

# Solving the Traveling Salesman Problem: a multithreaded genetic approach

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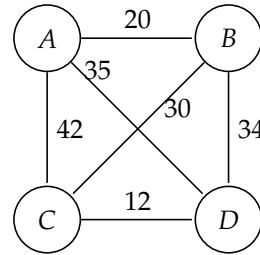
## Abstract

*The Traveling Salesman Problem is a one of the most common NP-Complete problems. As one of the most complicated problems in the history of Computer Science, there currently are no algorithms that can solve it in polynomial time. The problem's description is simple: given  $N$  cities that a salesman has to visit, find the order in which he must visit them to minimize the total distance traveled if he has to visit all cities once and come back to the first city after visiting the last one. For each number of cities  $N$ , the number of permutations of cities is  $N!$ , which makes the problem's size grow very fast. We approach the problem via genetic algorithms.*

## I. INTRODUCTION

**T**HE goal of this project is to obtain the optimal solution for the Traveling Salesman Problem, a problem that consists of a salesman and a set of cities which have to be visited. The salesman has to visit each city once and return to the same city after the last one has been visited.

Consider the following image. The problem lies in finding the shortest path visiting all vertices once. For example the path 1:A,C,D,B,A and 2:A,B,C,D,A visit all the vertices once, but path 1 has a length of 108 while path 2 has a length of 97.



The number of cities in this problem is 4, and there are  $4! = 24$  possible routes, which makes the problem exponentially complex as the number of cities grow.

We approach this problem with genetic

algorithms. We receive the number of cities and its geographic coordinates. We calculate the distance between every city ( $n \times n$ ), and a permutation of the  $N$  cities.

## II. MATHEMATICAL FORMULATION

For a given  $n \times n$  distance matrix  $C = (c_{ij})$ , find a cyclic permutation  $\pi$  of the set  $\{1, 2, \dots, n\}$  that minimizes the function

$$c(\pi) = \sum_{i=1}^n C_{i\pi(i)} \quad (1)$$

where  $c(\pi)$  is the length of the permutation  $\pi$ , computed through a distance metric. In our case, the metric is the Haversine function to calculate the distance between two fixed points on Earth given the latitude and longitude of each point.

## III. RELATED WORK

The traveling salesman problem was first considered mathematically in the 1930s by Merrill Floyd. In the 1950s and 1960s the problem became increasingly popular in scientific circles in Europe and the USA. Notable contributions were made by George Dantzig, Delbert Ray Fulkerson and Selmer M. Johnson; they expressed the problem as an integer linear problem and developed the cutting plane method.

In the following decades, the problem was studied by many researchers from mathematics, computer science, chemistry, physics and other sciences.

A chemist, V. Černý, created a thermodynamical approach to the Traveling Salesman Problem. He created a Monte Carlo algorithm to find approximate solutions of the TSP. The algorithm generates random permutations, with probability depending on the length of the corresponding route. Reasoning by analogy with statistical thermodynamics, we

use the probability given by the Boltzmann-Gibbs distribution. Using that method they could get very close to the optimal solution.

## IV. METHODS

### i. Input

The input to the program is a text file containing a line with an integer  $N$ , the number of cities the traveling salesman has to visit. The next  $N$  lines contain each two floating-point numbers corresponding to the latitude and longitude of the  $i$ -th city for  $i = 1, 2, \dots, N$ .

### ii. Output

The output of the program is the best generated chromosome in terms of the distance required to visit all cities and come back to the first one.

### iii. Algorithm

The algorithm used to solve this problem is as follows:

#### iii.1 Genetic Algorithm with Ordered Crossover

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##### Algorithm 1 Genetic Algorithm with ordered crossover

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1: procedure GENETIC ALGORITHM WITH ORDERED Crossover
2:   Set  $C$ , the total amount of chromosomes per generation
3:   Create  $C$  chromosomes each with a random permutation
4:   Set  $G$ , the total amount of chromosome generations
5:   for  $i \leftarrow 0, G - 1$  do
6:     Sort the array with the  $C$  chromosomes at generation  $i$ 
7:     Let the first  $\frac{C}{4}$  elite chromosomes live to the next generation
8:     Create  $\frac{3C}{4}$  child chromosomes from the  $\frac{C}{4}$  elite chromosomes
9:     Sort the array of chromosomes one last time
10:  return the first chromosome in the array

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#### iii.2 Pairing Schema

Use the following pairing schema to generate child chromosomes:

1. The  $i$ -th chromosome with the  $(i + 1)$ -th chromosome  $\left(1 \leq i \leq \frac{C}{4}\right)$

2. The  $i$ -th chromosome with the  $(i + 2)$ -th chromosome  $\left(1 \leq i \leq \frac{C}{4}\right)$
3. The  $i$ -th chromosome with the  $(i + 3)$ -th chromosome  $\left(1 \leq i \leq \frac{C}{4}\right)$

Note: all indices are taken modulo  $\frac{C}{4}$ .

### iii.3 Ordered Crossover

Perform the ordered crossover in the following fashion:

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#### Algorithm 2 Ordered crossover

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1: procedure ORDERED_CROSSOVER(permutation1, permutation2)
2:   Select a random range  $[i, j]$  of the first parent's permutation of cities
3:   Place those  $(j - i + 1)$  cities in the same range of the child permutation
4:   Get the remaining cities from the other parent's permutation in the
   same order in which they appear
5:   return the new permutation

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### iii.4 Multithreading

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#### Algorithm 3 Multithreading

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1: procedure MULTITHREADING
2:   Set  $P$ , the number of processors to be used.
3:   Create an array of  $P$  threads
4:   for  $i \leftarrow 0, P - 1$  do
5:     Start the  $i$ -th thread
6:     Let the  $i$ -th thread execute  $\text{threadSolution}()$ 
7:     Let the  $i$ -th thread call  $\text{solve}()$ 
8:     Let the  $i$ -th thread print its winning chromosome

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## iv. Time Complexity Analysis

ID	Operation	Complexity
1	Creating $C$ random chromosomes	$\mathcal{O}(C^2N)$
2	Sorting the array of $C$ chromosomes	$\mathcal{O}(C \log C)$
3	Creating $\frac{3C}{4}$ child chromosomes $G$ times	$\mathcal{O}(CNG)$
4	Multithreading	$\mathcal{O}(P)$

**Table 1:** Complexity Analysis of the Algorithm

As we set the amount of chromosome generations  $G$  as 10000 and the amount of chromosomes per generation  $C$  as 100 in all cases, we can see that operation 3 has the highest time complexity. Thus,  $\mathcal{O}(CNG)$  is the complexity of our algorithm, where  $C$ ,  $N$  and  $G$  are the amount of chromosomes per generation, the amount of cities in the input and the amount of generations, respectively.

## V. RESULTS

The following table shows a comparison across four sets of input ranging from 10 to 25 cities each.

Input size (cities)	CPU Time (s)	
	1 core	4 cores
10	17	8
15	19	10
20	22	14
25	25	13

**Table 2:** Performance comparison across four sets of input

## VI. DISCUSSION

We can see that in all four cases, the multithreaded approach is around twice as fast as the single-threaded one, taking into account that the former version of the program makes finds four solutions separately, while the latter only finds one. Nevertheless, both versions of the program always get the same solution in terms of the total distance of the permutation that was found, even if the permutation of one of the versions is a rotation of that of the other.

At first, we hadn't considered rotations of the same cycle as possibilities to reach the same output. However, after a few tests we discovered this, although we also discovered cases in which a two different permutations (none of which is a cycle of the other) reached the same total distance, thus being both valid solutions.

## VII. CONCLUSION

The Traveling Salesman Problem is a very interesting problem not only because it concerns daily tasks in the lives of lots of people, but also because of its difficult nature, yet simple description. Although we were a bit afraid to tackle such a problem, we think that, in the end, we developed a solution which could be good enough for general purposes. Nevertheless, if we were to use the program's results for scientific or more serious purposes, we would have to work on the logic of the child generation and the ordered crossover, while also thinking deeper in the amount of generations and the amount of chromosomes per generation.

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