Volume 3, Issue 4, April 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Hill Climbing Based Hybrid Crossover in Genetic Algorithms

Manju Sharma
Kurukshtera University, Kurukshetra
Haryana, India.

Girdhar Gopal
Kurukshtera University, Kurukshetra
Haryana, India

Abstract— Genetic Algorithms are biologically inspired optimization algorithms. Performance of genetic algorithms mainly depends on type of genetic operators – Selection, Crossover, Mutation and Replacement used in it. Crossover operators are used to bring diversity in the population. This paper studies different crossover operators and then proposes a hybrid crossover operator that incorporates knowledge based on existing population and uses the concept of Hill climbing search. Performance of the proposed hill climbing based hybrid crossover is compared with existing PMX and OX operator in genetic algorithm. Implementation is carried out in MATLAB on benchmark TSP Oliver30 problem. The results are optimistic and clearly demonstrate that the proposed hybrid crossover is better than the existing crossovers in terms of convergence towards optimal solution.

Keywords— Crossover, genetic algorithm, hill climbing, memetic algorithm.

I. INTRODUCTION

Evolutionary algorithms are the ones that follow the Darwin concept of “Survival of the fittest” mainly used for optimization problems for more than four decades [1]. Evolutionary algorithms are heuristic search algorithms which do not always guarantee to provide the exact optimal solutions, but they will definitely find better optimal solutions within less amount of time. Some of them are Genetic algorithms, Genetic programming, Evolutionary programming Evolutionary Strategies etc. Genetic algorithms are adaptive optimization algorithms that mimic the process of natural selection and genetics [2]. Important operators used in genetic algorithms are selection, crossover and mutation. In nature, crossover is a complex process that occurs between a pair of homologous chromosomes. Two chromosomes are physically aligned and break over the one or more location so as to exchange their fragments. In genetic algorithms, chromosomes represented as linear strings of symbols [3]. Crossover operator is a complicated process that exchanges substrings between two chromosomes depends on the encoding schemes .In order to increase the performance of genetic algorithm problem specific crossover must be applied. After reproduction (selection) process, the population is enriched with better individuals. Reproduction makes clones of better individual but does not create new ones. Crossover operator is applied to the mating pool with the hope that it creates a better offspring by combination of meaningful building blocks. The performance of genetic algorithms depends on the balancing between the exploitation and exploration techniques. Exploitation means to use the already available knowledge to find out the better solution and Exploration is to investigate new and unknown area in search space. The power of genetic algorithms comes from their ability to combine both exploration and exploitation in an optimal way. In practice, the population size is finite that influences the performance of genetic algorithm and leads to the problem of genetic drift that occurs mostly in case of multimodal search space. Incorporating a local search method within the genetic operators can introduce new genes than can overcome the problem of genetic drift and accelerate the search towards global optima [4]. A combination of genetic algorithm and a local search method is called as hybrid genetic algorithm or memetic algorithm. Some crossover operator focuses more on exploitation while other focuses more on exploration. This main focus of this paper is to study different crossover and then proposed a hill climbing based hybrid crossover in order to maintain balance between exploitation and exploration at crossover stage.

II. LITERATURE REVIEW

Holland [1] and David Goldberg [2] by using k-armed bandit analogy showed that both exploration and exploitation are used by genetic algorithm at the same time. Due to certain parameters, it has been observed that, stochastic errors occur in genetic algorithm that leads to genetic drift [5- 6]. Rakesh Kumar et al. proposed a novel crossover operator that uses the principle of Tabu search. They compared the proposed crossover with PMX and found that the proposed crossover yielded better results than PMX [7]. H.A. Sanusi et al. investigated the performance of genetic algorithm and memetic algorithm for constrained optimization knapsack problem. The analysis results showed that memetic algorithm converges faster than genetic algorithm and produces more optimal result [8]. A comparative analysis of memetic algorithm based on hill climbing search and genetic algorithm has been performed for the cryptanalysis on simplified data encryption standard problem by Poonam Garg [9].She concluded that memetic algorithm is superior for finding number of keys than genetic algorithm. Antariksha [10] proposed a hybrid genetic algorithm based on GA and Artificial Immune network Algorithm (GAIN) for finding optimal collision free path in case of mobile robot moving in static environment filled with obstacles. She concluded that GAIN is better for solving such kind of problems. E. Burke et al. proposed a memetic algorithm based on Tabu search technique to solve the maintenance scheduling problem. The proposed MA performs better and can be usefully applied to real problems [11]. Malin et al [12] proposed a memetic algorithm for feature selection in volumetric data containing spatially distributed clusters of informative features in neuroscience application. They concluded that the proposed MA identified a majority of relevant features as compared to genetic algorithm. Sivaraj et al [13] discussed about a novel approach to improve the performance of genetic algorithm by using selective initialization, which aims at supplying more fit individuals in the beginning. The result shows that the selective initialization enhances the convergence velocity and produces more optimal solution than existing schemes used in generic genetic algorithm. A novel initialization approach has been proposed by Sharyar et al which employs opposition based learning to generate initial population. The experiments conducted over a comprehensive set of benchmark functions demonstrated that replacing the random initialization with the opposition based population initialization can accelerate the convergence speed [14].

III. TYPES OF CROSSOVER

A. Single Point Crossover

Single point crossover is the most commonly used crossover [15]. A crossover site is selected randomly along the length of the mated strings and bits next to the cross-sites are exchanged. If appropriate site is chosen, better children can be obtained by combining good parents else it severely hampers string quality. In one point crossover the head and tail of one chromosome separates and if both head and tail contains the good genetic material then none of the offspring will obtained the both good features directly.

B. N-Point Crossover

The N-point crossover was first implemented by De Jong in 1975 [16]. It consists of more than one cross over sites but principle used is same as that of single point crossover [15]. In 2-point crossover value of crossover sites is 2. Adding of the more crossover sites causes more disruptions of building blocks that sometimes reduce the performance of genetic algorithm. But it allows the head and tail portion of a chromosome to be passed together in the offspring.

C. Uniform Crossover

Uniform crossover do not fragments the chromosomes for recombination. Each gene in offspring is created by copying it from the parent chosen according to the corresponding bit in the binary crossover mask of same length as the length of the parent chromosomes [15]. If the bit in crossover mask is 1, then the corresponding gene is copied from the first parent and if the bit in crossover mask is 1, then the corresponding gene is copied from the second parent. A new crossover mask is generated randomly for each pair of parent chromosomes. The number of crossover point is not fixed initially. So, the offspring contains a mixture of genes from both the parents.

D. Three Parent Crossover

In three parent crossover, three parents are chosen randomly. Each gene of the first parent is compared with the corresponding gene of the second parent. If both genes are same, the gene is taken for offspring otherwise the corresponding gene from the third parent is taken for the offspring [15]. It is mainly used in case of binary encoded chromosomes.

E. Arithmetic Crossover

Arithmetic crossover is used in case of real-value encoding. Arithmetic crossover operator linearly combines the two parent chromosomes [15]. Two chromosomes are selected randomly for crossover and produce two offsprings which are linear combination of their parents according to the following computation:

offspring1 = a.P1gen + (1-a). P2gen
offspring2 = a.P2gen + (1-a). P2gen

Where Pgen represent the corresponding gene either from parent1 or parent2, and 'a' is the weight which governs dominant individual in reproduction and it is between 0 and 1.

F. Partially mapped Crossover

Partially Matched or Mapped Crossover (PMX) is the most commonly used crossover operator in permutation encoded chromosomes. It was proposed by Goldberg and Lingle [17] for Travelling Salesman Problem. In Partially Matched Crossover, two chromosomes are aligned and two crossover sites are chosen randomly. The portion of chromosomes between the two crossover points gives a matching selection that undergoes the crossover process through position-by-position exchange operations [2, 15]. PMX tends to respect the absolute positions.

G. Order Crossover (OX)

It was proposed by Davis and also used for chromosomes with permutation encoding [18]. The order crossover begins in a manner similar to PMX by choosing two crossover points. But instead of using point-by-point exchanges as in case of PMX, order crossover applies sliding motion to fill the left out holes by transferring the mapped positions. It copies the fragment of permutation elements between the crossover points from the cut string directly to the offspring, placing them in the same absolute position [2, 15]. OX tends to respect the relative positions.

H. Cycle Crossover(CX)

Cycle crossover is used for chromosomes with permutation encoding. During recombination in cyclic crossover there is a constraint that each gene either comes from the one parent or the other [19]. The basic principle behind cycle crossover is that each allele comes from one parent together with its position. To make a cycle of alleles from parent1, start with the first allele of parent1. Then look at the allele at the same position in parent2 and go to the position with the same allele in Parent1.Add this allele to the cycle and repeat step the above until you arrive at the first allele of parent1. Put the alleles of the cycle in the first child on the positions they have in the first parent and the remaining alleles of first child come from the second parent along with their position. Generate next cycle from parent2.

IV. MEMETIC ALGORITHM & HYBRID GENETIC ALGORITHM

Incorporating problem specific information in a genetic algorithm at any level of genetic operation form a hybrid genetic algorithm [20].The technique of hybridization of knowledge and global genetic algorithm is memetic algorithm. Memetic Algorithm is motivated by Dawkins notation of a meme. A meme is a unit of information that reproduces itself as people exchange ideas [21]. Memetic Algorithm binds the functionality of genetic algorithm with several heuristic's search techniques like hill climbing, simulated annealing, Tabu search etc. A number of issues should be carefully addressed when an effective hybrid genetic algorithm is constructed .Two popular ways of hybridization depends on the concepts of "Baldwin effect" [22] and "Lamarckism" [23]. According to Baldwinian search strategy, the local optimization can interacts and allow the local search to change the fitness of individual but genotype itself remain unchanged. The disadvantage of Baldwin's is that it is slow. According to Lamarckism, the characteristics acquired by individual during its lifetime may become heritable traits. According to this approach both the fitness and genotype of individuals are changed during local optimization phase.

V. HILL CLIMBING LOCAL SEARCH

Hill Climbing algorithm searches for a better solution in the neighborhood. If it finds a better solution, it changes the current solution with this new one. If the new solution is not the better one then the algorithm stops and keeps the current local optimum solution. The simplex method of linear programming is also a hill climbing procedure that moves from one extreme point solution to another, using an exact neighborhood [24].

Algorithm Hill Climbing (Iterative improvement)
begin
i:=initial solution
repeat
generate an *s* ϵ *Neighbour(i);*
if fitness(*s*) > fitness(*i*) **then** *i*:=*s*;
until f(*s*) ≤ f(*i*) for all s ϵ *Neighbour(i);*
end

VI. PROPOSED HYBRID CROSSOVER

Crossover operator mainly depends on the type of encoding used in the problem. Crossover operator applicable in one encoding scheme sometimes leads to infeasible solution in other encoding scheme. By using any of the crossover operator one cannot achieve the optimal result. Still there is a scope of improvement in terms of performance in all the crossovers. In this paper, a crossover operator is proposed which incorporates certain knowledge component along with existing crossover like PMX, OX etc during crossover operation to generate better offspring using the principle of hill climbing search as shown in figure 1. In the proposed hybrid crossover one has to apply any problem specific crossover then do the improvement by using the hill climbing local search. A simple crossover operator is not able to make small moves in the particular search area. In order to make a small move that may result into the better optimal result, one has to apply a local search. Let us consider the example of TSP problem that uses the permutation encoding. In case of permutation encoding one can use the PMX or OX crossover.

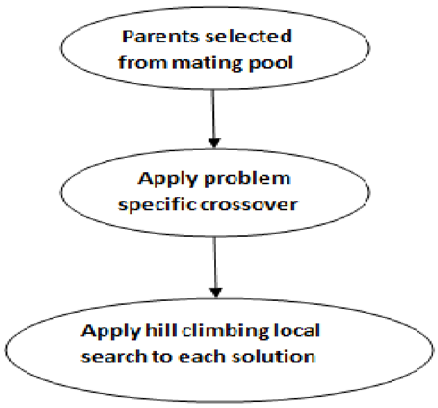

Fig.1 Proposed hybrid crossover methodology

Apply PMX crossover

Parent A	9	8	4	5	6	2	1	3	7	10
Parent B	2	3	10	8	7	1	6	4	5	9
Offspring A	9	5	4	8	7	1	2	3	6	10
Offspring B	1	3	10	5	6	2	7	4	8	9

Apply hill Climbing

Hybrid A	10	5	4	8	7	1	2	3	6	9	(Tour length better than Offspring A)
Hybrid B	1	8	10	5	6	2	7	4	3	9	(Tour length better than Offspring B)

Apply the hill climbing process on the offspring until the improved solution is not obtained. Similarly one can use other operator like OX, CX etc. The proposed crossover operator has the benefit of including the good solutions in search while avoiding the inferior ones.

VII. IMPLEMENTATION & OBSERVATION

In this paper, MATLAB code is developed for genetic algorithm. The problem considers is the Travelling salesman problem. Travelling salesman problem (TSP) is one of the important NP hard problems often used as a benchmark for optimization techniques. TSP has several applications like planning, logistics, manufacture of microchips and DNA sequencing. TSP problem is to find the Hamiltonian Path or shortest distance through a set of vertices, such that each vertex is visited exactly once [14]. Code considers the benchmark TSP problem namely Oliver30 as the test problem.
Parameters used for implementation are-

- Population size: 10
- Selection: Rank selection + Elitism
- Mutation: Inversion Mutation
- Crossover probability (p_c=0.7)
- Mutation probability (p_m=0.01)

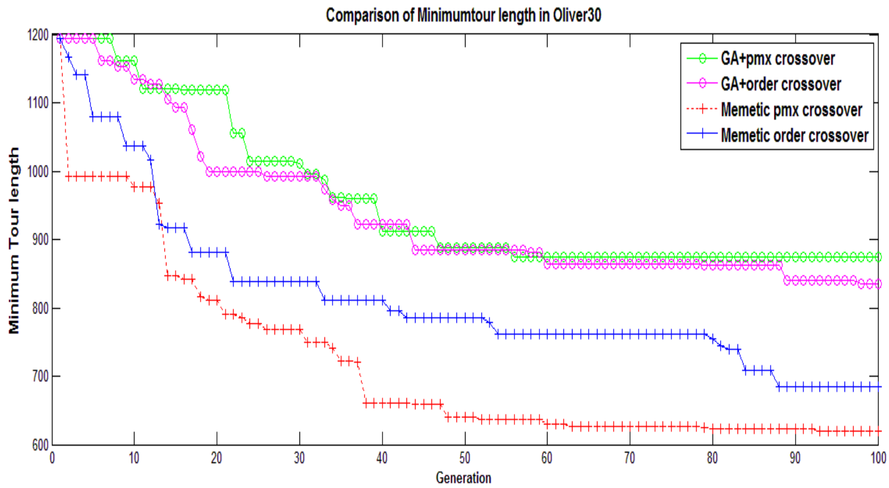

Fig.2 Comparison of Minimum Tour Length

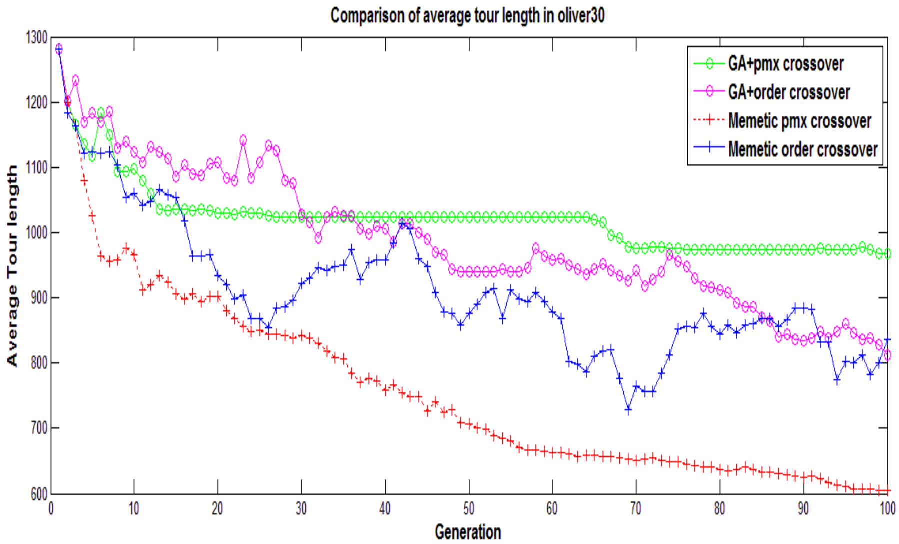

Fig.3 Comparison of Average Tour length

Min and Average value of Tour length is computed for different generation and plotted to compare the performance of two approaches using PMX and order crossover. Figure 2 and Figure 3 depicts the comparison of minimum and average tour length in two approaches. Code checks the performance of genetic algorithm by using PMX & OX crossover first, then using the proposed hybrid of them.

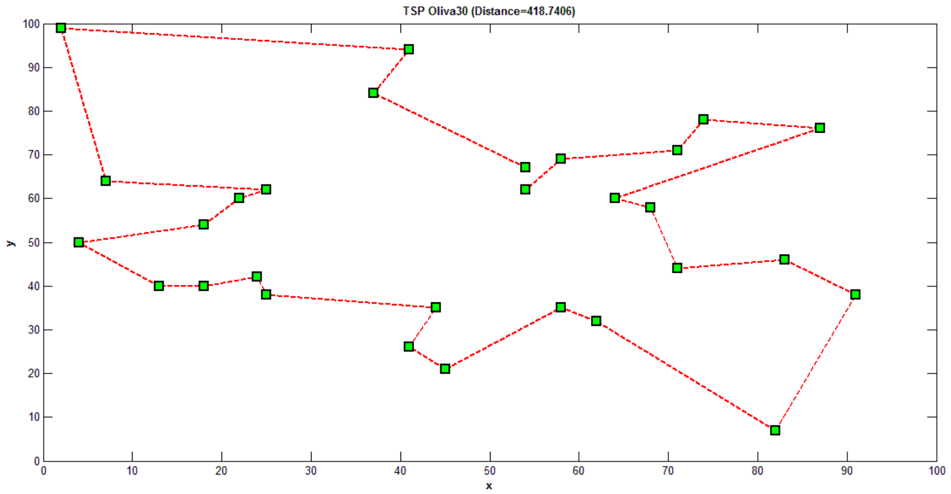

Fig.4 Optimal Tour

Figure 4 depicts the optimal tour using the proposed hybrid crossover achieved after 1000 iterations. Figure 5 and Figure 6 depicts the comparison of minimum and average tour length for different iterations.

Optimal Tour cities sequence is:

1 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 25 24 26 27 28 29 30 2 (Distance= 418.7406)

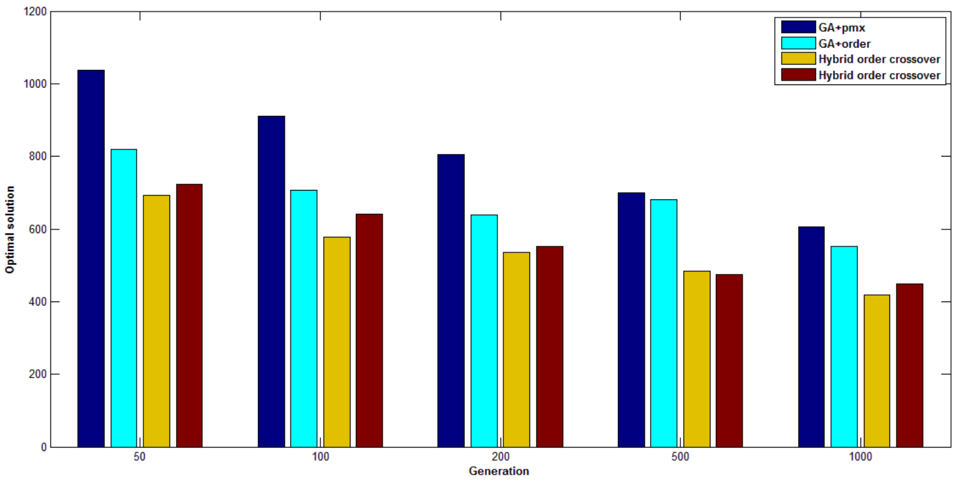

Fig.5 Minimum Tour length for different Generations

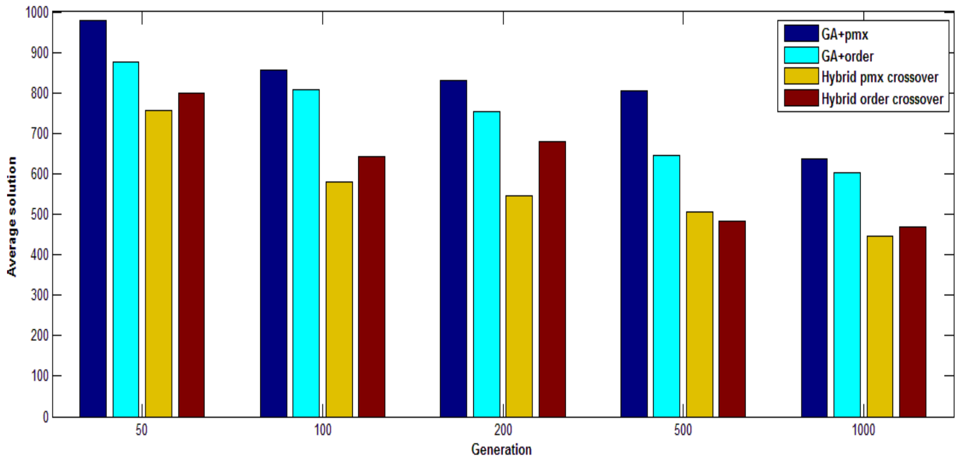

Fig.6 Average Tour length for different Generations

It has been observed from the Figures that the proposed hybrid crossover has outperformed genetic algorithm in terms of convergence and optimal solution. The proposed crossover maintains more diversity in population and prevent algorithm to stick in local optima and genetic drift problem. The genetic algorithm usually results in premature convergence due to finite population size. But in proposed crossover, due to the incorporation of local search after normal crossover, the more fit offspring are generated that accelerates the search towards optima.

VIII. CONCLUSIONS

The paper has compared normal crossover operators and proposed hybrid crossover. The code considers the two crossover operators namely partially matched crossover (PMX) and Order crossover (OX) on the benchmark TSP oliver30 problem. It was found that the proposed hybrid crossover yielded better results than the PMX and OX. The proposed hill climbing based hybrid crossover operator uses the knowledge concept along with the hill climbing principle. The proposed crossover operator has the advantage of retaining the good solutions in search while avoiding the inferior ones. Hybridization of crossover improves the performance of genetic algorithm in terms of convergence and optimal solution. The Proposed algorithm can prove to be better for different NP Hard problems also. It can be tested and implemented with different combination of selection, mutation to substantiate its performance.

REFERENCES

[1] J. Holland, *Adaptation in natural and artificial systems*, University of Michigan Press, Ann Arbor, 1975.

[2] D.E. Goldberg, *Genetic algorithms in search, optimisation, and machine learning*, Addison Wesley Longman, Inc., ISBN 0-201-15767-5, 1989.

[3] C. Ryan, *Automatic re-engineering of software using genetic programming*, Genetic Programming Series. Kluwer Academic Publishers, ISBN 0-7923-8653-1, 2000.

[4] W. E. Hart, "Adaptive global optimization with local search, Doctoral diss.", San Diego, University of California, 1994.

[5] D. E. Goldberg and P. Segrest, "Finite Markov chain analysis of genetic algorithms", Proceedings of 2nd International Conf. on Genetic Algorithms, Lawrence Erlbaum Associates, 1987, pp 1-8.

[6] L .Booker, *Improving search in genetic algorithm, genetic algorithm and simulated annealing*, Pitman,1987, pp 61-73, vol 5.

[7] Rakesh kumar and Jyotishree, "Novel knowledge based tabu crossover in genetic algorithms", International Journal of Advanced research in Computer science and software Engineering, vol 2, No. 8, pp 78-82, Aug 2012.

[8] H. A. Sansi, A. Zubair and R. O. Oladele, "Comparative assessment of genetic and memetic algorithms", Journal of Emerging Trends in Computing and Information Science, vol 2, No. 10, pp 498-508, Oct 2011.

[9] Poonam Garg, " A comparison between memetic algorithm and genetic algorithm for the cryptanalysis of simplified data encryption standard algorithm", International Journal of Network Security and its Applications,vol 1, No. 1, pp 34-42, April 2009.

[10] Antariksha Bhaduri, "A mobile robot path planning using genetic artificial immune network algorithm", Proceedings of World Congress on Nature and biologically Inspired Computing, NaBIC, IEEE, 2009, pp 1536-1539.

[11] E. K. Burke and A. J. Smith, "A memetic algorithm for the maintenance scheduling problem", Proceedings of International Conf on Neural Information Processing and Intelligent Information, Springer 2010, pp 469-473.

[12] Malin Bjornsdotter and Johan Wessberg, "A memetic algorithm for selection of 3D clustered featured with applications in neuroscience", Proceedings of International Conference on Pattern Recognition, IEEE, 2010, pp 1076-1079.

[13] R. Sivaraj, T. Ravichandran, R. Devipriya " Boosting performance of genetic algorithm through selective Initialization.", European Journal Of Scientific Research, ISSN 1450-216X , Vol 68, No 1, pp 93-100, 2012.

[14] S. Rahnamayan, H. R. Tizhoosh, M. A. Salama, "A novel population initialization method for accelerating evolutionary algorithms", An International Journal Computers and mathematics with applications, Vol 53, pp 1605-1614, 2007.

[15] S.N. Sivanandam and S. N. Deepa., *Introduction to Genetic Algorithms*, Springer, ISBN 9783540731894, 2007.

[16] K.A. De Jong, "An Analysis of the behavior of a class of genetic adaptive systems" Doctoral dissertation, University of Michigan, Dissertation Abstracts International 36(10), 5140B University Microfilms No. 76/9381, 1975.

[17] D.E.Goldberg. and R.Lingle, "Alleles, loci and the travelling salesman problem", Proceedings of an International Conference on Genetic Algorithms, Morgan Kauffman, 1985, pp 10-19.

[18] L. Davis, *Handbook of Genetic Algorithms*, New York, Van Nostrand Reinhold, 1991.

[19] I.M.Oliver, D.J. Smith and J.H. Holland, "A study of permutation crossover operators on the travelling salesman problem", Proceedings of the Third International Conference on Genetic Algorithms, London, Lawrence Eribaum Associates, 1987.

[20] P. Mascato and P. C. Cotta, "A gentle introduction to memetic algorithms", *Handbook of Metaheuristics*, 2003, pp 105-144.

[21] R. Dawkins, *The selfish gene* , Oxford University Press, Oxford, 1976.

K. Ku, M. Mak, "Empherical analysis of the factors that affect the Baldwin effect: Parallel problem solving from nature", Proceedings of 5th International Conference on lecture notes in computer science, Berlin, Springer, Heidelberg, 1998, pp 481-90. G. M. Morris, D. S. Goodsell, R. S. Halleday, W. E. Hartand and R. K. Belew, "Automated docking using a Lamarckian genetic algorithm and an empherical bending free energy function", Journal of Computational Chemistry, vol 19, pp 1639-62, 1998.

