Volume 5, Issue 5, MAY 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Effect of Hybrid Annealed Selection Operator in Genetic Algorithms on Knapsack 0/1 Problem

[1]Kirti Saini, [2]Dr. Rakesh Kumar
[1]Research Scholar (M.Tech), [2]Professor
[1, 2] Department of Computer Science and Applications
Kurukshetra University, Kurukshetra, Haryana, India

Abstract- Successful performance of Genetic algorithms depends upon the balance between Exploration and Exploitation. In genetic algorithms, the roulette wheel selection operator uses exploitation technique in its approach while rank selection has essence of exploration. In this paper, a combination of these two selection operators is performed to produce a perfect fusion of exploration and exploitation. Similar to the concept of simulated annealing, the hybrid annealed selection operator has been proposed which shows exploratory nature initially and with the passage of time, it gradually shifts to exploitation. The experiments have been conducted using Knapsack 0/1 problem and implementation is carried out using MATLAB. The results obtained were compared with roulette wheel selection and rank selection with different problem sizes (population size, no. of generation).

Keywords-Genetic algorithm; Hybridization; Knapsack 0/1; Rank selection; Roulette wheel selection; Simulated annealing;

I. INTRODUCTION

The genetic algorithm is based upon Darwinian Theory of Natural Evolution "the survival of the fittest". In this theory Sir Charles Darwin implies that one individual who is fit among the population will survive and reproduce to next generation. Genetic algorithm is modeled on a relatively simple interpretation of the evolutionary process; however, it has proven to a reliable and powerful optimization technique in a wide variety of applications. Holland [10]in 1975 was first proposed the use of genetic algorithms for problem solving. Goldberg [7] was also pioneers in the area of applying genetic processes to optimization. The GA maintains an initial population of chromosomes associated with fitness values. Parents are selected to enter into the mating pool on the basis of their evaluated fitness, producing offspring via a reproductive plan. Consequently, highly fit chromosomes are given more chances to reproduce, so that children inherit characteristics from each parent. Once an initial population is randomly generated, the algorithm evolves through operators:

- *Selection* which selects individuals on the basis of survival of the fittest.
- *Crossover* which performs recombination between individuals.
- *Mutation* which introduces random alterations.

Genetic Algorithm works as follows:

A. *Encoding***:** First step towards solving problem using genetic algorithm is the encoding of solution. In this stage, phenotype is mapped to genotype. It means data is represented in genes.
B. *Initialization:* Take input parameter like population size, crossover probability, mutation probability, and iteration number.
C. *Evaluation:* Find the fitness value of each individual in the population using fitness function.
D. *Selection:* Retain best fit individual and elimination of bad population is the task of selection.
E. *Crossover:* Recombination is another name for crossover which combines genes of two selected parents from the mating pool and creates new children.
F. *Mutation:* Mutation alters one or more gene values in a chromosome from its original state, result in completely new gene values being added to the gene pool.
G. *Replacement:* During the last step, individuals from the old population are killed and replaced by the new ones
H. *Repeat* steps C to G until terminate the loop.
I. *Decoding:* Decode the final solution back to phenotype.

Unlike other search and optimization techniques, a genetic algorithm guarantees convergence but not optimality. This infers that the choice of when to halt the genetic algorithm is not well-defined. As there is no assurance of optimality, there is always the chance that some superior chromosome lurking somewhere in the search space.
The main errors that a traditional GA suffers from are slow convergence rate and premature convergence. To improve upon these flaws a new GA known as hybrid GA was developed. Hybridization is defined as the insertion of problem-dependent knowledge in a general search algorithm.

Although genetic algorithms can rapidly locate the region in which the global optimum exists, they take a relatively long time to locate the exact local optimum in the region of convergence [4], [13]. A combination of a genetic algorithm and a local search method can accelerate the search to locate the exact global optima.

Utilizing a local search method within a genetic algorithm can improve the exploiting ability of the search algorithm without limiting its exploring ability [9]. If the right balance between global exploration and local exploitation capabilities can be achieved, the algorithm can easily produce solutions with high accuracy [12].

II. LITERATURE REVIEW

Holland [10] and David Goldberg[7] 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 arise in genetic algorithm causes genetic drift [8] [2].In certain cases,Roulette wheel selection can possibly miss the best individuals of a population. There is no guarantee that good individuals will find their way into next generation. This problem can be avoided by use of Rank Selection technique. Rank selection ranks the individuals in the population according to their raw objective value[7] .Genetic algorithms also suffers from the problem of premature convergence which occurs when the population reaches a state where genetic operators can no longer produce offspring that outperforms their parents[5].

Genetic algorithms and simulated annealing are widely used in search and optimization problems. Tsenov proposed a combined way of using simulated annealing and genetic algorithm on telecommunications concentrator networks and obtained good performance [14].Jeong et al. [11] suggested a hybrid approach with a genetic algorithm (GA) and a simulation technique. The GA is used for optimization of schedules, and the simulation is used to minimize the maximum completion time for the last job with fixed schedules obtained from the GA model.

Van Dijck et.al.proposed 2-stage GA based feature subset selection algorithm in which the correlation structure of the features was exploited [15]. Simulations on a real-case data set with correlated features showed that the 2-stage GA found better solutions in fewer generations compared to a standard GA. Al jaddan et al. compared the roulette wheel selection GA (RWS) and ranked based roulette wheel selection GA (RRWS), by applying them on eight test functions from the GA literature [1]. They concluded that RRWS outperformed the conventional RWS in convergence, time, reliability, certainty, and more robustness.

Dan Adler proposed a method of hybridizing genetic algorithms with simulated annealing and replaced standard mutation and recombination operator by their simulated annealing variants – SAM and SAR [3]. Ganesh and Punniyamoorthy[6]proposed a hybrid GA – simulated annealing (SA) algorithm for continuous-time aggregate production-planning problems. The motivation behind the GA–SA combination is the power of GA to work on the solution in a global sense while allowing SA to locally optimize each individual solution [6].

III. PROPOSED WORK

In this section, combination of two selection operators is performed to produce a new selection operator with an intention to obtain perfect mixture of exploration and exploitation. Initially the blended selection operator shows exploratory nature and later on changes to exploitation. To generate the hybrid annealed selection, concept of simulated annealing which starts from a high temperature and then decreases exponentially, is used. In hybrid annealed selection, rank fitness and absolute fitness of each individual in the mating pool is computed. Two weighting factors 'w_r' and 'w_a' is used which gets multiplied with individual's rank fitness and absolute fitness. Initially the value of 'w_r' is set to 0 and value of 'w_a' is set to 1.There is an inverse relation between 'w_r' and 'w_a' means 'w_r' increases and 'w_a' decreases generation by generation.

New fitness of hybrid annealed selection is given by the formula:

SAF_fitness = Rank_fitness * w_r+ Absolute_fitness*w_a; → (1.1)

Rank_fitness of each individual is obtained from rank selection and Absolute_fitness is obtained using roulette wheel selection. Both the Rank_fitness and Absolute_fitness is taken in terms of percentage.

Rank_fitnessis given by the formula:

Rank_fitness= (individual's rank/ sum of all individuals's rank) * 100; → (1.2)

Absolute_fitness is given by the formula:

Absolute_fitness = (individual's fitness/ sum of all individuals's fitness) * 100 → (1.3)

In the Hybrid genetic algorithm, following steps are followed:

A. Initialization (using binary encoding).
B. Set the parameter values that Hybrid Genetic Algorithm uses (population size, probabilities of operators, no. of generations).
C. Apply Hybrid Annealed Selection (using SAF_fitness given in equation (1.1))
D. Two-point Crossover (which exchange the contents between two crossover sites of two mated parents).
E. Flipping Mutation (which change the bit from 1 to 0 and 0 to 1 based on a mutation probability).
F. Partial Replacement (best individuals will be taken from both old population and new population).
G. Terminate when generation number reached maximum generation number.

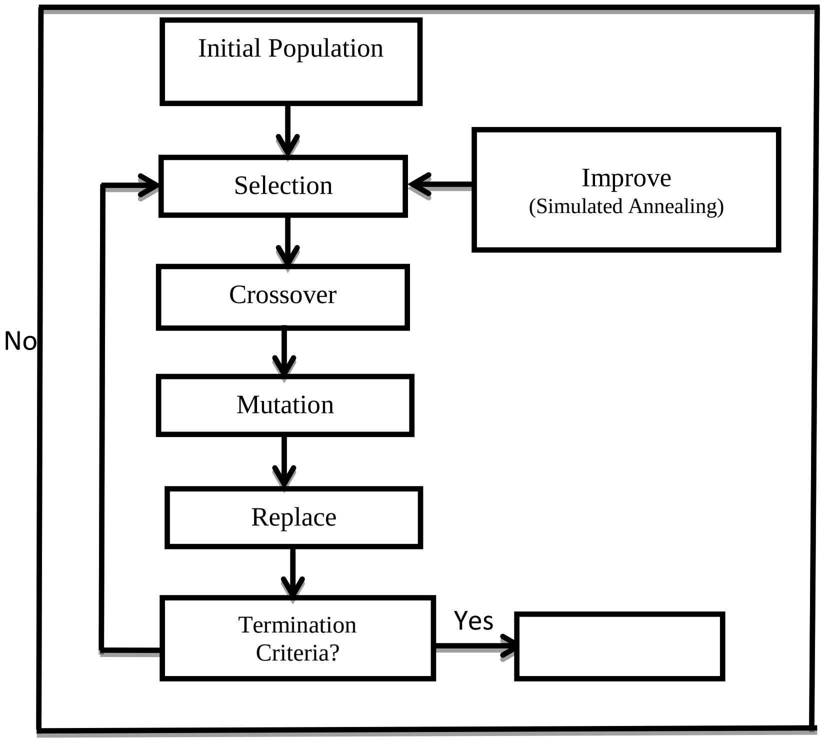

Fig 1.Flow chart of Hybrid Genetic Algorithm

Termination condition for the algorithm would be, when the number of generation becomes equal to the maximum number of generation.

IV. IMPLEMENTATION AND OBSERVATION

In this paper, MATLAB code has been developed to compare the performance of genetic algorithm with hybrid genetic algorithm by using three different selection techniques (rank selection, roulette wheel selection and hybrid annealed selection). Except selection criteria, all other factors affecting the performance of genetic algorithm are kept constant. The problem considers for its implementation is the knapsack 0/1 problem. Knapsack 0/1 problem is a combinatorial optimization. In this problem a set of items is given each having some specific weight and profit, determine the number of item to be include in collection such that the total weight is less than or equal to a given limit and the total profit is as large as possible.

The problem is solved under following consideration:

a) If weight of any item exceeds the sack's capacity then leave that item.
b) If this does not exceed the knapsack capacity than add that item in the knapsack and check what is the remaining allowed weight and the number of items allowed.

Firstly, the roulette wheel selection is applied and then the rank selection followed by the implementation of hybrid annealed selection operator on the same population.

In graphs, x-axis represents Iteration number and y-axis represents Profit.

-o-	Hybrid annealed selection
-+-	Roulette wheel selection
-*-	Rank selection

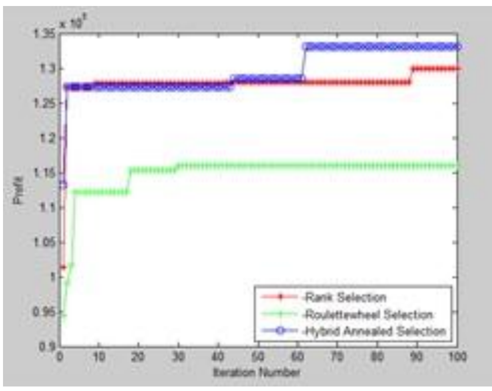

Fig 2.Comparison of Rank, Roulette wheel and Hybrid annealed selection with pop size=20

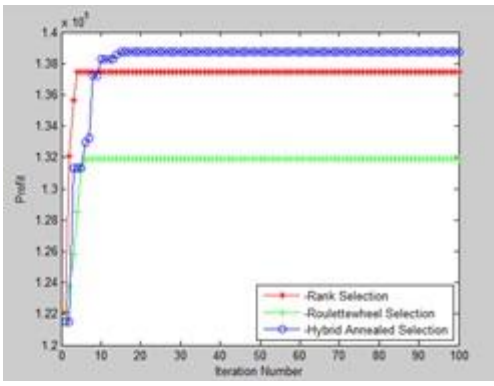

Fig 3.Comparison of Rank, Roulette wheel and Hybrid annealed selection with pop size=60

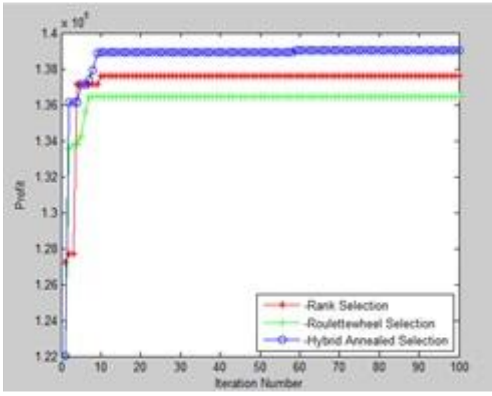

Fig 4.Comparison of Rank, Roulette wheel and Hybrid annealed selection with pop size=100

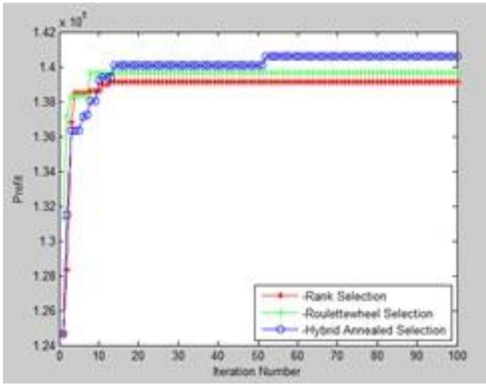

Fig 5.Comparison of Rank, Roulette wheel and Hybrid annealed selection with pop size= 140

Table II Results of Knapsack Problem with Number of Generations=100

		PROFIT		
Figure Number	Population Size	Rank Selection	Roulette wheel Selection	Hybrid annealed Selection
2	20	129936	115943	133126
3	60	137428	131922	138737
4	100	137587	136423	139027
5	140	139108	139637	140587

In this paper, comparison between these three different selection techniques has also made with varying generations number and constant population size.Convergence point of population was noted when no further changes occurred in the generation.

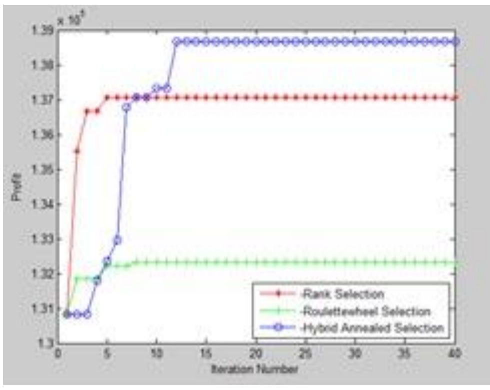

Fig 6.Comparison of Rank, Roulette wheel and Hybrid annealed selection for Knapsack problem with number of generation=40

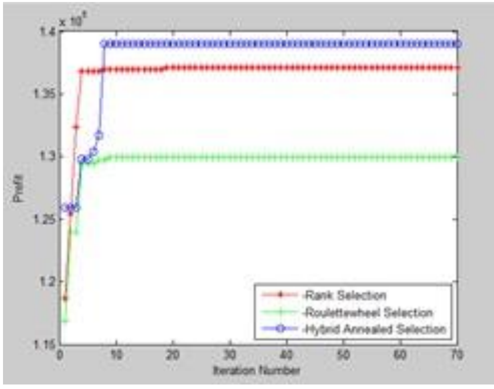

Fig 7.Comparison of Rank, Roulette wheel and Hybrid annealed selection for Knapsack problem with number of generations=70

Table I Results of Knapsack problem with pop size=80

		PROFIT		
Figure Number	Number of Generations	Rank Selection	Roulette wheel Selection	Hybrid annealed Selection
6	40	137058	132342	138668
7	70	137093	129929	139038

V. CONCLUSION

In this paper, hybrid annealed selection technique is proposed having the features of exploitation and exploration both. In early generations, there is less pressure on selection, so it had exploratory in nature. As the number of generation increased, selection pressure also increased and exploratory nature gradually turned into exploiting nature. For different problem sizes, hybrid annealed selection has compared with rank selection and roulette wheel selection. From the above results it was found that hybrid annealed selection yielded better results and outperformed the other two techniques. In future, this approach can be tested on other problems of same nature.

REFERENCES

[1] Al jaddan, O., Rajamani, L., andRao, C. R., "*Improved Selection Operator for GA",* Journal of Theoretical and Applied InformationTechnology, 2005, pp 269–277.

[2] Booker, L., *Improving search in genetic algorithms, Genetic Algorithms and Simulated Annealing,* Pitman, chapter 5, 1987, pp 61-73

[3] Dan Adler, *"Genetic Algorithms and Simulated Annealing: A Marriage Proposal"*, IEEE International Conference on Neural Networks 1993, San Francisco (CA), 1993.

[4] De Jong, K., *"Genetic algorithms: a 30 year perspective,"* in Perspectives on Adaptation in Natural and Artificial Systems, L. Booker, S. Forrest, M. Mitchell, and R. Riolo, Eds.: Oxford University Press, 2005.

[5] Fogel, D., *"An introduction to simulated evolutionary optimization",* IEEE Trans. Neural Networks 5 (1), 1994, pp 3-14.

[6] Ganesh, K., and Punniyamoorthy, M., *Optimization of continuous-time production planning using hybrid genetic algorithms-simulated annealing,* International Journal of Advanced Manufacturing Technology, 26(1), 2004, pp. 148–154

[7] Goldberg, D.E., *"Genetic Algorithms in Search, Optimization and Machine Learning",* Addison-Wesley, Reading, 1989.

[8] Goldberg, D. E., and Segrest, P., *"Finite Markov chain analysis of genetic algorithms",* Proceedings of the the Second International Conference on Genetic Algorithms, Lawrence Erlbaum Associates, 1987, pp 1-8.

[9] Hart, W. E. ,*"Adaptive global optimization with local search,"* Doctoral Dissertation. San Diego: University of California 1994.

[10] Holland, J., *"Adaptation in Natural and Artificial Systems",* University of Michigan Press, AnnArbor, 1975.

[11] Jeong, S.J., Lim, S.J., and Kim, K.S., *Hybrid approach to production scheduling using genetic algorithm and simulation*, International Journal of Advanced Manufacturing Technology, 28(1), 2005, pp. 129–136

[12] Lobo, F. G., and Goldberg, D. E., *"Decision making in a hybrid genetic algorithm,"* in IEEE International Conference on evolutionary Computation. Piscataway, USA: IEEE Press, 1997, pp. 122-125.

[13] Preux, P., and Talbi, E.-G.,*"Towards hybrid evolutionary algorithms,"* International Transactions in Operational Research, vol. 6, 1999, pp. 557-570.

[14] Tsenov, A.,*"Simulated Annealing and Genetic Algorithm in Telecommunications Network Planning",* International Journal of Information and Mathematical Sciences 2:4, 2006, pp 240-245.

[15] Van Dijck, G., Van Hulle, M. M and Wevers, M.,*"Genetic Algorithm for Feature Subset Selection with Exploitation of Feature Correlations from Continuous Wavelet Transform: a real-case Application",* International Journal of Information and Mathematical Sciences 1:4, 2005, pp 233-237.

