

## 1 INTRODUCTION

The Traveling Salesman Problem (TSP) is an NP-Complete computational problem which has been studied extensively for several decades [2]. In this paper, techniques for obtaining/approximating the solution to the symmetric Traveling Salesman Problem are developed and compared. A branch-and-bound algorithm using a minimum spanning tree to inform a lower bound on sub-problems is presented; which, given enough time, produces an exact solution to the problem. The use of approximation algorithms proves more prudent for larger problems while sacrificing solution quality; a fact which motivated the development of a greedy local search algorithm which explores 1-exchange neighbors. In addition, two local search algorithms a 2-Opt Hill Climb and Simulated Annealing Algorithm are explored. These local search algorithms are ideal for finding low error solutions in limited time, although no performance bounds are guaranteed beyond what is expected from the Greedy Algorithms that initially seed them. The results derived showed that the local search algorithms were extremely adept at providing relatively good solutions even in the presence of large data sets, however they struggled to consistently return optimal solutions even for the smaller data-sets. Of the two local search algorithms explored, the simulated annealing algorithm provided clear benefits especially for larger data sets which contain a higher number of local optima which can frequently trap other algorithms in a non optimal neighborhood.

## PROBLEM DEFINITION

The symmetric traveling salesman optimization problem is formalized as follows:

Given a connected undirected graph  $G$  consisting of  $n$  nodes,  $\{v_0, \dots, v_{n-1}\}$ , with edge weights  $d_{ij}$  between nodes  $i$  and  $j$ . Find a Hamiltonian Cycle, a path  $P^*$  where each node has degree 2, with minimum weight.

In this paper, nodes in a 2 dimensional space were considered:  $v_i = \begin{bmatrix} v_{ix} \\ v_{iy} \end{bmatrix} \in \mathbb{R}^2 \quad \forall i \in [0, n-1]$

With edge weights calculated using the Euclidean distance:  $e_{ij} = \|v_i, v_j\|_2 = \sqrt{(v_{ix} - v_{jx})^2 + (v_{iy} - v_{jy})^2} \quad \forall i \neq j, i \in [0, n-1], j \in [0, n-1]$

The solution is an element in the set of vertex sequences which are Hamiltonian Cycles given by:

$$\mathcal{H} = \{(v_i)_{i=0}^{n-1} : v_0 = v_{n-1}, v_i \neq v_j \quad \forall i, j \in [0, n-1]\}$$

The symmetric TSP is given by following optimization problem:

$$P^* = \underset{(v_i)_{i=0}^{n-1} \in \mathcal{H}}{\operatorname{argmin}} \sum_{i=0}^{n-2} \|v_i, v_{i+1}\| + \|v_0, v_{n-1}\|$$

## RELATED WORK

The Traveling Salesman Problem has been a widely studied in the fields of graph theory and computational algorithms for almost 200 years. Long considered impossible, formal methods for restricting the problem space using approximation algorithms, similar to the 2MST approximation used here. With formal methods to approximate routes to given accuracies solving the problem for large data-sets became feasible in practice. With a good starting point for lower bounds, methods such as the Branch-and-Bound method used in this paper could now solve large data-sets by limiting the search space using the previously calculated lower bounds given by the approximation guarantee. Recently in 2011 researchers from Stanford and McGill Universities were able to improve upon the approximation algorithm developed by Nicos Christofides in 1976 which had defined performance bounds of at most 50% greater than the true optimal solution when they developed an approximation technique which improved upon Christofides' algorithm by four hundredths of a trillionth of a trillionth of a percent, a staggeringly small value in most other scenarios. Although this improvement was relatively minimal, it broke open a wall that existed in the world of computer science for over 35 years, proving that in practice a better solution was possible. With the rise of Quantum Computing improved results for the Traveling Salesman Problem will not only be made possible by improved algorithms, but also by the exponential increase in processing power that the Quantum Technology brings. With this technology on the rise we are poised to see major improvements in the runtime of NP-Hard algorithms such as the TSP problem which will be extremely important given the increase in the use of Big Data throughout virtually every industry. [1]

## ALGORITHMS

---

**Algorithm 1** BnB(  $\{v_0, \dots, v_{n-1}\}$  ): Find minimum cost Hamiltonian Cycle for euclidean distances

---

Data:  $\{v_0, \dots, v_{n-1}\}$  set of 2-D points

**for all** Unordered Pairs  $\{i, j\}$  **do**

    Construct edge  $e = (v_i, v_j, d_{ij})$

    Add  $e$  to list  $E$  of edges in increasing weight order:  $E = E \cup \{e\}$

**end for**

---

---

**Algorithm 2** 2-Opt\_HC(  $\{v_0, \dots, v_{n-1}\}$  ): Approximate the minimum cost Hamiltonian Cycle for euclidean distances using a Hill Climbing local search algorithm with 2-Opt exchange Neighborhood Creation

---

Data:  $\{v_0, \dots, v_{n-1}\}$  set of 2-D points  
**for all** Unordered Pairs  $\{i, j\}$  **do**  
    Construct edge  $e = (v_i, v_j, d_{ij})$   
    Add  $e$  to list  $E$  of edges in increasing weight order:  $E = E \cup \{e\}$   
**end for**  
**while** Unassigned nodes in  $v$  **do**  
    Assign Nodes to Route based on Greedy Nearest Neighbor implementation  
**end while**  
**for**  $i = 1$  to length(Route Matrix) **do**  
    **for**  $j = i + 1$  to length(Route Matrix) **do**  
        reverse array (route[i] to route[j]) and add it to newroute[i] to newroute[j]  
        **if** cost(newroute) < cost(route) **then**  
            route  $\leftarrow$  newroute  
        **end if**  
    **end for**  
**end for**

---



---

**Algorithm 3** Sim\_Anneal(  $\{v_0, \dots, v_{n-1}\}$  ): Approximate the minimum cost Hamiltonian Cycle for euclidean distances using a Hill Climbing local search algorithm with 2-Opt exchange Neighborhood Creation

---

Data:  $\{v_0, \dots, v_{n-1}\}$  set of 2-D points  
Current\_Route:  $\{c_0, \dots, c_{n-1}\}$  Set of Location Nodes denoting the current route for annealing  
Best\_Route:  $\{b_0, \dots, b_{n-1}\}$  Set of Location Nodes denoting the best route calculated so far for annealing  
Temperature:  $T$  Current Annealing Temperature used  
Cooling Ratio:  $\alpha$  Ratio used to cool the temperature as Simulated Annealing is run  
**for all** Unordered Pairs  $\{i, j\}$  **do**  
    Construct edge  $e = (v_i, v_j, d_{ij})$   
    Add  $e$  to list  $E$  of edges in increasing weight order:  $E = E \cup \{e\}$   
**end for**  
**while** Unassigned nodes in  $v$  **do**  
    Assign next node in route as the remaining node with the shortest distance between itself and the current node  
**end while**  
**while** Temperature  $\geq$  Ending Temperature **do**  
    Generate Random 2 Exchange Permutation  
    **if** Current Solution Cost > Neighbor Route Cost **then**  
        Update Current Route  
    **else**  
        Calculate Probability Using Current Temperature  
        **if** Probability > Randomly Generated Probability **then**  
            Update Current Route  
        **end if**  
    **end if**  
    **if** Current Cost  $\leq$  Best Cost **then**  
        Update Best Route  
    **end if**  
**end while**

---

## EMPIRICAL EVALUATION

### DISCUSSION

#### Branch-and-Bound

#### Approximation Algorithm

**Local Search** The 2-Opt Exchange and Simulated Annealing algorithms each performed relatively well for the majority of data-sets based

on algorithm run-time versus performance. For each algorithm instance, a short algorithm runtime was able to produce results which were in most cases within 5% of the optimal solution. Each algorithm setup used a simple Greedy approximation algorithm as the initial path for local search. When testing different initial paths, the Greedy path proved to provide a good mix between accuracy and execution time as a strong initial solution was presented quickly by the algorithm, allowing more local search iterations per time-frame. The Simulated Annealing provided a clear benefit over the 2-opt exchange hill climbing setup however, which was due mainly to the ability of the algorithm to consider a broader neighborhood than the strict neighborhood that the 2-Opt exchange argument considered. To more clearly identify this, the  $\alpha$  value was varied with a clear decrease in performance observed when the  $\alpha$  value was deviated far from the eventual selection of .98 in either direction. This  $\alpha$  value proved to have a reasonable affect on the annealing time-frame which allowed the algorithm to consider the entire search space thoroughly enough while still reaching a reasonable solution in a relatively short period of time. The 2-Opt algorithm struggled with a smaller neighborhood as only 2-Opt exchanges starting from all Greedy solutions were considered, and only those neighborhoods who provided a clear one to one improvement over the current best were used. The power of the Simulated Annealing setup becomes clear when looking at both of these local search algorithms as a similar 2-Opt Exchange neighborhood is considered in both, however the ability of Simulated Annealing to allow worse routes temporarily with the hope that they eventually lead to a more desirable solution proved to be key.

## CONCLUSION

## REFERENCES

- [1] ERICA KLARREICH. 2013. Computer Scientists Take Road Less Traveled. <https://www.quantamagazine.org/computer-scientists-find-new-shortcuts-to-traveling-salesman-problem-20130129/>
- [2] Gilbert Laporte. 1992. The traveling salesman problem: An overview of exact and approximate algorithms. *European Journal of Operational Research* 59, 2 (1992), 231–247. [https://doi.org/10.1016/0377-2217\(92\)90138-y](https://doi.org/10.1016/0377-2217(92)90138-y)