Evolutionary Computation - Assignment 1 Report

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Imports

In [2]:
```
import pandas as pd
import numpy as np
import networkx as nx
import matplotlib.pyplot as plt
import matplotlib.colors as mcolors
from matplotlib.cm import ScalarMappable
from matplotlib import MatplotlibDeprecationWarning
import warnings
```

Problem instance reading and cost scaling

In [3]:
```
dfTSPA = pd.read_csv('.\\TSPA.csv', sep=';', names=['X', 'Y', 'Cost'])
dfTSPB = pd.read_csv('.\\TSPB.csv', sep=';', names=['X', 'Y', 'Cost'])

min_cost_A = dfTSPA['Cost'].min()
max_cost_A = dfTSPA['Cost'].max()
dfTSPA['Normalized_Cost'] = (dfTSPA['Cost'] - min_cost_A) / (max_cost_A - min_cost_

min_cost_B = dfTSPB['Cost'].min()
max_cost_B = dfTSPB['Cost'].max()
dfTSPB['Normalized_Cost'] = (dfTSPB['Cost'] - min_cost_B) / (max_cost_B - min_cost_
```

Problem description

Problem

We were to find a cycle that consisted of exactly 50% of the available nodes, where each node had its own cost along with x and y coordinates. The objective function was a sum of node costs and distances (Euclidean) between each traveled node.

Solution implementation

We have implemented 4 methods to solve this problem. All of them were created in C++.

- **Random solution**

- **Input:**
  - `distance_matrix` : A symmetric matrix of distances between nodes
  - `nodes_cost` : An array of nodes cost
  - `nodes_in_cycle` : An integer defining the desired number of nodes in the cycle
- **Output:**
  - An array of `nodes_in_cycle` node IDs
- **Function:**

```
func generateRandomCycle():
    n = length(nodes_cost)
    cycle = [ add i for i from 0 to n-1 ]
    cycle = randomly_shuffle_array(cycle)
    return first nodes_in_cycle elements from cycle
```

- **Nearest Neighbour on Last Node**
  - **Input:**
    - `starting_node_id` - ID of the first node added to the cycle
    - `distance_matrix` - A symmetric matrix of distances between nodes
    - `nodes_cost` - An array of nodes cost
    - `nodes_in_cycle` - An integer defining the desired number of nodes in the cycle
  - **Output:**
    - An array of `nodes_in_cycle` nodes IDs
  - **Function:**

```
func generateNNLastCycle():
    n = length(nodes_cost)
    cycle = []
    node_visited = [ add false for i from 0 to n-1 ]
    current_node_id = starting_node_id
    cycle[0] = current_node_id
    node_visited[current_node_id] = true
    for i from 1 to nodes_in_cycle:
        best_increase_in_function = maximum_value_of_int_variable()
        best_node_to_add = None
        for j from 0 to n - 1:
            if not node_visited[j]:
                current_node_increase =
distance_matrix[current_node_id][j] + nodes_cost[j]
                if current_node_increase <
best_increase_in_function:
                    best_increase_in_function =
current_node_increase
                    best_node_to_add = j
```

```
            if best_node_to_add is set:
                node_visited[best_node_to_add] = true
                cycle[i] = best_node_to_add
                current_node_id = best_node_to_add
        return cycle
```

- **Nearest Neighbour on All Nodes**
  - **Input:**
    - `starting_node_id` - ID of the first node added to the cycle
    - `distance_matrix` - A symmetric matrix of distances between nodes
    - `nodes_cost` - An array of nodes cost
    - `nodes_in_cycle` - An integer defining the desired number of nodes in the cycle
  - **Output:**
    - An array of `nodes_in_cycle` nodes IDs
  - **Function:**

```
func generateNNAddAnywhereCycle():
    n = length(nodes_cost)
    cycle = []
    node_visited = [ add false for i from 0 to n-1 ]
    current_node_id = starting_node_id
    cycle[0] = current_node_id
    node_visited[current_node_id] = true
    for i from 1 to nodes_in_cycle:
        best_position_to_put_node = []
        best_increase_in_function_for_node = [ add
maximum_value_of_int_variable() for i from 0 to n-1 ]
        for j from 0 to n-1: // Try adding node at the end
            if not node_visited[j]:
                current_increase_in_function =
distance_matrix[last_element(cycle)][j] + nodes_cost[j]
                best_increase_in_function_for_node[j] =
current_increase_in_function
                best_position_to_put_node[j] = length(cycle)
        for j from 0 to n-1: // Try adding node at the beginning
            if not node_visited[j]:
                current_increase_in_function =
distance_matrix[first_element(cycle)][j] + nodes_cost[j]
            if current_increase_in_function <
best_increase_in_function_for_node[j]:
                best_increase_in_function_for_node[j] =
current_increase_in_function
                best_position_to_put_node[j] = 0
        for j from 0 to n-1: // Try all other possibilities
            if not visited[j]:
                for position_in_cycle from 1 to length(cycle) - 1:
                    left_n = cycle[ position_in_cycle -1 ]
```

```
                    right_n = cycle[ position_in_cycle ]
                    current_increase_in_function =
distance_matrix[j][left_n] + distance_matrix[j][right_n] +
nodes_cost[j] - distance_matrix[left_n][right_n]
                        if current_increase_in_function <
best_increase_in_function_for_node[j]:
                            best_increase_in_function_for_node[j] =
current_increase_in_function
                            best_position_to_put_node[j] =
position_in_cycle
        best_node_to_add = arg_min(best_increase_in_function)
        best_position = best_position_to_put_node[best_node_to_add]
        cycle.insert(value = best_node_to_add, at = best_position)
        node_visited[best_node_to_add] = true
    return cycle
```

- **Greedy Cycle**

  - **Input:**

    - `starting_node_id` - ID of the first node added to the cycle
    - `distance_matrix` - A symmetric matrix of distances between nodes
    - `nodes_cost` - An array of nodes cost
    - `nodes_in_cycle` - An integer defining the desired number of nodes in the cycle

  - **Output:**

    - An array of `nodes_in_cycle` nodes IDs

  - **Function:**

```
func generateGreedyCycle():
    n = length(nodes_cost)
    cycle = []
    node_visited = [ add false for i from 0 to n-1 ]
    current_node_id = starting_node_id
    cycle[0] = current_node_id
    node_visited[current_node_id] = true
    for i from 1 to nodes_in_cycle:
        best_position_to_put_node = []
        best_increase_in_function_for_node = [ add
maximum_value_of_int_variable() for i from 0 to n-1 ]
        for j from 0 to n-1: // Try adding node at the beginning/
end
            if not node_visited[j]:
                current_increase_in_function =
distance_matrix[last_element(cycle)][j] + nodes_cost[j]
                if length(cycle) > 1:
                    current_increase_in_function +=
distance_matrix[first_element(cycle)][j]
                best_increase_in_function_for_node[j] =
current_increase_in_function
```

```
                best_position_to_put_node[j] = length(cycle)
        for j from 0 to n-1: // Try all other possibilities
            if not visited[j]:
                for position_in_cycle from 1 to length(cycle) - 1:
                    left_n = cycle[ position_in_cycle -1 ]
                    right_n = cycle[ position_in_cycle ]
                    current_increase_in_function =
distance_matrix[j][left_n] + distance_matrix[j][right_n] +
nodes_cost[j] - distance_matrix[left_n][right_n]
                        if current_increase_in_function <
best_increase_in_function_for_node[j]:
                            best_increase_in_function_for_node[j] =
current_increase_in_function
                            best_position_to_put_node[j] =
position_in_cycle
        best_node_to_add = arg_min(best_increase_in_function)
        best_position = best_position_to_put_node[best_node_to_add]
        cycle.insert(value = best_node_to_add, at = best_position)
        node_visited[best_node_to_add] = true
    return cycle
```

Presenting the results

Results presented as minimum, average and maximum of objective function

Presented in a table below, each method and each problem instance is shown.

In [4]:
```
file_paths = ['.\\TSPAGreedy.csv', '.\\TSPANNAll.csv', '.\\TSPANNLast.csv', '.\\TSP
methods = ['TSPA Greedy Cycle', 'TSPA NN on all vertices', 'TSPA NN on last node',
results = []
best_solutions = []

for file_path, method in zip(file_paths, methods):
    df = pd.read_csv(file_path)
    costs = df.iloc[:, -1]
    minimum = costs.min()
    maximum = costs.max()
    mean = round(costs.mean(), 2)
    results.append([minimum, mean, maximum])

    min_sol = df.loc[costs.idxmin()][:-1].to_list()
    best_solutions.append(min_sol)

result_df = pd.DataFrame(results, columns=['Minimum', 'Average', 'Maximum'], index=
result_df
```

Out[4]:

	Minimum	Average	Maximum
TSPA Greedy Cycle	71237	73036.23	75002
TSPA NN on all vertices	71227	73293.75	76036
TSPA NN on last node	83182	85110.16	89433
TSPA Random	236302	263481.34	293567
TSPB Greedy Cycle	48898	51852.88	58531
TSPB NN on all vertices	44377	47444.68	53019
TSPB NN on last node	52319	54385.49	59030
TSPB Random	188701	213568.36	239495

Aditional information regarding the running time of each method (in milliseconds).

In [19]:

```
methods_for_times = ['Random', 'NN on last node', 'NN on all vertices', 'Greedy Cyc
times_df = pd.read_csv('times.csv', header=None, names=methods_for_times)
times_df = times_df.drop(columns=['Extra'])
times_stats = []
for method in methods_for_times[:-1]:
    min_value = times_df[method].min()
    max_value = times_df[method].max()
    avg_value = times_df[method].mean()
    times_stats.append([min_value, avg_value, max_value])
stats_time_df = pd.DataFrame(times_stats, columns=['Minimum', 'Average', 'Maximum']
stats_time_df
```

Out[19]:

	Minimum	Average	Maximum
Random	0.0062	0.007379	0.0411
NN on last node	0.3182	0.359385	0.8055
NN on all vertices	11.2167	11.826113	14.0679
Greedy Cycle	11.5659	12.360844	14.9002

Visualization of the best path for each method

Additionally, a list of node indices is presented.

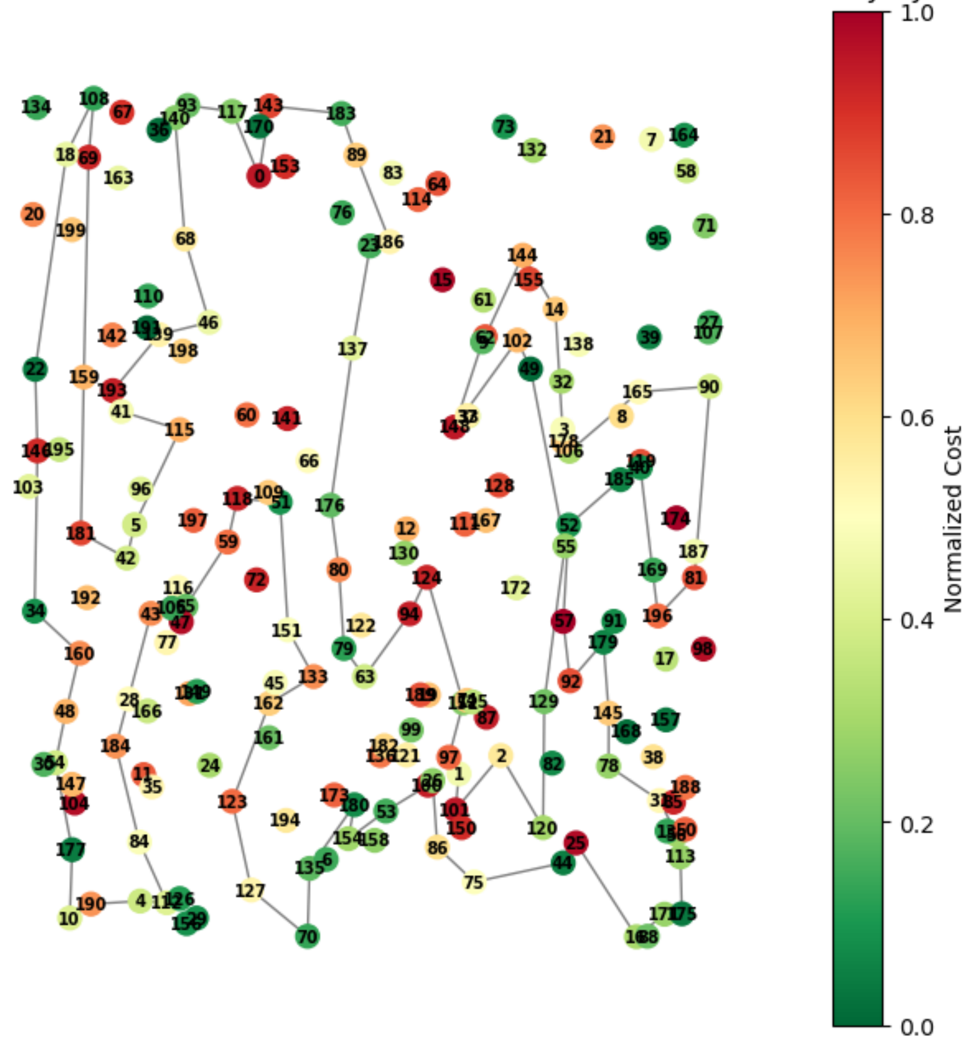
In [21]:

```
warnings.filterwarnings("ignore", category=MatplotlibDeprecationWarning)
cmap = plt.cm.get_cmap('RdYlGn_r')

for count, method in enumerate(methods):
    print(method)
    print(best_solutions[count])

    G = nx.Graph()
```

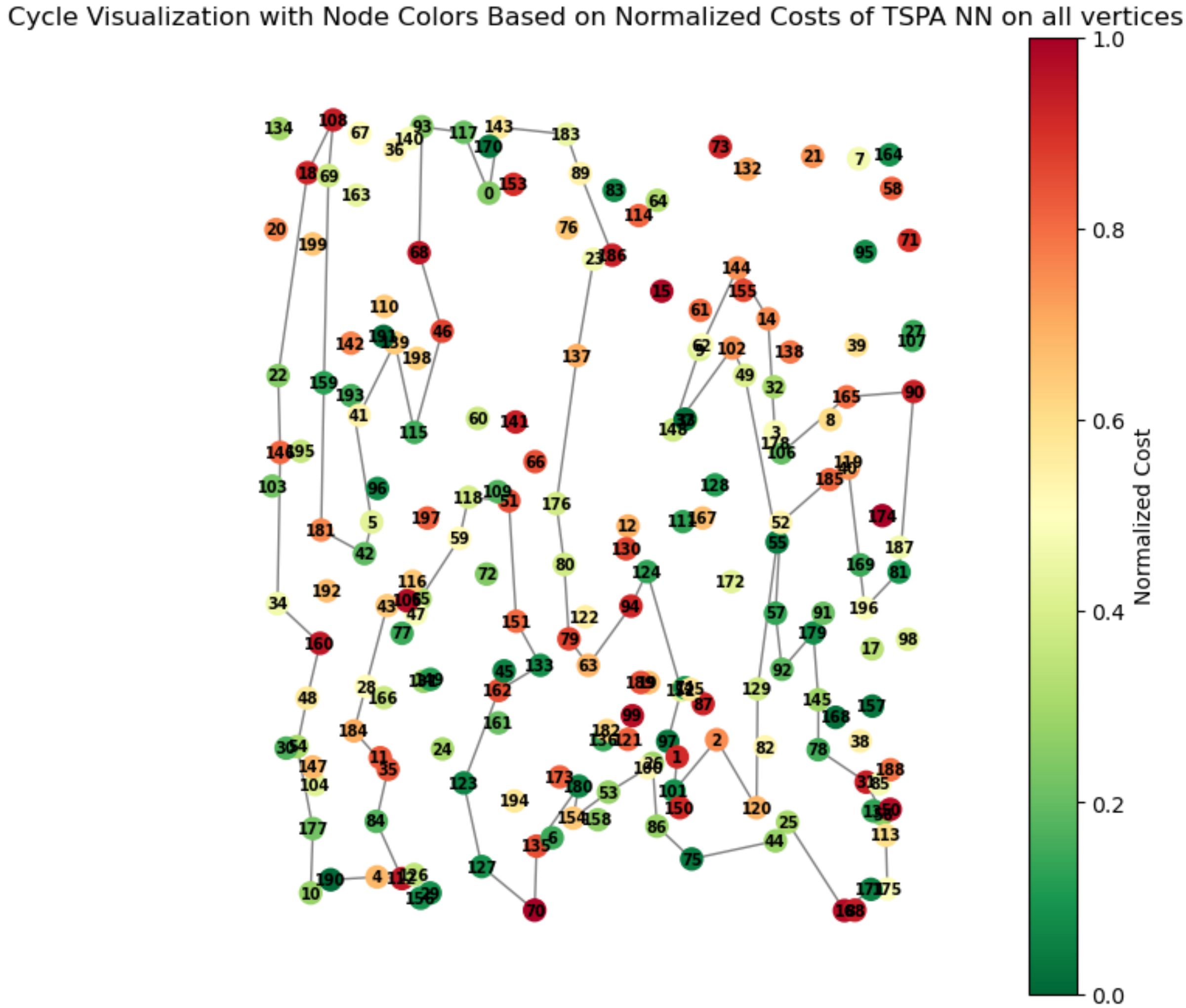
```
    positions = {}

    if count < 4:
        for idx in best_solutions[count]:
            G.add_node(idx, size=dfTSPA.loc[idx, 'Normalized_Cost'])
            positions[idx] = (dfTSPA.loc[idx, 'X'], dfTSPA.loc[idx, 'Y'])

        for idx in [i for i in range(0,200) if i not in best_solutions[count]]:
            G.add_node(idx, size=dfTSPA.loc[idx, 'Normalized_Cost'])
            positions[idx] = (dfTSPA.loc[idx, 'X'], dfTSPA.loc[idx, 'Y'])

        for i in range(len(best_solutions[count]) - 1):
            G.add_edge(best_solutions[count][i], best_solutions[count][i + 1])
        G.add_edge(best_solutions[count][-1], best_solutions[count][0])


        normalized_costs = dfTSPA['Normalized_Cost']
        norm = mcolors.Normalize(vmin=normalized_costs.min(), vmax=normalized_costs
        node_colors = [cmap(norm(dfTSPA.loc[idx, 'Normalized_Cost'])) for idx in ra

    else:
        for idx in best_solutions[count]:
            G.add_node(idx, size=dfTSPB.loc[idx, 'Normalized_Cost'])
            positions[idx] = (dfTSPB.loc[idx, 'X'], dfTSPB.loc[idx, 'Y'])

        for idx in [i for i in range(0,200) if i not in best_solutions[count]]:
            G.add_node(idx, size=dfTSPB.loc[idx, 'Normalized_Cost'])
            positions[idx] = (dfTSPB.loc[idx, 'X'], dfTSPB.loc[idx, 'Y'])

        for i in range(len(best_solutions[count]) - 1):
            G.add_edge(best_solutions[count][i], best_solutions[count][i + 1])
        G.add_edge(best_solutions[count][-1], best_solutions[count][0])

        normalized_costs = dfTSPB['Normalized_Cost']
        norm = mcolors.Normalize(vmin=normalized_costs.min(), vmax=normalized_costs
        node_colors = [cmap(norm(dfTSPB.loc[idx, 'Normalized_Cost'])) for idx in ra

    fig, ax = plt.subplots(figsize=(8, 8))  # Explicitly define the axes
    nx.draw(G, pos=positions, with_labels=True, node_color=node_colors, node_size=1

    # Create a ScalarMappable for the colorbar
    sm = ScalarMappable(cmap=cmap, norm=norm)
    sm.set_array([])  # Required for colorbar

    # Add colorbar to the plot
    cbar = plt.colorbar(sm, ax=ax)
    cbar.set_label('Normalized Cost')

    plt.title(f"Cycle Visualization with Node Colors Based on Normalized Costs of {
    plt.show()
```

TSPA Greedy Cycle
[117, 93, 140, 68, 46, 139, 193, 41, 115, 5, 42, 181, 159, 69, 108, 18, 22, 146, 34,
160, 48, 54, 177, 10, 190, 4, 112, 84, 184, 43, 116, 65, 59, 118, 51, 151, 133, 162,
123, 127, 70, 135, 180, 154, 53, 100, 26, 86, 75, 44, 25, 16, 171, 175, 113, 56, 31,
78, 145, 179, 92, 57, 52, 185, 119, 40, 196, 81, 90, 165, 106, 178, 14, 144, 62, 9,
148, 102, 49, 55, 129, 120, 2, 101, 1, 97, 152, 124, 94, 63, 79, 80, 176, 137, 23, 1
86, 89, 183, 143, 0]

Cycle Visualization with Node Colors Based on Normalized Costs of TSPA Greedy Cycle

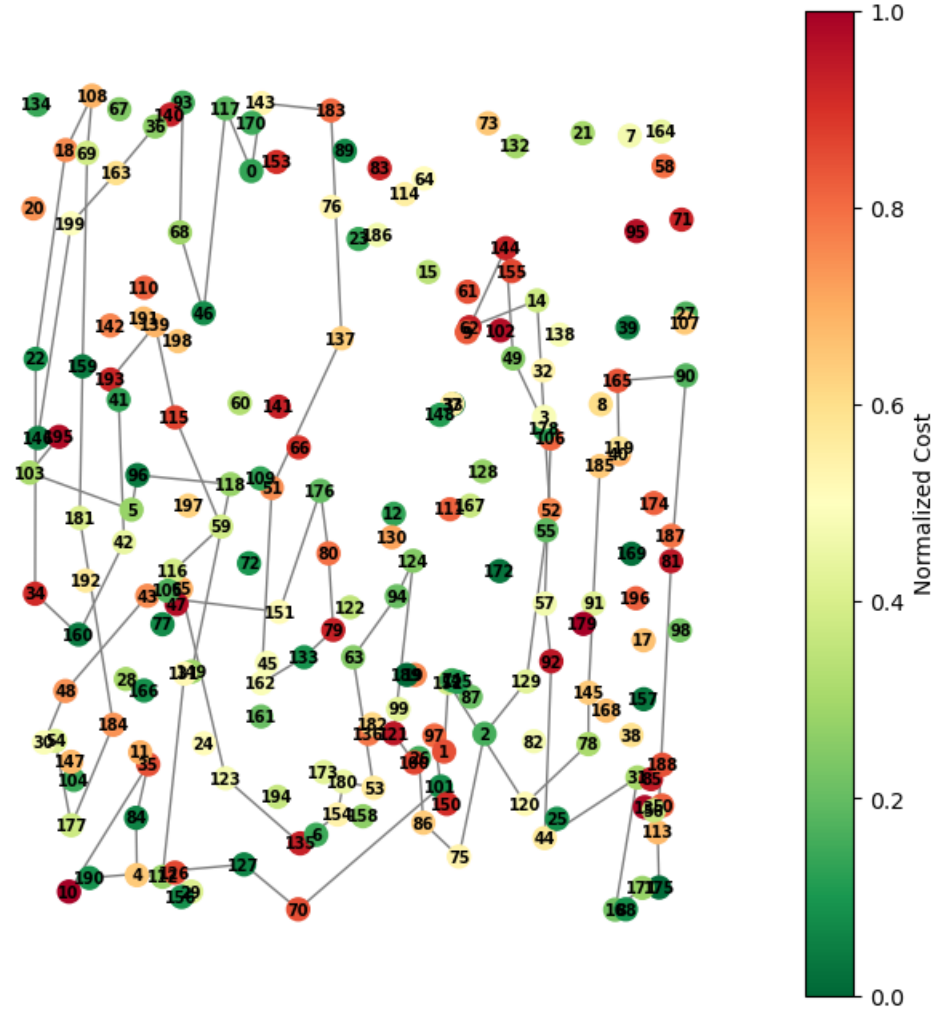


TSPA NN on all vertices
[93, 117, 0, 143, 183, 89, 186, 23, 137, 176, 80, 79, 63, 94, 124, 152, 97, 1, 101,
2, 120, 129, 55, 49, 102, 148, 9, 62, 144, 14, 178, 106, 165, 90, 81, 196, 40, 119,
185, 52, 57, 92, 179, 145, 78, 31, 56, 113, 175, 171, 16, 25, 44, 75, 86, 26, 100, 5
3, 154, 180, 135, 70, 127, 123, 162, 133, 151, 51, 118, 59, 65, 116, 43, 184, 35, 84
, 112, 4, 190, 10, 177, 54, 48, 160, 34, 146, 22, 18, 108, 69, 159, 181, 42, 5, 193,
41, 139, 115, 46, 68]



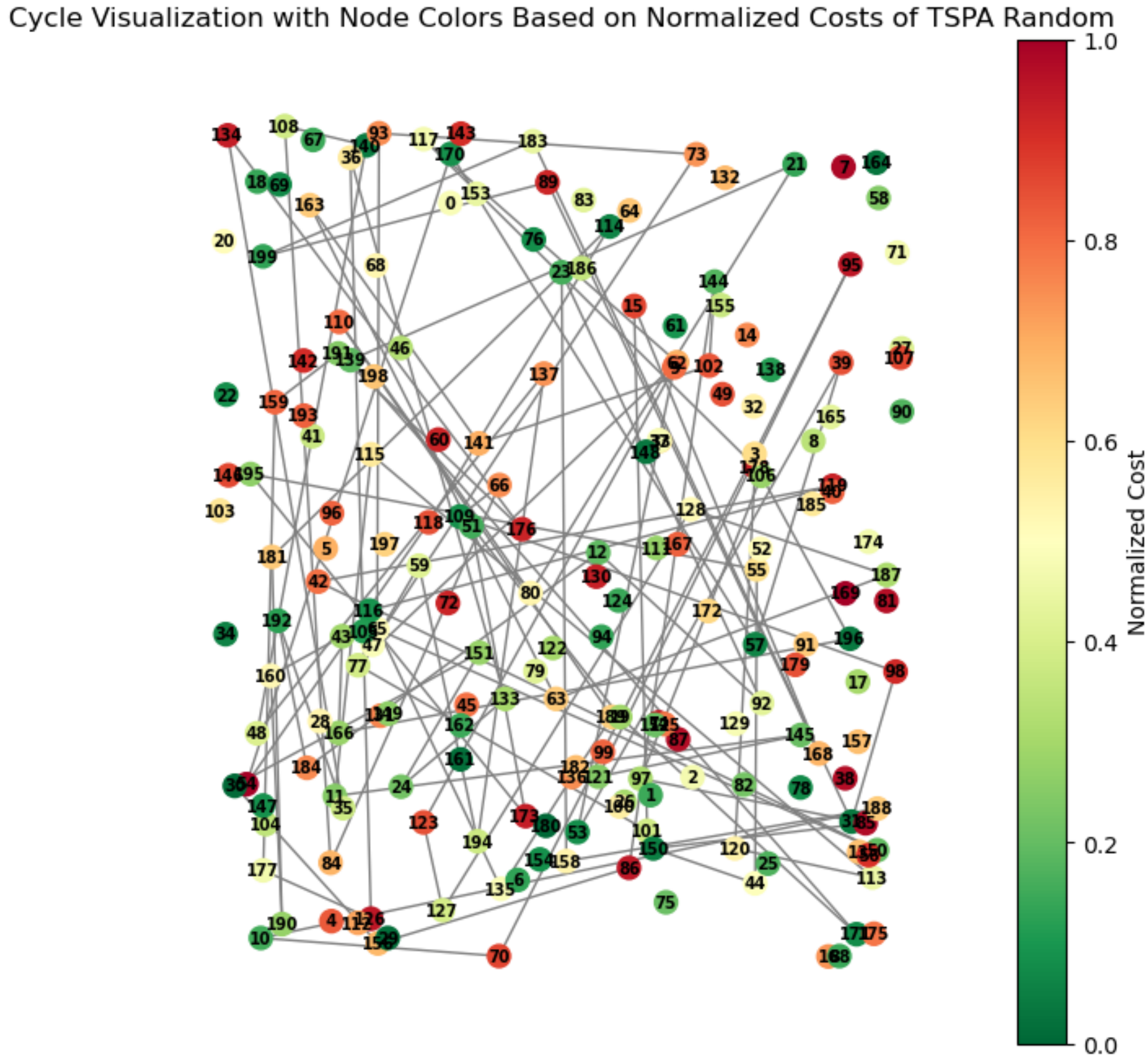

```
TSPA NN on last node
[124, 94, 63, 53, 180, 154, 135, 123, 65, 116, 59, 115, 139, 193, 41, 42, 160, 34, 2
2, 18, 108, 69, 159, 181, 184, 177, 54, 30, 48, 43, 151, 176, 80, 79, 133, 162, 51,
137, 183, 143, 0, 117, 46, 68, 93, 140, 36, 163, 199, 146, 195, 103, 5, 96, 118, 149
, 131, 112, 4, 84, 35, 10, 190, 127, 70, 101, 97, 1, 152, 120, 78, 145, 185, 40, 165
, 90, 81, 113, 175, 171, 16, 31, 44, 92, 57, 106, 49, 144, 62, 14, 178, 52, 55, 129,
2, 75, 86, 26, 100, 121]
```

Cycle Visualization with Node Colors Based on Normalized Costs of TSPA NN on last node

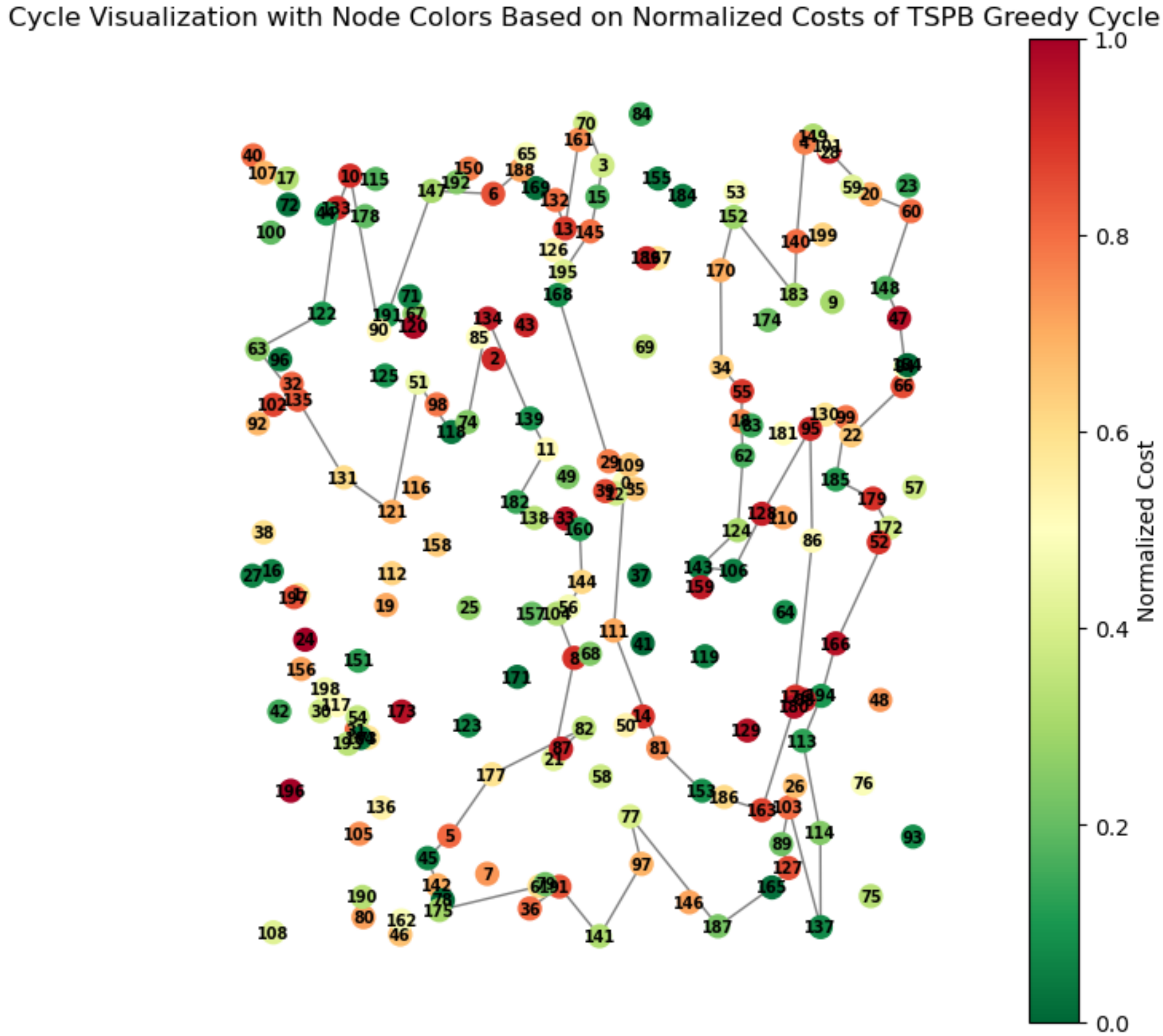


TSPA Random

[121, 145, 11, 115, 113, 120, 178, 117, 62, 77, 101, 15, 168, 89, 199, 183, 31, 98, 109, 66, 84, 108, 140, 48, 137, 194, 59, 47, 73, 93, 65, 50, 42, 119, 116, 135, 136, 189, 110, 80, 21, 139, 171, 19, 51, 173, 195, 55, 44, 150, 85, 97, 106, 196, 166, 43, 160, 190, 181, 114, 118, 54, 170, 57, 39, 53, 9, 123, 127, 128, 187, 63, 163, 141, 102, 144, 86, 156, 30, 151, 24, 133, 36, 126, 177, 159, 191, 176, 134, 35, 192, 184, 12, 92, 23, 158, 188, 10, 70, 95]

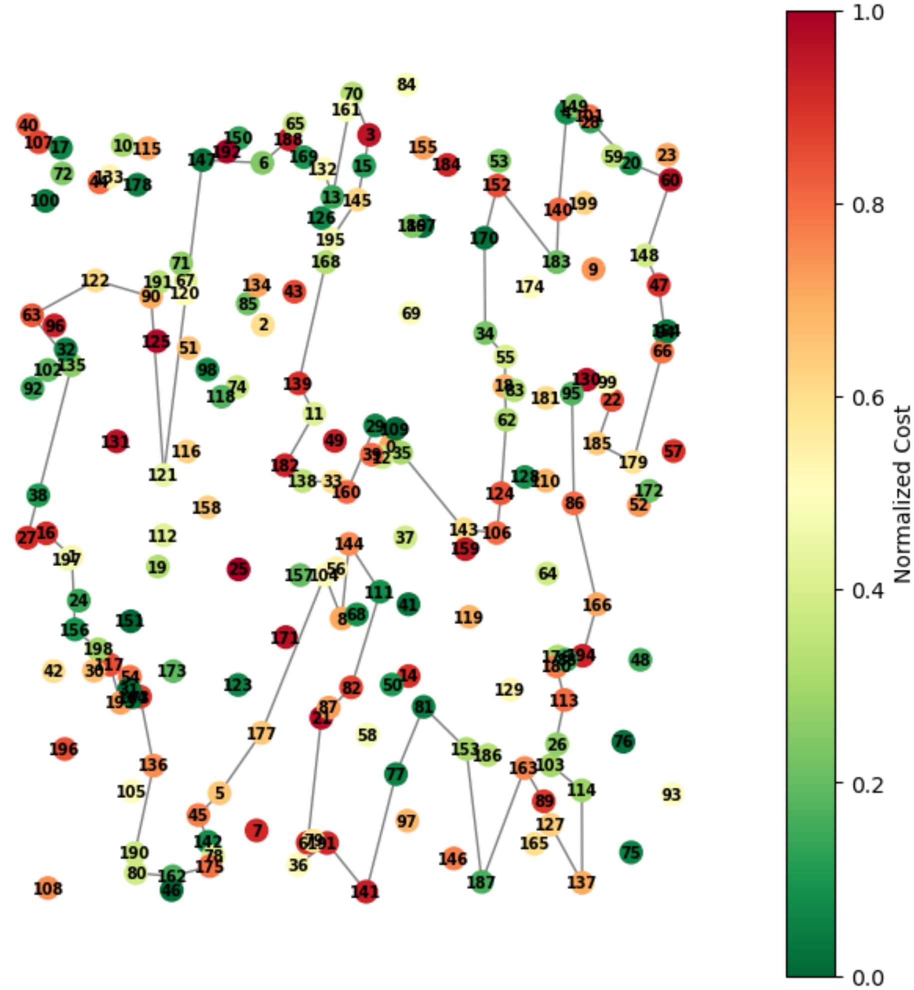


TSPB Greedy Cycle
[118, 74, 134, 139, 11, 182, 138, 33, 160, 144, 56, 104, 8, 21, 87, 82, 177, 5, 45,
142, 78, 175, 61, 36, 91, 141, 97, 77, 187, 165, 127, 89, 103, 137, 114, 113, 194, 1
66, 172, 179, 185, 99, 130, 22, 66, 94, 47, 148, 60, 20, 28, 149, 4, 140, 183, 152,
170, 34, 55, 18, 62, 124, 143, 106, 128, 95, 86, 176, 180, 163, 153, 81, 111, 0, 35,
109, 29, 168, 195, 145, 15, 3, 70, 161, 13, 132, 169, 188, 6, 147, 191, 90, 10, 133,
122, 63, 135, 131, 121, 51]

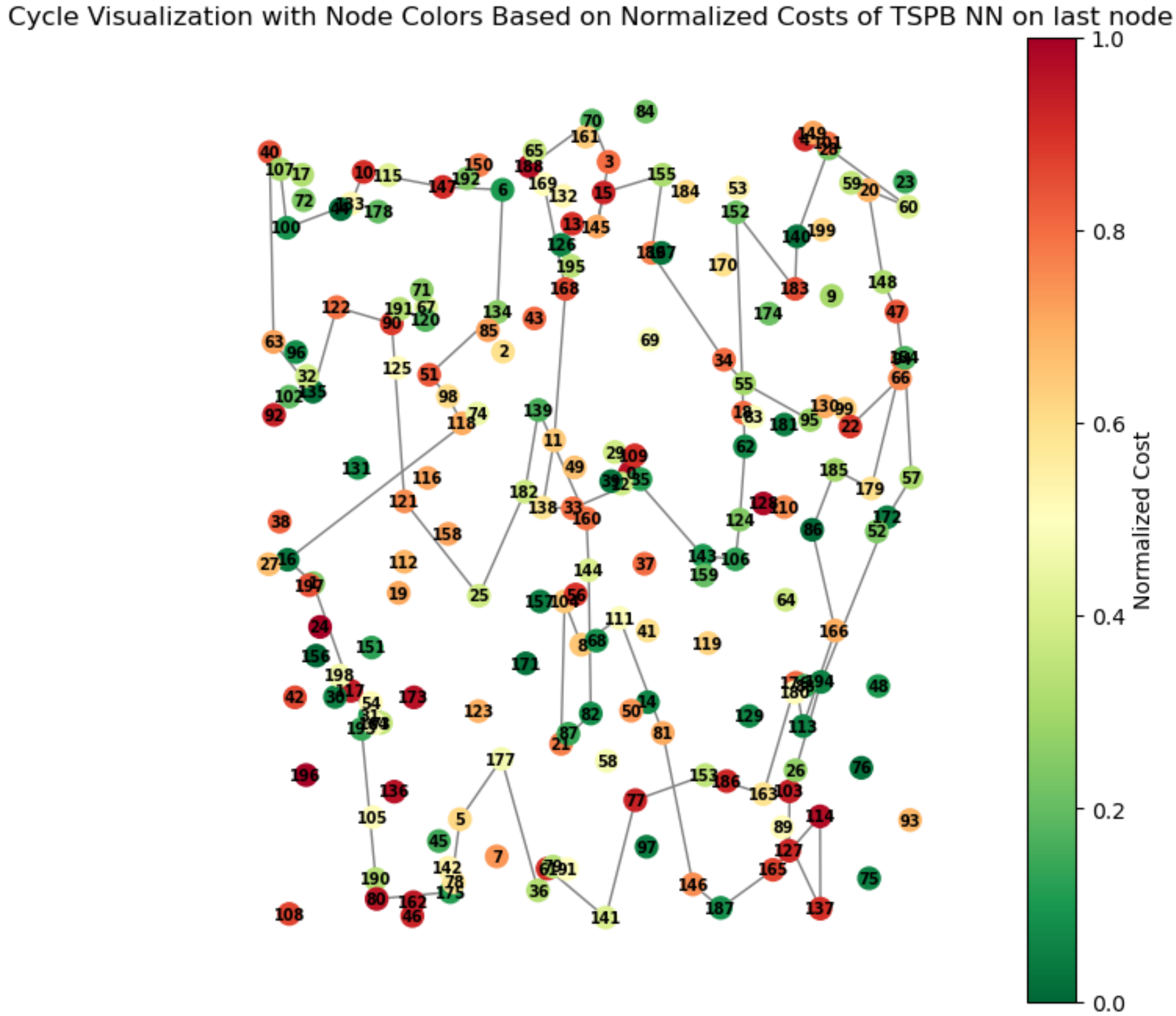



```
TSPB NN on all vertices
[147, 6, 188, 169, 132, 13, 70, 3, 15, 145, 195, 168, 139, 11, 182, 138, 33, 160, 29
, 0, 109, 35, 143, 106, 124, 62, 18, 55, 34, 170, 152, 183, 140, 4, 149, 28, 20, 60,
148, 47, 94, 66, 179, 185, 22, 99, 130, 95, 86, 166, 194, 176, 180, 113, 103, 114, 1
37, 127, 89, 163, 187, 153, 81, 77, 141, 91, 36, 61, 21, 82, 111, 144, 8, 104, 177,
5, 45, 142, 78, 175, 162, 80, 190, 136, 73, 54, 31, 193, 117, 198, 156, 1, 16, 27, 3
8, 135, 63, 122, 90, 121]
```

Cycle Visualization with Node Colors Based on Normalized Costs of TSPB NN on all vertices

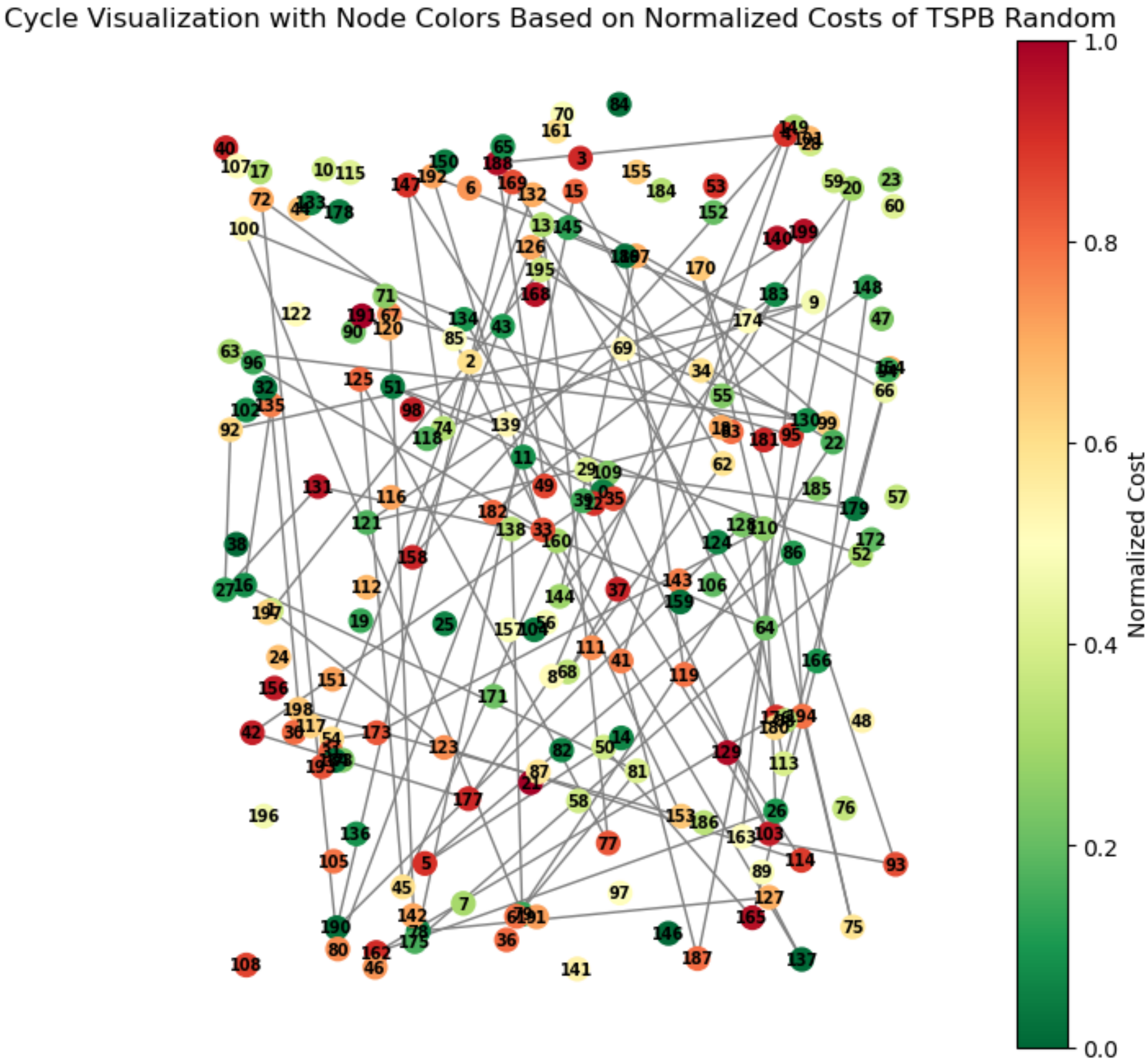


TSPB NN on last node
[16, 1, 117, 31, 54, 193, 190, 80, 175, 5, 177, 36, 61, 141, 77, 153, 163, 176, 113, 166, 86, 185, 179, 94, 47, 148, 20, 60, 28, 140, 183, 152, 18, 62, 124, 106, 143, 0, 29, 109, 35, 33, 138, 11, 168, 169, 188, 70, 3, 145, 15, 155, 189, 34, 55, 95, 130, 99, 22, 66, 154, 57, 172, 194, 103, 127, 89, 137, 114, 165, 187, 146, 81, 111, 8, 10
4, 21, 82, 144, 160, 139, 182, 25, 121, 90, 122, 135, 63, 40, 107, 100, 133, 10, 147
, 6, 134, 51, 98, 118, 74]



TSPB Random

[179, 109, 103, 134, 100, 79, 138, 131, 27, 92, 9, 74, 147, 29, 37, 68, 62, 15, 78, 127, 137, 160, 45, 125, 77, 13, 154, 113, 128, 190, 169, 64, 182, 183, 55, 148, 166, 165, 50, 5, 86, 194, 75, 170, 93, 163, 199, 121, 83, 126, 158, 149, 41, 187, 20, 144 , 167, 99, 95, 67, 175, 52, 51, 0, 42, 177, 8, 4, 188, 49, 11, 80, 72, 85, 153, 198, 135, 16, 81, 61, 22, 195, 1, 123, 114, 119, 189, 192, 33, 63, 130, 69, 176, 162, 26, 110, 173, 54, 132, 66]



Additional Information

Solution checker

We have checked all of the best solutions via the solution checker provided.

Source code link

The source code is available in a repository here under the Lab1 folder.

Conclusions

The algorithms implemented to address the Hamiltonian cycle problem exhibit a range of performance in terms of the objective function score.

- Random Selection: As anticipated, the solutions generated by random selection yielded the poorest results. This approach lacks a structured method for optimizing node selection, resulting in the worst cycles.

- Nearest Neighbour Variants: Among the variations of the Nearest Neighbour algorithm, the version restricted to adding only the nearest neighbor from the last added node performed worse than the more flexible variant. This limitation hinders the exploration of potentially better paths, leading to less favorable outcomes.
- Greedy Cycle Method: Surprisingly, the Greedy Cycle method, which aims to create a cycle by selecting the least costly edge iteratively, consistently performed slightly better than the restricted version of Nearest Neighbour algorithm and slightly worse than the unrestricted version.

While the results are satisfactory, it is evident that there is considerable room for improvement. More advanced algorithms can still provide far better results, than the methods implemented now.

In summary, while the current algorithms provide reasonable results, further refinement and the exploration of more sophisticated optimization techniques are necessary to achieve significantly better solutions for the Hamiltonian cycle problem.

Authors

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