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Age Constraints Effectiveness on the Human Community Based Genetic Algorithm (HCBGA)

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Article Info	ABSTRACT
	In this paper, we use under-age constraints and apply it to the Traveling Salesman Problem (TSP). Values and results concerning the averages and best fits of both, the Simple Standard Genetic Algorithm (SGA), and an improved approach of Genetic Algorithms named Human Community Based Genetic Algorithm (HCBGA) are being compared. Results from the TSP test on Human Community Based Genetic Algorithm (HCBGA) are presented. Best fit solutions towards slowing the convergence of solutions in different populations of different generations show better results in the Human Community Based Genetic Algorithm (HCBGA) than the Simple Standard Genetic Algorithm (SGA).

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1. 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 [2], [5], [6], [8], [9]. These search techniques solve hard complex problems in various disciplines, and they rely mainly on the biological process of evolution [3], [5], [8]. As a matter of fact, Genetic Algorithms (GAs) are routines which could manage self-adoption, same as neural networks. They mimic nature in a way that the survival of the fittest is to provide new generations, of approximate solutions [5], [8]. Additionally, genetic algorithms (GAs) work with various elements "individuals" 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 [1]-[3], [8], [9]. In solving academic problems Genetic Algorithms (GAs) were first used. These problems are such as the traveling salesman problem and the 8 Queens problem [3], [5], [6], [9]. 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 [7].

2. THE TRAVELING SALESMAN PROBLEM (TSP)

One of the most important combinatorial problems is the traveling salesman problem (TSP). This problem is simple to define [24, 25]-[27]. 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 [23], [28]-[30]. The 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 [24], [28], [29], [30].

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 [29]. It provides a standard optimization test bed, to find near optimum solutions to NP-hard problems [1], [31], [36], [38].

The traveling salesman problem (TSP) is called Symmetric TSP (Standard), if the cost between any two cities are equal in both directions, this means, the distance from city i to city j is the same as the distance from city j to city i. Otherwise, the Traveling Salesman Problem (TSP) is to be known as an Asymmetric TSP, which means that the distance between city i to city j, differs than the distance from city j to city i [24], [27], [31].

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, to find an approximate solution in a short period of time [27].

Applying the Traveling Salesman Problem using methods from many specific areas mostly based on search heuristic methods such as local search [34], [36], simulated annealing [32], [37], tabu search [33], [37], neural networks [32], [35],and genetic algorithms [34], [38]. Actually, there are wide applications of the TSP, such as, traffic route, computer cabling, robot control and many others [25], [27].

3. MATERIALS AND METHODS

In the selection part in the Simple Standard Genetic Algorithm (SGA) there are no constraints. The Simple Standard Genetic Algorithm (SGA) works randomly [11]. Due to this randomness, many researches are working to tackle this problem by designing structured population and putting some constraints to control the individual's interaction [11]. In the last few years many types and models of GAs appeared such as the Cellular GA [11], Island GA [12], Patchwork GA [13], [14], Terrain-Based GA [15], and religion-Based GA [16].

3.1. Cellular GAs (CGA)

A diffusion model of a two-dimensional grid in which each individual interacts with another by its direct neighbour [17], [11]. The Genetic Algorithm is designed as a probabilistic cellular automation in this type of GAs. These individuals will be distributed on a graph which is connected together, having a neighborhood of some genetic operator to work with. This type of GAs is designed as a probabilistic cellular. A self-organizing schedule is added to reproduce an operator [18]. The individual which can interact with its immediate neighbors can only be held in the cell.

3.2. Terrain-based GA (TBGA)

In a comparison between the Terrain-based GA (TBGA) and the Cellular GA (CGA), the first shows a more self-tuning model in which many combination parameter values will be located in different physical locations and better performance with less parameter tuning than the second [15]. At every generation each individual should be processed, and the mating will be selected from the best of four strings, located above, below, left, right.

3.3. Patchwork Model

Krink [13] introduced this model which consists of several ideas merged together from cellular evolutionary algorithms, island models, and traditional evolutionary algorithms. Here the grid is a two dimensional grid of fields, each field can have a fixed number of individuals. The patchwork model is considered a self-organized, spatial population structure [19]. In a GA population, in order to allow self-adaptation, patchwork model is used as a base. It contains a grid world and some interesting agents. In modelling biological systems the patchwork model is considered as a general approach.

3.4. Island Models

Island models are considered a family of more advanced models of evolutionary algorithms (EAs) [20]. These 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. These island models are able to solve problems in a better performance than standard models [18]. 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 of, and without these migrations, each island is considered as a set of separate run. Therefore migration is very important [20], [22].

3.5. Religion-Based EA Model (RBEA)

This model has a religious concept introduced by Rene Thomsen et al. The Religion-Based EA Model (RBEA) attracts new believers to a religion which puts more control than other models such as cellular EA and the patchwork models [16].

3.6. 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. Social constraints applied to this new approach were affective. Figure 1 shows the model of the human community based Genetic Algorithm (HCBGA) [6].
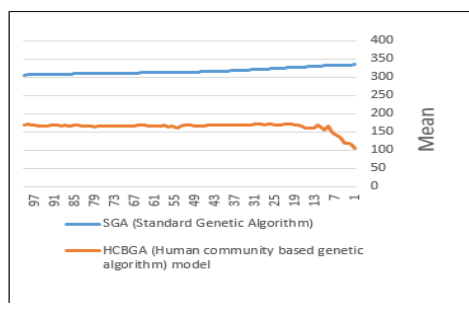

Figure 1. The Total Average of 10 runs each between SGA & improved HCBGA with Seven
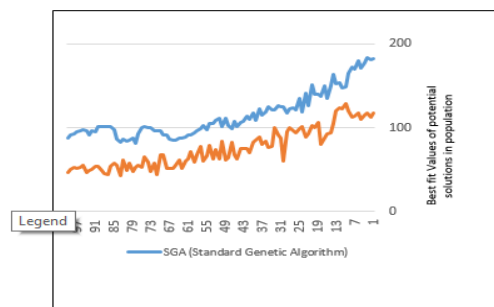

Figure 2. The Total Average of Best fits of 10 runs each between SGA & Improved HCBGA with seven cities

3.7. Chromosome Representation in the Improved HCBGA

According to the Human Community Based Genetic Algorithm (HCBGA) [6], which is based on nature and social selection, authors improve the HCBGA. This is done by using the under-age as constraints on proposing marriages between males and females as in the real human community life. As such, an attribute is given to each individual in the population specifying its 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. The problem of age is considered also by adding an attribute for the age. The age attribute takes three values: youth, parent, and grandparent. In addition, a new restriction of age is added, as such any individual less than 15 is not eligible to be selected. This chromosome representation (the presence of father and mother pointers) will keep all family relations which divides the subgroups into a Directed Acyclic Graph (DAG). All the standard operations in the GA will be changed in order to add restrictions on each operation including: Social constraints such as the Male/Female 'operator' and under-age restrictions will be added in the selection part which will restrict choosing two different couples. In addition the Birth operator which is generating a new population, and the Death operator which will discard the worse individuals.

3.8. The (HCBGA) Method

Initially, the first individual is selected randomly from the population according to its grownup age-this will 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 satisfied, accordingly, the second parent will be chosen such that it is the opposite type of the first parent in addition to its restricted grownup age. This process is repeated for a number of individuals creating the initial population. Next comes the stages of selection and crossover, bringing up two new children or offspring's. Repeating this for a number of couples a second population will be generated. Again, the previous process is repeated until the maximum number of generations is reached. (The next main important thing is that the two individuals must not share the same parents).

4. RESULTS AND DISCUSSION

In this research we have used the Traveling salesman Problem (TSP) to test the improved Human Community Based Genetic Algorithm (HCBGA) of [6]. We also used it as a test on the Simple Standard Genetic Algorithm (SGA) in order to compare between both algorithms.

A population size of 350 with seven cities and a randomly selected one-point crossover are used in a process that is both standard and simple [39]. A random integer (crossover point) and a crossover rate of 5% are chosen according to the maximum length of the chromosome in the model. This is the place in the chromosome at which, with probability, the crossover will occur. If the crossover does occur, then the bits up to the random integer of the two chromosomes are swapped. The mutation of a solution is a random change to a gene value [39], [40]. After several experiments of different mutation rates, the most suitable mutation rate is 0.04. 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 (5.0) on a Pentium 4, HP-Compaq laptop.

By applying the Traveling Salesman Problem (TSP) on both the Simple Standard Genetic Algorithm (SGA) and on the improved Human Community Based Genetic Algorithm (HCBGA) [6] we can compare the performance of both algorithms. The following comparisons below will show that the constraints put on the improved new Human Community Based Genetic Algorithm (HCBGA) gave better performance to SBGA than the Simple Standard Genetic Algorithm (SGA) which depends mainly on its randomness in finding the best fit solution. It is shown that in the improved Human Community Based Genetic Algorithm (HCBGA) the average converge toward the optimal solution better than the Simple Standard Genetic Algorithm (SGA), and the best fit values in the improved Human Community Based Genetic Algorithm (HCBGA) also show better findings of best fit values in a comparison to the basic Simple Standard Genetic.

In the following Figures we can see the comparative results of applying the Traveling Salesman Problem (TSP) on both the Simple Standard Genetic Algorithm (SGA) and the improved Human Community Based Genetic Algorithm (HCBGA). Figures 1 and 2 show that the average of the improved Human Community Based Genetic Algorithm (HCBGA) has a better performance than the Standard Genetic Algorithm (SGA) towards the minimum. In addition, they show a better finding of best fit solutions for the improved Human Community Based Genetic Algorithm (HCBGA) than the Standard Genetic Algorithm (SGA).

5. CONCLUSION

The Traveling Salesman Problem is used as a test function to compare results of both the Simple Standard Genetic Algorithm (SGA) and an improved approach for structured population of GA called the Human Community Based Genetic Algorithm (HCBGA) [6]. The evaluation concluded based on the analysis results that the improved Human Community Based Genetic Algorithm (HCBGA) is better in terms of best finding as shown in our given results than the Simple Standard Genetic Algorithm (SGA). The Average of the improved Human Community Based Genetic Algorithm (HCBGA) is trying to converge towards the minimum despite its restricted constraints to the best values. In addition, the findings of the best solutions of best fit values are in a better condition in the improved Human Community Based Genetic Algorithm (HCBGA) than in the Simple Standard Genetic Algorithm (SGA).

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