International Journal of Applied Engineering and Technology ISSN: 2277-212X (Online)
An Open Access, Online International Journal Available at http://www.cibtech.org/jet.htm
2015 Vol. 5 (3) July-September, pp.38-41/Patil and Pawar
Research Article

THE OPTIMAL CROSSOVER OR MUTATION RATES IN GENETIC ALGORITHM: A REVIEW

***Patil V.P.[1] and Pawar D.D. [2]**
[1]Department of Farm Structures and Rural Electrification, Dr. A.S. College of Agril. Engineering, MPKV, Rahuri (M.S.)
[2]Department of Mathematical Sciences, SRTMU, Nanded, (M.S.)
**Author for Correspondence*

ABSTRACT
Choice of crossover and/or mutation probabilities is critical to the success of genetic algorithms. Earlier researches focused on finding optimal crossover or mutation rates, which vary for different problems, and even for different stages of the genetic process in a problem. This paper investigates the optimal cross-over probabilities and mutation probabilities for the optimum performance of GA. Cross over probability are positively associated with the mutation probability in the implementation of GA but correlation is not significant. However, self-adapting control parameters also give better results. Further, the Inverted Displacement mutation operator introduced by Kusum and Hadush (2011) has a great potential for future research along with the crossover operators.

Keywords: *Cross over Probability, Mutation Probability, Genetic Algorithm*

INTRODUCTION
In 1975 Holland published a framework on genetic algorithms (Holland, 1975). Genetic Algorithms (GAs) are robust search and optimization techniques that were developed based on ideas and techniques from genetic and evolutionary theory. Today GAs is used for optimization of diverse problems in various domains. For today's more complex problems, to better represent reality, heuristics like GAs have increased in importance. Basic problems in using GAs are questions of genetic representation e.g. binary/real coded, single/multi-chromosome and the question of the optimal values for the control parameters, e.g. population size, reproduction and mutation rates.
There is evidence showing that the probabilities of crossover and mutation are critical to the success of genetic algorithms (Black, 1993; John, 1999). Traditionally, determining what optimal probabilities of crossover and mutation were determined should by means of trial-and-error. The optimal crossover or mutation rates vary with the problem of concern. In the past few years, some researchers have investigated schemes for automating the parameter settings for Gas and the schemes for adapting the crossover and mutation probabilities. The review of these schemes is presented in this paper.

Review
DeJong (1975) found optimal control parameters for GA on single chromosome representation and concluded that if the mutation rate is too high, search is like a random search, regardless of other parameter settings. He suggested optimal values for population size (50-100), a mutation probability (0.001) and single point crossover with a rate of 0.6. His parameter set has been used in many GA implementations. Grefenstette (1986) designed a secondary Meta-GA to tune the optimal control parameters for the primary GA. He showed that in small populations (20 to 40), good performance is associated with either a high crossover rate combined with a low mutation rate or a low crossover rate combined with a high mutation rate. He concluded that mutation rate above 0.05 is in general harmful for the optimal performance of GAs. He also suggested optimal control parameters: population size of 30 individuals, a mutation rate of 0.01 and for two point crossover a rate of 0.95.
Schaffer *et al.*, (1989) observed that there is a grater sensitivity of the GA performance to mutation rate than to crossover rate. The optimal parameter setting was nearly the same as that of Grefenstette (1986) i.e. the optimal mutation rate was seen between 0.005 and 0.01, optimal crossover rate in a range of 0.75-0.95 and a population size of 20-30 individuals.

Fogarty (1989) introduced first the concept of varying the control parameters during GA run. He stated that varying mutation probability significantly improves performance of GA.

Hesser and Manner (1991) showed that mutation probability should be decreased during convergence, in agreement with the results of Fogarty (1989).

Srinivas and Patnaik (1994) proposed a mechanism for adapting operator probabilities in a generational GA. Each chromosome has its own crossover probability p_c and mutation probability p_m necessary for it to undergo crossover and mutation, respectively. During the execution of GAs, both p_c *and* p_m are adapted in proportion to the population to the population maximum and mean fitness, with probabilities being larger when the mean fitness is near the maximum and smaller for particular chromosomes with larger finesses.

Hinterding (1997) introduced self-adapting control parameters within the genetic representation itself to get the parameters independent from the problem. He added an extra chromosome for a numeric representation of crossover and mutation probability. It was demonstrated that a GA that uses self-adoption, gives better results.

The above mentioned researchers on variable or self adapting control parameters focused on a single chromosome representation.

Lin *et al.,* (2003) presented an adaptive genetic algorithm for automatically adjusting suitable crossover and mutation rates to reduce the effort of searching for appropriate crossover and mutation rates in genetic algorithm. The crossover and mutation rates are adapted in response to the evaluation results of the respective offspring in the next generation. Their approach took into account the interaction between crossover and mutation in adapting the operator rates. Experimental results showed that the proposed scheme significantly improves the performance of genetic algorithms and outperforms previous work.

Juliff (1993), Cavill *et al.,* (2005) and Davidor (1991) worked with multi-chromosome representation in GA to solve more complex problems. They showed that it is possible to decompose a complex problem into a number of simpler parts by representing each part of the problem by a separate chromosome and each chromosome using a different representation.

Pierrot and Hinterding (1997) showed that mutation and crossover rates need an adaption in regard to the number of chromosomes. They furthermore indicated, that a steady mutation of one variable per chromosome gives a better result than the average of one mutated variable per chromosome.

Kusm and Hadush (2011) introduced two mutation operators known ad Inverted Exchange and Inverted Displacement for TSP problem. The Inverted Exchange mutation is a combination of Inversion and Exchange mutations and Inverted Displacement is a combination of Inversion and Displacement mutation.

They found that Inverted Displacement mutation is superior in finding better minimal values than the existing mutation operators: Inversion, Displacement, Exchange and Insertion Mutation and the Inverted mutation operator outperforms the existing displacement, exchange and insertion mutation operators. They also confirmed that the three new variation of order cross-over proposed by Kusum and Mebrathu (2011) are superior to Davis's (1991) two existing basic variants of order crossover.

Rubiyah *et al.,* (2012) proposed a new mutation operation for faster feature selection by GA based on elitism of the allele. The highest fit allele is preserved and the fitness of the chromosome is evaluated based on the frequency of the occurrences. The chromosome undergoing this mutation process is having a high if not the highest fitness because it is created based on a high fir allele. It acts as the catalyst to increase the rate of convergence towards achieving an optimal features combination. They conducted the experiments for using this method using a database of tropical wood species which has a large variation of features. Results of the experiments created by the new mutation operator have high fitness and the rate of optimal convergence was improved substantially while maintaining classification accuracy which reduces the computational time considerably. The new mutation operator is not only useful for large database but also can be used for small and medium sized database.

Matthias *et al.,* (2013) showed for a multi-chromosome representation that decreasing mutation probability has a positive effect on GA performance, as observed by Hesser and Manner (1991) or

Fogarty (1989) for single chromosome representation. They also showed that the GA performance was faster or in a very good range in comparison to the scenarios with constant mutation rates.
Waghoo *et al.,* (2013) studied on random mutation technique in order to find out the optimum probability of mutation. Their results indicated that as the mutation factor lies in the range of 0-0.3 there is not much change in the fitness function but as the value increases beyond 0.3 the fitness function changes.
Haruna *et al.,* (2013) conducted a survey of optimum parameters values for GA reported in literature and further investigated the relationship between mutation and crossover probability is positively associated with the use of mutation probability in the implementation of genetic algorithms but the correlation is not significant.

RESULTS AND DISCUSSION

From the literature reviewed it is observed that the optimal values for mutation probability (0.001) and single point crossover with probability (0.6) with population size (50-100) as suggested by DeJong (1975) have been used in many GA implementations. Mutation probability above 0.05 is in general harmful for the optimal performance of GAs as concluded by Grefenstelle (1986). Schaffer *et al.*, (1989) suggested optimal parameter settings which are nearly the same as that of Grefenstelle (1986). Forgarty (1989) showed that the varying mutation probabilities significantly prove the performance of GA and Hesset & Mannar (1991) showed that the mutation probability should be decreased during the convergence in agreement with the results of Forgarty (1989).
Self adaptive control parameters introduced by Shrinivas & Patnaik (1994), Hinterding (1997), Pierrot (1997) and Lin *et al.*, (2003) has shown that GA which adapts self-adapting control parameters give better results.
Rubiyah *et al.,* (2012) proposed a new mutation operation for faster feature selection GA based on elitism which has shown that optimal convergence was improved satisfactarily. The studies of Waghoo & Pervez (2013) on random mutation technique has shown that optimum probability of mutation lies between 0.0-0.3. Haruna *et al.,* (2013) revealed that the cross-over probability is positively associated with the mutation probability in the implementation of GA but correlation is not significant.

Conclusion

Many researchers have introduced optimal mutation and cross over probabilities for better performance of GA. The cross-over probability is positively associated with the mutation probability in the implementation of GA but correlation is not significant. However, self-adapting control parameters also give better results. Further, the Inverted Displacement mutation operator introduced by Kusum and Hadush (2011) has a great potential for future research along with the crossover operators.

REFERENCES

Back T (1992). Self-Adaption in Genetic Algorithms. *Proceedings of the 1st European Conference on Artificial Life* 263-271.

Back T (1993). Optimal mutation rates in genetic search. In: *Proceedings of the 5th International Conference on Genetic Algorithms,* edited by Forrest S 2-8.

Cavill R, Smith S and Tyrrell A (2005). Multi-chromosomal Genetic Programming. *Proceedings of Genetic and Evolutionary Computation Conference (GECCO), Washington D.C.* 1753-1759.

Davis L (1991). *Handbook of Genetic Algorithms* (New York: Van Nostrand Reinhold).

DeJong KA (1975). Analysis of the behavior of a class of genetic adaptive. Ph.D. thesis, Univ. of Michigan.

Fogarty TC (1989). Varying the probability of mutation in the genetic algorithm. *Proceedings of the 3rd International Conference on Genetic Algorithms* 104-109.

Goldberg DE (2004). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley, Reading, Mass.

Grefenstette JJ (1986). Optimization of control parameters for genetic algorithms. *IEEE Transactions on Systems, Man and Cybernetics* **16**(1) 122-128.

Haruna Chiroma, Sameem Abdulkareem, Adamu Abubakar, Akram Zeki, Abdulsalam Ya'u Gital and Mohammed Joba Usman (2013). Correlation study of genetic Algorithm operators: Crossover and Mutation Probabilities. *International Symposium on Mathematical Sciences and Computing Research*, Paper ID: CS 22 33-43.

Hesser J and Manner R (1991). Towards an Optimal Mutation Probability for Genetic Algorithms. *Proceedings of 1st Workshop: Parallel Problem Solving from Nature* 23-32.

Hinterding R (1997). Self-adaptation using multi-chromosomes. *Proceedings of the IEEE International Conference on Evolutionary Computation, Indianapolis* 87-91.

Holland JH (1975). Adaption in natural and artificial systems: an introduction. Analysis with applications to biology, control and artificial intelligence, Univ. of Michigan, Ann. Arbor.

Juliff K (1993). A multi-chromosome genetic algorithm for pallent loading. *Proceedings of the 5th International Conference on Genetic Algorithms* 467-473.

Kusum D and Mebrahtu H (2011). Combined Mutation Operators of Genetic Algorithm for the Travelling Salesman problem. *International Journal of Combinatorial Optimization Problems and Informatics* **2**(3) 1-23.

Kusum D and Mebrahtu H (2011). New variations of order crossover for traveling salesman problem. *International Journal of Combinatorial Optimization Problems and Informatics* **2**(1) 2-13.

Ochoa G, Harvey I and Buxton H (1999). On recombination and optimal mutation rates. In: *Proceedings of Genetic and Evolutionary Computation Conference* 488-495.

Ochoa G, Harvey I and Buxton H (1999). Error thresholds and their relation to optimal mutation rates. In: *Proceedings of the Fifth European Conference on Artificial Life*, edited by Floreano J *et al.*, **1674** 54-63.

Ochoa G, Harvey I and Buxton H (2000). Optimal Mutation Rates and Selection Pressure in Genetic Algorithms. *Proceedings of Genetic and Evolutionary Computation Conference* 315-322.

Rubiyah Yusof, Uswah Khairuddin and Marzuki Khalid (2012). A new mutation operation for further convergence in genetic algorithm feature selection. *International Journal of Innovative Computing, Information and Control* **8**(10(B) 7763-7379.

Schaffer JD, Caruana RA, Eshelman LJ and Das R (1989). A study of control parameters affecting online performance of genetic algorithms for function optimization. *Proceedings of the Third International Conference on Genetic Algorithms* 51-60.

Srinivas M and Patnaik LM (1997). Adaptive probabilities of crossover and mutation in genetic algorithms. *IEEE Transactions on System, Man and Cybernetics* **24** 656-667.

Waghoo Parvez and Sonal Dhar (2013). Study of Optimal Mutation Factor for Genetic Algorithm. *International Journal of Application or Innovation in Engineering and Management* **2**(6) 429-432.

Wen-Yang Lin, Wen-Yuan Lee and Tzung-Pei Hong (2003). Adopting crossover and mutation rates in Genetic Algorithms. *Journal of Information Science and Engineering* **19** 889-903.