Two metaheuristic algorithms solving an optimization problem

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Abstract

This report contains the results of tow metaheristic algorithms solving an optimization problem. To have a better overview we will user tho diffent type of algorithms: a probabilistic one 'simulated annealing' and an evolutionary one a 'genetic algorithm'. Seeing the difference between these thwo we can make a better idea which one is bettwer.

1 Introduction

We already saw how these two types of algorithms work in the previous reports. Now, we can make them solve the same problem to see which one is better. The optimization problem to be solved is Asymetric Travelling Salesman Problem(ATSP). The algorithms are included in two different classes of metaheristic techniques: simulated annealing(SA) and genetic algorithm(GA). The main difference between these is that SA is a probalistic method and GA is inspired from evolution. 10 instances will be used of ATSP to see what results they give on different inputs: br17, ftv33, ftv47, ft53, ftv70 kro124, ftv170, rbg323, rbg358, rbg443. The temperature for SA is 100, and the number of iterations is 10000. The GA has a number of generation equal to 1000 and the population size is 400.

1.1 Motivation

Both methods are good in finding an approximate solution. But which one? We know from previous raports that GA algorithms have more flexibility and we can make them fit better on different problems. SA on the other hand is less flexible so we may expect that GA is better.

2 Methods

2.1 Simulated Annealing

We initialize a random member and start the exploration. The solution has to be represented as a permutation that represents a Hamiltonian cycle. To be easier for us to find

a neighbour, we will make a simple mutation with a codification based on OX Crossover like in our genetic algorithm. The start temperature is 100 and the stop temperature is 10^{-8} with a changind rate of 90%. The number of iteration is 10000.

The score is calculated as the cost of the Hamiltonian cycle. The fitness has the next formula: $fit(m) = 1/m.score \cdot 1000$.

The final result for all iterations is the smallest cost found.

2.2 Genetic Algorithm

When a member in the population is created the cromozome is randomly picked. This way we start with a population of 400 and for every generation we keep this number constant. Having the TSP, we have to find a way to encode a possible solution into a cromozome. A solution is represented as a permutation which is a cycle in the graph. So, a possible encoding can be the exact permutaion of the nodes. But, the problem is that the corssover and mutation will be difficult to make. A better approach is to user OX Crossover, so we can apply the operators easily. The mutation can be made by incrementing the current gene modulo $n-1-i$ where i is the current position of the gene.

There are three types of mutation. The first one is a greedy mutation and is applying only if the fitness is better. The mutations probability is 10% This operator is applied only for the first 10 members. The second one, is a mutation that is applied for the last 20 members and the increment number is randomly choose, so a part of the population will have more diversity. The last one is an adaptive normal mutation starting from 0.1% to 2%.

For every 10 generations, a normal mutation is applied to population just in case a wall is encountered.

The score is simply the cost of the cycle, and the fitness is calculated this way: $fit(m, minSc) = (pow(5.0, 1.0/(m.sc - minSc + 10) + 2) - 25) * 100$ where minSc, is the minimum score in the population.

The selection is made by keeping only the best members.

The number of generations is 1000.

3 Experimental Setup

Each algorithm will be tested with 10 instances of ATSP. These are: br17, ftv33, ftv47, ft53, ftv70, kro124, ftv170, rbg323, rbg358, rbg443.

Simulated Annealing

Number of iterations: 10000
Start temperature: 100 — 90%
End temperature: 10^{-8}
The sample size is 30.

Genetic Algorithm

Number of generations: 1000
Population size: 400
Simple mutation probability: $0.1\% - 2\%$
Greedy mutation probability: 10%
Strong mutation probability: 40%
The sample size is 30.

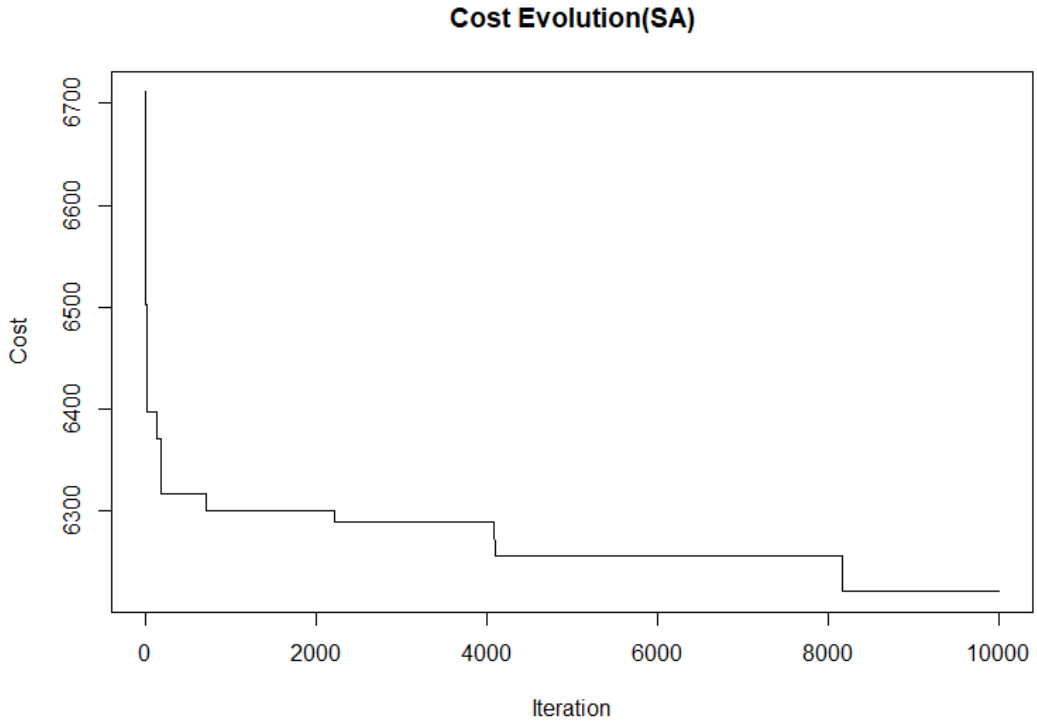
Processor : Intel i5 - 8265U with 4 phisical and 8 virtual cores
Compiler : TDM-GCC

4 Results and Comparisons

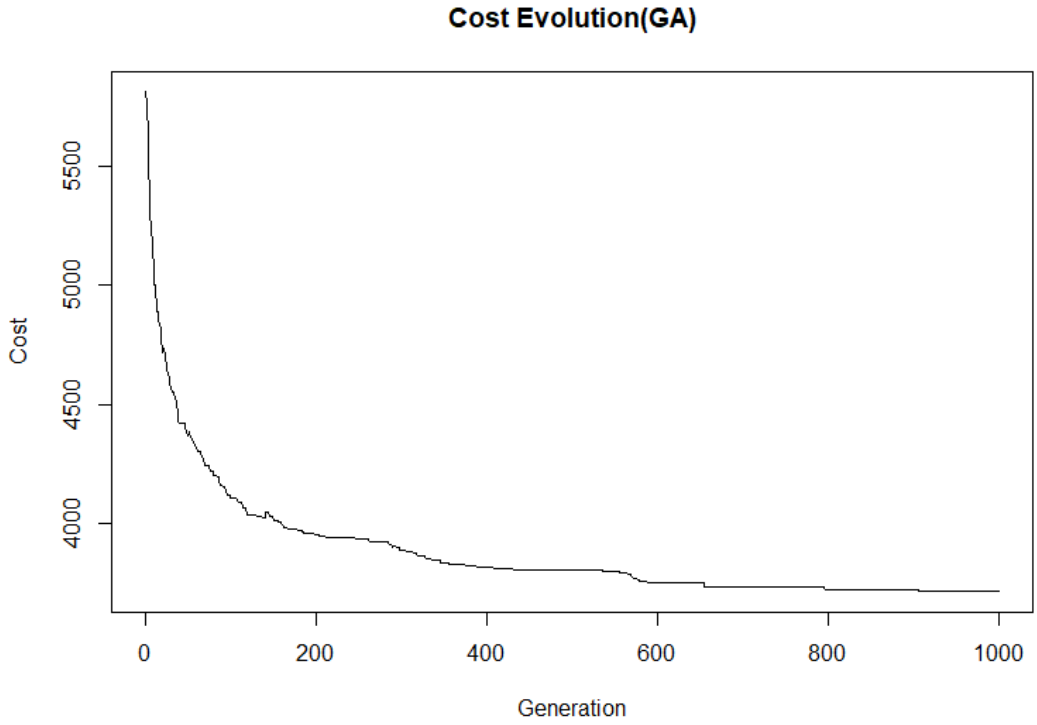
Simulated Annealing					
Instance	Expected	Best Value	Mean	StDev	Duration
br17	39	206	238	14.39907	6min 33s
ftv33	1286	4268	4396.3	73.17415	7min 23s
ftv47	1776	6913	6979.3	42.789	13min 06s
ft53	6905	24587	25356.6	461.0455	15min 16s
ftv70	1950	9367	9687.4	123.0558	18min 33s
kro124	36230	187001	194459	3228.695	26min 06s
ftv170	2755	24436	24776.7	163.0741	36min 18s
rbg323	1326	6152	6198.8	27.8799	1h 3m
rbg358	1163	6791	6925.3	58.248	1h 12m
rbg443	2720	8082	8169.26	41.859	1h 18m

Genetic Algorithm					
Instance	Expected	Best Value	Mean	StDev	Duration
br17	39	39	39.3	0.48304	7min 46s
ftv33	1286	1980	2041	26.969	8min 43s
ftv47	1776	3539	3554.1	47.7503	18min 9s
ft53	6905	15481	15495.7	10.1439	18min 32s
ftv70	1950	5114	5114	0	26m 23s
kro124	36230	102327	102327	0	42m 12s
ftv170	2755	14915	15184.3	294.581	1h 06
rbg323	1326	3448	3547.5	74.723	3h 14m
rbg358	1163	3839	3935.8	202.655	3h 43m
rbg443	2720	4956	5024	77.661	4h 46m

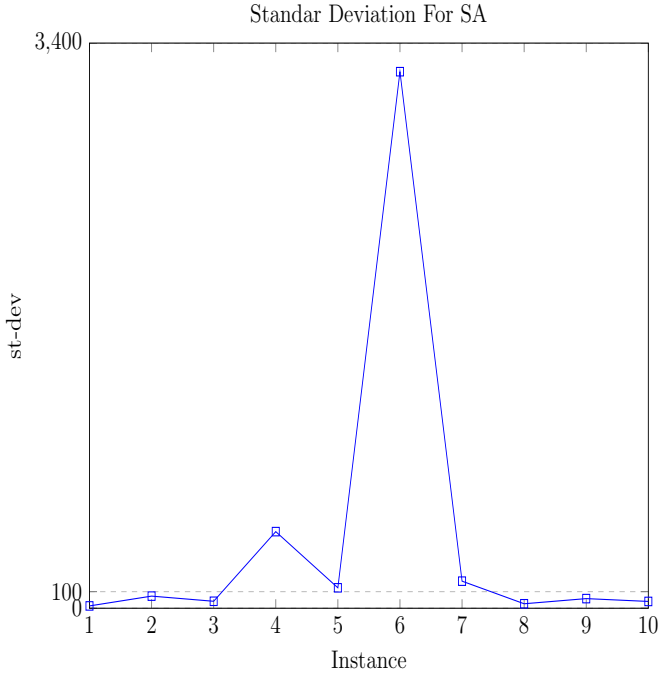
Below is the cost evolution of the rbg323 input in one runtime.

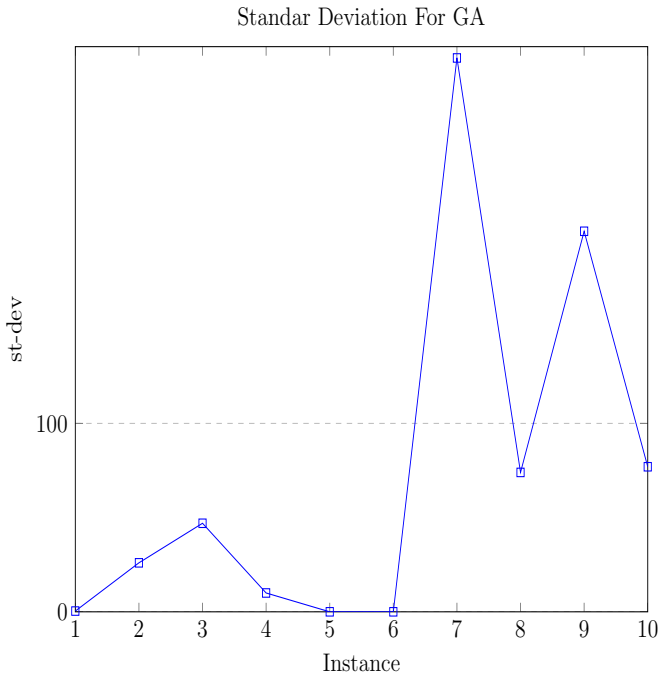


Unlike the GA graph, the values remain constant for many iterations before a suddenly decrease.



The values are evolving like an inverse function and it's starting to decrease less between 600 and 1000 generations.





Having these two graphs we can see what instances were 'harder' for each algorithm. For example, SA the kro124 instance is harder but for GA the instances are ftv170 and rbg358.

5 Conclusions

We study the results given by two metaheuristic algorithms: simulated snnealing and a genetic algorithm solving a common hard problem: travelling salesman problem. We see what values each one gives as well as their evolution in one runtime. As we expected from the beginning, GA is bettwer than SA because it have more operators giving us more flexibilty. But, SA is good as well because is easier to implement and we should use it as a tradeof when it comes to result precision.

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