes in the summit are as follows (5) (3).

$$\begin{cases} \boldsymbol{h_i(t) = h_i(t-1) + height_{severity}.\ \sigma} \\ \boldsymbol{w_i(t) = w_i(t-1) + width_{severity}.\ \sigma} \\ \boldsymbol{\vec{p}_i(t) = \vec{p}_i(t-1) + \vec{v}_i(t)} \\ \boldsymbol{\sigma \in N(0,1)} \end{cases} \quad (5)$$

Which in above equation, and as $h_i(t)$, $w_i(t)$ $\vec{p}_i(t)$ are i-thpeak height, i-thpeak width and peak location vector at time t. Parameters$height_{severity}.\ \sigma$ and$width_{severity}.\sigma$todrastically change the height and width of each peak specify. Vector$\vec{v}_i(t)$ (i-thpeak motion vector at the moment) of equation (6) is calculated where the random vector $\vec{}$by creating random numbers for each dimension and then normalize the length of s. Location, height and width of each peak is randomly determined by a series of specific limitations [3].

v⃗_i (t) = s . | r⃗ + (v_i) ⃗ (t-1) |((1-λ) r ⃗ + λ (v_i) ⃗ (t-1)) (6)

Table 1:Setting the standard formovingPeakfunction

$$\vec{v}_i(t) = \frac{s}{|\vec{r}+\vec{v}_i(t-1)|}((1-\lambda)\vec{r} + \lambda\vec{v}_i(t-1)) \qquad (6)$$

Table 1:Setting the standard formovingpeakfunction

Parameter	Value
The number ofpeaks	10
Frequency of change	**In5000**
Severity ofpeakheight	7
Thepeakintensitychanges	1
Figurepeaks	**Conical**
Themovingpeaks Number ofdimensions	1
Number ofdimensions	5
Range ofpeakheight	[70،30]
Range ofpeakwide	[12،1]
Standardheightpeaks	50
The scope ofthe search space	[100،0]

Figure13shows a two-dimensionalexampleof movingpeaksin thelandscapeworthy.

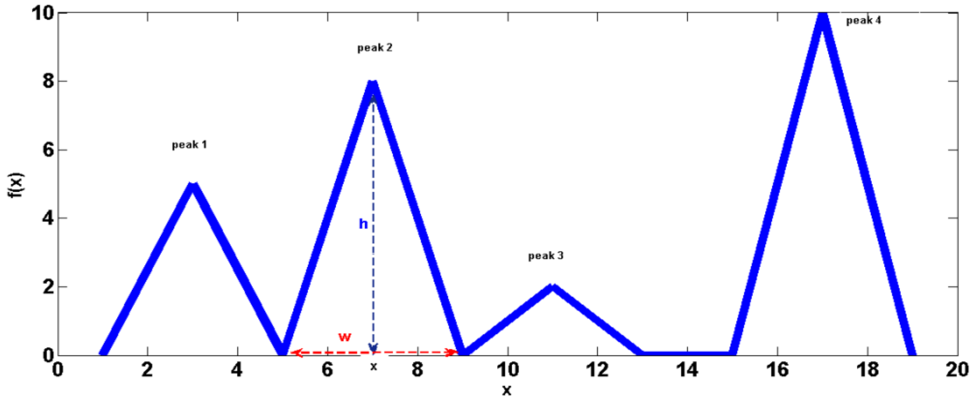
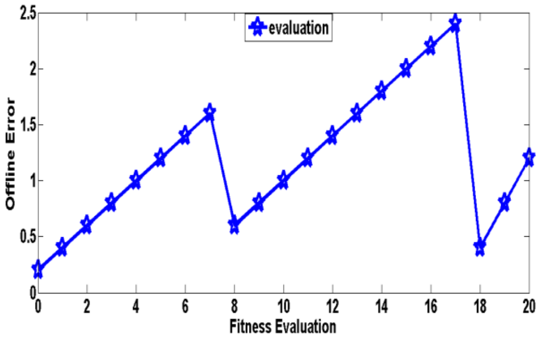


Figure 14:A two-dimensionalexampleof movingpeaks in landscapeofcompetence



5. Outliner error standard

To measure the effectiveness of evolutionary algorithms to quantify the dynamic environment of the criteria, out-line error used. Out-line error according to equation(7) is calculated.

$$OfflinError = \frac{1}{FE_s} \sum_{t=1}^{FE_s} (h(t) - f(t)) \quad (7)$$

In equation (7), FE_ss is the maximum number of performance evaluations for individuals and $h(t)$ is changing the global optimum and $f(t)$to find the best position by the particles at t time. Figure (14) outline error average in the assessment by the performance. In this way it is supposed to evaluate the eighth and eighteenth environment has changed. It is different criteria for measuring the efficiency for evolutionary algorithms in dynamic environments in recent years. But most researchers used outline error standard to measure the efficiency.

Figure 14: Offline error calculation in 20 evaluations by algorithm, in this way it is supposed that the eighth and eighteenth environmental assessment changed.

6. The basic configuration for testing

The proposed algorithm of component of social and cognitive factors c1 and c2, respectively, 8.2 and 3.1 in velocity and inertia weight w average c1 and c2 is assumed (05.2). The total number of particles is considered to be 100. The proposed method has been created for the two clusters and each cluster 25 and 25 neutral particle is quantum particle. The algorithm for quantum radius 5.0 times and 5.31 times the radius of the disposal and the radius of convergence determined.

The threshold for failure sequence of 10 is considered. The proposed algorithm with mQSO algorithms [4], FMSO [14], Cellular PSO [5] and Multi-Swarm [9] is analyzed.

Here for mQSO configuration 10 (5 + 5 q) used to create in which 10 groups where each group has a 5 neutral particles and 5 quantum particles.

As well as to the radius of the quantum algorithm 5.0 and 5.31 times the radius of the disposal and the radius of convergence determined. FMSO algorithms for the maximum number of groups 10, radii disposed between groups of children to 25, the number of particles in the group parent and child groups, respectively 100 and 10 is considered. For CellularPSO 5-dimensional cellular automata with 105 cells and Moore neighborhood with a radius of 2 cells in the search space is used. The maximum velocity times the radius of the neighborhood and the maximum number of particles per cell and a radius of 10 local searches 5.0have been set. As well as local search of all the particles after the change in setting the stage for a run. Methods for multi-swarm, the number of particles and particle number for groups of children for the parent group, respectively 5 and 10 has been set. Disposal radius between groups of children and radius of quantum particles 30 and 5.0 set respectively. Table 2 shows the default settings for the proposed method.

Table 2: The default setting for the proposed methodology

Parameter	Value
c_1	2.8
c_2	1.3
w	**c1 and c2average**
The number of clusters	2
The total number ofparticles	100
The number ofquantumparticles	50
The number ofneutral particles	50
The brink offailure	10
Quantumradius	0.5
Disposal Radius	31.5
Radius of convergence	31.5
Memorysize	10

6.1 The effect of the number of peaks and efficiency of the proposed method

The impact of the number of peaks and varying sizes and in different frequency is measured on the efficiency of the proposed method. In designed issues in this sector, the number of peaks from 1 to 200, the dimensions of 1 to 5 and frequencies vary from 500 to 10,000 changed. The results are shown in Tables 2 to 5. As the number of peaks in the frequency of 500, 1000 and 10000 will increase efficiency of the proposed method, but at the frequency of 5000, with an increase in peak efficiency is reduced, since the peak increase in the environment, not only to pursue a peak when the peak height is changing, it is essential to jumping from one peak to peak in the other.The proposed method increases the number of peaks in the low frequencies, the error is significantly reduced offline, but subtle error is reduced at high frequencies.This decrease can be due to two: first, because of the high number of peaks in the environment, peaks are close to each other would be easy to jump from one peak to peak, and second, because of the character of the landscape, which always evaluates the maximum all the peaks.The mean fitness landscape increases with the number of peaks and peak shorter and wider with higher peaks are covered, so that the maximum possible error is reduced.

Table 3: offline error and the standard error of the proposed method f = 500 for different aspects

5	4	3	2	1	**Peaks anddimensions**
12.49±0.17	11.86±0.26	10.00±0.39	8.24±0.27	7.37±0.18	1
11.87±0.20	9.96±0.36	8.93±0.29	7.33±0.33	5.24±0.15	5
9.26±0.15	8.99±0.11	8.87±0.27	6.90±0.28	5.16±0.20	10
7.39±0.17	6.97±0.18	6.66±0.26	6.49±0.16	4.87±0.11	20
7.74±0.10	7.67±0.25	7.52±0.15	6.14±0.18	4.69±0.21	30
6.32±0.13	6.17±0.12	6.02±0.16	5.94±0.24	4.34±0.11	40
5.97±6.15	5.63±0.21	5.27±0.26	5.04±0.18	4.25±0.22	50
5.65±0.13	4.89±0.16	4.45±0.12	3.73±0.11	2.55±0.17	100
5.55±0.12	3.88±0.17	3.62±0.11	2.80±0.19	1.41±0.14	200

Table 4:out-linearandstandard error ofthe proposedmethodf = 1000forthe different dimensions

5	4	3	2	1	**Peaks anddimensions**
6.12±0.25	6.09±0.48	5.69±0.52	5.31±0.68	4.80±0.35	1
5.66±0.21	5.44±0.51	5.16±0.65	4.78±0.60	4.28±0.55	5
5.88±0.17	5.41±0.68	5.01±0.60	4.67±0.48	4.23±0.55	10
5.36±0.18	5.32±0.54	4.70±0.44	4.19±0.49	3.97±0.41	20
5.37±0.15	4.95±0.55	4.28±0.54	3.83±0.76	3.34±0.38	30
4.45±0.12	4.25±0.46	3.98±0.61	3.45±0.62	2.92±0.42	40
4.49±0.15	4.16±0.61	3.82±0.79	3.44±0.87	2.80±0.47	50
3.79±0.10	3.41±0.54	2.81±0.61	2.29±0.75	1.68±0.16	100
3.93±0.09	3.04±0.69	2.77±0.70	2.03±0.60	1.43±0.15	200

Table 5: out-linearandstandard error ofthe proposedmethodf = 5000forthe different dimensions

5	4	3	2	1	**Peaks anddimensions**
2.54±0.19	2.25±0.38	2.13±0.32	1.88±0.30	1.67±0.32	1
1.49±0.11	1.81±0.22	1.45±0.14	1.38±0.19	1.01±0.17	5
1.34±0.10	1.83±0.28	1.80±0.27	1.59±0.34	1.18±0.28	10
1.85±0.11	1.81±0.20	1.77±0.20	1.48±0.27	1.30±0.25	20
2.00±0.09	1.95±0.29	1.93±0.23	1.76±0.36	1.51±0.26	30
2.02±0.08	1.87±0.19	1.71±0.46	1.64±0.33	1.59±0.30	40
2.03±0.08	2.06±0.23	1.95±0.40	2.05±0.35	2.03±0.29	50
2.23±0.04	2.16±0.35	2.15±0.27	1.88±0.32	2.10±0.22	100
2.38±0.03	2.62±0.31	2.68±0.37	2.62±0.28	2.55±0.10	200

Table 6: out-linearandstandard error ofthe proposedmethod at f = 10000fordifferent aspects

5	4	3	2	1	**Peaks anddimensions**
1.52±0.17	1.19±0.02	1.00±0.03	0.62±0.04	0.38±0.01	1
0.88±0.11	0.76±0.02	0.93±0.03	0.56±0.03	0.13±0.02	5
0.91±0.06	1.01±0.01	0.84±0.05	0.33±0.01	0.26±0.05	10
1.32±0.07	1.20±0.03	0.88±0.04	0.55±0.04	0.13±0.02	20
1.35±0.05	1.23±0.18	0.60±0.03	0.54±0.18	0.16±0.03	30
1.27±0.04	1.15±0.04	0.81±0.05	0.52±0.11	0.15±0.02	40
1.30±0.03	0.93±0.04	0.76±0.06	0.69±0.35	0.16±0.05	50
1.32±0.03	1.01±0.03	0.73±0.04	0.57±0.14	0.08±0.02	100
1.51±0.02	1.14±0.05	0.81±0.15	0.66±0.11	0.04±0.01	200

6.2 The effect of various parameters on the proposed algorithm and compared it with a variety of PSO algorithms

In this section, the experiments carried out on the model at frequencies of 500 to 10,000 and the number of peaks 1 to 200 will be discussed. This is the default setting for the animated summit in Table 6 below.Results for all algorithms, the mean error CI offline95 percent are running 100 times. The proposed algorithm with mQSO10 (5 + 5q), FMSO, CellularPSO and Multi-Swarm algorithms were compared.Offline error and standard error obtained from tests for environments with different dynamics are shown in Tables 7 to 10.Better results are in bold. As can be seen, the difference between off-line error of the proposed algorithm to other algorithms with increasing frequency as well as the increasing complexity of the space environment (increasing the number of peaks) increased.The reason for this is that the proposed algorithm can be faster and better solutions to obtain after the change in environment.

Table 11 Average linear offline for the proposed method with a fixed size population size of 100 is intended to show the memory.

The table shows that the best size for memory 10 that it expresses the same 1.0 * (population size). Chart offline convergence of the proposed algorithm to 10,000 and the number 10 peak frequency in the form of (14) is given.Drawing diagram in Figure (15) show average off-line error for the proposed change at different frequencies with different number of failures particles.
Figure (15) it is clear that the number of failures for more particles, efficiency decreases for the proposed method.

Figure (16) show the rhetorical offline for the proposed method with different variations of the number 1 and 3 defeat. Figure (17) the proposed method with different clusters change in frequency reveals the top 500 and 10.

Table: **Standard setting formovingpeakfunction**

Parameter	**Value**
The number ofpeaks	[1-200]
Frequency of change	[500-10000]
Severity ofpeakheight	7
Thepeakintensitychanges	1
Figurepeaks	**Conical**
Themovingpeaks Number ofdimensions	1
Number ofdimensions	5
Range ofpeakheight	[30-70]
Range ofpeakwide	[1-12]
Standardheightpeaks	50
The scope ofthe search space	[0-100]

Table 8comparedofflineerrorandthe standard error ofthe proposed methodwithother methodsforf = 500

Proposed algorithm	Multi Swarm PSO	Cellular PSO	FMSO	mQSO10 (5+5q)	**The number ofpeaks**
8.49±0.21	5.46±0.30	13.4±0.74	7.58±0.9	33.67+3.4	1
7.87±0.24	5.48±0.19	9.63±0.49	9.45±0.4	11.91±0.7	5
7.26±0.12	5.95±0.09	9.42±0.21	18.26±0.3	9.62±0.34	10
7.19±0.17	6.45±0.16	8.84±0.28	17.34±0.3	9.07±0.25	20
6.44±0.11	6.60±0.14	8.81±0.24	16.39±0.4	8.80±0.21	30
6.22±0.14	6.85±0.13	8.94±0.24	15.34±0.4	8.55±0.21	40
5.17±6.16	7.04±0.10	8.62±0.23	5.54±0.2	8.72±0.20	50
5.10±0.12	7.39±0.13	8.54±0.21	2.87±0.6	8.54±0.16	100
5.05±0.11	7.52±0.12	8.28±0.18	11.52±0.6	8.19±0.17	200

Table 9 comparedofflineerrorandthe standard error ofthe proposed methodwithother methodsforf = 1000

Proposed algorithm	Multi Swarm PSO	Cellular PSO	FMSO	mQSO10 (5+5q)	**The number ofpeaks**
4.72±0.22	2.90±0.18	6.77±0.38	14.42±0.4	18.6±1.6	1
4.26±0.20	3.35±0.18	5.30±0.32	10.59±0.2	6.56±0.38	5
4.18±0.16	3.94±0.08	5.15±0.13	10.40±0.1	5.71±0.22	10
3.26±0.16	4.33±0.12	5.23±0.18	10.33±0.1	5.85±0.15	20
3.30±0.16	4.41±0.11	5.33±0.16	10.06±0.1	5.81±0.15	30
3.15±0.11	4.52±0.09	5.61±0.16	9.85±0.11	5.70±0.14	40
2.79±0.15	4.57±0.08	5.55±0.14	9.54±0.11	5.87±0.13	50
2.19±0.09	4.77±0.08	5.57±0.12	8.77±0.09	5.83±0.13	100
2.03±0.10	4.76±0.07	5.50±0.12	8.06±0.07	5.54±0.11	200

Table 10: Comparisonofflineerrorandthe standard error ofthe proposed method withother methodstof = 5000

Proposed algorithm	Multi Swarm PSO	Cellular PSO	FMSO	mQSO10 (5+5q)	**The number ofpeaks**
2.14±0.19	0.56±0.04	2.55±0.12	3.44±0.11	3.82±0.35	1
1.29±0.11	1.06±0.06	1.68±0.11	2.94±0.07	1.90±0.08	5
1.34±0.10	1.51±0.04	1.78±0.05	3.11±0.06	1.91±0.08	10
1.85±0.11	1.89±0.04	2.61±0.07	3.36±0.06	2.56±0.10	20
2.01±0.09	2.03±0.06	2.93±0.08	3.28±0.05	2.68±0.10	30
2.12±0.08	2.04±0.06	3.14±0.08	3.26±0.04	2.65±0.08	40
2.15±0.08	2.08±0.02	3.26±0.08	3.22±0.05	2.63±0.08	50
2.33±0.04	2.14±0.02	3.41±0.07	3.06±0.04	2.52±0.06	100
2.48±0.03	2.11±0.03	3.40±0.06	2.84±0.03	2.36±0.05	200

Table 11: Comparisonofflineerrorandthe standard error ofthe proposed method withother methodsforf = 10000

Proposed algorithm	Multi Swarm PSO	Cellular PSO	FMSO	mQSO10 (5+5q)	**The number ofpeaks**
1.12±0.17	0.27±0.02	1.53±0.12	1.90±0.06	1.90±0.18	1
0.78±0.11	0.70±0.10	0.92±0.10	1.75±0.06	1.03±0.06	5
0.81±0.06	0.97±0.04	1.19±0.07	1.91±0.04	1.10±0.07	10
1.22±0.07	1.34±0.08	2.20±0.10	2.16±0.04	1.84±0.08	20
1.30±0.05	1.43±0.05	2.60±0.13	2.18±0.04	2.00±0.09	30
1.26±0.04	1.47±0.06	2.73±0.11	2.21±0.03	1.99±0.07	40

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1.35±0.03	1.47±0.04	2.84±0.12	2.60±0.08	1.99±0.07	50
1.22±0.03	1.50±0.03	2.93±0.09	2.20±0.03	1.85±0.05	100

Table 12: The mean offline error for the proposed method with different sizes of memory

Average error Offline	Memory size	Population size	**The number ofpeaks**
1.34±0.10	10	100	1
2.02±0.24	20	100	5
2.71±0.39	30	100	10
3.51±0.42	40	100	20
4.34±0.58	50	100	30
4.63±0.65	60	100	50
5.21±0.93	70	100	100

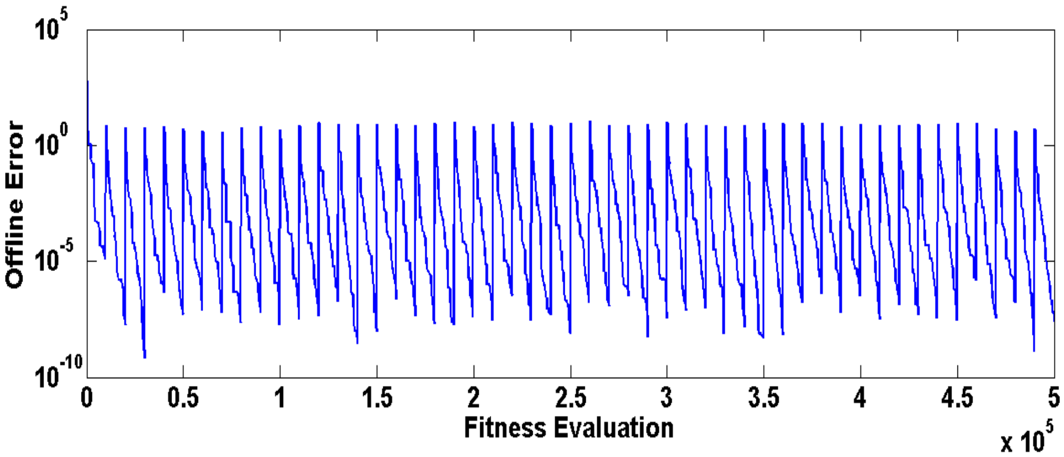

Figure 15: Graph linear convergence offline proposed at a frequency of 10,000 with 10 peaks

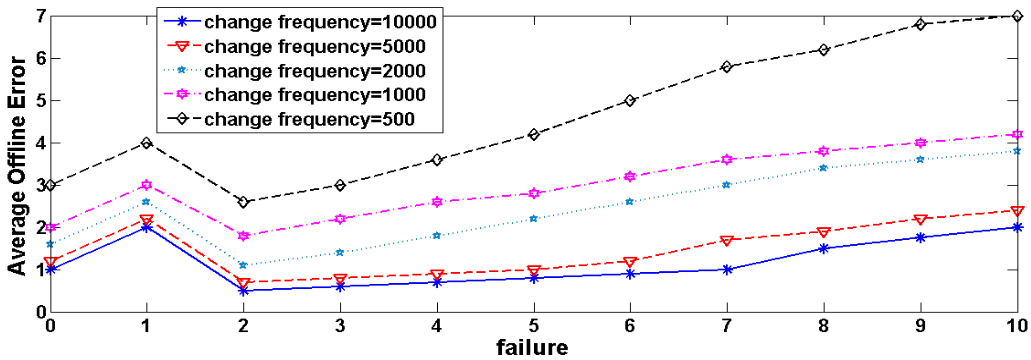

Figure 16: Average number of failures and offline errors proposed method with different frequencies change

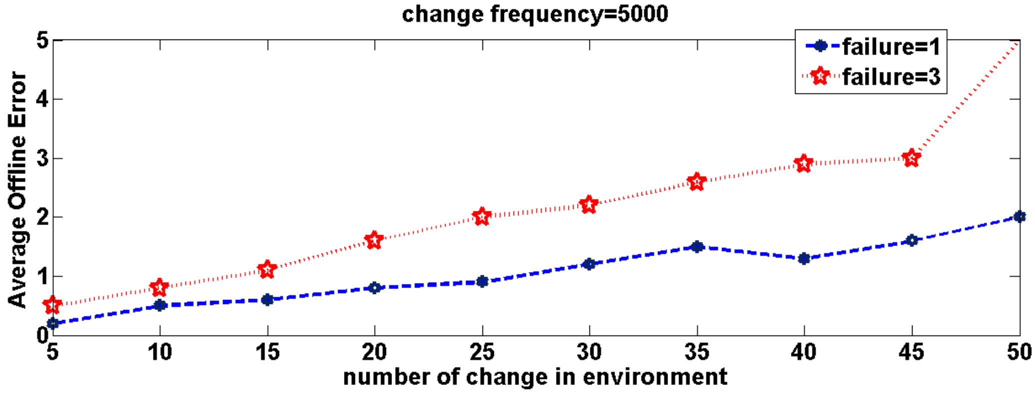

Figure 17: Average number of different variations offline error proposed method and frequency changes by 1 and 3 defeats in 5000 and a peak of 10

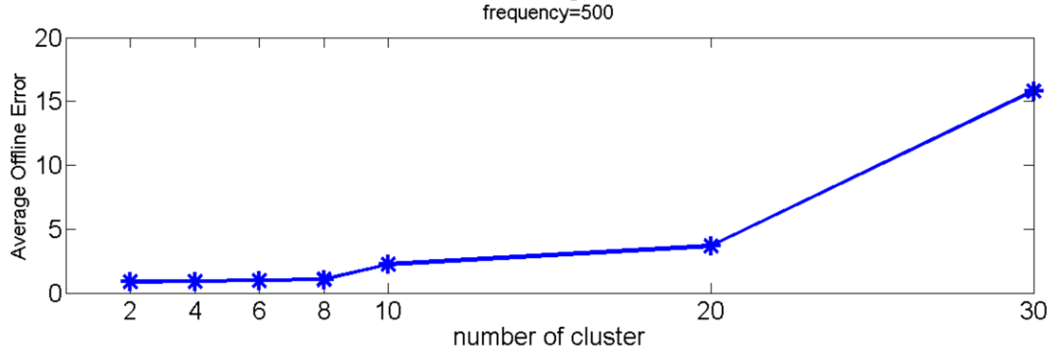

Figure 18: Average error of off-line method at a frequency of 500 and the number of different clusters

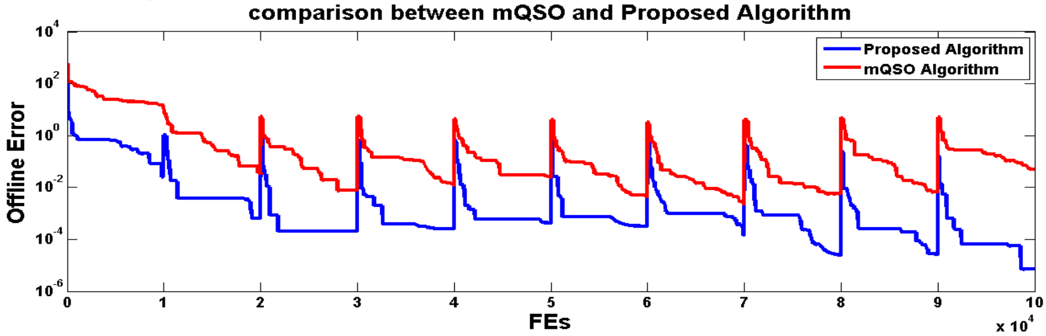

Figure 19: Comparison of the proposed method with the same method on the same terms and with 10 mQSO change and change frequency 10000

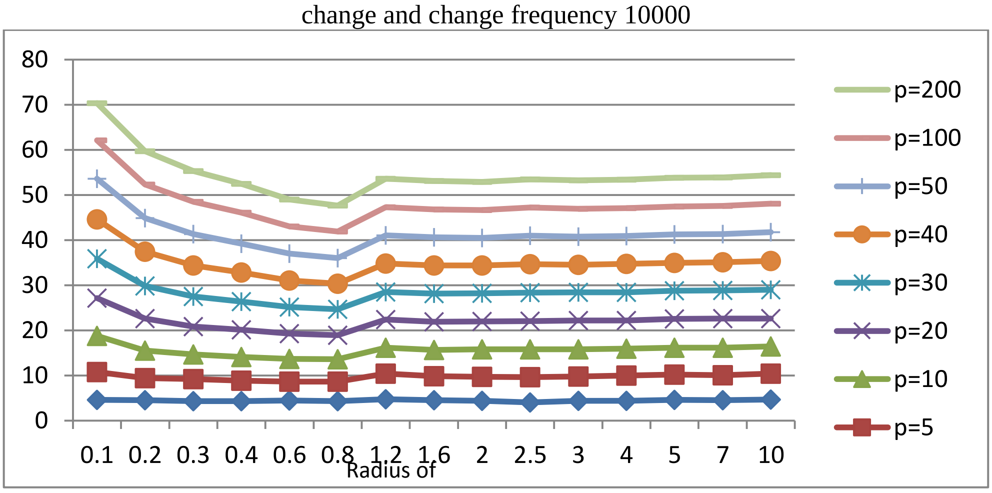

Figure 20: The error generated off-line based on the radius of convergence on the proposed method at a frequency of 500 and for the number of different peaks

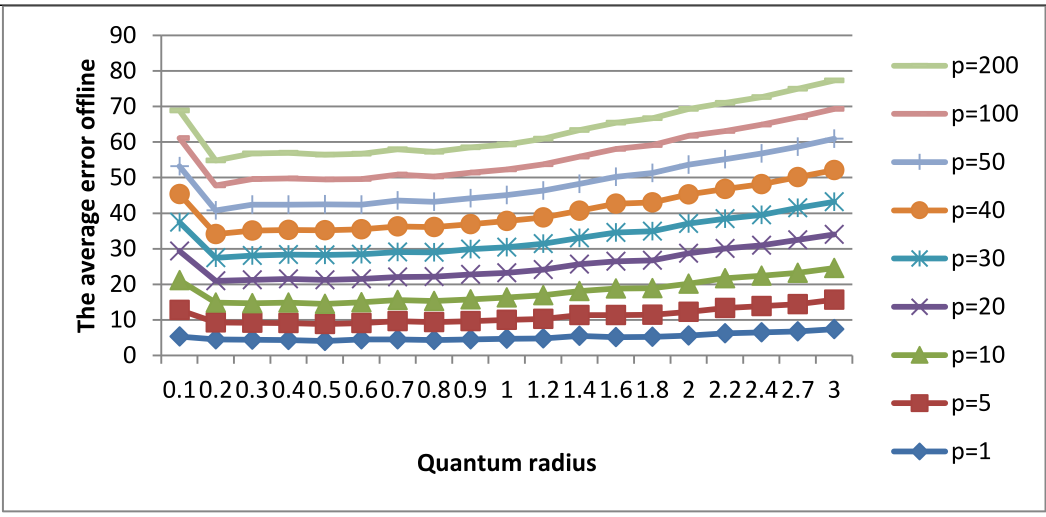

Figure 21: The trend of linear output error based on quantum radius at frequency 500 for the number of different peaks

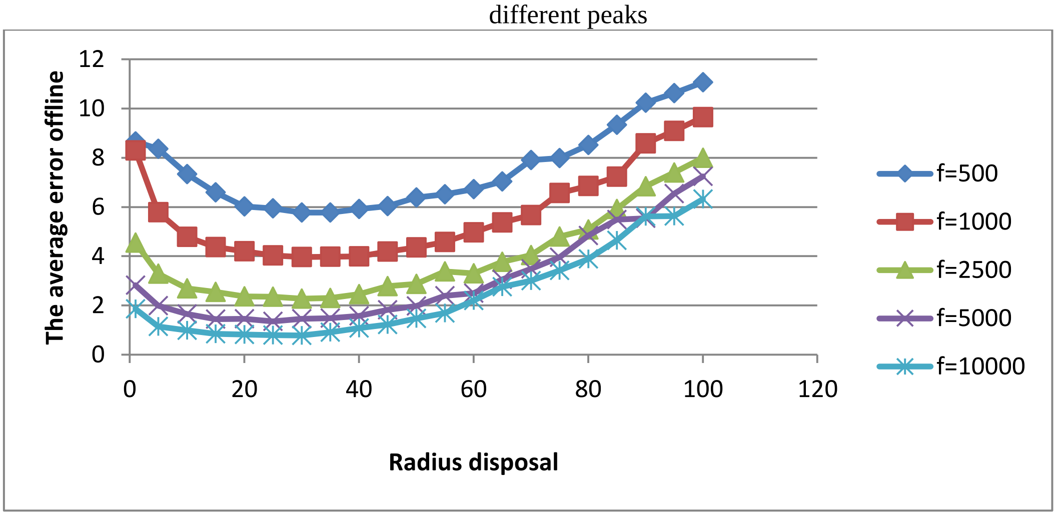

Figure 22: Impact Radius disposed between the group of children on an error in the 10 peak and off-line for different frequencies change

7. Conclusion

The clustering approach to teach algorithm helps always some scattering of particles is optimized algorithms. So dynamic optimization problems, algorithms are moving quickly back-track to track. Offline difference error of the proposed algorithm rather other algorithms as well as the increasing complexity of the space environment by reducing the frequency (the number of peaks). Also, this difference becomes more pronounced as the number of shifts. The reason for this is that the proposed algorithm can be faster and better solutions to obtain after the change in environment. Use the appropriate solutions as well as local search solution by hill-climbing algorithm convergence rate has increased dramatically. The other thing has helped in this way to improve the control algorithm is used. In this way it is possible to increase the speed of convergence and using such chaotic behavior of particles in the atmosphere can increase the convergence of the algorithm.

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