

Acquired Intelligence & Adaptive Behaviour:

Impact the of Mutation Rate on the Performance  
of Full-Microbial Genetic Algorithm and a  
Population of Hill-Climbers

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## 1 Abstract

The purpose of this paper is to present and evaluate the differences between Full-Microbial Genetic Algorithm (MGA) and Hill-Climber population (HC) in the scope of the Knapsack Problem. The Knapsack problem (KP) is an NP-Hard combinatorial problem that deals with resource allocation. The main focus of the problem is to maximize the total benefit ( $\sum_i^N B_i$ ) by putting the weighted items in a knapsack while staying in the boundaries of weight limit constraint ( $\sum_i^N C_i \leq C$  where  $C$  is the maximum capacity of the knapsack).

## 2 Introduction

Even though MGA and HC show similarities in terms of purpose and goal, Within the scope of the knapsack problem, the approaches used to seek for the local and possibly global maxima are differ. HC involves local search using a population, whereas MGA includes crossover in a sexually active population from a more successful "winning fighter" genotype (candidate solution) to a "loser fighter" genotype. While both algorithms are impacted by random mutations over generations, Only the MGA shows genetic recombination. To assess the importance of mutation rate and genetic crossover for population genetic diversity and success, the findings of both algorithms are analysed and their differences are compared.

## 3 Hill-Climbing

Hill-Climbing is a local search optimization algorithm that begins with the initialization of a single randomly generated candidate solution. The initial candidate solution is being adjusted through numerous mutations in order to find a more beneficial and optimal solution. After a genotype has been mutated, its fitness is assessed and compared to the fitness of its predecessor. If the fitness of the child genotype is higher than its parent, the most recent genotype is selected as the current functioning best. See the flowchart below (Figure 1)[3] for the steps of HC algorithm.

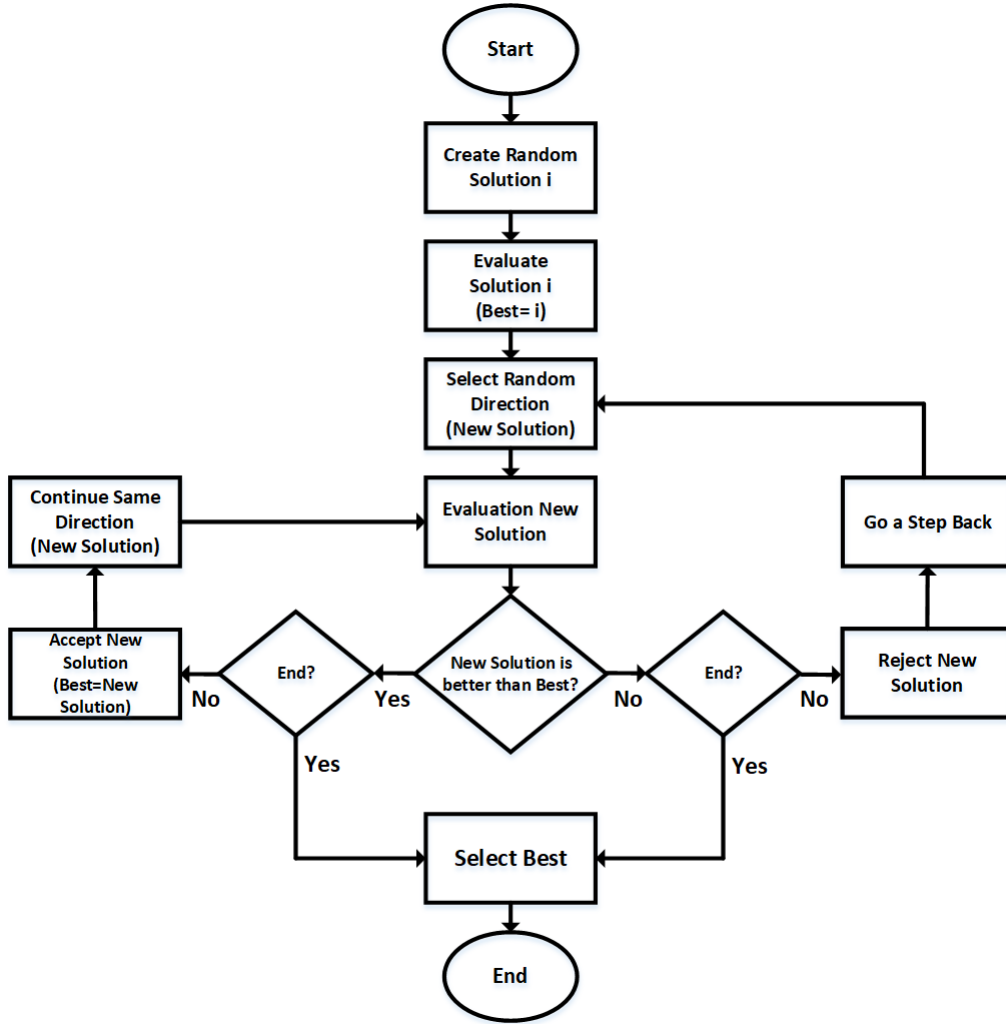


Figure 1: Hill-Climbing Algorithm Flowchart

### 3.1 Local Maxima vs. Global Maxima

HC could work well in basic problems (Figure 2a). With the addition of a space containing several maxima, if the HC starts with a less than optimum starting solution (i.e. the Hill-Climber started from a disadvantageous point), the algorithm may stuck at a lower maximum, never reaching the global maxima. Therefore it may become trapped on non-optimal solution (Figure 2b). Since KP contains non-convex functions [2], HC is likely to fail in reaching global maxima and stuck on a local maxima in most cases (Figure 3). Adjusting mutation rates and iteration counts might be beneficial to find the best local maxima.

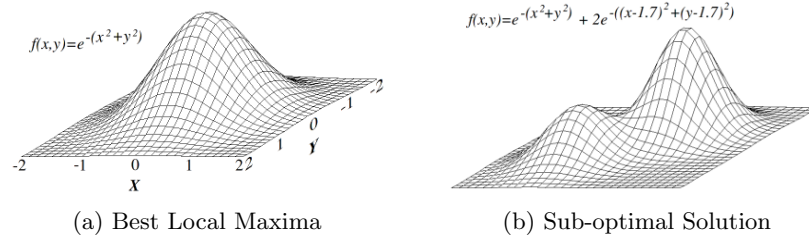


Figure 2: Local Maxima graphs

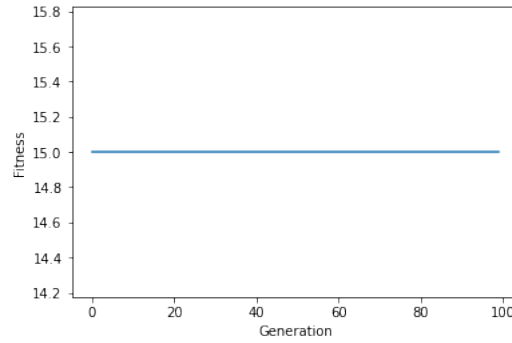


Figure 3: Single Hill-Climber stuck in a sub-optimal solution (Mutation rate is 20%)

### 3.2 Methods and Results

Since getting stuck in a sub-optimal solution is a significant concern in Hill-Climbing algorithm, introducing a population of hill-climbers is a method to reach the global maxima. In this version of the algorithm, many of HCs run in parallel and only the most fitted genotype across all parallel HCs is selected, until another better solution appears or the algorithm has run its course. In the figures below, the performance of a population with 5 and 100 climbers over 100 generations with 10% and 90% mutation rates are illustrated.

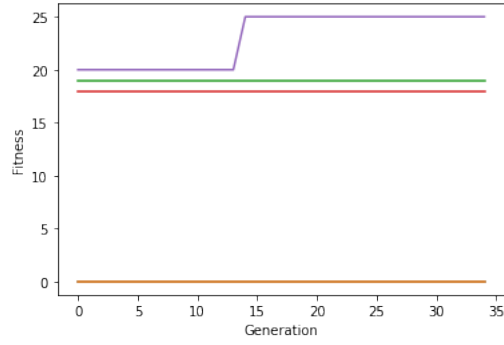


Figure 4: 5 climbers population with 10% mutation rate in 35 generations, Maximum fitness is 25.0, Average fitness is 12, Standard deviation of fitness is 10

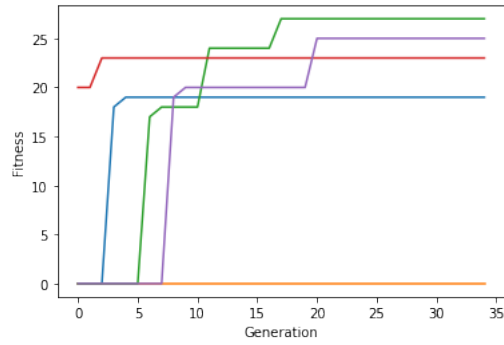


Figure 5: 5 climbers population with 90% mutation rate in 35 generations, Maximum fitness is 27.0, Average fitness is 15.65, Standard deviation of fitness is 10.47

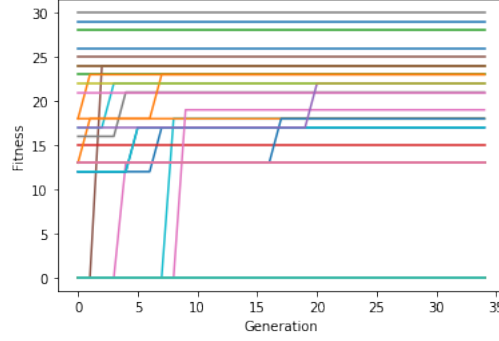


Figure 6: 100 climbers population with 10% mutation rate in 35 generations, Maximum fitness is 30.0, Average fitness is 5.56, Standard deviation of fitness is 9.44

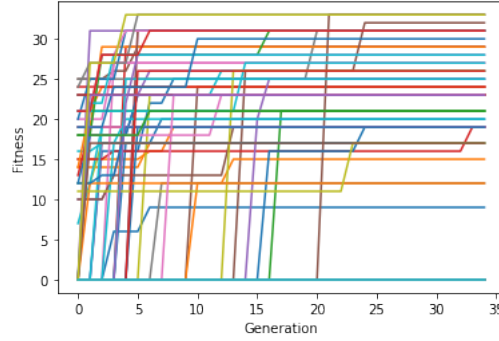


Figure 7: 100 climbers population with 90% mutation rate in 35 generations, Maximum fitness is 33.0, Average fitness is 13.7, Standard deviation of fitness is 11.98

As can be seen in the figures above, as the mutation rate increases, climbers have higher chance to find the global maximum (which is 33, for our knapsack problem and its default parameters, see the code for the default parameters). Also, in both 5 and 100 climbers population, increasing the mutation rate also increased the maximum fitness.

## 4 Full-Microbial Genetic Algorithm

Genetic algorithms are a type of evolutionary algorithm that is becoming increasingly prevalent in modern computing and optimization. The objective of GA algorithms was to imitate Darwin's idea of population evolution [4]. The Full-Microbial Genetic Algorithm (MGA) shows similarities with traditional

genetic algorithm, but it's simplified to illustrate horizontal gene transfer which simulates bacterial conjugation, a process in which bacteria transfer genetic material between cells by direct contact [1]. See the flowchart below (Figure 5)[3] for the steps of a GA algorithm.

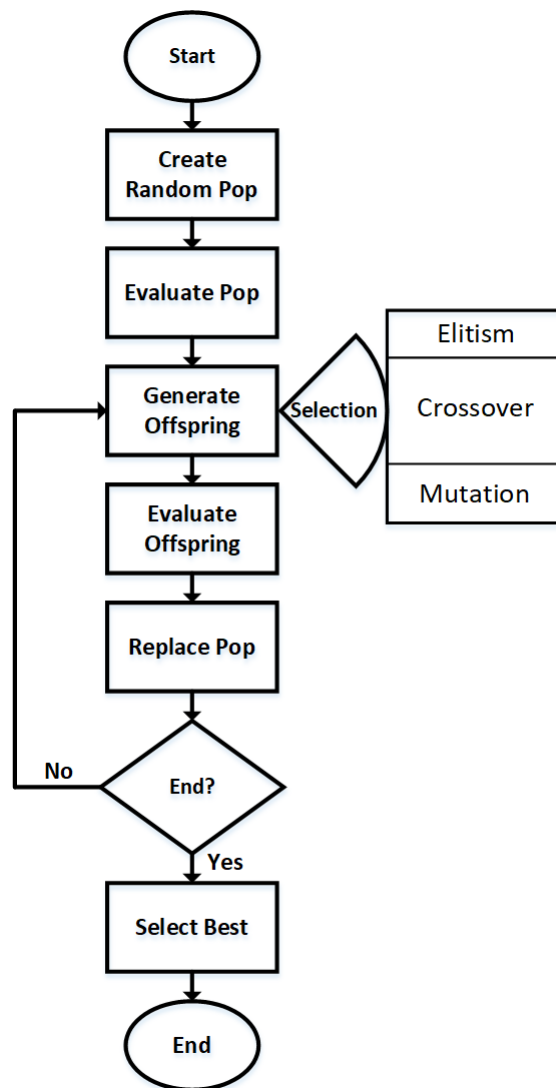


Figure 8: Genetic Algorithm Flowchart

## 4.1 Methods and Results

In order to perform heredity, variation and selection which are the prerequisites of evolution, the MGA employs selection, crossover, mutation, and evaluation. Crossover is a stochastic method for creating new solutions by combining genetic information from two genotypes. Crossover might well be considered as an infection in terms of the MGA and also asexual reproduction in bacteria, where the winning genotype transfers a component of itself to the loser while being untouched by the operation [1]. In the figures below, the average fitness of a population in each generation can be seen.

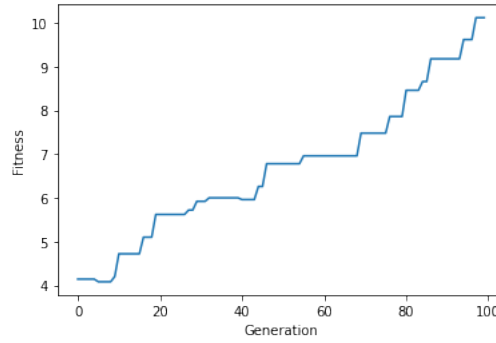


Figure 9: Average fitness of a MGA population. Mutation rate is 10%, Crossover rate is 50%, Population size is 50 and  $k = 2$ , Standard deviation of the fitness is 1.60

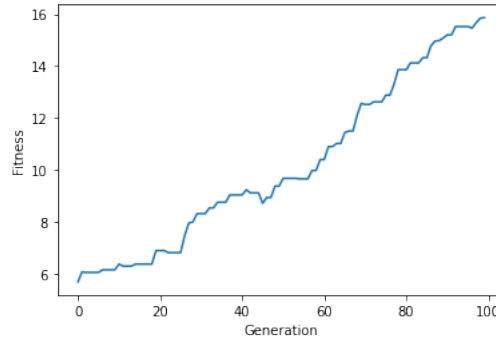


Figure 10: Average fitness of a MGA population. Mutation rate is 90%, Crossover rate is 50%, Population size is 50 and  $k = 2$ , Standard deviation of the fitness is 3.16



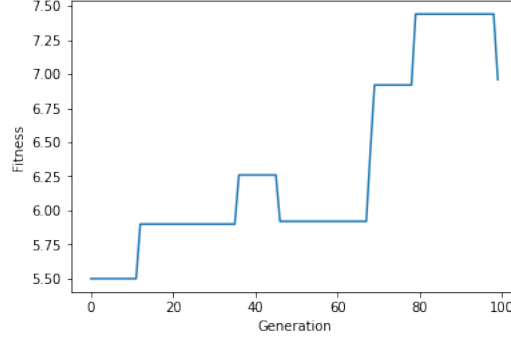


Figure 11: Average fitness of a MGA population. Mutation rate is 50%, Crossover rate is 10%, Population size is 50 and  $k = 2$ , Standard deviation of the fitness is 0.67

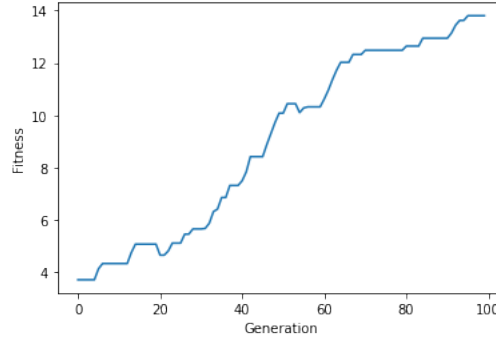


Figure 12: Average fitness of a MGA population. Mutation rate is 50%, Crossover rate is 90%, Population size is 50 and  $k = 2$ , Standard deviation of the fitness is 3.49

As can be seen in the Figure 9 and Figure 10, when keeping the crossover rate and  $k$  constant, lower mutation rate cause the change in the average fitness over the generations occur more drastically. However, when the same experiment is performed by keeping the mutation rate constant and changing the crossover rate; it can be seen that the rate of change of the average fitness is affected more by the change of crossover rate, compared to the change of mutation rate. Moreover, in both experiments, increasing the probability (either crossover or mutation) lead larger final fitness over generations.

## 5 Discussion

In terms of the impact of the mutation rate on the performance of the algorithm, the change in the fitness of the individuals in a hill-climbers population

is more noticeable. In a hill-climbers population with a lower mutation rate, individuals tend to get stuck in a local maxima more often (most individuals does not improve their fitness at all). In other words, since they mostly fail to improve their fitness, most individuals cannot reach the global maxima at all and once they started to mutate with higher rates, individuals tend to improve themselves more and reach the greater fitnesses. On the other hand, when keeping the other parameters constant, the impact of the change in the mutation rate on the average fitness of a population in a full microbial genetic algorithm is not as noticeable as in a hill-climber population. In fact, the change in the crossover rate has more significant impacts on the average fitness of the population than the mutation rate. The reason why the effects mutation rate on a hill-climber population are more noticeable is because, since hill-climbers cannot backtrack, mutation is a hill-climber population's only chance to improve themselves, find better fitness and explore new peaks in the gradient descent. However, for a full-microbial genetic algorithm population, there are more parameters that affect the genetic variation, as a matter of fact, some of those parameters have more significant impact on the performance than mutation rate.

## 6 Conclusion

The main advantage of full microbial genetic algorithm over hill-climbing is the ability to share the genetic information amongst a population. Within several runs, both MGA and HC might manage to reach to the global maxima, but due to the fact that the HC's are unable to backtrack and therefore take up a weaker position, the chance of HC's exploring new points and peaks is limited. Because it lacks some of the more complex evolutionary functions, the HC concentrates all of its emphasis on its mutation rate, which, as previously stated, may make a significant impact. If a low rate is set, the HC instance will become stagnated and will never be able to explore, relying on a lucky start to locate the maximum. An optimal mutation rate combined with a decent crossover rate offers more stable and better solutions for the MGA population.

## References

- [1] Inman Harvey. The microbial genetic algorithm. *Advances in Artificial Life. Darwin Meets von Neumann*, page 126–133, 2011.
- [2] S. Kameshwaran and Y. Narahari. Nonconvex piecewise linear knapsack problems. *European Journal of Operational Research*, 192(1):56–68, 2009.
- [3] D.G. Reina, T. Camp, A. Munjal, and S.L. Toral. Evolutionary deployment and local search-based movements of 0th responders in disaster scenarios. *Future Generation Computer Systems*, 88:61–78, 2018.
- [4] Gary Taubes. Computer design meets darwin. *Science*, 277(5334):1931–1932, 1997.