Evolutionary Computation - Assignment 1 Report

Imports

In [73]:
```
import pandas as pd
import numpy as np
import networkx as nx
import matplotlib.pyplot as plt
```

Problem instance reading and cost scaling

In [74]:
```
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 [79]:

```python
file_paths = ['.\\TSPAGreedy.csv', '.\\TSPANNAll.csv', '.\\TSPANNLast.csv', '.\\TSP
methods = ['A Greedy', 'A Nearest Neighbour on all vertices', 'A Nearest Neighbour
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)

results = np.array(results).T
result_df = pd.DataFrame(results, columns=methods, index=['Minimum', 'Average', 'Ma
result_df
```

Out[79]:

	A Greedy	A Nearest Neighbour on all vertices	A Nearest Neighbour on last node	A Random	B Greedy	B Nearest Neighbour on all vertices	B Nearest Neighbour on last node
Minimum	71237.00	71227.00	83182.00	236302.00	48898.00	44377.00	52319.00
Average	73036.23	73293.75	85110.16	263481.34	51852.88	47444.68	54385.49
Maximum	75002.00	76036.00	89433.00	293567.00	58531.00	53019.00	59030.00

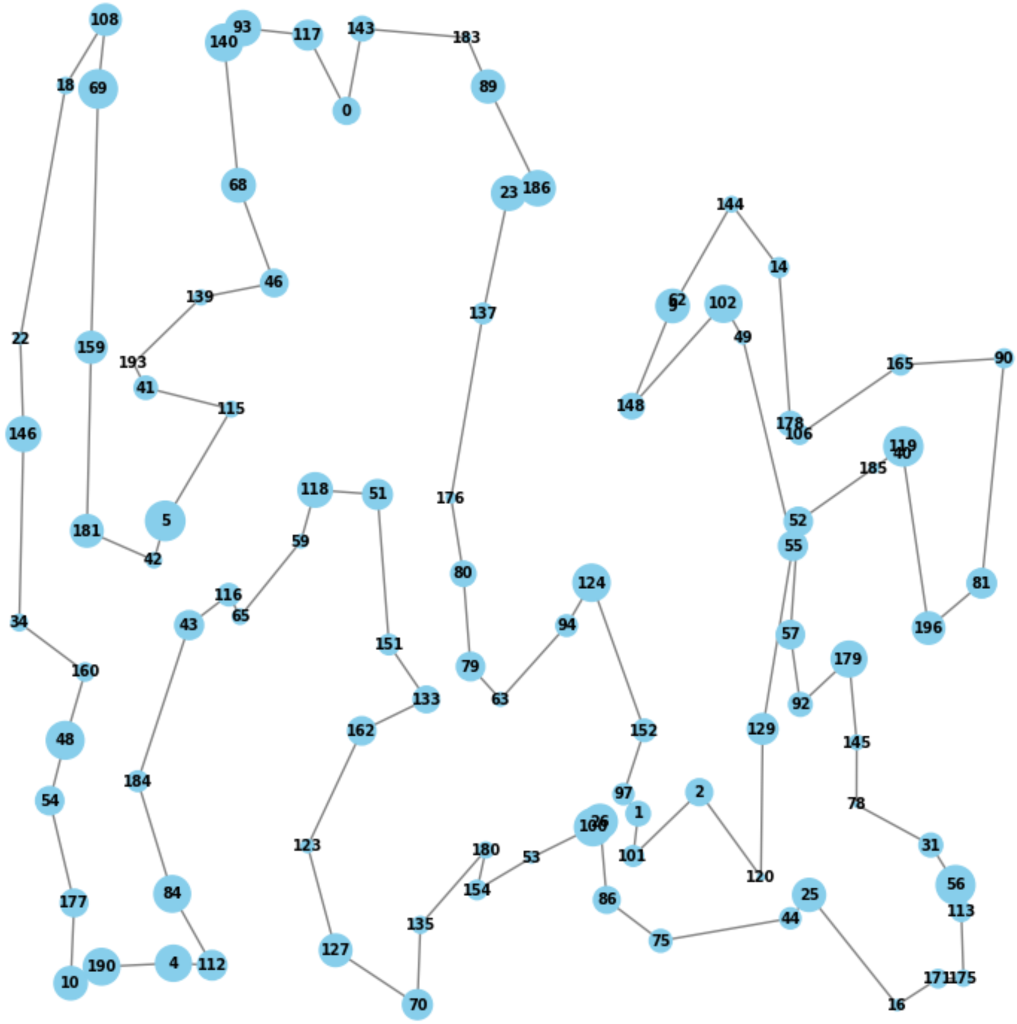
Visualization of the best path for each method

Additionally, a list of node indices is presented.

In [78]:
```
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 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])

        node_sizes = [dfTSPA.loc[idx, 'Normalized_Cost'] * 650 for idx in best_solu

    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 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])

        node_sizes = [dfTSPB.loc[idx, 'Normalized_Cost'] * 650 for idx in best_solu

    plt.figure(figsize=(8, 8))
    nx.draw(G, pos=positions, with_labels=True, node_size=node_sizes, node_color='s

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

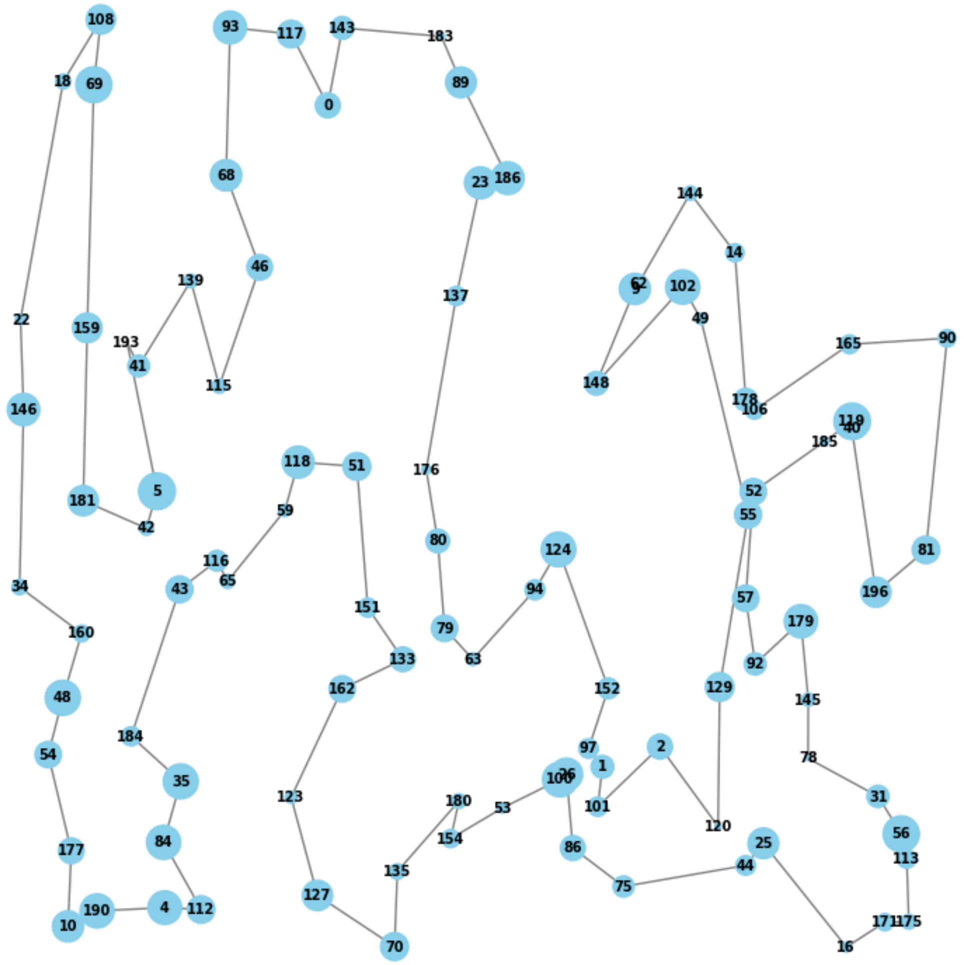
```
A Greedy
[117, 93, 140, 68, 46, 139, 193, 41, 115, 5, 42, 181, 159, 69, 108, 18, 22, 146, 34,
160, 48, 54, 177, 10, 190, 4, 112, 84, 184, 43, 116, 65, 59, 118, 51, 151, 133, 162,
123, 127, 70, 135, 180, 154, 53, 100, 26, 86, 75, 44, 25, 16, 171, 175, 113, 56, 31,
78, 145, 179, 92, 57, 52, 185, 119, 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 Sizes Based on Normalized Costs of A Greedy



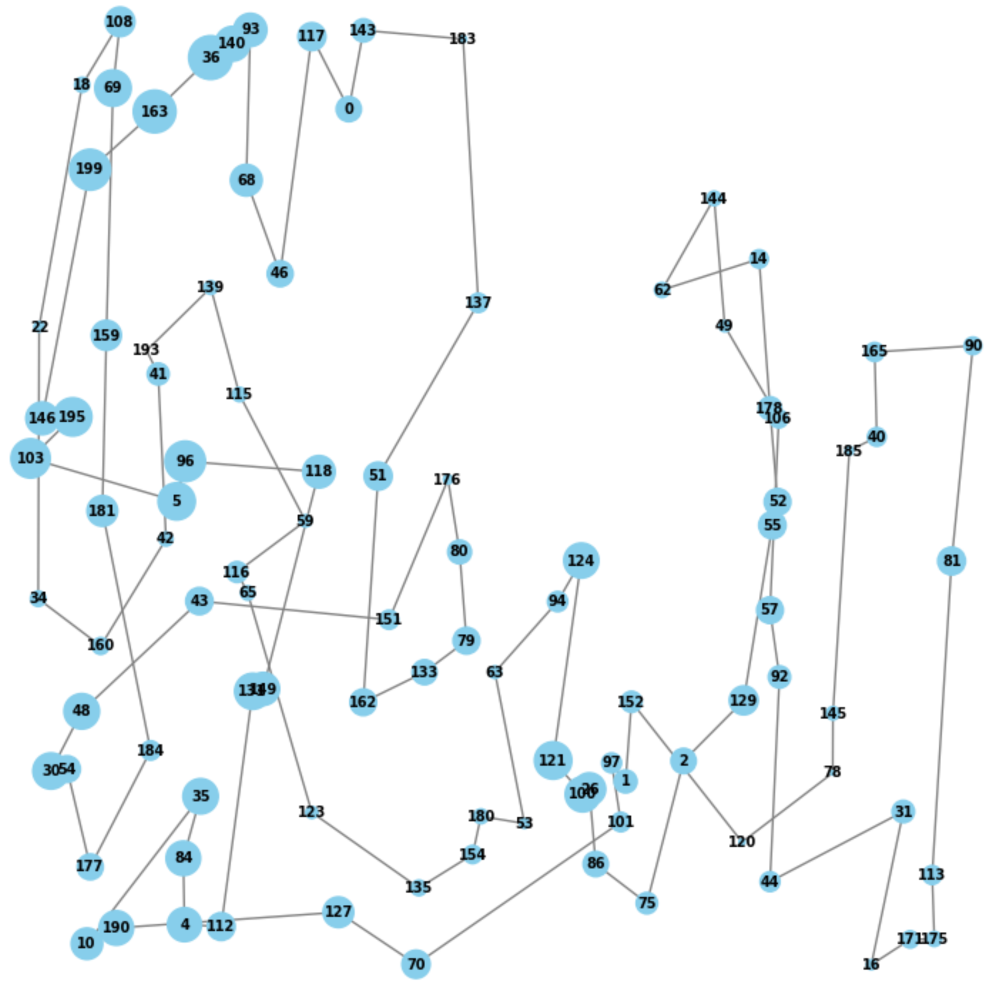
```
A Nearest Neighbour on all vertices
[93, 117, 0, 143, 183, 89, 186, 23, 137, 176, 80, 79, 63, 94, 124, 152, 97, 1, 101,
2, 120, 129, 55, 49, 102, 148, 9, 62, 144, 14, 178, 106, 165, 90, 81, 196, 40, 119,
185, 52, 57, 92, 179, 145, 78, 31, 56, 113, 175, 171, 16, 25, 44, 75, 86, 26, 100, 5
3, 154, 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]
```

Cycle Visualization with Node Sizes Based on Normalized Costs of A Nearest Neighbour on all vertices



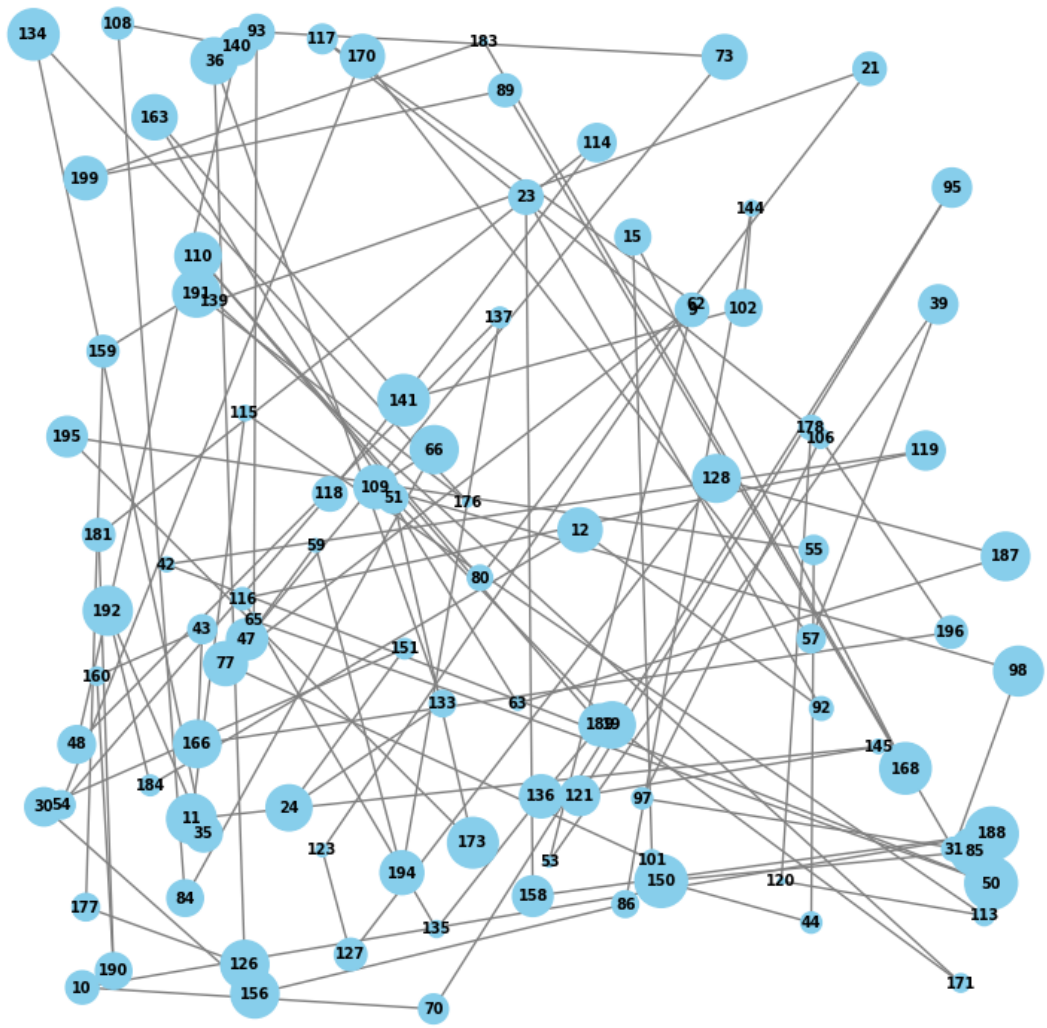
```
A Nearest Neighbour on last node
[124, 94, 63, 53, 180, 154, 135, 123, 65, 116, 59, 115, 139, 193, 41, 42, 160, 34, 2
2, 18, 108, 69, 159, 181, 184, 177, 54, 30, 48, 43, 151, 176, 80, 79, 133, 162, 51,
137, 183, 143, 0, 117, 46, 68, 93, 140, 36, 163, 199, 146, 195, 103, 5, 96, 118, 149
, 131, 112, 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 Sizes Based on Normalized Costs of A Nearest Neighbour on last node

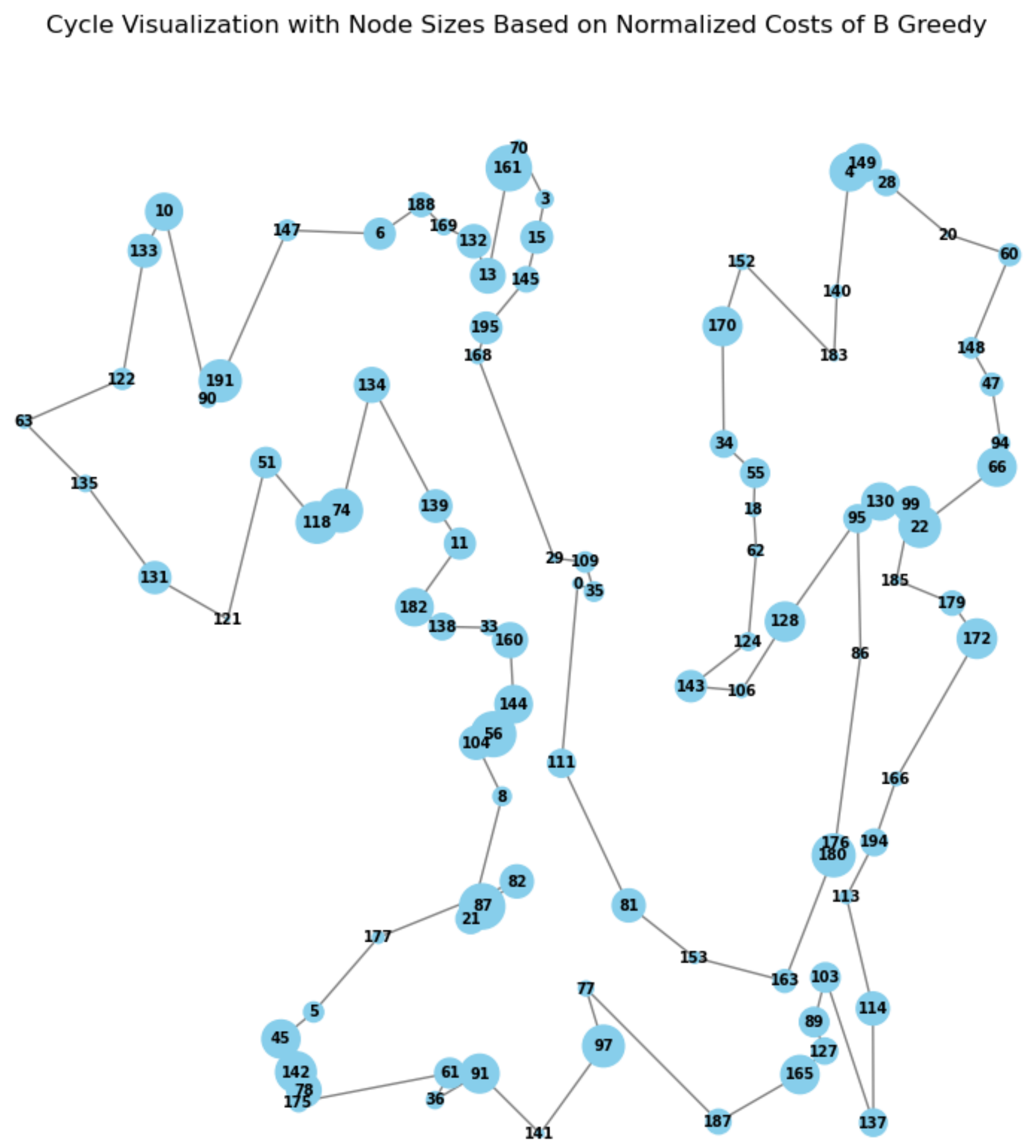


A Random
[121, 145, 11, 115, 113, 120, 178, 117, 62, 77, 101, 15, 168, 89, 199, 183, 31, 98, 109, 66, 84, 108, 140, 48, 137, 194, 59, 47, 73, 93, 65, 50, 42, 119, 116, 135, 136, 189, 110, 80, 21, 139, 171, 19, 51, 173, 195, 55, 44, 150, 85, 97, 106, 196, 166, 43 , 160, 190, 181, 114, 118, 54, 170, 57, 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]

Cycle Visualization with Node Sizes Based on Normalized Costs of A Random

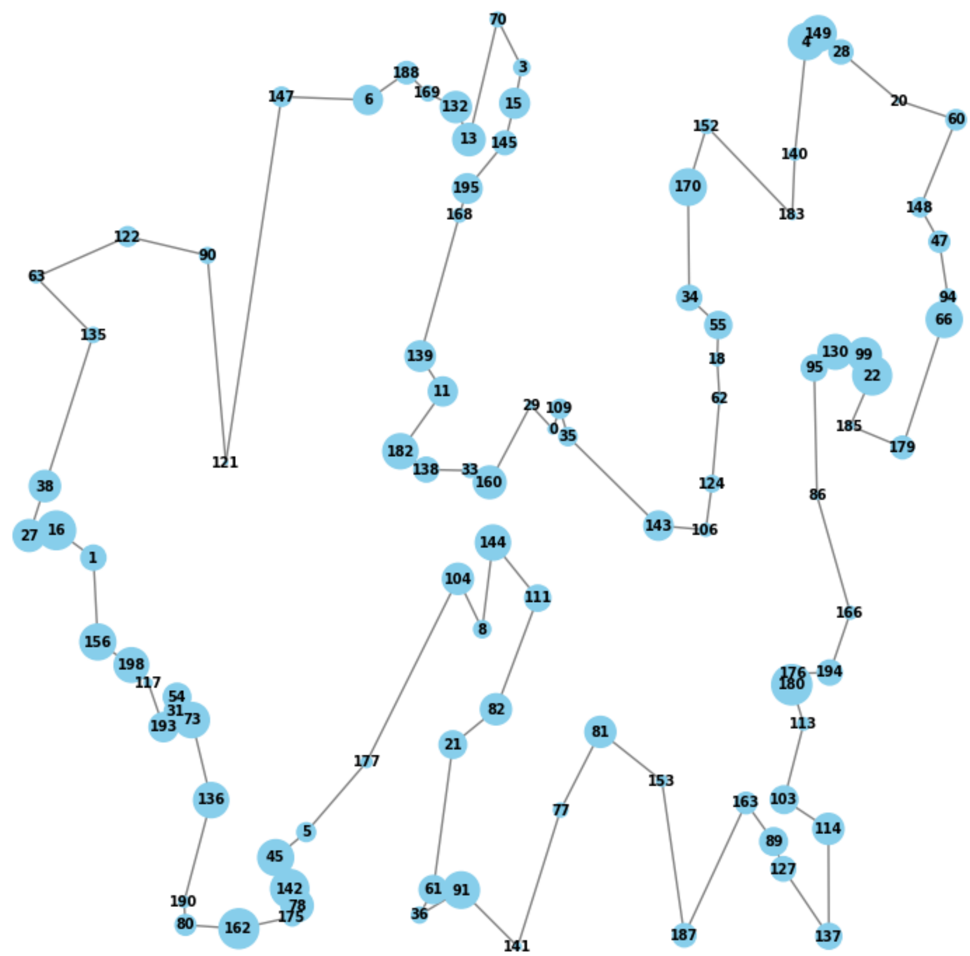


```
B Greedy
[118, 74, 134, 139, 11, 182, 138, 33, 160, 144, 56, 104, 8, 21, 87, 82, 177, 5, 45,
142, 78, 175, 61, 36, 91, 141, 97, 77, 187, 165, 127, 89, 103, 137, 114, 113, 194, 1
66, 172, 179, 185, 99, 130, 22, 66, 94, 47, 148, 60, 20, 28, 149, 4, 140, 183, 152,
170, 34, 55, 18, 62, 124, 143, 106, 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]
```



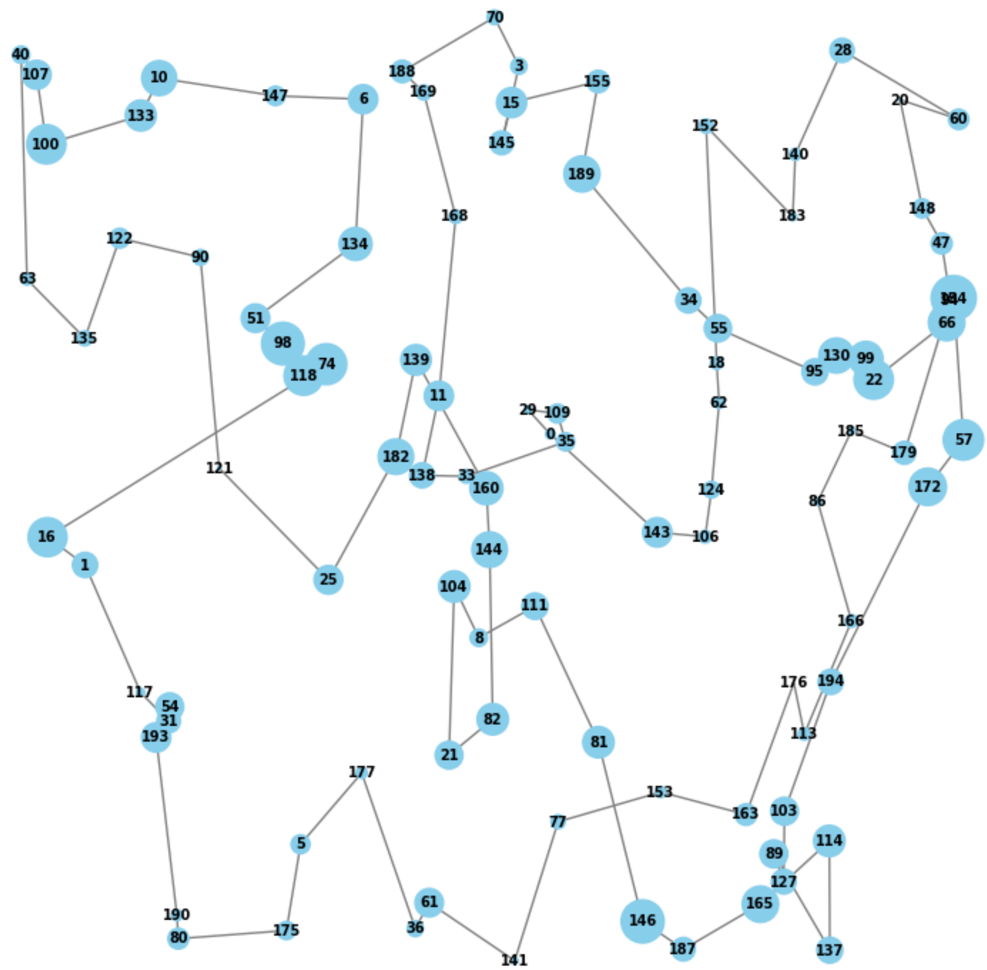

```
B Nearest Neighbour on all vertices
[147, 6, 188, 169, 132, 13, 70, 3, 15, 145, 195, 168, 139, 11, 182, 138, 33, 160, 29
, 0, 109, 35, 143, 106, 124, 62, 18, 55, 34, 170, 152, 183, 140, 4, 149, 28, 20, 60,
148, 47, 94, 66, 179, 185, 22, 99, 130, 95, 86, 166, 194, 176, 180, 113, 103, 114, 1
37, 127, 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 Sizes Based on Normalized Costs of B Nearest Neighbour on all vertices

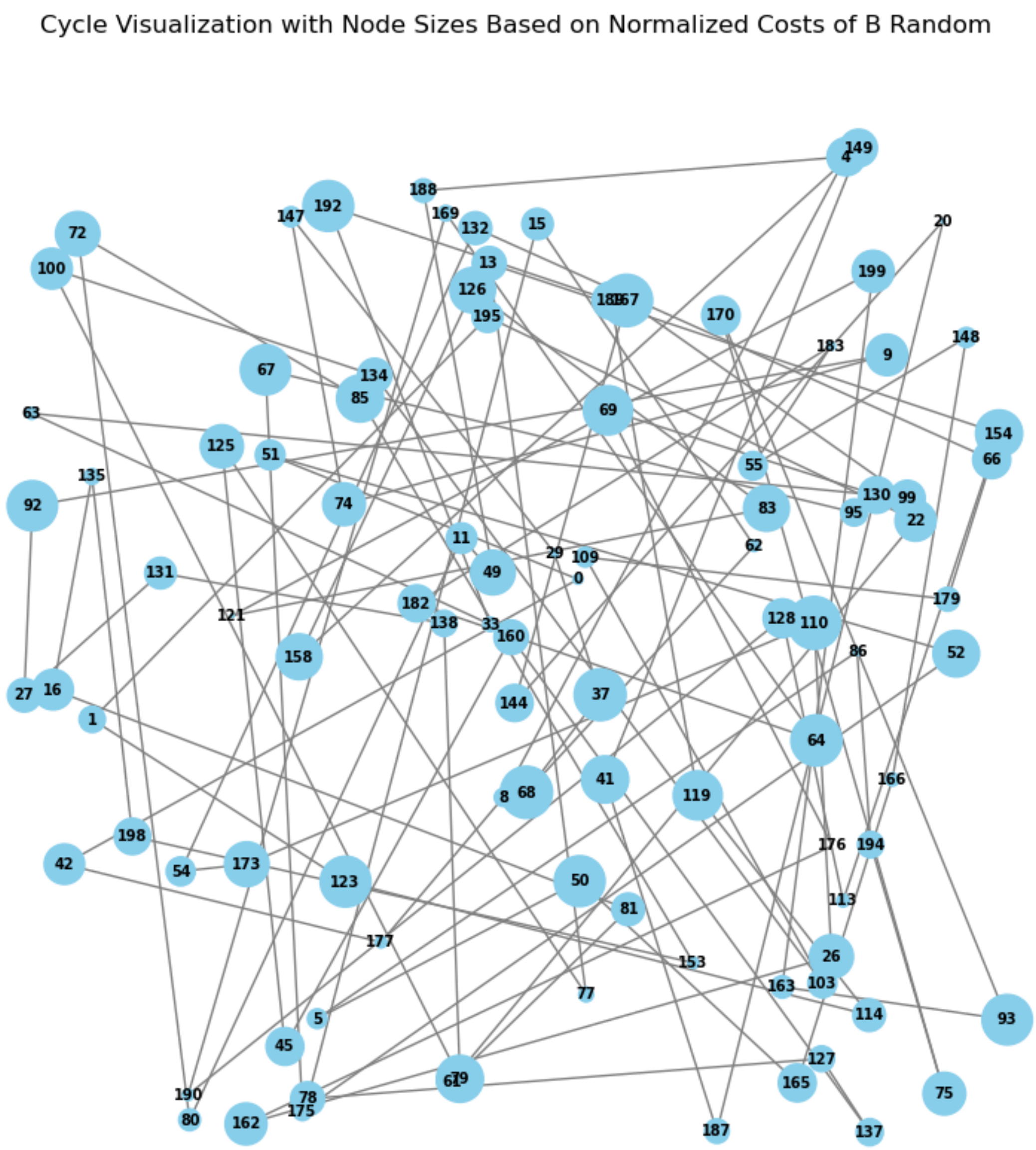


```
B Nearest Neighbour on last node
[16, 1, 117, 31, 54, 193, 190, 80, 175, 5, 177, 36, 61, 141, 77, 153, 163, 176, 113,
166, 86, 185, 179, 94, 47, 148, 20, 60, 28, 140, 183, 152, 18, 62, 124, 106, 143, 0,
29, 109, 35, 33, 138, 11, 168, 169, 188, 70, 3, 145, 15, 155, 189, 34, 55, 95, 130,
99, 22, 66, 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]
```

Cycle Visualization with Node Sizes Based on Normalized Costs of B Nearest Neighbour on last node



B 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.