

# **CS6380 AI Assignment 1 Report**

**Author Name: N K Sagar  
Reddy**

**Roll no: CS18B029**

**Department of Computer Science and  
Engineering**

**October 16, 2021**

# Contents

<b>1</b>	<b>Aim/objective</b>	<b>2</b>
<b>2</b>	<b>Introduction</b>	<b>2</b>
<b>3</b>	<b>Experimental details</b>	<b>2</b>
3.1	Entities Involved . . . . .	3
3.2	Additional Details . . . . .	3
<b>4</b>	<b>Input and Output Formats</b>	<b>3</b>
<b>5</b>	<b>Learnings</b>	<b>4</b>
<b>6</b>	<b>Conclusion</b>	<b>4</b>
<b>7</b>	<b>References</b>	<b>4</b>

# 1 Aim/objective

- The purpose of this project is to implement a heuristic(s) to solve the Traveling Salesman problem under a given time limit(300 seconds).

# 2 Introduction

- The TSP problem is an NP hard problem and can not be correctly solved given a large input.
- Hence there are multiple heuristics derived to partially solve the problem, which can be implemented.
- Some basic ones include best first search,greed tour, savings tour and more sophisticated ones are genetic algorithms,simulated annealing,ant colony optimization,etc.
- In this assignment, I have implemented genetic algorithm for TSP using cyclic crossover , Simulated Annealing and had to combine them in such a way that the set of results were optimal.)

# 3 Experimental details

- For the first 20 seconds, the Genetic algorithm runs and finds a temporary optimal path.
- The Genetic algorithm creates a population of size 2000, partitions it into 2 halves and randomly selects 2 paths for 2000 times and executes cyclic crossover to generate off-springs.
- Once we have 2000 off-springs we replace  $k = 1000$  worst species of the population with  $k$  best off-springs and with a very little probability(0.01) we mutate the offspring.
- This process is repeated for every generation until the time exceeds 20 seconds,when we take the best tour and give it as input for the Simulated Annealing algorithm.
- In Simulated Annealing , we generally start with a random tour but in this assignment I have started with the pre-computed best tour from genetic algorithm.
- Simulated Annealing uses a time varying parameter, temperature  $T$  which makes the method to look for better solutions(escaping the local optima) when the Temperature is high. We also use a cooling function to make sure temperature decreases and to find an optima after a certain instant.
- The Temperature parameter is what makes the algorithm escape the local optima, in the beginning we make random moves and gradually the randomness is decreased.
- For the Simulated Annealing algorithm I have used an initial temperature of 10000 and a cooling function  $f(T) = 0.999 * T$ .

### 3.1 Entities Involved

- $n = 2000$  , size of the population
- $k = 1000$  , number of off-springs replaced every generation
- $p = 0.01$  , probability that an offspring is mutated.
- $T = 10000$ , Initial temperature of Simulated Annealing
- $f(T) = 0.999 * T$  , Cooling function of the temperature

### 3.2 Additional Details

- The size of the population (size = 2000) has been selected in such a way so as to make sure the genetic algorithm runs for a significant amount of time ( $t = 20$  sec) and makes a significant impact even for larger graphs.
- I have used random sub-string selection in a tour and have reversed it in order to make a 2-edge perturbation to get the neighbour in the Simulated annealing algorithm.
- I have used the cooling function only if the neighbour's cost is lesser than the node's cost and the node is updated to be the neighbor. If the neighbor's cost is more and the node is updated, I have not varied the temperature as much exploration needs to be done and an optima needs to be obtained.

## 4 Input and Output Formats

- This section contains a sample input and output for the submission.
- The submission also contains the makefile and run ,makefile compiles the program, and use `./run < input.txt` format to execute the process.
- The program keeps outputting optimal tours as I have used an infinite loop and hence an interrupt must be used at the 300 sec time constraint mark.

Sample Input:

non euclidean

3

0 0

0 1

0 1.5

0 1 2

1 0 1

1 2.3 0

Sample Output:

0 1 2

0 1 2

0 1 2

.

.

.

## 5 Learnings

- Implementations of two important search methods for the Travelling salesman problem.
- Several kinds of crossovers were tested, and the parameters were hyper-tuned after many hit and trial attempts and some were optimized through intuition as well.

## 6 Conclusion

- We can understand the complexity of the traveling salesman problem through this assignment, the total possible tours are about factorial( $n-1$ ). Since that is a large number we develop heuristics to solve and search for the optima. This particular assignment helped me develop and understand 2 such heuristics for the traveling salesman problem.

## 7 References

1)<https://medium.com/opex-analytics/heuristic-algorithms-for-the-traveling-salesman-problem>

2)<http://160592857366.free.fr/joe/ebooks/ShareData/Heuristics%20for%20the%20Traveling%20Salesman%20Problem%20By%20Christian%20Nillson.pdf>