Examining Genetic Algorithms as an effective Computational tool in Education-Domain

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Abstract— *This paper employs Genetic algorithms (GA's) for the enhancement of computational capabilities to achieve reduction in time complexities. These algorithms can be applied on diverse problems related to different fields like Civil Engineering, Bio Informatics, Bio Technology, Basic Sciences etc. Solution is evident and already provided by the nature; but how to look for it, depends upon individual. So, learning inspired from natural phenomenon can help in improving quality of higher education. Genetic algorithms mimic natural process of preserving the best and still try to improve solutions at each step. This paper focuses on less amount of time taken by these algorithms for performing calculations and generating results as compared to conventional techniques. These can be implemented very efficiently at various levels to deliver quality education.*

Keywords — *Genetic Algorithm, Neural Networks, Education-domain, Computational tool.*

I. Introduction

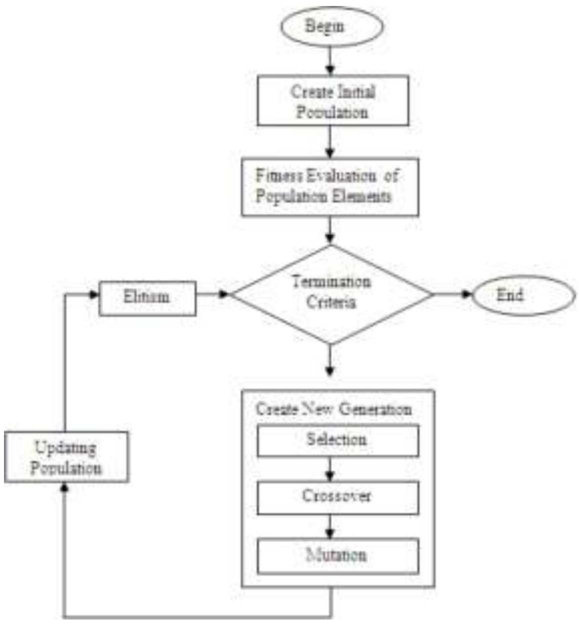
Technology is playing significant role in development and advancement of education. There is need to incorporate new techniques in various disciplines to raise the level of education and set new challenges for further betterment of society. Quality in Higher Education can be improved by use of GAs at various levels such as these can be applied for a) Selection of projects in research and development institutions [1], b) Optimization of online teaching resource management [2], Quality improvement in Higher Education through normalization of student feedback data [3] etc.

Conventional techniques such as deterministic algorithms take considerable amount of time to reach at optimal solution. GAs on the other hand can perform similar tasks in very less time because they work on randomness rather than evaluating each and every solution available. So, incorporation of these techniques can be done in various disciplines due to their ability of closeness to nature, adaptability, better computational powers and availability for wide range of problems and data.

II. Genetic Algorithm

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics (David E Goldberg). These algorithms are useful in solving optimizations problems by emulating biological theories. Based on Darwin's theory of evolution, they work for survival of fittest. Genetic algorithms can automatically access the search space and adaptively adjust the search direction to improve solution. GAs work in specified cycle shown in following flow chart:

Fig. 1 Flowchart depicting working of GA



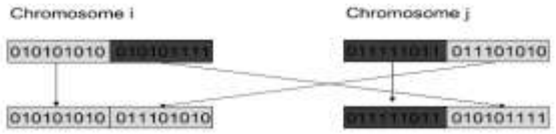
Population: Population consists of collection of possible solutions (referred as Chromosomes). Initial population is made up of randomly chosen Chromosomes from given search space. GA's work in improving average fitness of population from generation to generation, keeping in mind objective function of given problem [6].

Chromosome: Each individual element of any population is called Chromosome. Chromosome is any feasible solution available in search space represented in structured manner. Representation is problem dependent and can be done in many ways such as these can be encoded in form of Integer Strings, Real Strings, and Hybrid Strings etc.

Fitness Function : Keeping objective function in mind, fitness functions are designed in such a manner that strength of each Chromosome can be evaluated using these functions. So, fitness functions are provide a quantitative base to check position of current chromosome in given search space and to decide right direction towards optimal solution to make improvements at each and every step.

Selection: From given population of chromosomes (treated as mating pool), each candidate receives reproduction probability based upon fitness value of its own and fitness value of other chromosomes. This reproduction probability decides whether any chromosome will be selected as parent for mating or not. Any selection criteria can be used based upon problem given such as Roulette Wheel Selection, Rank Selection, Tournament Selection, Stochastic Selection etc

Crossover: This genetic operator operates on every pair of parents selected based upon selection probability. Child Strings are generated from parent Strings by exchanging information among strings of mating pool. Single Point or Multi Point Crossover can be applied depending upon given problem. Same type of crossover should be used throughout the run to main consistency in approaching optimal solution. Single point crossover can be shown as:



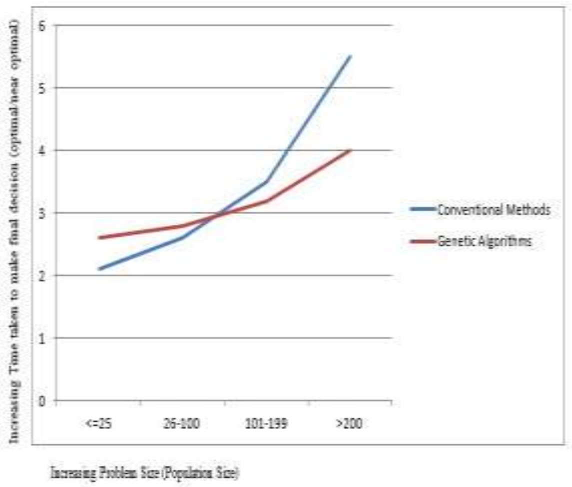
Mutation: Each chromosome goes under mutation after performing crossover with very low mutation probability. Main objective of using mutation is to select neighboring point instead of current point in given search space. Sudden alteration is made in few genes of any chromosome under this operator.

Elitism: Preservation of best fit chromosomes in new generations by replacing newly found chromosomes with lesser fitness value is performed.

Termination Criteria: Termination Criteria could be predefined in form of number of generations to be produced or it could be left for later. In second case, when there is no improvement in overall average for few generations, then decision for termination is made.

III. Computational Capabilities

This section of paper discusses computational capabilities of GAS and various areas where these algorithms can be applied. Main focus is on optimization of selection of various available services in Higher Education.[4,5] Information technology provides various services for improving quality of higher Education such as teleconferencing, audio-conferencing audio-video conferencing, online lectures etc. Selection among these services depend upon many factors like resources available, target audiences etc. This selection can be optimized in very short time by use of GAs because of better computational capabilities of these algorithms. Genetic algorithms do not guarantee optimal solution. These algorithms try to find optimal or near optimal solution, but this cannot be considered as disadvantage. These algorithms are still preferred because decision can be made in lesser time as compared to various conventional methods. Such as, In case of online job scheduling system if a batch of jobs can be completed in 100 milliseconds considering it as optimal solution and conventional deterministic algorithms take 5 milliseconds to make this decision. Then overall time taken to complete this process is 100+5- 105 milliseconds. Now, if GA approach is used in place of these conventional methods for same set of jobs, these can make the decision say in 2 seconds. So, here in this case even near optimal solution < 103 can be considered beneficial as overall time taken to complete this process remain less than 105 milliseconds (as on case of conventional methods). Deterministic algorithms in most of the cases evaluate each and every feasible solution and decide optimal solution at the end. So, at least single pass is required through each point of available solution space while searching for optimal solution. On the other hand, GAs perform this task very intelligently as they look for direction towards optimal solution at each step. There is no need to go through all possible solutions, GAS move from good to better ones. So, numbers of comparisons in case of GAS keep on decreasing as compared to other conventional methods with increase in problem size [7]. Hence time needed to solve given problems comparatively keep on decreasing with increase in problem size as compared to other conventional methods. This comparison can be shown in following graph:



Above fact can be proved by applying genetic algorithms on learning phase of neural networks. Such implementation performed by Sergi Perez justifies this comparison. As expected, the GA approach gives better results than the back-propagation method with almost all the iterations used. Only when the number of iterations is very small, the back-propagation method gives better precision performance. The time performance using GA was better than using back-propagation as follows: [8]

IV. TABLE I
BACK-PROPAGATION VS. GENETIC ALGORITHMS

	Back-propagation vs. Genetic Algorithms	
	Back propagation	**GA**
Time	86	72
Hits training data	36	46
Hits test data	32	37

Genetic algorithms are often used for optimization problems in which the evolution of a population is a search for a satisfactory solution given a set of constraints [9]. GA's not only take less computational time, but also they produce accurate results and able to predict errors in search space. If search process focused on error regions, then genetic algorithms can be considered suitable for generating training data for neural networks for under-represented or rare events. This can provide efficient model-based executions for performance improvements, replacing real target system executions. To investigate the potential of using neural networks, a genetic algorithm can be used to generate test cases for training data, based on errors injected into a distributed system test-bed. Two training sets of equal size, with the flrst set generated by the genetic algorithm and the second by random generation can be used for comparison. A comparison of the two is shown in Table 2 [10]. The random trained was accurate 96% of the time, however, as there are far more non-error cases than errors, it is easy to achieve overall accuracy by predicting success. Therefore, a more appropriate comparison is based on predicting errors. In this situation, the performance of the random trained network deteriorates to 76% compared to 96% for the genetic algorithm-trained network In fact, the random-trained network achieved reasonable performance on only two errors (hence the low per error accuracy), while the GA-trained network was able to identify errors in all but one case [10].

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V. TABLE III
ACCURACY COMPARISON FOR RANDOM VS. GENETIC ALGORITHMS BASED TEST CASES

	Back-propagation vs. Genetic Algorithms	
	Random	**GA**
Overall Accuracy	96%	81%
Error Accuracy	76%	96%
Average per error Accuracy	29%	83%

This shows diversity of problems where GA's can be useful in getting results in short time with desired accuracy

VI. CONCLUSIONS

The use of GAs is highly recommended for various disciplines because of their better performance for wide range of problems. [11][12][13]Incorporation of these algorithms can improve performance levels while looking for optimal solution in given solution space. Information Technology is already playing significant role in improving quality of education by providing alternative ways to deal with information. Use of GAs is another step in this direction to further optimize and improve the way information is handled. These algorithms can be used not only in optimized selection of various services used in Higher Education but also this can be done using GAs in very short time.

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REFERENCES

[1] Sanjay S, Pradeep S , Manikanta V , Kumara S.S and Harsha P, *Genetic Algorithm Based Approach for the Selection of Projects In Public R&D Institutions,Indian Journal of Computer Science and Engineerin*, 2011

[2] Xing Lining, Chen Yingwu, Cai Huaiping, and Tao Fengyuan, *The intelligent genetic algorithm with solving the whole optimited problems, Journal of System Simulation*,2006.

[3] S. Vishnupriyan, L. Govindarajan, G. Prabhakaran & K.P. Ramachandran, *Quality Improvement in Higher Education through Normalization of Student Feedback data Using Evolutionary Algorithm, The International Journal of Applied Management and Technology, Vol 6, Num 3*

[4] Simon mardle & Sean pascol.(1999) .*An overview of genetic algorithms for the solution of optimization problems, Computers in Higher Education Economics Review*, 13(1),pp.16-20.

[5] Ahmed A A Radwan; Abdel Mgeid A Ali;Bahgat A Abdel Latef & Osman A Sadek. (2006).*Using genetic algorithm to improve information retrieval systems*, Proceedings of the *World Academy of Science Engineering and Technology*, 17, pp.6-12.

[6] Cong Mingyu and Wang Liping, *The intelligentized genetic algorithm , High Technology Letters*, 2003.

[7] Fernando G. Lobo, David E. Goldberg, Martin Pelikan, *Time complexity of genetic algorithms on exponentially scaled problem*, 1991, pp. 51-58*s*

[8] Sergi Perez. *Apply Genetic Algorithm to the learning phase of Neural Network*, Department of Mechanical and Aerospace Engineering, University of California, Irvine

[9] Goldberg D E, *Genetic Algorithms: In search, optimization and machine learning*, New York: Addison-Wesley Publishing Co. Inc.,1989, pp. 59-75.

[10] Donald J. Berndt and Alison Watkins, *Investigating the Performance of Genetic Algorithm-Based Software Test Case Generation,* Eighth IEEE International Symposium on High Assurance Systems Engineering (HASE'04)

[11] E.hussein, Sherif, and Mahmoud Abo El-Nasr. "Resources Allocation in Higher Education Based on System Dynamics and Genetic Algorithms." *International Journal of Computer Applications IJCA* 77.10 (2013): 40-48. Web.

[12] Tian, Yu Guang, and Liang Ma. "Research on Limited Resources Optimal Allocation Model." *Proceedings of the 2015 International Conference on Education, Management, Information and Medicine* (2015). Web.

[13] Zhu, Yulan, Linlin Zhang, and Shaorong Sun. "Class Hour Allocation Optimization Model between E-education and Traditional Education in the Process of Higher Vocational Technology Education." *2011 International Conference on E-Business and E-Government (ICEE)* (2011). Web.

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