Analysing the Performance of G.A. by Changing Replacement Strategies

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Abstract— *Genetic algorithm is the evolutionary technique used for optimizing the result and searching the best match. Genetic algorithms are powerful & widely applicable stochastic search and the optimization methods based on the concepts of natural selection &natural evaluation. Researcher has done a lot of work in replacement phase of Genetic algorithm. In this paper researcher has compare the performance of the two types of replacement strategies, researcher has observed the performance of generational replacement and μ+λ replacement.*

Keywords— *Chromosome, Genetic algorithm, Mating pool, Replacement, Selection.*

I. Introduction

Genetic Algorithms [1] are adaptive search algorithms based on the evolutionary ideas concepts of natural selection and evolution. In nature, an individual in population competes with each other for virtual resources like food, shelter and so on. Also in the same species, individuals compete to attract mates for reproduction. Due to this selection, poorly performing individuals have less chance to survive, and the most adapted or "fit" individuals produce a relatively large number of offspring's. It can also be noted that during reproduction, a recombination of the good characteristics of each ancestor can produce "best fit" offspring whose fitness is greater than that of a parent. So it means Good initial population facilitates a GA's convergence to good solutions while poor initial population can hinder Genetic Algorithms (GA) convergence.For selecting the population G.A. uses the repeated (iterative) process.G.A. Stops this iteration when the population concentre towards the optimal solution. The G.A. study based on the four steps and these are as follow:-

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Initialization
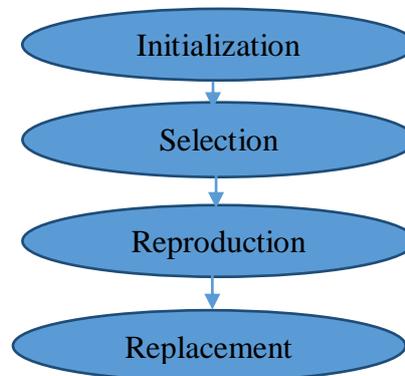
Selection

Reproduction

Replacement

Fig 1:- GA Cycle

1. Initialization: Initialization is the process by which population of chromosomes are generated randomly.
2. Selection: This phase determines which individuals are chosen for reproduction and how many offspring each selected individual produces. The main principle of selection strategy is "the better is an individual; the higher is its chance of being parent."
3. Reproduction: Reproduction is a process with the help of which the genetic material in two or more parent is combined so as we obtain one or more offspring. For selecting individuals' crossover and mutation operators are applied.
4. Replacement: Replacement is the last stage of any breeding cycle [2].This technique used to decide in a population which individual stay and which are replaced in on a par with the selection in influencing convergence. The new ones Individuals are replaced by old population. Basically, there are two kinds of methods for maintaining the population; generational updates and steady state updates.

 In this paper μ+ λ strategy is used to replace the population and then the performance was compared with generational replacement. In the section II, related work in the domain was discussed followed by section III where the problem statement and methodology were discussed. In the section IV implementation was carried out and results were discussed.

II. RELATED WORK

Haque Sardar, Anisul et. al have introduced Optimization Model for Opportunistic Replacement Policy Using Genetic Algorithm with Fuzzy Logic Controller[4].The paper presents a genetic algorithm with fuzzy logic controller for descending components of an equipment or system. So, as to determining opportunistic replacement policy In order to reduce the computational burden involving complete enumeration of all possible policies. By maximizing net benefit to he gained from an opportunistic replacement, genetic algorithm has been used to find the near optimal solution. Mohammad A. S., Masoum et. Al. have introduced a paper Optimal Placement, Replacement and Sizing of Capacitor Banks in Distorted Distribution Networks by Genetic Algorithms[5].This paper presents a new genetic algorithm (GA)– based approach for the simultaneous power quality improvement and optimal placement and sizing of fixed capacitor banks in radial distribution networks in the presence of voltage and current harmonics. A suitable combination of objective and constraints is defined as a criterion to select (among the candidates) the most suitable buses for capacitor placement By Using a proposed fitness function. The main contribution of this paper is the computation of the near global solution, with weak dependency on initial conditions. Ciesielski, Vic et. Al. Have purposed a paper Prevention of Early Convergence in Genetic Programming by Replacement of Similar Programs [6]. This paper presents an approach to preventing or minimising the occurrence of premature convergence by measuring the similarity between the programs in the population and replacing the most similar ones with randomly generated programs. **A** significant discovery from our experimental work is that a small change to the way mutation is carried out can result in significant reductions in premature convergence.Kumar, Rakesh et. Al have purposed a paper Study of Annealed Selection and Replacement on Performance of GeneticAlgorithms [7]. The paper compares the performance of genetic algorithm using three selection approaches with generational replacement and $\mu+\lambda$ replacement. The results are optimistic and clearly demonstrate that the genetic algorithm with $\mu+\lambda$ replacement is better than the one with generational replacement. Out of the three selection operators, annealed selection outperforms the other two. Smith, J. et. Al. proposed Replacement strategies in steady state genetic algorithms: Static environments. They considered both random and worst fit replacement strategy [8]. They observed that replacing the oldest member or replacing randomly may result in loss of optimal value. They noted that the loss can be corrected simply by using an elitist replacement strategy that the best individual in current generation survives to the next. Lozano, Manuel et. Al. have purposed a paper Replacement strategies to preserve useful diversity in steady-state genetic algorithms [9]. This paper propose a replacement strategy for steady-state genetic algorithms that considers two features of the candidate chromosome to be included into the population: a measure of the contribution of diversity to the population and the fitness function. The proposal tries to replace an individual in the population with worse values for these two features. In this way, the diversity of the population becomes increased and the quality of the solutions gets better, thus preserving high levels of useful diversity.

III. PROPOSED WORK

In this paper researcher has replace the individual by $\mu+\lambda$ technique in place of generational technique. As in G.A.once off springs are produced, a method must determine which of the current members of the population, if any, should be replaced by the new solutions. The technique used to decide which individual stay in a population and which are replaced is determined from the two methods for maintaining the population: generational updates and steady state updates. The proposed flowchart for the replacement strategy shows in the below figure. The termination criteria is the maximum number of generation met:-
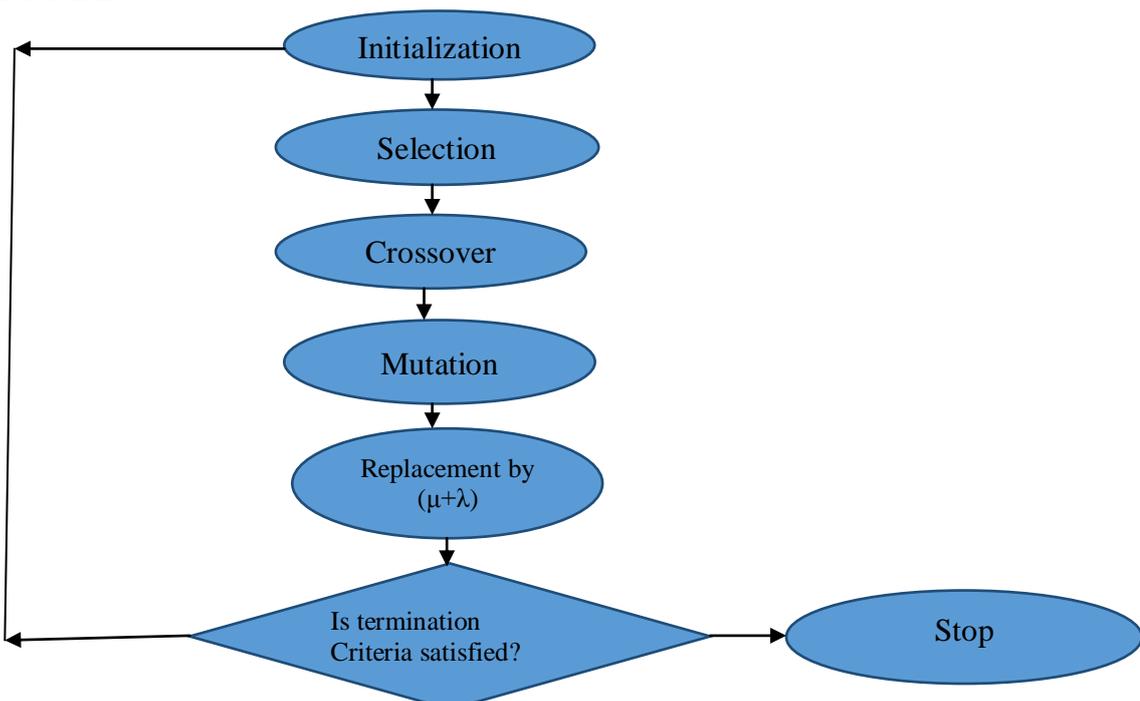

Fig 2: Flow chart of Replacement strategy

IV. IMPLEMENTATION & OBSERVATION

In this paper we has been developed matlab coding for replacement in genetic algorithm. Dejong function we taken as the test problem which is one of the important NP hard problems often used as a benchmark for optimization. The code we developed has been for dejong functions as for Benchmark Dejong's Sphere Function (F1), Axis parallel hyper-ellipsoid Function (F2) and Rastrigin's Function. Same crossover as well as mutation operator used for the code, probability uses for crossover n mutation are also same. Minimum values are compared and graph are plotted to compare the result of simple generation with extended generation.

Dejong function 1(sphere model function):-

The simplest test function is Delong's function 1because It is continues, convex and unimodal.

Function definition:

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

$f_1(x) = sum(x(i)^2)$, i=1:n, -5.12<=x(i)<=5.12.

Global minimum:

f(x)=0, x(i)=0, i=1 to n

Dejong function 2(Axis parallel hyper-ellipsoid function):-

The axis parallel hyper-ellipsoid is similar tosphere model function. It is also known as the weighted sphere model. Again, it is continuous, convex and unimodal.

Function definition:

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

$f_{1a}(x) = sum(i \cdot x(i)^2)$, i=1:n, -5.12<=x(i)<=5.12.

Global minimum:

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

Dejong function 3(Rastrigin's function):-

Rastrigin's function is based on function 1 with the addition of cosine modulation to produce many local minima. Thus, the test function is highly multimodal. However, the location of the minima is regularly distributed.

Function definition:

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

A. $\quad f_6(x) = 10 \cdot n + sum(x(i)^2 - 10 \cdot \cos(2 \cdot pi \cdot x(i)))$, i=1:n; -5.12<=x(i)<=5.12.

Global minimum:

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

The optimization problem was run for 3 different cases of generation 100 generation, 200 generation, and 300 generation. Parameters used for implementation are as follow:-

i)   Encoding:- Real value encoding

ii)   Selection:- Roulette wheel selection

iii)   Crossover operator:- Arithmetic crossover operator

iv)   Mutation operator:- Uniform mutation

v)   Replacement:- Generational replacement and μ+ λ replacement

vi) $P_{c :- 0.6}$

vii) P_m:-0.01

viii)   Termination criteria:- Maximum Number Of Generation

Table 1

Algorithm	Dejong function 1		
	100 generation	**200 generation**	**300 generation**
Simple replacement	7.508	3.293	3.467
Extended replacement	0.01048	0.00831	0.01311

Table 2

Algorithm	Dejong function 2		
	100 generation	**200 generation**	**300 generation**
Simple replacement	4.777	14.01	6.258
Extended replacement	0.217	0.007845	0.2403

Table3

Algorithm	Dejong function 3		
	100 generation	**200 generation**	**300 generation**
Simple replacement	17.34	8.555	9.81
Extended replacement	2.027	4.378	1.103
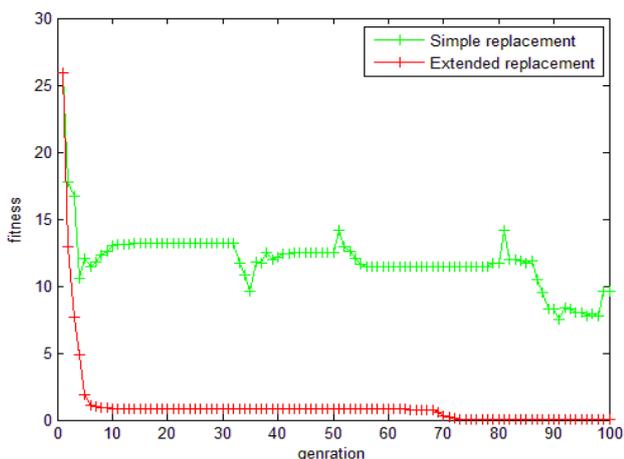
Fig 3: Dejong function 1(sphere) 100 generation graph
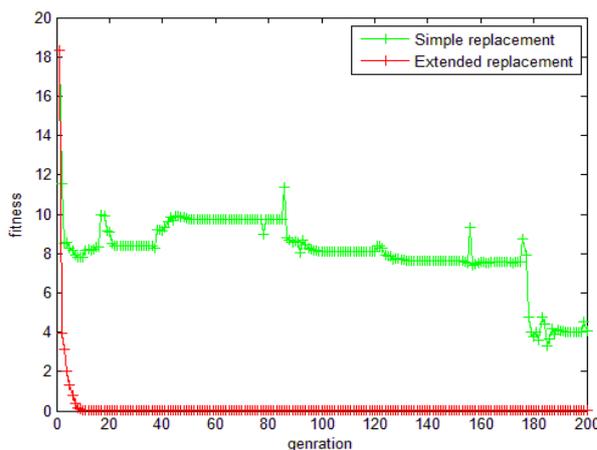
Fig 4: Dejong function1 (sphere) 200 generation graph
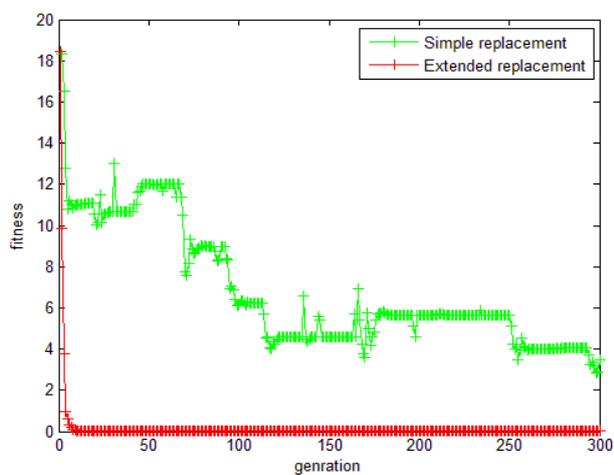
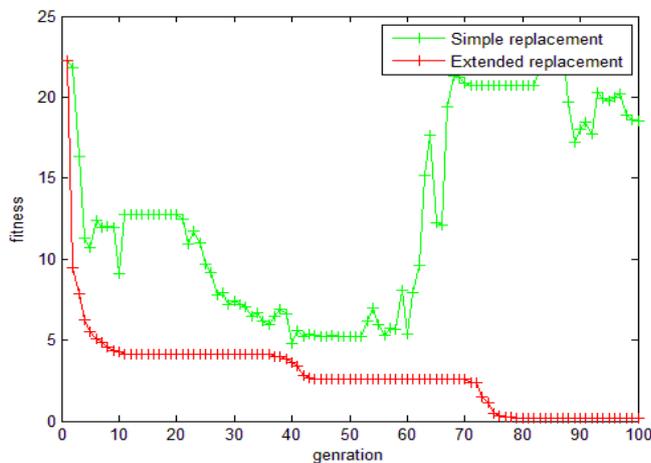Fig 5:Dejong function1 (sphere) 300 generation graph

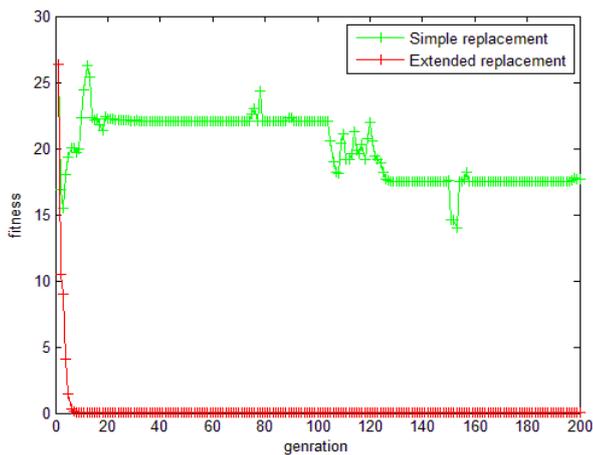Fig 6: Dejong function2(Axis/hyper-ellipsoid)100 generation graph

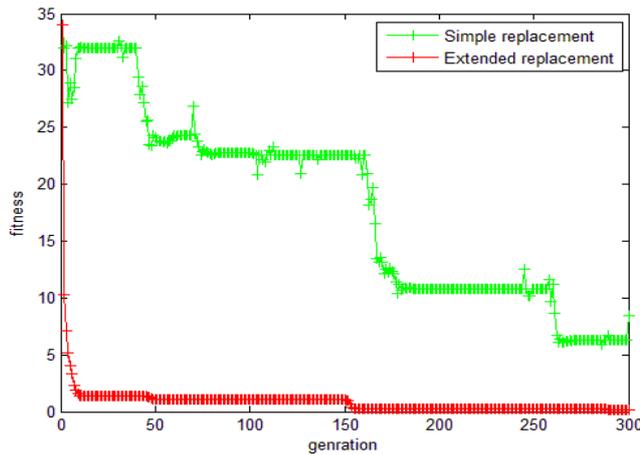Fig 7: Dejong function2(Axis/hyper-ellipsoid) 200 generation graph   Fig 8: Dejong function2(Axis/hyper-ellipsoid) 300 generation graph
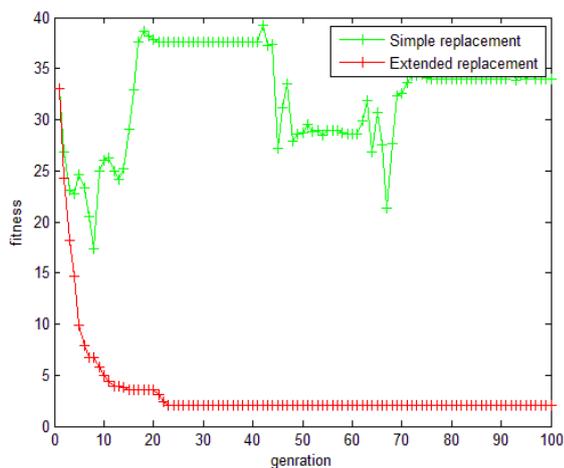

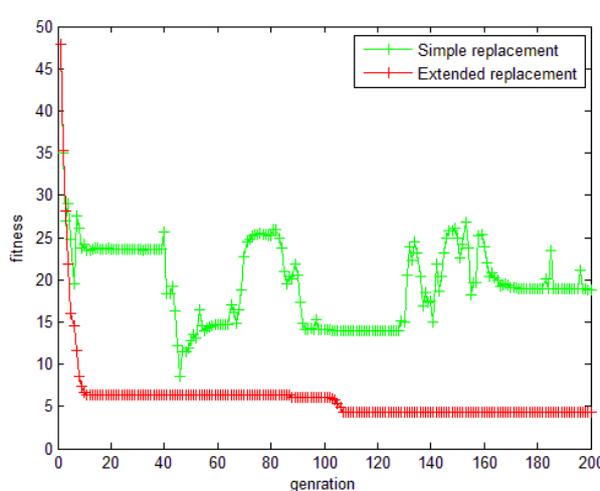Fig 9:Dejong function3(Rastrigin's Function)100 generation graph   Fig10: Dejong function3(Rastrigin's Function)200 generation graph
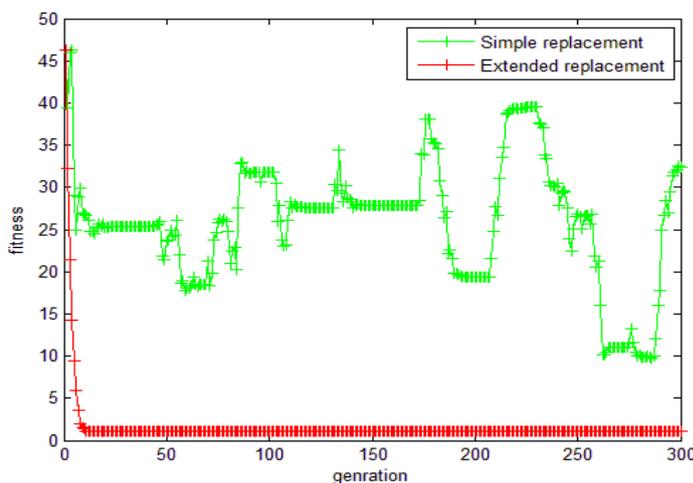

Fig 11: Dejong function3 (Rastrigin's Function) 300 generation graph

V.   Conclusion

 As Generational and μ+λ replacement operators are implemented in this paper. In generational replacement, entire population of chromosomes is replaced by new set of chromosomes at each generation. Two consecutive generations are non-overlapping using this replacement. In (μ+λ) replacement strategy, both parent and offspring set of chromosomes is grouped into one unit. Both parents and offspring compete for survival and sorted on the basis of fitness value. Then, the chromosomes with the best traits are chosen to form the next generation of population. Implementation is carried out using MATLAB code on three test problems – Benchmark Dejong's Sphere Function (F1), Axis parallel hyper-ellipsoid Function (F2) and Rastrigin's Function. According to the Darwin theory of natural selection, the competition is so severe

between the individuals that only few of them will survive to go into next generation. The same concept is used in µ+λ replacement in which only best individual of a generation will survive and passed into next generation along with the best individual of previous generations. It is clear from the implementation results that the µ+λ replacement strategy gives better solutions than the simple generational replacement. The value of average fitness and minimum fitness is gradually improved with the increase in population size and generations. The graphs clearly show that the genetic algorithm is converging towards optima more quickly in µ+λ replacement than other approach.

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