Hybridization In Genetic Algorithm

[1]Prateek , [2]Dr. Rainu Nandal
[1]M.Tech Reaserch Scholar, Software Engineering, U.I.E.T., MDU, Rohtak
[2]Assistant Professor, CSE, Department, U.I.E.T., MDU, Rohtak

Abstract: ***In this research paper Optimization and Optimization Techniques are quickly clarified and a definite perspective of Genetic Algorithm is given. The standard of Genetic Algorithm is that it impersonate genetics and natural assortment by a computer program.The parameters of the issue are coded the majority normally as DNA- like linear data structure,a vector or a string. A genetic algorithm (GA) is a hunt heuristic procedure that impersonates the procedure of natural advancement. This heuristic is consistently utilized to make valuable answers for enhancement and pursuit issues.In the paper a point by point depiction of GA is given including the general terms,steps to finish GA, algorithm,applications and limitations. Hybridization in GA is required in light of the fact that dissimilar to other pursuit and enhancement methods, a genetic algorithm guarantees meeting yet not optimality, not even that it will discover nearby maxima. GA's are visually impaired streamlining agents which don't utilize any helper data, for example, subordinates or other particular information about the extraordinary structure of the goal function.In the event that there is such information, be that as it may it is impulsive and wasteful not to make utilization of it. In this way, there is a need emerges for hybridization of GA. In Introduction part a concise portrayal is given about hybridization of GA including its need and after that another hybridized procedure Memetic Algorithm is likewise described.In this theory analyst purposes to expel one of the confinement of GA i.e worried about the meeting speed.GA's utilization the parameters' esteems rather than parameters themselves. Along these lines they scan for the entire parameter space, and it prompts moderate joining speed.To defeat this disadvantage, in the theory work GA will be hybridized with Hill Climbing Approach. In the proposed work populace is introduced utilizing Hill Climbing Approach and afterward unique strides of GA are connected including encoding, choice, hybrid and change. The examination is made utilizing the Benchmark Functions i.e De Jong Functions and entire research is done with the assistance of C enviornment.***

Keywords: Genetic Local search algorithms, Hybridization, Genetic Algorithm(GA), Evolutionary computation, Hybrid Genetic Algorithms.

INTRODUCTION

Optimization is the way toward improving something superior. An architect or researcher invokes another thought and optimization enhances that idea. Optimization is a procedure of finding the optimal solution from a set of possible solutions.

Optimization includes in endeavoring minor takeoff from a basic thought and using the information got to upgrade the idea. Optimization is the math tool that we depend on to find these solutions. Optimization incorporates finding the best arrangement. The wording “best” arrangement suggests that there is more than one arrangement and the arrangements are not of equivalent value. The definition of best is in respect to the current issue, its technique for arrangement, and the tolerances allowed.[18] Hence the ideal arrangement relies upon the individual planning the issue. An adaptive GA is inspired by the human reproduction was proposed in [22] and the constraints like consanguinity, reproduction age, same sex reproduction etc have been carefully addressed. An assortment of systems have been crossbred to exemplify the best of both the procedures in genuine applications [17,21]. Population estimate is likewise a basic component in a GA. A model was introduced [8] in which size of the population banks on standard deviation of populace and the signal contrast amongst best and second best chromosome. In this model if a nearby hunt strategy is implemented in such that it reduces the standard deviation and increase the signal difference the concluding hybrid could be very efficient even in small population size. Espinoza [7] showed the impact of a local pursuit technique in reduction of populace measure. For the most part, the transformation and the hybrid administrators create infeasible answers for an exceedingly compelled problem. To maintain a strategic distance from age of infeasible arrangements numerous strategies have been proposed like like partial matched crossover (PMX) [9] for utilize all together based issues. To settle the highly compelled time tabling problem[2] a heuristic crossover operator was presented with coordinate portrayal of the timetable so crucial requirements are never disregarded for taking care of voyaging sales representative issue altered modified crossover (MOX)[11], order crossover(OX) [14] Genetic algorithms are adaptive algorithms depicted as heuristic inquiry algorithms [3] based on the developmental thoughts of characteristic determination and natural genetics by David Goldberg. These are intense advancement procedures that utilize ideas of developmental science to advance ideal arrangements of a given issue. A neighborhood look technique can guarantee reasonable portrayal of the distinctive inquiry regions by inspecting their nearby optima which thusly can decrease the probability of untimely merging. Consolidating a local inquiry strategy can present new qualities which can battle the genetic drift issue [4] [9] caused by the aggregation of stochastic mistakes because of limited populaces. Furthermore, a limited populace can make a genetic algorithm deliver arrangements of less streamlined arrangement as contrasted and the arrangement that can be delivered utilizing nearby pursuit techniques because of the trouble of finding the best arrangement in the best discovered area for the GA operators [1]. A local strategy inside a GA can enhance the abusing function of the hunt algorithm without influencing its investigating function. In the event that the stability stuck between worldwide investigation and nearby abuse capacities can be be accomplished, the algorithm can undoubtedly deliver arrangements of high exactness [6]. They contrasted the proposed hybrid and PMX and found that the planned crossover yielded better outcomes over PMX [22]. Sanusi used the two Evolutionary Algorithm techniques, that is, Genetic Algorithm and Memetic Algorithm have been applied to solve knapsack problem. Memetic algorithm converges the faster than genetic algorithm even as it produce more optimal result [10]. Pisinger [5] gave an outline of all current correct arrangement approaches for the Knapsack issue, and demonstrated that the Knapsack issue is as yet troublesome for these algorithms to tackle. Maya Hristakeva utilize the genetic algorithm to tackle the rucksack issue in this paper she implements two selection functions that is roulette wheel and group selection and the result from these two are different depending upon the usage of elitism used or not. The result of program shows that implementation of good selection method and elitism is very important [15]. Bjornsdotter et al. [16] proposed a memetic algorithm for include determination in volumetric information containing spatially circulated groups of enlightening highlights in neuroscience application. They presumed that the proposed MA distinguished a greater part of pertinent highlights when contrasted with GA. Sivaraj et al. [19] examined about a novel way to deal with enhance the execution of GA by utilizing specific introduction, which goes for providing more fit people in the beginning. A PBS mixed determination administrator was proposed, which has adjusted exchange off amongst investigation and abuse, [13].New advancement in hybrid administrator was proposed in genetic algorithm with Tabu pursuit, [14].

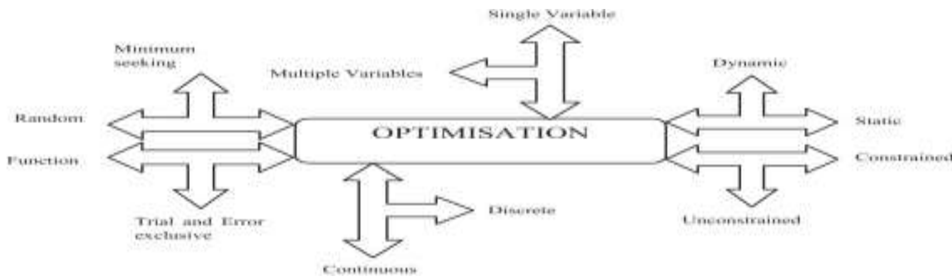

Figure 1.1

Fig. 1 divides optimization algorithms into six categories.

PROBLEM FORMULATION

1.Objective of this research work is to compare the performance of Simple GA with hybridized GA. In this work the hybridization is carried out in the initialization phase of simple GA.
2.In simple GA initial population is produced using a random function while in the Modified GA it was generated using Hill climbing approach.
3.To compare the performance of SGA with MGA following six De Jong's functions were used:

1) De Jong's Function 1:

The most straightforward test work is De Jong's capacity 1. It is otherwise called sphere model. It is continuous, convex and unimodal. function definition:

$$f_1(x) = \sum_{i=1}^{n} x_i^2 \qquad -5.12 \le x_i \le 5.12$$

f1(x)=sum(x(i)^2), i=1:n, -5.12<=x(i)<=5.12.

global minimum:

f(x)=0, x(i)=0, i=1:n.

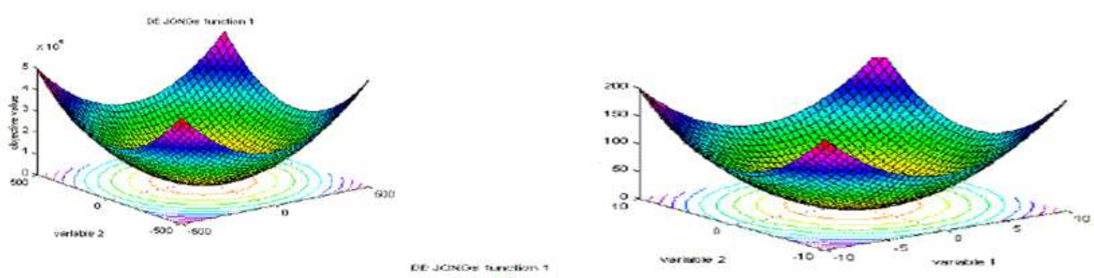

Fig. 2: Visualization of De Jong's function 1 utilizing diverse domains of the factors; in any case, the two graphics appear to be comparable, simply the scaling changed; left: surf plot of the function in a vast region from - 500 to 500 for each of the two factors, right: the function at a littler zone from - 10 to 10.

2) Axis Parallel Hyper-Ellipsoid Function:

The hub parallel hyper-ellipsoid resembles to De Jong Function1. It is also called the weighted sphere model. Again, it is continuous, raised and uni-modal.Function definition:

$$f_{1a}(x) = \sum_{i=1}^{n} i \cdot x_i^2 \qquad -5.12 \le x_i \le 5.12$$

f1a(x)=sum(i·x(i)^2), i=1:n, -5.12<=x(i)<=5.12.

global minimum:

f(x)=0; x(i)= 0, i=1:n.

This function is implemented as objfun1a.

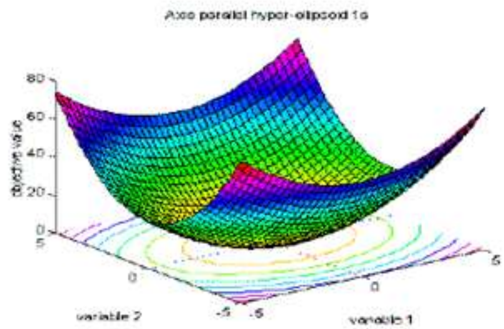

Fig. 3: Visualization of Axis parallel hyper-ellipsoid function; surf/mesh plot of the function in an area from -5 to 5.

3) Moved axis parallel hyper-ellipsoid function:

This capacity is gotten from the hub parallel hyper-ellipsoid. There is a slight qualification between these two capacity definitions. Finally the moved hub parallel hyper-ellipsoid capacity is more elliptic than the first capacity and the base of the capacity isn't at x(i)= 0

$$f_{1c}(x) = \sum_{i=1}^{n} 5i \cdot x_i^2 \qquad -5.12 \le x_i \le 5.12$$

f1c(x)=sum(5*i·x(i)^2), i=1:n, -5.12<=x(i)<=5.12.

global minimum:

f(x)=0; x(i)= 5*i, i=1:n.

This function is implemented in objfun1c.

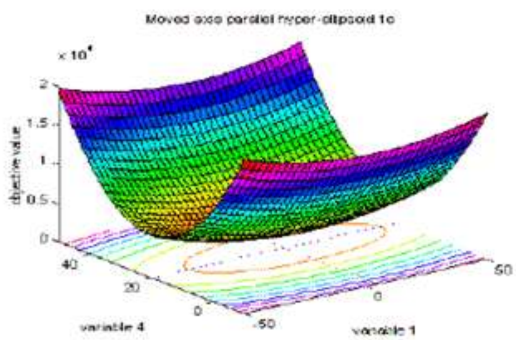

Fig. 4: Visualization of Moved axis parallel hyper-ellipsoid function; surf/mesh plot of the of the first and fourth variable, the objective values were calculated from the 4-dimensional function with second and third variable set to 0.

4) Rastrigin's function 6:

Rastrigin's capacity is relies upon work 1 with the expansion of cosine balance to produce numerous neighborhood minima. In this way, the test work is to a great degree multimodal. However the area of the minima are frequently dispersed.Function definition:

$$f_6(x) = 10 \cdot n + \sum_{i=1}^{n} \left(x_i^2 - 10 \cdot \cos(2 \cdot \pi \cdot x_i) \right) \qquad -5.12 \le x_i \le 5.12$$

f6(x)=10·n+sum(x(i)^2-10·cos(2·pi·x(i))), i=1:n; -5.12<=x(i)<=5.12.

global minimum:

f(x)=0; x(i)=0, i=1:n.

This function is implemented in objfun6.

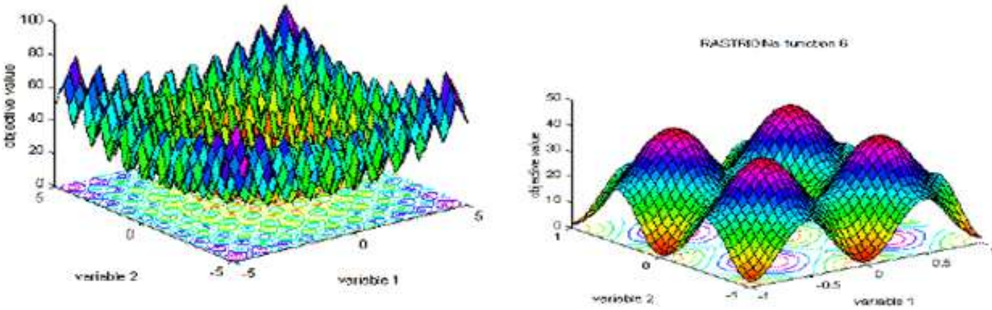

Fig.5: Visualization of Rastrigin's function; left: surf plot in an area from -5 to 5, right: focus around the area of the global optimum at [0, 0] in an area from -1 to 1.

5) Griewangk's function 8:

Griewangk's capacity is identified with Rastrigin's capacity. It has different broad neighborhood minima. However, the area of the minima are reliably appropriated.function definition:

$$f_8(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \qquad -600 \le x_i \le 600$$

f8(x)=sum(x(i)^2/4000)-prod(cos(x(i)/sqrt(i)))+1, i=1:n

-600<=x(i)<= 600.

global minimum:

f(x)=0; x(i)=0, i=1:n.

This function is implemented in objfun8.

The representations in Figure 4.7 underneath depict Griewangk's capacity using three particular resolutions. Every one of the outlines addresses different properties of the capacity. The practical on the upper left side exhibits the full definition extent of the capacity. Here, the capacity looks on a very basic level the same as De'Jong's capacity 1. While pushing toward the internal region, the capacity seems, by all accounts, to be extraordinary. Various little zeniths and valleys are evident in the right practical. While zooming in on the area of the perfect, grahic on the base left side, the apexes and valleys look smooth.

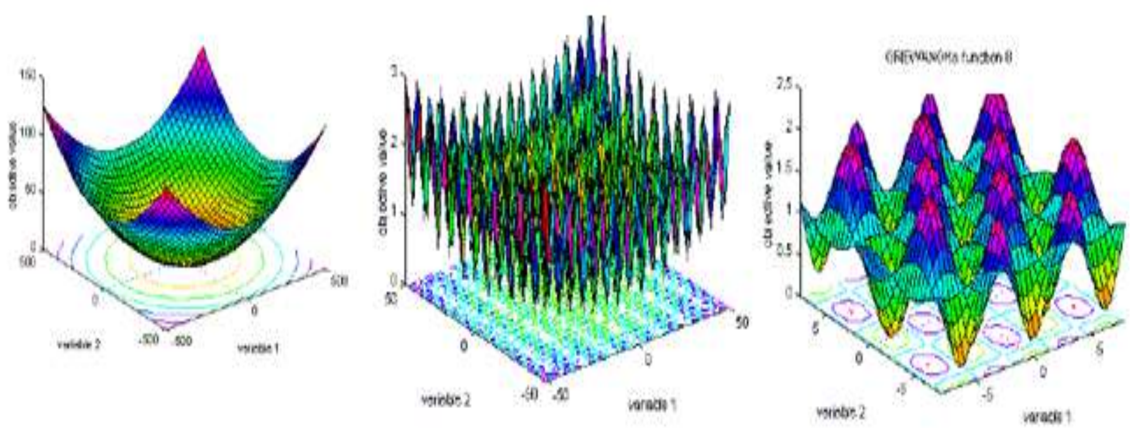

Fig. 6: Visualization of Griewangk's function; upper left: full definition territory from - 500 to 500, right: internal zone of the function from - 50 to 50, base left: region from - 8 to 8 around the ideal at [0, 0].

6) Sum Of Different Power Function 9:

The whole of various powers is a normally utilized unimodal test function.

function definition:

$$f_9(x) = \sum_{i=1}^{n} |x_i|^{(i+1)} \qquad -1 \le x_i \le 1$$

f9(x)=sum(abs(x(i))^(i+1)), i=1:n; -1<=x(i)<=1.

Global minimum:

f(x)=0; x(i)=0, i=1:n.

This function is implemented in objfun9.

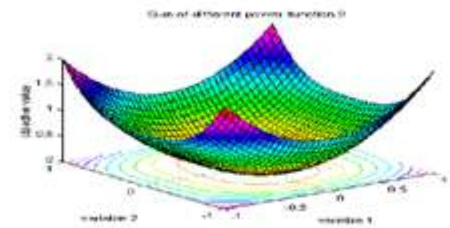

Fig. 7: Visualization of Sum of dissimilar power function; surf plot in an area from -1 to 1.

IMPLEMENTATION AND RESULTS

Researcher intents to carry out the work in the field of hybridization of genetic algorithms i.e introducing the optimization techniques like Hill Climbing,Tabu search, Simulated Annealing etc in GA.To achieve the said objective we have studied:

1.The areas in GA are to be identified where the above mentioned optimization techniques can be introduced in the given frame.

2.A detailed study of Optimization Techniques which are described above.

3.A detailed study of De Jong's Function, which are described in above.

7) Proposed Work:

In SGA, if some changes has been done in initialization step then better convergence can be possible. In proposed work we are initializing the population which will be using the Hill Climbing Approach with an idea that selected population will result early convergence and the proposed work is termed as MGA. The work is implied in C enviornment.

7.1) Modified Genetic Algorithm:

MGA is developed for achieving better optimality and convergence. When SGA is hybridized with Hill Climbing Approach than we can achieve better optimality because the basic idea is that in initialization step of SGA we will be initializing population randomly but if we will initialize population using Hill Climbing Approach and then apply basic steps of SGA than we can achieve better convergence and it results better optimality and this proposed work is termed as MGA.

7.2) Proposed Algorithm of MGA:

1. Initialize the population using the Hill Climbing Approach.
2. Encode that population using value encoding.
3. Select the parent chromosomes from a set of population using roulette wheel selection.
4. Apply the crossover to produce further offspring. Crossover is applied in proposed work is arithmetic crossover.
5. Then perform mutation, for enabling the algorithm to avoid local optima.
6. Repeat 3, 4 and 5 until the stopping criteria is met.

7.3) Steps of MGA:

MGA is developed for achieving better optimality and convergence. When SGA is hybridized with Hill Climbing Approach than we can achieve better optimality because the basic idea is that-in initialization step of SGA we will be initializing population randomly but if we will initialize population using Hill Climbing Approach and then apply basic steps of SGA than we can achieve better convergence and it results better optimality.

7.3.1) Initialization:

Initialize the population using the Hill Climbing Approach. According to Hill Climbing approach a point x has been randomly selected and then calculate the objective function f(x) again randomly choose another point x1 and calculate its objective function f(x1). If the objective function is to minimize then check this condition (f(x1) <f(x)).If it satisfies then accept point x1 otherwise reject the point. If the objective is to maximize than check (f(x1)>f(x)) and then accept point x1 otherwise reject that.

7.3.2) Encoding:

Encoding is another important step of GA. Encoding is a procedure of speaking to individual genes.The process can be performed utilizing bits,numbers,trees,arrays.The encoding generally depends upon the type of the problem.For analyzing the performance of SGA and MGA we are using De Jong functions and for them we are using value encoding.

7.3.3) Selection:

During each progressive age, an extent of the current populace is chosen to breed another age. Singular arrangements are chosen through a wellness based process, where fitter solution are commonly more prone to be chosen. Roulette wheel determination is utilized as a part of the proposed work.

7.3.3.1) Roulette Wheel Selection:
Parents are chosen by their wellness. The better the chromosomes are, the more opportunities to be chosen they have. The algorithm has been clarified as beneath:

7.3.3.1.1) Algorithm:
1.[Sum] Calculate sum of all chromosomes fitness in population-sum S.
2.[Select]Generate random numbers from (0,S) - r.
3.[Loop] Go through the populace and total fitness from 0 to sum s. At the point when aggregate s is more prominent than r ,stop and restore the chromosome where you are.
Step 1 is repeated only once.

7.3.4) Crossover:
Crossover is that process in which two selected parent chromosomes are combined to produce a new chromosome. It is a hereditary administrator that joins two chromosomes (offspring) to deliver another chromosome (posterity). The thought behind hybrid is that the new chromosome might be superior to anything both of the guardians on the off chance that it takes the best qualities from each of the parents. Crossover happens amid development as per a client quantifiable crossover probability.For various kinds of encoding different types of crossover is used. When one will use binary encoding then one point or two point crossover is utilized. Similarly if real or value encoding is utilized than arithmetic, BLX crossover are used. In this paper arithmetic crossover is used :
7.3.4.1) Arithmetic crossover:
It is that crossover operator that directly consolidates two parent chromosome vectors to deliver two new offsprings as indicated by the accompanying conditions:
Offspring1 =w* *Parent1* +(1-w)* *Parent2*
Offspring2 =(1–w)* *Parent1* +w* *Parent2*
where w is a random weighting factor.
7.3.5) Mutation:
After crossover, the strings are subjected to mutation. Mutation keeps the algorithm to be caught in neighborhood minima. Mutation assumes the part of recouping the lost hereditary materials and additionally for haphazardly dispersing hereditary information.It is the protection strategy against the irreversible loss of hereditary material. In proposed work we are using mutation 0.001% and if the chromosome is mutated it is decreased by 0.5 value.

7.4) Flowchart:

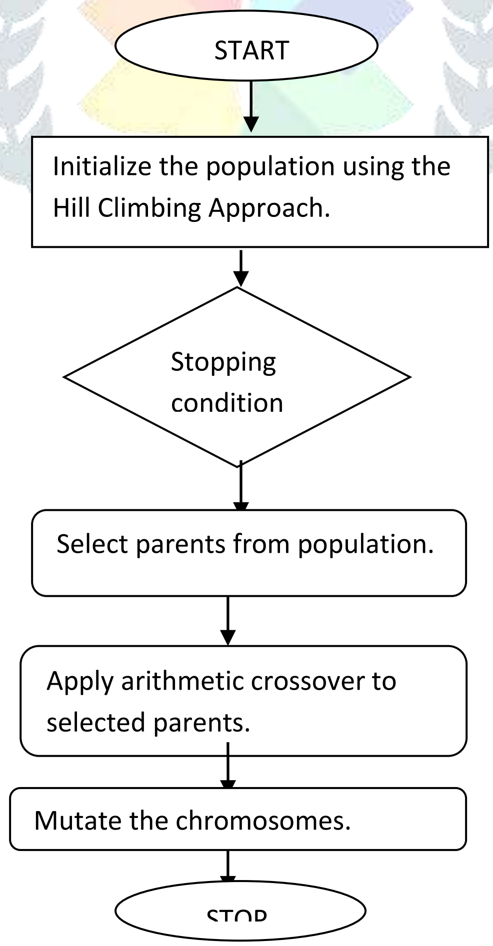

Fig.8 Flowchart

8) Results

Researcher intents to carry out the work in the field of hybridization of genetic algorithm i.e introducing optimization techniques like Hill Climbing, Simulated Annealing in Genetic Algorithm. In proposed work we have integrated Hill Climbing Approach with Genetic Algorithm in initialization step and the proposed algorithm is termed as MGA.

In this the performance of simple genetic algorithm(SGA) is contrasted with modified genetic algorithm (MGA). It has been observed by the researchers that the proposed genetic algorithm outsmart the simple genetic algorithm.The performance is compared with the help of De Jong's Functions.Proposed work is carried out on six De Jong Functions and graphically it is shown:

8.1) Function 1:

$$f_1(x) = \sum_{i=1}^{n} x_i^2 \qquad -5.12 \le x_i \le 5.12$$

f1(x)=sum(x(i)^2), i=1:n, -5.12<=x(i)<=5.12.

global minimum:

f(x)=0, x(i)=0, i=1:n.

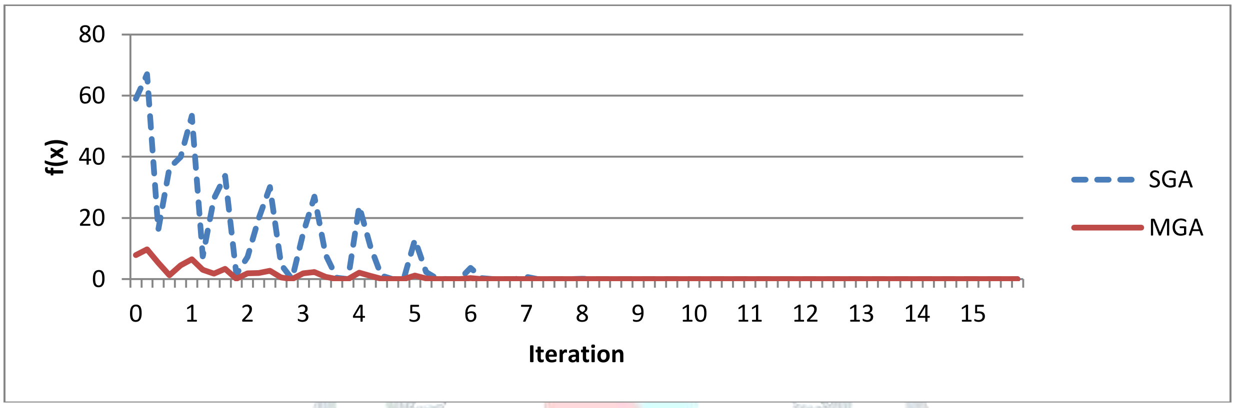

Fig. 9

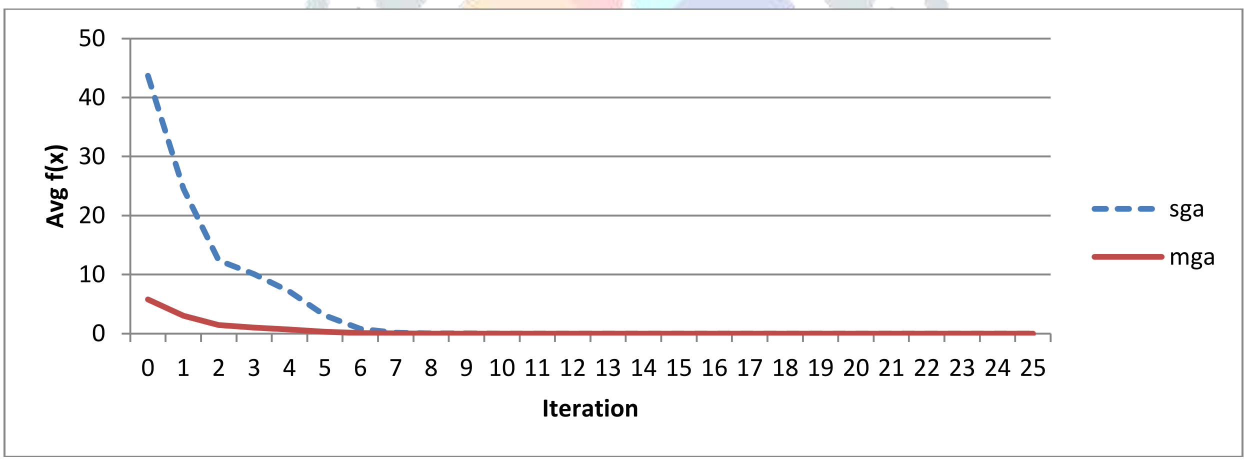

Fig. 10

8.2) Function 2:

$$f_{1a}(x) = \sum_{i=1}^{n} i \cdot x_i^2 \qquad -5.12 \le x_i \le 5.12$$

f1a(x)=sum(i·x(i)^2), i=1:n, -5.12<=x(i)<=5.12.

global minimum:

f(x)=0; x(i)= 0, i=1:n.

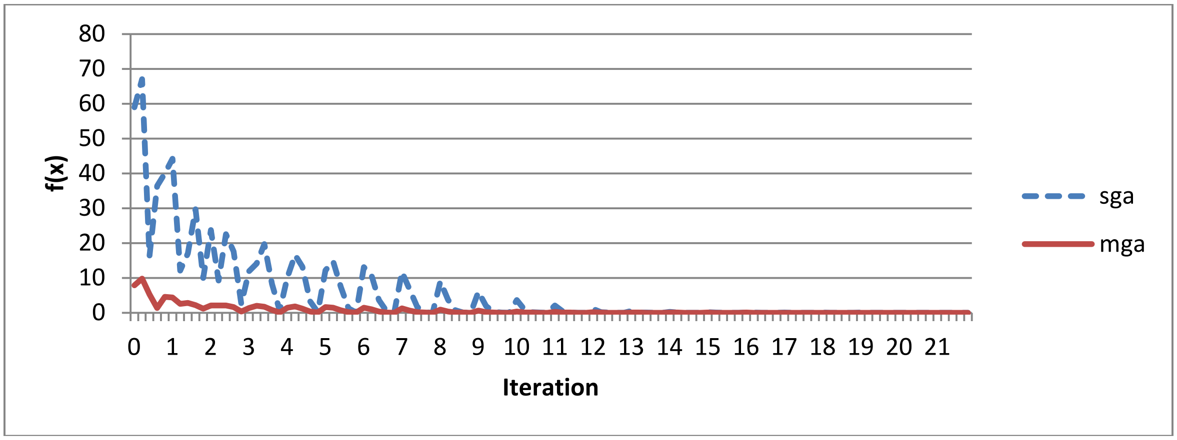

Fig. 11

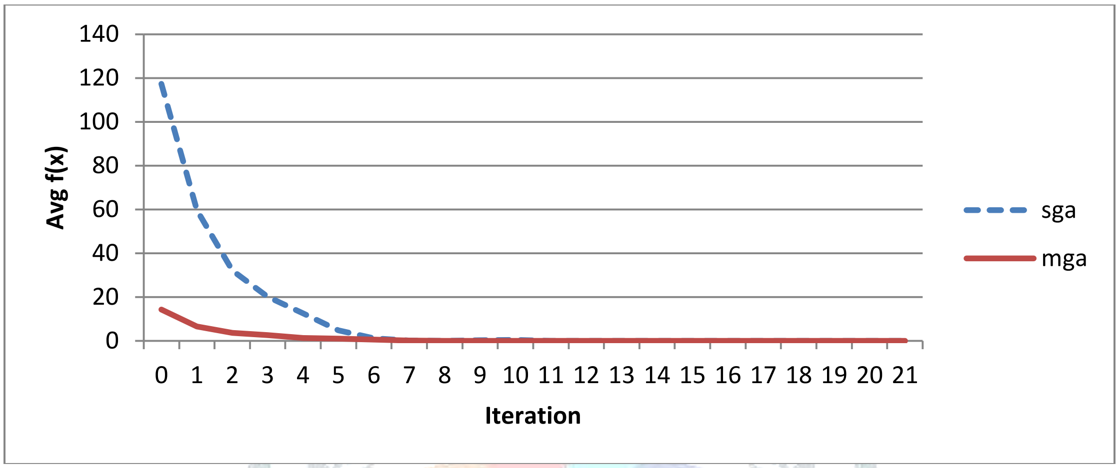

Fig. 12

8.3) Function 4:

$$f_{1c}(x) = \sum_{i=1}^{n} 5i \cdot x_i^2 \qquad -5.12 \le x_i \le 5.12$$

f1c(x)=sum(5*i·x(i)^2), i=1:n, -5.12<=x(i)<=5.12.

global minimum:

f(x)=0; x(i)= 5*i, i=1:n

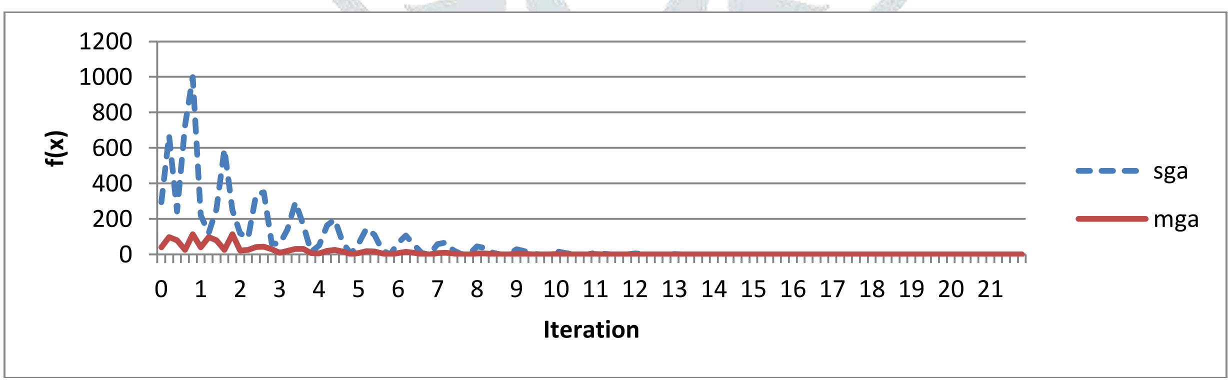

Fig. 13

Fig. 14

8.4) Function 6:

$$f_6(x) = 10 \cdot n + \sum_{i=1}^{n} \left(x_i^2 - 10 \cdot \cos(2 \cdot \pi \cdot x_i)\right) \qquad -5.12 \le x_i \le 5.12$$

f6(x)=10·n+sum(x(i)^2-10·cos(2·pi·x(i))), i=1:n; -5.12<=x(i)<=5.12.

global minimum:

f(x)=0; x(i)=0, i=1:n

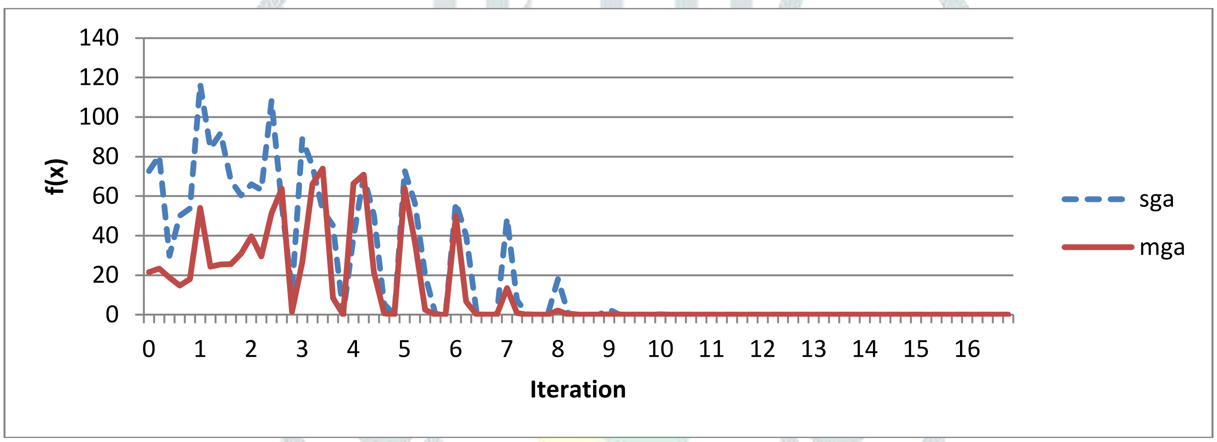

Fig. 15

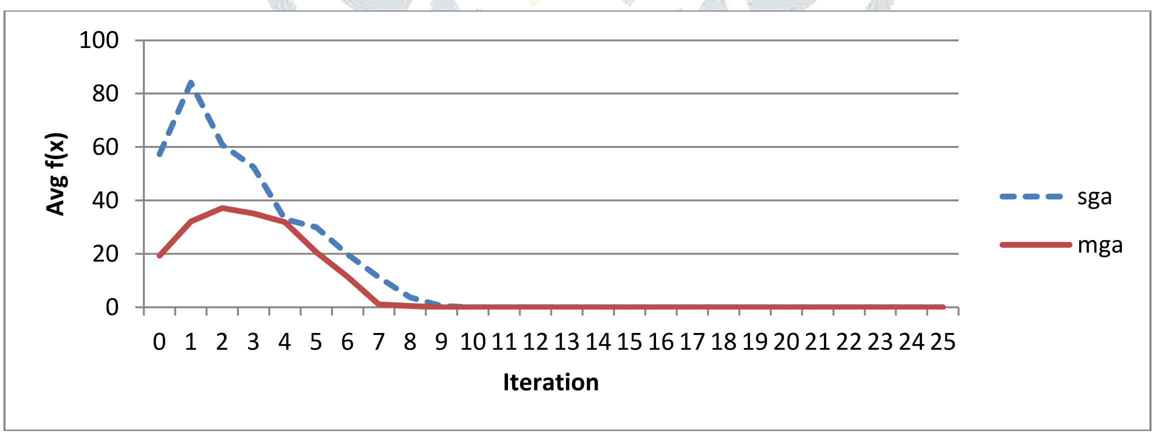

Fig. 16

8.5) Function 8:

$$f_8(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \qquad -600 \le x_i \le 600$$

f8(x)=sum(x(i)^2/4000)-prod(cos (x(i)/sqrt(i)))+1, i=1:n
-600<=x(i)<= 600.

global minimum:

f(x)=0; x(i)=0, i=1:n.

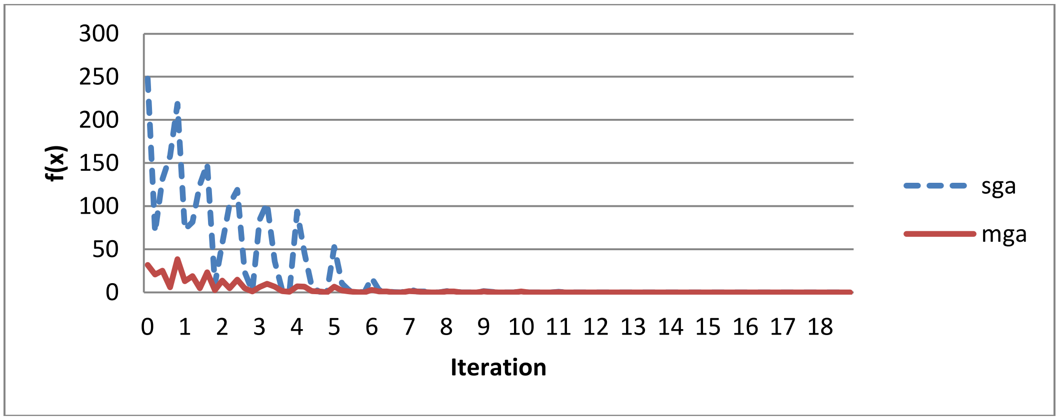

Fig. 17

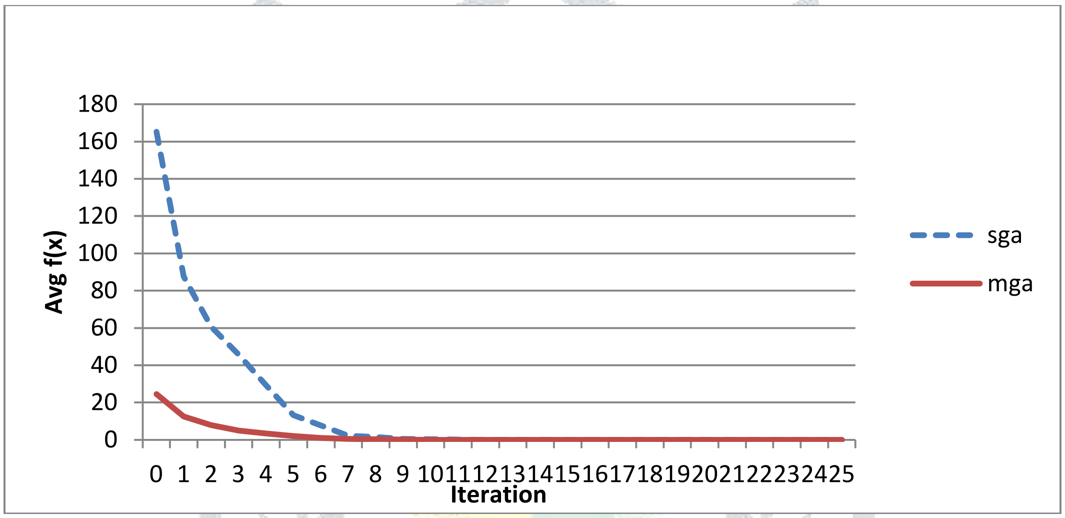

Fig. 18

8.6) Function 9:

$$f_9(x) = \sum_{i=1}^{n} |x_i|^{(i+1)} \qquad -1 \le x_i \le 1$$

f9(x)=sum(abs(x(i))^(i+1)), i=1:n; -1<=x(i)<=1

global minimum:

f(x)=0; x(i)=0, i=1:n.

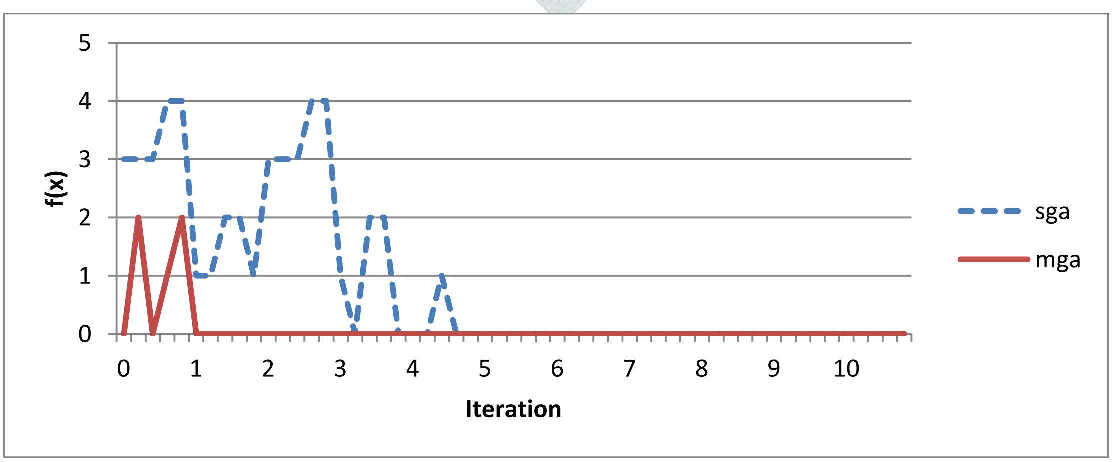

Fig. 19

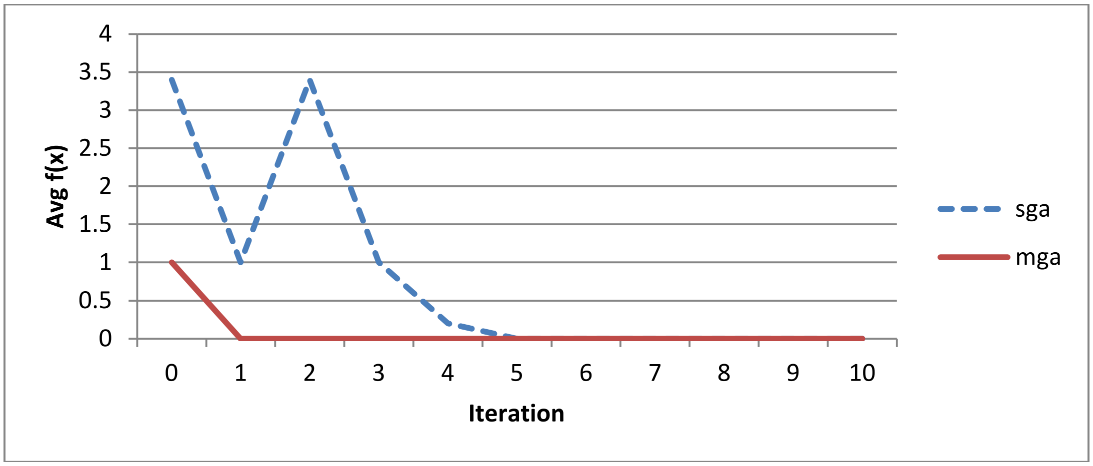

Fig. 20

CONCLUSION AND FUTURE WORK

A genetic algorithm (GA) is a hunt heuristic that imitates the technique of regular improvement. This heuristic is consistently utilized to produce valuable responses for streamlining and hunt issues. Hereditary counts have a place with the greater class of evolutionary algorithms (EA). Genetic Algorithms are known to be one of best techniques for seeking and enhancement. By applying hereditary administrators generation, hybrid and transformation in a populace of people, we can find the most suitable and optimum solution. Subsequently they join to the ideal arrangement by developing the best people in every age. The primary favorable position of the GAs is that they utilize the parameter esteems rather than the parameter themselves. Along these lines they scan for the entire parameter space. Be that as it may, GAs experience significant issues concerning the merging pace and the finding of the correct estimation of worldwide ideal. It experiences when they need to manage functions that contain an excessive number of local optima.

This thesis presents a study of fields, where the hybridization is carried out in Genetic Algorithm. Hybridization can be carried out with the help of different optimization techniques like Tabu Search, Hill Climbing Approach, Simulated Annealing, Particle Swarm Optimization(PSO),Ant Colony Optimization(ACO) in the GA. Hybridization is carried out in GA to achieve better optimality and convergence. Because of stipulated time researcher has hybridized GA with Hill Climbing Approach in initialization step and that hybridized Genetic Algorithm is termed as MGA in thesis. It has been shown that MGA is better than Simple Genetic Algorithm(SGA).This comparison is shown with the help of De Jong's Functions, results show that MGA outsmart than SGA. This approach is developed because GA converge to the optimal solution by evolving the best individuals in each generation. If we include the best generation in initialization step with the help of Hill Climbing Approach and then apply different steps of GA encoding, selection, crossover and mutation, then better convergence can be achieved.
It is further opined that the hybridization may be carried out at other phases of Genetic Algorithm and different techniques can be applied at initialization step. We can enhance the optimality and convergence by introducing another optimization techniques like Simulated Annealing, Tabu Search technique like or any another technique like clustering technique. These techniques enhances the features of Genetic algorithm. We can hybridize the GA at any another step. It include five basic steps, we can hybridize any one step or two steps and then compare the proposed work with the benchmark problems.

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