OPEN ACCESS Information Technology Journal

ISSN 1812-5638
DOI: 10.3923/itj.2017.

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Research Article
Enhanced Structured Population Approach for Genetic Algorithm

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Abstract
Objective: The objective of the study was to present the enhancement model of the Simple Standard Genetic Algorithm (SGA). This model is based on custom, behavior, age, gender and pattern of human community. It is an enhanced structured population approach for genetic algorithm so it is called the Human Community Based Genetic Algorithm (HCBGA). **Methodology:** The Traveling Salesman Problem (TSP) was used as a test problem, which is a minimization problem. This test shows the differences of each model based on the human community based genetic algorithm's best fit values and averages in different generations. Tests were conducted over three models, the simple standard genetic algorithm, the Island Genetic Algorithm (IGA) and the enhanced human community based genetic algorithm. **Results:** Best fit solutions in different populations of different generations show better performance of the enhanced human community based genetic algorithm over the other two models, the simple standard genetic algorithm and the island genetic algorithm. In addition, results in relation to slowing the convergence of solutions are significantly better in the enhanced human community based genetic algorithm than the other two, the simple standard genetic algorithm and the island genetic algorithm. **Conclusion:** The enhanced human community based genetic algorithm indicates that a population structure model based on the rules of marriage concepts can clearly improve the performance of the simple standard genetic algorithm and the island genetic algorithm.

Key words: Structured population, simple standard genetic algorithm, island genetic algorithm model, traveling salesman problem, enhanced human community based genetic algorithm, convergence

Received: Accepted: Published:

Citation: Nagham Azmi AL-Madi, Amnah Ahmad EL-Obaid and Mohammad Azmi AL-Madi, 2017. Enhanced structured population approach for genetic algorithm. Inform. Technol. J., CC: CC-CC.

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Genetic algorithms are used to solve search and optimization problems[1]. In the early 1960s, 1970s and 1980's John Holland and his students developed these kinds of algorithms[1-3]. Such search techniques can solve hard complex problems in various disciplines and they rely mainly on the biological process of evolution[1-3]. They mimic nature in a way that the survival of the fittest would provide new generations of approximate solutions[1-3]. Furthermore, Genetic Algorithms (GAs) work with various elements "Individuals", where each element is referred to a chromosome or genotype. A fitness score is assigned to each individual representing a possible solution to a given problem[2,3]. Genetic Algorithms (GAs) were first used in solving academic problems. These problems are such as the traveling salesman problem and the 8 Queens problem[3]. Years later, Genetic Algorithms (GAs) increased their applications to optimize many types of complex problems such as the complex scheduling problems, spatial layout and many other problems that are hard to efficiently solve[3]. The enhanced model is a structured population model for SGA. Such model enhances the SGAs performance in finding best solutions over the space of potential solutions. As such, a new theory of SGA may be arrived at. Islamic rules were used to measure the performance of such model in achieving better solutions.

One of the most important combinatorial problems is the Traveling Salesman Problem (TSP). This problem is simple to define[4-7]. It is stated as an NP-hard optimization problem. In this problem N cities must be visited by a salesman, starting from one of them, passing through each city only once and returning to the first city. The cost is given for the journey. Finally, the minimum cost is required to solve this problem[5,8].

Traveling Salesman Problem (TSP) is determined as follows: Given N cities, known as nodes, a distance matrix where, D = [dij], consists of the distance between city i and city j[4,5].

In an attempt to finding near optimal solutions for NP-hard problems; the Traveling Salesman Problem (TSP) is considered a standard benchmark problem for combinatorial methods[7]. It provides a standard optimization test bed to find near optimum solutions to NP-hard problems[7,9].

The TSP is called symmetric TSP (Standard), if the cost between any two cities are equal in both directions, this means that the distance from city i to city j is the same as the distance from city j to city i. Otherwise, the TSP is to be known as an asymmetric TSP, which means that the distance between city i and city j is different to the distance from city j to city i[6,7].

To solve the Traveling Salesman Problem (TSP), there are two alternative approaches, first is to find its solution and try proving its optimality, which takes a long period of time, second is to find an approximate solution in a short period of time[7].

The traveling salesman problem is being applied on methods from many specific areas, mostly based on search heuristic methods such as simulated annealing[2], tabu search[2,10], neural networks[2], genetic algorithms,[1,2] and local search[8].

In this study, performance was referred to the quality of the results which are the best fit values. The mean fitness of all the fitness values obtained from all the runs was also compared to analyze the diversity of each model. As the Travelling Salesman Problem (TSP) is a permutation minimization problem, the experiment was conducted to find the behavior of the enhanced model in such problem. The experiments were conducted on the models by using the TSP as a test problem. Comparison was made between the performances of the various models to show the difference between them in finding the best solutions.

MATERIALS AND METHODS

Simple Standard Genetic Algorithm (SGA): In the selection part in the Simple Standard Genetic Algorithm (SGA) there are no constraints[1]. The SGA works randomly[1,2]. Due to such randomness, many researchers are working to tackle this problem by designing structured population and applying some constraints to control the individual's interaction[1,2].

In the last few years, many types and models of GAs appeared such as Patchwork GA[11,12], Terrain-Based GA[13], Religion-Based GA[14,15], Cellular GA[16] and Island GA[17].

Island Genetic Algorithm model (IGA): Island Genetic Algorithm models (IGA) are considered a family of more advanced models of Evolutionary Algorithms (EAs)[17-19]. Such models where developed in order to solve more complex problems which are increasing rapidly. Here the individuals are divided into sections. We call each section a subpopulation which is referred to as an island. Such island models are capable of solving problems in a better performance than standard models[16,20]. There is a specific relation between islands through some exchange of some individuals between islands. This process is called migration; this is what island models are famous for and without these migrations, each island is considered as a set of separate run. Therefore, migration is very important[17].

Human Community Based Genetic Algorithm (HCBGA): The process of mating in a human community is normally conducted through marriage. Marriages in most communities allow an eligible male and female to form a family. As such, HCBGA has marriage as the new enhancement besides gender segregation and balanced population from the previous enhancements[2]. Social constraints applied to this new approach were affective.

Chromosome Representation in the Enhanced HCBGA: According to the Human Community Based Genetic Algorithm (HCBGA)[2], which is based on nature and social selection such as custom, behavior, age, gender and pattern of human community; authors enhance the Human Community Based Genetic Algorithm (HCBGA). This is done by giving an age attribute to each individual in the population.

The age attribute takes three values: Youth, parent and grandparent. Accordingly, the youth age will consider a specific attribute to specify whether this individual is approved to mate or not, in addition to the presence of the family relation which divides the subgroups into a Directed Acyclic Graph (DAG). As such, an attribute is given to each individual in the population specifying sex, whether male or female. In addition, being in the same society, as the population is divided into subgroups or islands, is a dependable constraint for recombination. Subsequently, all the standard operations in the Standard Genetic Algorithm (SGA) will differ in adding restrictions on each operation of the social constraints such as the male/female 'operator' and age restrictions. Such additions will be added to the selection part which will restrict choosing two different couples, in addition to the birth operator which generates a new population and the death operator which discards the worst individuals.

Enhanced HCBGA method: The first individual is initially selected randomly from the population according to age to be the first parent. In addition to the first parent's type (whether a male or a female), the normal age of marriage should be met. Accordingly, the second parent will be chosen such that it is the opposite type of the first parent in addition to its restricted age. In order to create the initial population, this process is repeated for a number of individuals. Stages of selection and crossover would follow, bringing up two new children or off springs. Such process is repeated for a number of couples to bring up a second population and this process will be repeated until the maximum number of generations is reached.

Experiments: The enhanced HCBGA of Al-Madi[2], the SGA and IGA are being tested and compared. The TSP is used as a test bed to compare the averages and best fit values between these algorithms.

The process used in the research test is simple and standard[2]. The size of population tested is 350, with seven cities and a randomly selected one-point crossover. According to the maximum length of the chromosome in the model, a random integer (crossover point) and a crossover rate of 5% are chosen. This is the place in the chromosome at which, with probability, the crossover will occur. If it occurs, the bits up to the random integer of the two chromosomes will be swapped. The mutation of a solution is a random change to a gene value[19]. The rate of the mutation is 0.04. It is chosen after different experiments of different mutation rates. The selection method used is the roulette wheel. The number of generations is 100. The implementation part was programmed in C# (C Sharp) Language Version (6.0) on an Intel® Core™ i7-3630QM CPU, with a 4.00 GB Ram and a 64-bit Operating System, Toshiba laptop.

The TSP is applied on SGA, IGA and enhanced HCBGA. The performance concerning best fit solutions and average values between these algorithms is obtained. Tests show better manner convergence of averages towards the optimal minimum solution of the enhanced HCBGA than the other two algorithms SGA and IGA. Moreover, HCBGA gives better findings of best fit values over both, the basic SGA and IGA.

RESULTS AND DISCUSSION

Figure 1 and 2 show comparative results of applying the TSP on SGA, IGA and enhanced HCBGA. It can also be seen that enhanced HCBGA diversifies better than the other two models SGA and IGA.

Comparisons between HCBGA and IGA: The TSP is a minimization problem. Subsequently, a convergence of enhanced HCBGA to an optimal minimum best fit value of the potential solutions in the population could be observed with a value of 40.4, whereas the IGA converges to a value of 175.0. This could be observed in Fig. 3.

Once again, the enhanced HCBGA diversifies better than the IGA, this gives more opportunity to find better solutions in the search space. The individuals in the IGA are sub-grouped to different subpopulations randomly without any restrictions. On the other hand, the HCBGA grouped the individuals depending on the relationships between individuals. It is grouped into communities similar to the human communities.

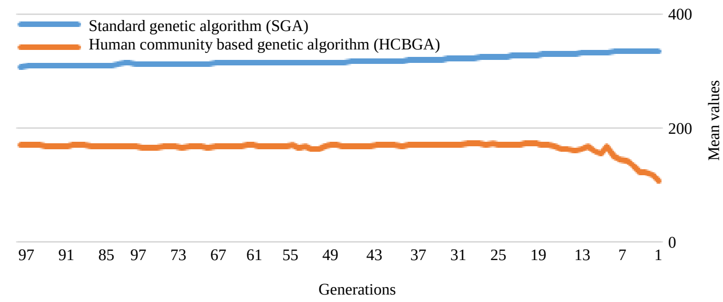

Fig. 1: Average solutions of SGA and enhanced HCBGA

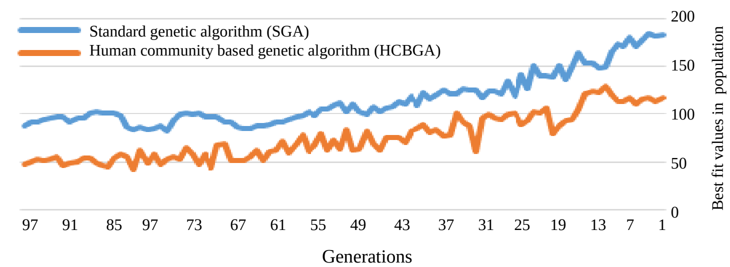

Fig. 2: Best solutions of SGA and enhanced HCBGA

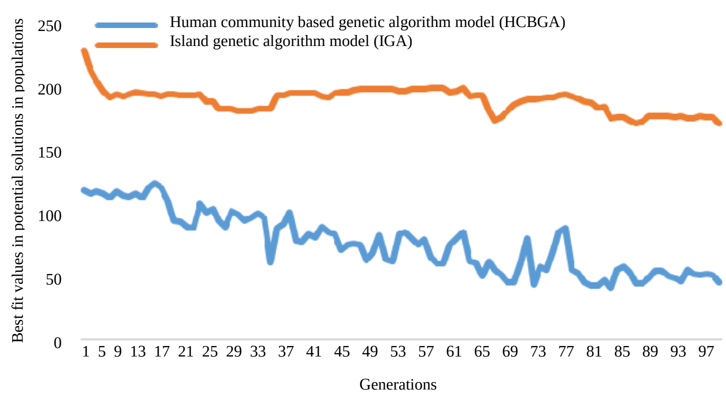

Fig. 3: Best solutions of HCBGA and IGA

The restrictions that come with the grouping in HCBGA diversifies the population which then contributes to the better performance of this enhanced model compared to IGA.

Models analysis: Analysis of the best fit values for the previous models will be presented. For the purpose of analysis, only the SGA, HCBGA and IGA are considered and compared.

Statistical analysis for the models: Traveling Salesman Problem (TSP) is a minimization problem. Subsequently, a convergence of enhanced HCBGA to an optimal minimum best fit value of the potential solutions in the population could be observed with a value of 40.4, whereas the IGA converges to a value of 175.0. This could be observed in Fig. 3.

This would mean that individuals in the population are spreading around mean in a balanced distribution. Moreover, the variance value of the enhanced HCBGA = 545.284 as shown in Table 1, meaning a variation in the data and that the enhanced HCBGA model has achieved a good diversity between its individuals[2]. Accordingly, the enhanced HCBGA model could achieve a better fitness value which means better performance than the other two models, SGA and IGA.

Friedman test shows mean ranks of the three models. Enhanced HCBGA model achieved the lowest rank 1.12,

Table 1: Statistical analysis of the population for SGA, IGA and enhanced HCBGA models

	No. of Generations				
Models	Statistic	Mean	Standard error	Standard deviation	Variance
SGA	100	115.785	2.6544	±26.3221	735.097
IGA	100	189.361	0.9319	9.3193	85.786
HCBGA	100	74.321	2.2536	22.5633	545.284

Table 2: Kendall's W test between SGA, IGA and the enhanced HCBGA models

Parameters	Values
N	100
Kendall's W(a)	0.789
Chi-square	424.850
Df	2
Asymptotic significance	0.000
Monte Carlo significance	0.000

No: No. of generations, DF: Degree of freedom

whereas SGA's mean rank is 4.35 and IGA's mean rank is 6.01. Since the lowest rank in a minimization problem is considered the best, it could be clearly seen that the enhanced HCBGA outperforms the other models as it yields the best rank against the other models. It means that this model has achieved better fitness values in its populations along the 100 generations towards the optimal minimum.

In the Kendall's test as shown in NIST, 200442; which is a test of independence, N is the number of generations. The chi-square's[21] value is very high (424.850) as shown in Table 2, which means that the enhanced HCBGA model was independent from the other models. The Df is the degree of freedom and its value is k-1, where k is the number of models tested where in this test there are 3 models, so the Df value is 2. In addition, the Kendall's W value is .789 which is a high value nearing 1 and this indicates a full agreement that the enhanced HCBGA model performs significantly better in exploring the search space for best solutions than the other models. Finally, Table 2 shows a Monte Carlo significant value of 0.000 which means the enhanced HCBGA model has a 100% effect and it has a high significant difference over the other models with a level of confidence of 99% due to 0.000 is less than 5%.

CONCLUSION

Based on the analysis results, it could be concluded that the HCBGA performed significantly better in terms of averages and best fit values than SGA and IGA. The average of the enhanced HCBGA is converging towards the optimum minimum solution despite its restricted constraints to the best values. Furthermore, findings of best solutions of best fit values are in a better condition in the enhanced HCBGA than in SGA and IGA.

The set of solutions generated by the enhanced HCBGA model achieves an almost perfect spread out and convergence to the optimum. The enhanced HCBGA model shows that a population structure model based on the rules of marriage concepts can clearly improve the performance of SGA and IGA.

SIGNIFICANCE STATEMENT

This study aims at discovering the construction and building of an enhanced and structured population model for SGA that can be beneficial for boosting the SGAs performance. This study will help a researcher to uncover the critical areas of SGA that many researchers were unable to explore before. Thus, a new theory of SGA may be reached. The enhanced HCBGA model will adapt Islamic rules as a case study to measure the effectiveness of such model in achieving better solutions.

REFERENCES

1. Stephens, C.R., P.F. Stadler, M. Toussaint and D. Whitley, 2007. Foundations of Genetic Algorithms. Vol. 4436, Springer, New York.
2. Al-Madi, N.A., 2014. De Jong's sphere model test for a human community based genetic algorithm model (HCBGA). Int. J. Adv. Comput. Sci. Applic., 5: 166-172.
3. Bagheri, E. and H. Deldari, 2006. Dejong function optimization by means of a parallel approach to fuzzified genetic algorithm. Proceedings of the 11th IEEE Symposium on Computers and Communications, June 26-29, 2006, Cagliari, Italy.
4. Nguyen, H.D., I. Yoshihara, K. Yamamori and M. Yasunaga, 2007. Implementation of an effective hybrid GA for large-scale traveling salesman problems. IEEE Trans. Syst. Man Cybern. Part B (Cybern.), 37: 92-99.
5. Hains, D.R., L.D. Whitley and A.E. Howe, 2011. Revisiting the big valley search space structure in the TSP. J. Operat. Res. Soc., 62: 305-312.
6. Whitley, D., D. Hains and A. Howe, 2010. A Hybrid Genetic Algorithm for the Traveling Salesman Problem using Generalized Partition Crossover. In: Parallel Problem Solving from Nature, PPSN XI, Schaefer, R., C. Cotta, J. Kolodziej and G. Rudolph (Eds.). Springer, New York, pp: 566-575.
7. Bianchi, L., J. Knowles and N. Bowler, 2005. Local search for the probabilistic traveling salesman problem: Correction to the 2-p-opt and 1-shift algorithms. Eur. J. Operat. Res., 162: 206-219.

8. Lamom, A., T. Thepchatri and W. Rivepiboon, 2008. Heuristic algorithm in optimal discrete structural designs. Am. J. Applied Sci., 5: 943-951.
9. Basu, S., 2012. Tabu search implementation on traveling salesman problem and its variations: A literature survey. Am. J. Operat. Res., 2: 163-173.
10. Belal, M.A. and M.H. Haggag, 2013. A structured-population genetic-algorithm based on hierarchical hypercube of genes expressions. Int. J. Comput. Applic., 64: 5-18.
11. Li, X., M.R. Bonyadi, Z. Michalewicz and L. Barone, 2014. A hybrid evolutionary algorithm for wheat blending problem. Sci. World J., Vol. 2014. 10.1155/2014/967254.
12. Michalewicz, Z., 2012. The emperor is Naked: Evolutionary algorithms for real-world applications. ACM Ubiquity, pp: 1-13.
13. Kotowski, S., W. Kosinski, Z. Michalewicz, P. Synak and L. Brocki, 2009. On stability and classification tools for genetic algorithms. Fundamenta Inform., 96: 477-491.
14. Azevedo, C.R.B. and V.S. Gordon, 2009. Adaptive terrain-based memetic algorithms. Proceedings of the 11th Annual conference on Genetic and Evolutionary Computation, July 8-12, 2009, Canada, pp: 747-754.
15. De, S., D.S. Nau and M.J. Gelfand, 2017. Understanding norm change: An evolutionary game-theoretic approach. Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems, May 8-12, 2017, Sao Paulo, Brazil, pp: 1433-1441.
16. Alba, E., B. Dorronsoro, F. Luna, A.J. Nebro, P. Bouvry and L. Hogie, 2007. A cellular multi-objective genetic algorithm for optimal broadcasting strategy in metropolitan MANETs. Comput. Commun., 30: 685-697.
17. Adel, A., E. El Fakharany and A. Badr, 2014. Clustering tweets using cellular genetic algorithm. J. Comput. Sci., 10: 1269-1280.
18. Skolicki, Z., 2007. An analysis of Island models in evolutionary computation. Ph.D. Thesis, George Mason University, Virginia.
19. Shakouri, H., K. Shojaee and H. Zahedi, 2009. An effective particle swarm optimization algorithm embedded in sa to solve the traveling salesman problem. Proceedings of the Control and Decision Conference, June 17-19, 2009, Chinese, pp: 5545-5550.
20. He, Y., G. Liu and Y. Qiu, 2004. A novel adaptive search strategy of intensification and diversification in Tabu search. J. Comput. Res. Dev., 41: 162-166.
21. Den Dekker, A.J. and J. Sijbers, 2014. Data distributions in magnetic resonance images: A review. Phys. Med., 30: 725-741.