Volume 3, Issue 12, December 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Hybridizing Genetic Algorithm with Hill Climbing in Replacement Operator

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Abstract- Genetic algorithm is a population-based search and exploiting objective function. Every basic genetic operators used in a simple GA utilizes "random choice" to an extent or another. Optimization ability can be improved when problem specific knowledge is incorporated and goal oriented operators are used. The population based local refinement mechanism, searches the local area for minima as well as takes out the solution for local trapping to go to better fitness landscape nearby. The traits are acquired during the learning process, passed from parents to their offspring. GA and neighborhood search technique will result in early findings of the optima. In this paper implementation of hill climbing in replacement operator and empirically analyze the convergence rate of hybrid algorithm with simple genetic algorithm. Both algorithms use the complementary property of exploitation to find optimal solution. Memetic algorithm performs good to find optimal result of complex problems. Performance of memetic algorithm is affected by population size and number of generated children. Proposed work also tries to analyze the convergence rate of memetic algorithm on different De jong's function.

Keywords: Genetic algorithm, hill climbing, hybridisation, Memetic algorithm, replacement operator

I. INTRODUCTION

Genetic algorithm (GA) refers to a technique of parameter search based on the procedure of natural genetics in order to find solution to optimization and search problem. It combines the principle of the survival of the fittest, with a random, yet structured information exchange among a population of artificial chromosomes [1]. A chromosome contains a group of numbers that completely specifies a candidate solution during the optimization process. The individuals with higher fitness values will survive and will be selected to produce a better generation, while the individuals with lower fitness values will be eliminated. Therefore, GA simulates the survival of the fittest among a population of artificial chromosome and it normally stops when the number of generation specified is met or there is no change in maximum fitness value. In this paper Memetic algorithm can be defined as genetic algorithm that include non-genetic local search to improve genotypes. Memetic algorithm can blend the functioning of genetic algorithm with several heuristic search techniques like simulated annealing, tabu search. Review of local search techniques as Hill climbing with replacement operator is presented and its pseudo code along with results are analysed.

II. HYBRID GENETIC ALGORITHM

In its broadest sense, hybridization refers to the inclusion of problem-dependent knowledge in a general search algorithm. Memetic algorithm is meta-heuristic search method and based on both the natural evolution and individual learning with information transmission among them [1]. Heuristic optimization algorithms such as Simulated Annealing or Genetic Algorithms often can locate near optimal solutions but can require many function evaluations. Local search algorithms, including both gradient and non-gradient based methods, are quite at finding the optimal within convex areas of the design space but often fail to find the global optimal in multimodal design spaces and non-differential function. The local search algorithm use greedy rather than steepest policy and work on principle of searching a neighbourhood as a means of identifying a better solution [2]. They continue until local optima are found. Population based search algorithm have advantages over the gradient type searches for not getting trapped in local optima. But some of the population based search algorithm like Particle Swarm Optimization (PSO) has a tendency of premature convergence. Stochastic local search is designed in which the stochastic search takes the solution out of a local trap. While the GA allow moving to good regions of the search space, the hill climbing allow exploring in an exhaustive way those regions of the search space. Many of the local search procedures embedded within the MAs are not standard, i.e. they usually perform a shorter truncated local search. Two major hybridization models are distinguished: *strong hybridization* in which knowledge has been included as specific non-conventional problem representations and/or operators and *weak hybridization* resulting from the combination of lower-lever hybrid algorithms [3].

Hybrid design issue

A. Local Search and Learning

B. Balance between Global and Local Search

A. Local Search and Learning

Local search methods use local knowledge to improve a solution's chances to propagate its characteristics into the next generations. Due to the similarities in the role of the local search within the genetic search and the role of learning within the evolution process, the local search is usually viewed as a learning process. Lamarckian evolution and Baldwin effect: One of the important issues of hybrid genetic algorithms is how the information gained during local search is used by the global algorithm [4]. Either the Lamarckian or the Baldwin approach can be used. In the Lamarckian approach the traits acquired during the learning process are passed from parents to their offspring. This means that both the genetic structure of an individual and its associated fitness value are modified to reflect the changes in phenotype structure as a result of performing local search. The Baldwin Effect is somewhat Lamarckian in its results but using different mechanisms. In the Baldwin approach the learning process can help the individual to adapt to its environment and as a result to survive and gain more chance to pass on its traits to the next generation [5]. In this case, only the improved fitness value is modified to reflect the effect of performing local search, thereby allowing individuals with the ability to learn to proliferate in the population.

B. Balance between Global and Local Search

The hybrid algorithm should strike a balance between exploration and exploitation, in order to be able to solve global optimization problems. According to the hybrid theory [4], solving an optimization problem and reaching a solution of desired quality can be attained in one of two ways. Either the global search method alone reaches the solution or the global search method guides the search to the basin of attraction from where the local search method can continue to lead to the desired solution. In the genetic-local hybrid, the main role of the genetic algorithm is to explore the search space in order to either isolate the most promising regions of the search space, or, to hit the global optimum [6]. However, the main role of the local search method is to exploit the information gathered by the global genetic algorithm. The division of the hybrid's time between the two methods influences the efficiency and the effectiveness of the search process. The optimal division of the algorithm's time is an important issue that is faced the designers of hybrid genetic algorithms.

III. HILL CLIMBING

An optimization problem can usually also be modelled as a search problem, since searching for the optimum solution from among the solution space [7]. Without any loss of generality, assuming that our optimization problems are of the maximization category. So, here is the hill climbing technique of search:

1. Start with an initial solution, also called the starting point. Set current point as the starting point
2. Make a move to a next solution, called the move operation
3. If the move is a good move, then set the new point as the current point and repeat (2). If the move is a bad move, terminate. The last current solution is the possible optimum solution.

The move operation is problem dependent. In a discrete optimization problem, such as the Travelling Salesman Problem, a move operation would probably shuffle a couple of positions in the original solution [7].To avoid getting stuck in local minima we adopt a random-restart hill-climbing. Random initial states are generated, running each until it halts or makes no discernible progress. The best result is then chosen. Hill climbing is used widely in artificial intelligence fields, for reaching a goal state from a starting node. Hill climbing is often used when a good heuristic function is available for evaluating states but when no other useful knowledge is available. Hill climbing can often produce a better result than other algorithms when the amount of time available to perform a search is limited, such as with real-time systems

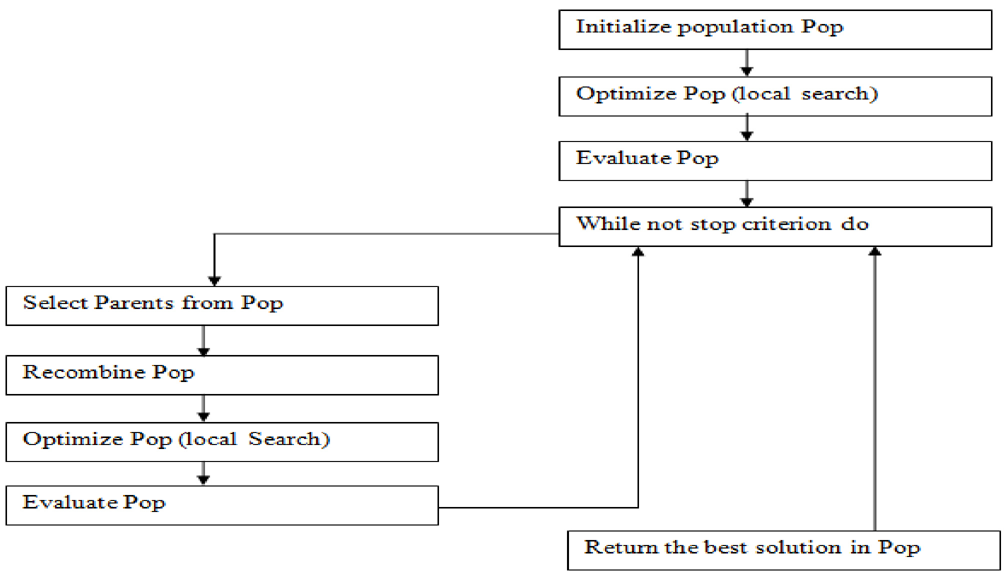

Figure 1 Two possible ways of combining local search with SGA

Description of the GA with hill-climbing method

Iteratively, GA produces better solutions using HC as an 'accelerator' mechanism thanks to the exploitative properties of HC [9]. When evaluating the fitness of each individual, GA use the results of HC working with an initial guess corresponding to this individual, there are thus as many HC running in parallel as individuals in the population [10]. During reproduction and genetic transformation (crossover, mutation) for the production of the individuals of the next generation, GA work on the new solution.

It must be noted that, when evaluating the individuals with HC, it is not necessary to reach complete convergence. Individual optimization (life) can be performed ova a limited number of steps for two reasons, one because the main part of the information given by the search with HC is acquired during the first few steps, and two the search is pursued and refined over the next generations anyway. In practice, the hybrid terminates with an 'extended-life' in which the best individual of the last GA generation is exploited by HC using the normal termination criteria (nearly complete convergence). Optimization problem of De Jong's function (finding the minimal value approaching zero) solved using simple genetic algorithm with Replace All scheme. In memetic algorithm, in spite of using the basic generational update, hill climbing helps in finding the better individuals for replacement. These improvements accumulate over all the generations, resulting in a larger improvement in the total performance. Genetic algorithm and local search have complementary properties, which helps in optimization of objective function with fast convergence

IV. METHODOLOGY

Procedure for memetic algorithm is same as simple genetic algorithm except that a local search method is implemented in one of the operator (crossover, selection, replacement) to exploit the search space. Applying Hill climbing in replacement operator work efficiently to find the optimal solution.

Simple GA represents an intelligent exploration, having a random search confined within a defined search space for solving a problem optimally. Simple GA starts with random initialization of population. After this fitness function is used to calculate the fitness of each individual and then reproduction is applied. In order to incorporate the offspring into original population replacement is used. Various replacement schemes are used for maintaining the useful diversity of population [11]. Elitist replacement schemes improve the performance of genetic algorithm. Using different replacement and selection schemes in steady state, genetics converge quickly and have a useful diversity. Diversity helps in finding the optimal solution. The time needed to reach the global optimum can be reduced if local search methods and local knowledge are used to accelerate locating the most promising region in addition to locating the global optimum starting within basin of attraction [12]. Meta heuristic search mechanism in the memetic algorithm offers the speed and quality of convergence. Reducing the population size can lead to an increase in the algorithm convergence speed.

Pseudo code for memetic algorithm

```
1. Encode solution space
2. Set pop_size, chrom_size, max_gen, Gen=0
3. Initialize population P randomly
4. For each individual i € P: calculate fitness (i);
5.  While ( Gen < Gensize)
    Apply generic GA
    *selection
    * cross-over
    *mutation
** For each individual i € P: do local_search(i);
     *replacement
6. Test: Test whether the termination condition is
Satisfied. If so, stop. If not, return the best solution in
current population and go to Step 5
```

Hill climbing is applied in replacement for hybridization. A chromosome is chosen randomly and its random gene value is replaced by a random value. If the newly generated chromosome have better fitness than it replace the old chromosome else check the loop condition. To analyse the optimization ability of the algorithm on different De jong's functions, work is applied on it. Algorithms that are not able to discover good directions underperform in some problems.

Pseudo code for memetic local search

1. Loop: if i < no_of_run
2. Select random chromosome
3. Select random gene position and Replaces its value by a randomly generated valid value
4. Calculate the fitness of new chromosome
5. If (fitness_new < fitness_old)

   Replace the old chromosome if better

The simplest test function is De Jong's F1. It is continuous, convex and unimodal. The performance on Sphere is a measure of the general efficiency of the algorithm Generalized Rastrigin Function is a typical example of non-linear multimodal function. This function is a fairly difficult problem due to its large search space and its large number of local minima. The Ackley Problem is a minimization problem. Originally this problem was defined for two dimensions, but the problem has been generalized to N dimensions. Number of local minima: several local minima. The global minimum: $\mathbf{x}^* = (0\ldots, 0), f(\mathbf{x}^*) = 0$.Schwefel's function is deceptive in that the global minimum is geometrically distant, over the parameter space, from the next best local minima. Therefore, the search algorithms are potentially prone to convergence in the wrong direction. The schwefel's function is symmetric, separable and multimodal (left). Rotating this function creates a non-separable surface with similar features [13].

V. EXPERIMENTAL RESULTS

Using the method described in the previous section we tried to determine the effect on the performance of GA. Using low probability for mutation removes an additional variable of consideration. Testing memetic algorithm may make use of different population size to that of Rastringin model function for better understand ability of results. Work is having arithmetic crossover taking alpha 0.3.

The general parameters used for all experiments, unless otherwise stated were:

1. Random initialization
2. Value encoding
3. Arithmetic crossover
4. Uniform mutation
5. 0.8 crossover probability
6. Breeding pool at 100% of population size
7. mutation probability .01
8. Generations at gap of 50 starting from 50 to 200.
9. Population size of 10 having 5 as gene size.

Graphs are plotted between minimum fitness and number of generations. We examined the minimum and average values of the optimization function.

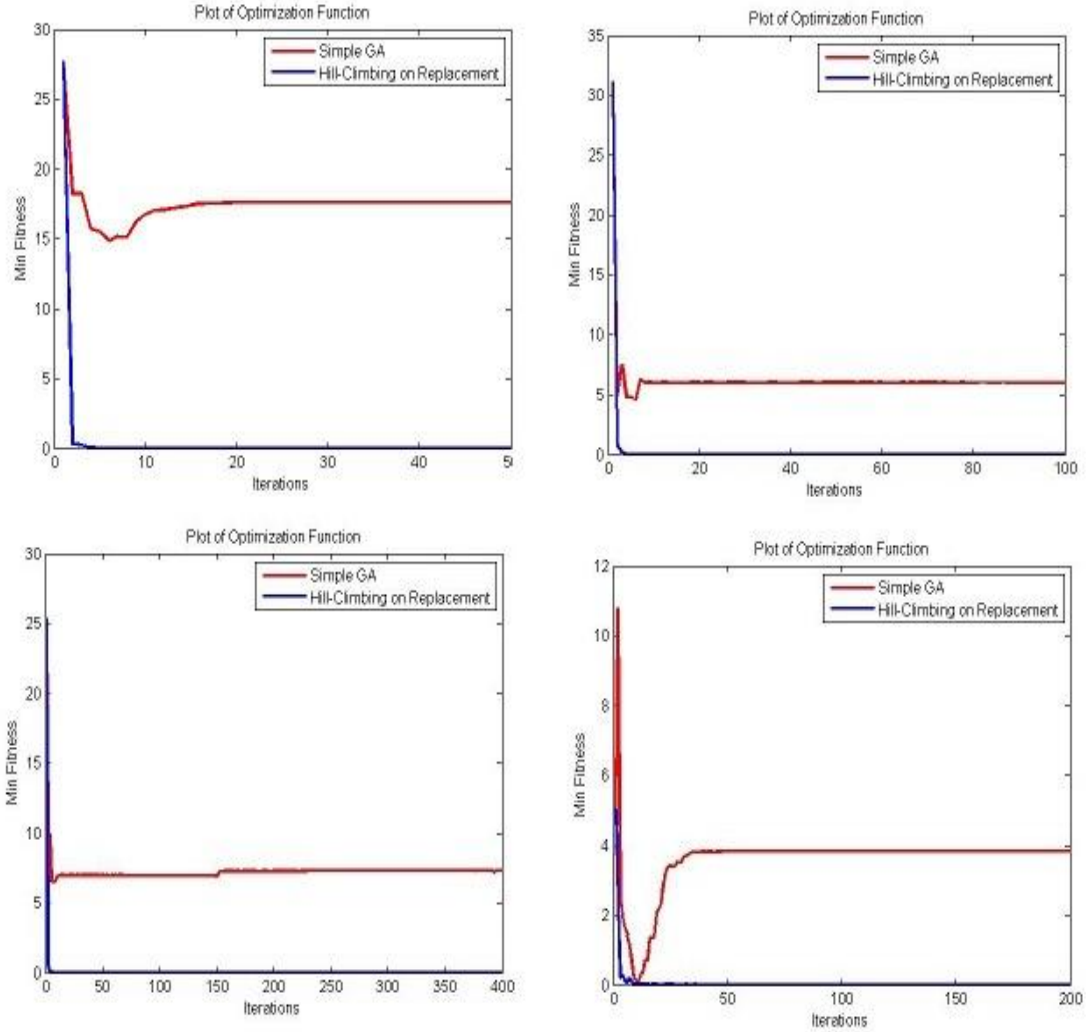

Figure 1: Plot of sphere model function (F1) with effect of population size

Table 1 Results of sphere model function

Number of Generation		Genetic algorithm	Memetic algorithm
50	Min	14.98	1.67e004
	Avg	17.28	0.46
100	Min	4	2.205e004
	Avg	5.5	0.39
150	Min	14	1.8e005
	Avg	16.79	0.11
200	Min	0.72	2.78e005
	Avg	3.7	0.1467
400	Min	5.5	1.5e005
	Avg	6.29	0.029

From analyzing the graph and result table, Sphere model function is totally optimized by the memetic algorithm and memetic algorithm performs better than simple genetic algorithm. Increasing the number of generation, implemented work give better optimal values. Runs of implemented work is done with various population sizes.

Follow the well-known fact that increasing the population size increase the convergence rate, up to a certain limit. After that it have little effect of increase in population size.

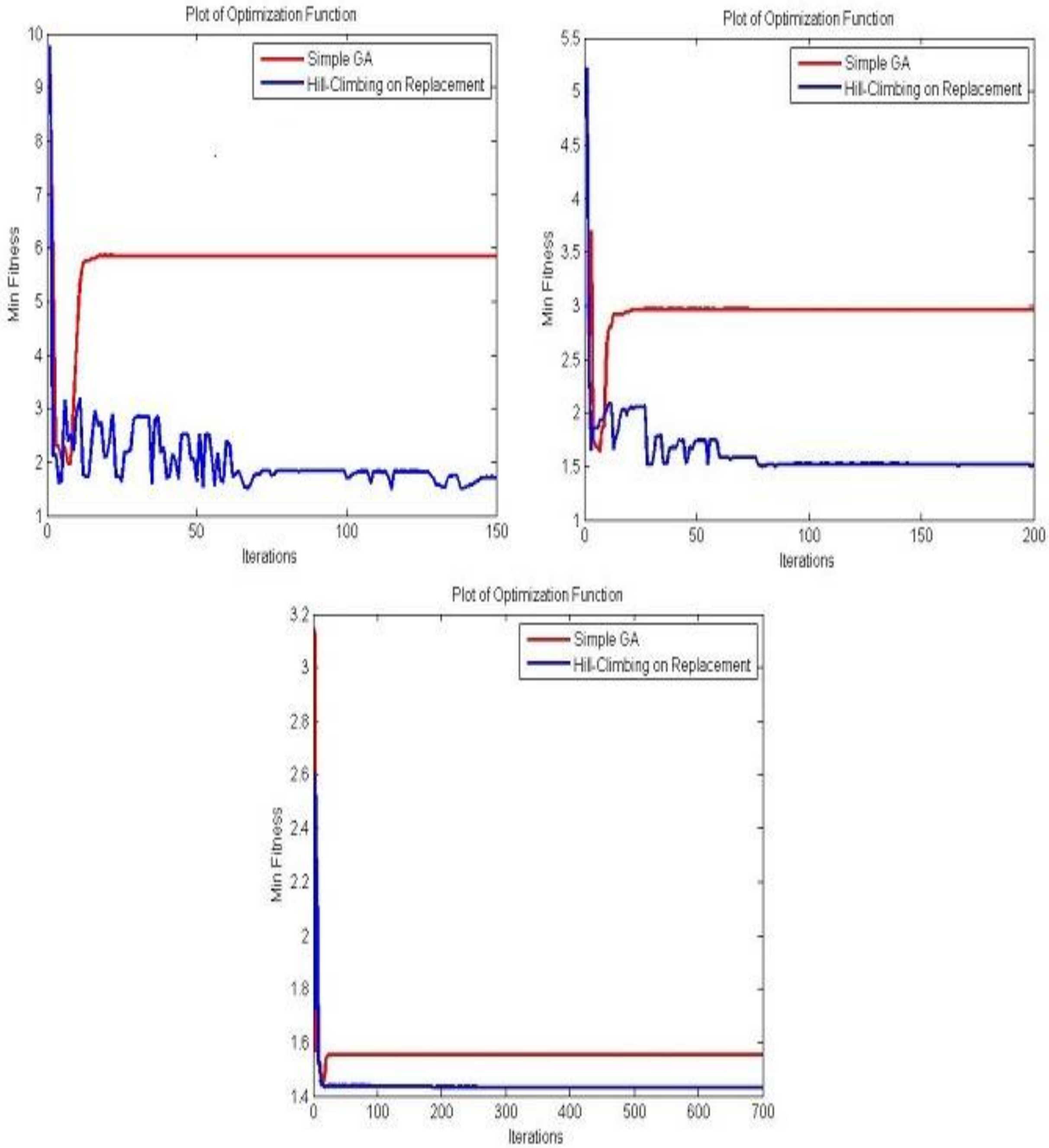

Figure 2: Plot of Ackley path function with different population size

Table II Results of Ackley path function

Number of Generation		Genetic algorithm	Memetic algorithm
150	Min	1.5	1.49
	Avg	5.8	1.64
200	Min	1.67	1.49
	Avg	2.72	1.56
700	Min	1.42	1.49
	Avg	1.49	1.53

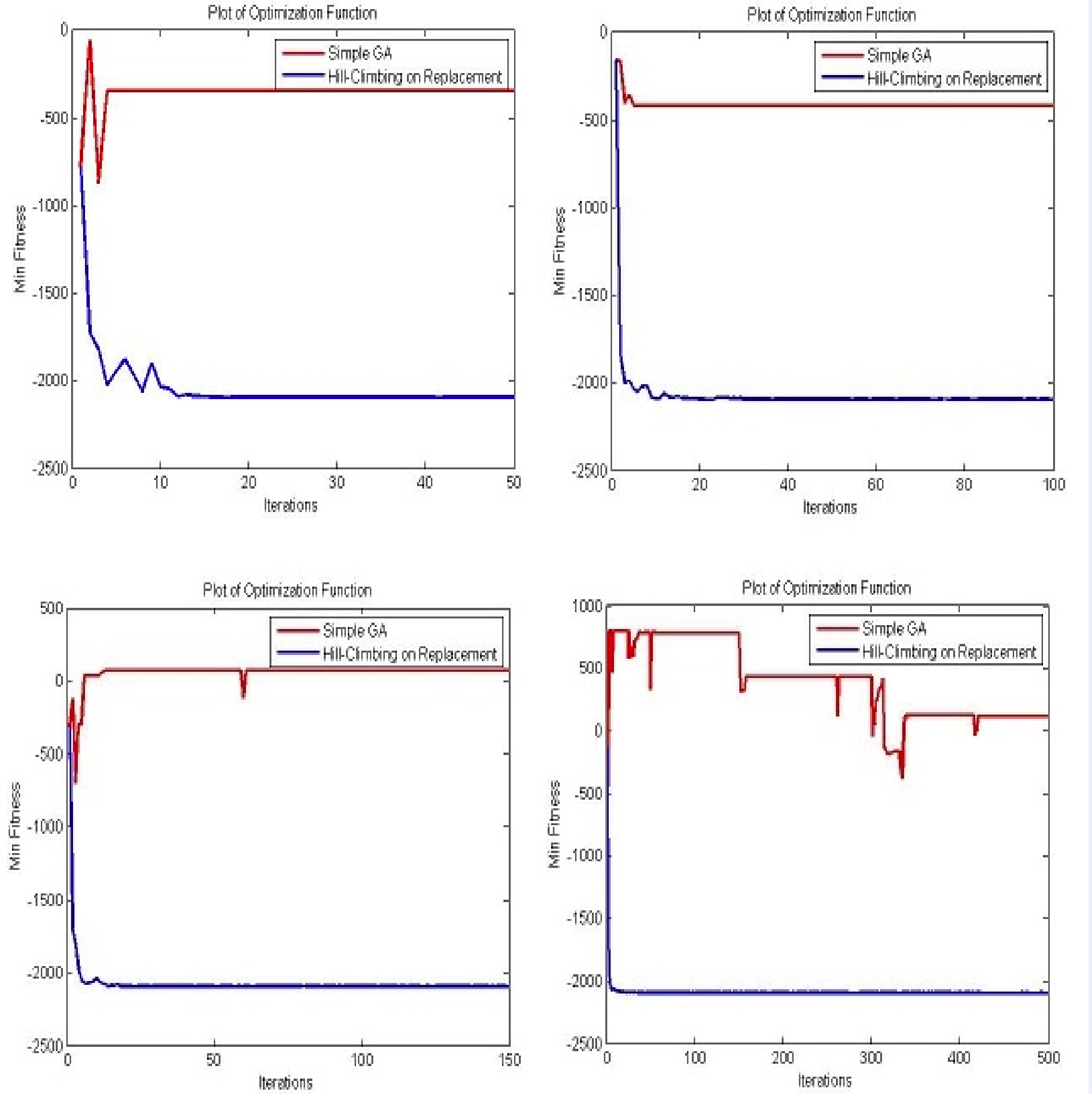

Figure 4: Plot of Schwefel's function with different population size

Table III Results of the Schwefel's [F6] function

Generation		Genetic algorithm	Memetic algorithm
50	Min	-9.08 e002	-2.09 e003
	Avg	-4.32 e002	-2.02 e003
100	Min	-7.3 e002	-2.09 e 003
	Avg	-86.43	-2.06 e003
150	Min	-5.6e 002	-2.09 e003
	Avg	28	-2.07 e003
500	Min	-6.9 e 002	-2.09 e003
	Avg	-1.2 e 002	-2.08 e003

With Ackley path function simple genetic algorithm optimal value decreases with increase in generation .While memetic algorithm have no effect of population size contradict the general behavior of SGA. Genetic algorithm shows unpredictable behaviour as implemented without elitism. For Rastrigin function [F7], memetic algorithms have negligible effect of population size and number of generation on the convergence speed giving same optimal value for each run.

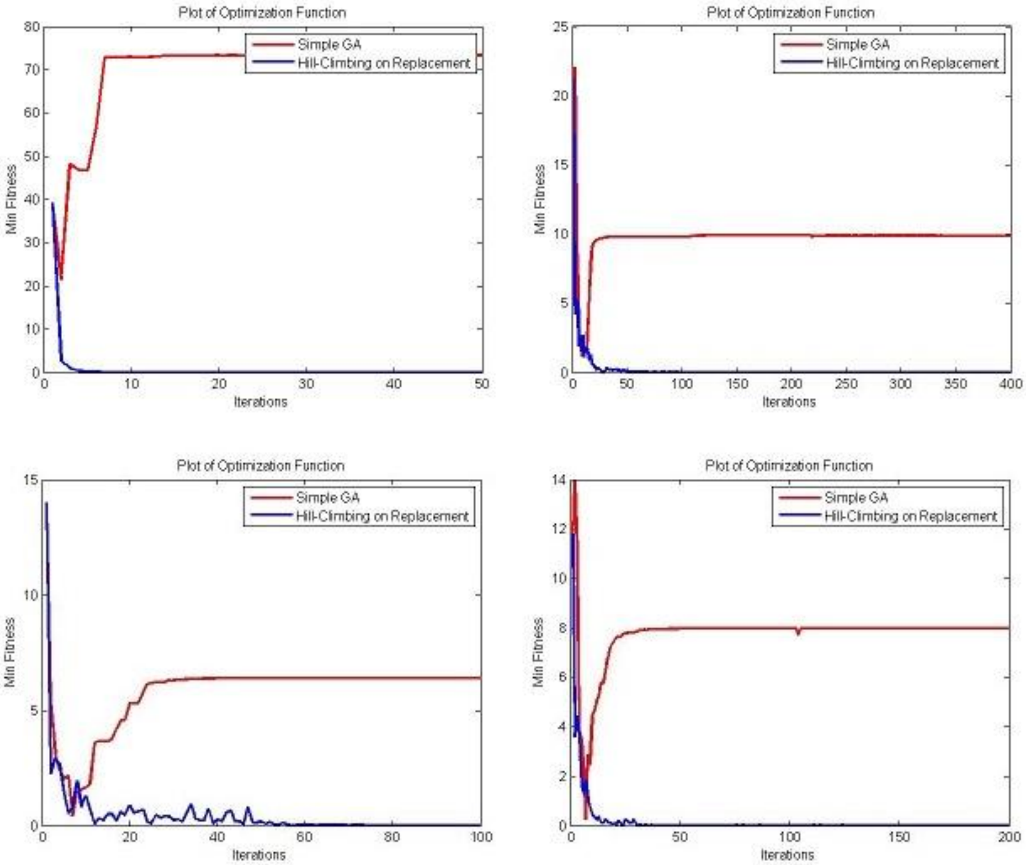

Figure 5: Plot of Rastrigin function [F7] with different population size

Table IV Result for Rastrigin function [F7]

Generation		Genetic algorithm	Memetic algorithm
50	Min	23	1.50
	Avg	48	1.83
100	Min	1.01	1.43
	Avg	6.1	1.72
200	Min	0.5	1.43
	Avg	7.3	1.865
400	Min	1.6	1.49
	Avg	8.3	1.76

VI Conclusion and Future work

This paper proposes a pseudo code of the algorithm and analyze the optimization ability of Hill climbing in replacement (by implementing the proposed algorithm in matlab). The memetic algorithm ability depends on the way of utilizing the information from both the searching mechanism i.e. genetic algorithm and local search. The optimization of different Dejong's function is implemented to evaluate the general computational behavior of Genetic and memetic algorithm. At the initial stage, the genetic algorithm is implemented as the basic architecture on this algorithm. Further, the analysis is performed on the different replacement operators. Here, replace all and hybridization of hill climbing in replacement Algorithm are discussed comparatively to identify the convergence scenario.

After executing the Memetic algorithm on De jong's function, it was concluded that function sphere model and rastrigin find better optimal result close to zero as compare to simple GA. Schwefel and Ackley path functions gives good result using memetic algorithm. Hill climbing works well as a replacement operator to exploit the search space and resulted in finding the better optima as compare to simple genetic algorithm with fast convergence. Memetic algorithm can somehow reduce its greediness by either not using elitist replacement strategies or by exploiting operators that can lead to deteriorated points from which progress can be achieved at a later stage of the search.

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