Evolutionary Computation - Assignment 5 Report

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Imports

In [1]:
```
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 [2]:
```
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 added an improved method for Local Search created in the previous laboratories in C++.

- **Local Search with the use of move evaluations from previous iterations**
  - **Input:**
    - `cycle` : An array of a previously generated cycle
    - `costDistanceInfo` : A symmetric matrix of distances and costs between nodes
  - **Output:**
    - An array of new `cycle` node IDs
  - **Function:**

```
FUNCTION generateCycle(start_pos)
    INITIALIZE currentCycle AS a COPY of initialCycle
    INITIALIZE positionInCycleCache[SIZE of costDistanceInfo] TO -1
    # Populate cache with initial cycle positions
    FOR EACH nodeId IN currentCycle
        positionInCycleCache[nodeId] = nodeId's index IN
currentCycle
    DO
        moveFound = False
        possibleMoves = EMPTY SET
        enteringNodesIds = ALL nodes IN currentCycle
        # Generate all moves
        CALL generateMoves(possibleMoves, currentCycle,
positionInCycleCache, enteringNodesIds)
        enteringNodesIds = EMPTY
        # Evaluate and apply the best move
        FOR EACH move IN possibleMoves
            IF move.isApplicable(currentCycle,
positionInCycleCache)
                move.performMove(currentCycle,
positionInCycleCache)
                # Update cache after move
                UPDATE positionInCycleCache USING move
                moveFound = True
                enteringNodesIds = move.getEnteringIds()
                BREAK
            ELSE IF NOT move.shouldBeLeftInLM(currentCycle,
positionInCycleCache)
                REMOVE move FROM possibleMoves
        # Clean up invalid or applied moves
        REMOVE ALL invalid moves FROM possibleMoves
    UNTIL NOT moveFound
    RETURN currentCycle
FUNCTION generateMoves(movesList, currentCycle,
positionInCycleCache, enteringNodesIds)
    INITIALIZE indicesNotInCycle AS EMPTY LIST
    FOR i FROM 0 TO costDistanceInfo.SIZE
        # Use cache to find nodes not in the current cycle
```

```
            IF positionInCycleCache[i] == -1
                APPEND i TO indicesNotInCycle
        # Generate Inter Moves
        FOR EACH nodeNotInCycleId IN indicesNotInCycle
            FOR EACH nodeInCycle IN enteringNodesIds
                CREATE InterNodeNeighbourhoodMove(nodeInCycle,
nodeNotInCycleId)
                CALCULATE functionDelta FOR move USING costDistanceInfo
AND cache
                IF functionDelta < 0
                    ADD move TO movesList
        # Generate Intra Moves
        FOR EACH enteringId IN enteringNodesIds
            enteringIdCyclePos = positionInCycleCache[enteringId]
            enteringIdSuccId = currentCycle[(enteringIdCyclePos + 1) %
SIZE of currentCycle]
            FOR EACH nodeInCycleId IN currentCycle
                nodeInCyclePos = positionInCycleCache[nodeInCycleId]
                nodeInCycleSuccId = currentCycle[(nodeInCyclePos + 1) %
SIZE of currentCycle]
                IF INVALID move pairing CONTINUE
                CREATE IntraNodeChangeEdgeNeighbourhoodMove(enteringId,
nodeInCycleId, enteringIdSuccId, nodeInCycleSuccId)
                CALCULATE functionDelta FOR move USING costDistanceInfo
AND cache
                IF functionDelta < 0
                    ADD move AND reversedMove TO movesList
```

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 [3]:
```python
file_paths = ['.\\TSPA_DeltaLocalSearch.csv', '.\\TSPA_NormalLocalSearch.csv', '.\\
              '.\\TSPB_DeltaLocalSearch.csv', '.\\TSPB_NormalLocalSearch.csv', '.\\
methods = ['LS with delta moves evaluation', 'Steepest LS', 'Random']
results = []
best_solutions = []
counter = 0
for file_path, method in zip(file_paths, methods * 2):
    df = pd.read_csv(file_path)
    costs = df.iloc[:, -1]
    minimum = costs.min()
    maximum = costs.max()
    mean = round(costs.mean(), 2)
    if counter < len(methods):
        results.append((method, 'TSPA', f"{mean} ({minimum} - {maximum})"))
    else:
        results.append((method, 'TSPB', f"{mean} ({minimum} - {maximum})"))
```

```
    if '..' not in file_path:
        min_sol = df.loc[costs.idxmin()][:-1].to_list()
        best_solutions.append(min_sol)
    counter += 1
result_df = pd.DataFrame(results, columns=['Method', 'Column', 'Value'])
result_df = result_df.pivot(index='Method', columns='Column', values='Value')
result_df.columns.name = None
result_df
```

Out[3]:

Method	TSPA	TSPB
LS with delta moves evaluation	74185.58 (71220 - 79601)	48743.82 (45480 - 52232)
Random	265574.29 (232959 - 297744)	213112.96 (184247 - 233038)
Steepest LS	73852.09 (71654 - 78313)	48379.05 (45987 - 51946)

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

In [4]:

```
methods_for_times = [['Steepest LS','LS with delta moves evaluation']]
times_files = ['.\\times.csv']

results_times = []
for method_list, time_file in zip(methods_for_times, times_files):
    df_temp = pd.read_csv(time_file, header=None).iloc[:, :-1]
    counter = 0
    for column, method in zip(df_temp.columns, method_list * 2):
        min_value = df_temp[column].min()
        max_value = df_temp[column].max()
        avg_value = df_temp[column].mean()
        if counter < len(method_list):
            results_times.append((method, 'TSPA', f"{round(avg_value, 4)} ({round(m
        else:
            results_times.append((method, 'TSPB', f"{round(avg_value, 4)} ({round(m
        counter += 1

times_df = pd.DataFrame(results_times, columns=['Method', 'Column', 'Value'])
times_df = times_df.pivot(index='Method', columns='Column', values='Value')
times_df.columns.name = None
times_df
```

Out[4]:

Method	TSPA	TSPB
LS with delta moves evaluation	39.1744 (30.066 - 54.5994)	39.4872 (29.6452 - 68.6829)
Steepest LS	144.6746 (126.956 - 176.132)	145.4435 (129.16 - 172.586)

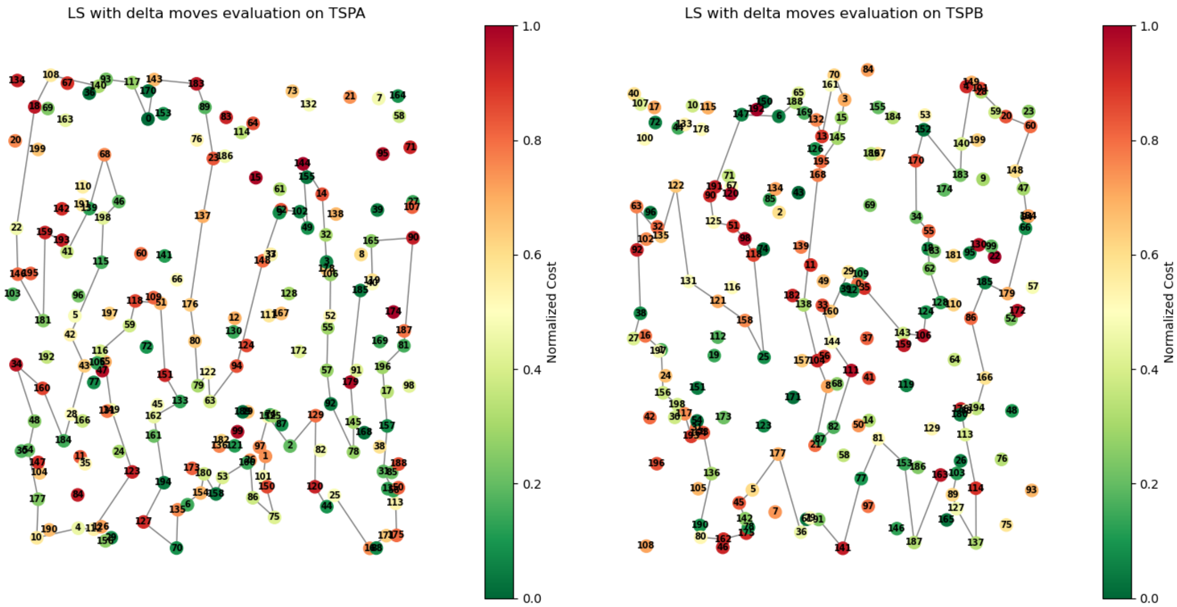
Visualization of the best path for each method

Additionally, a list of node indices is presented.

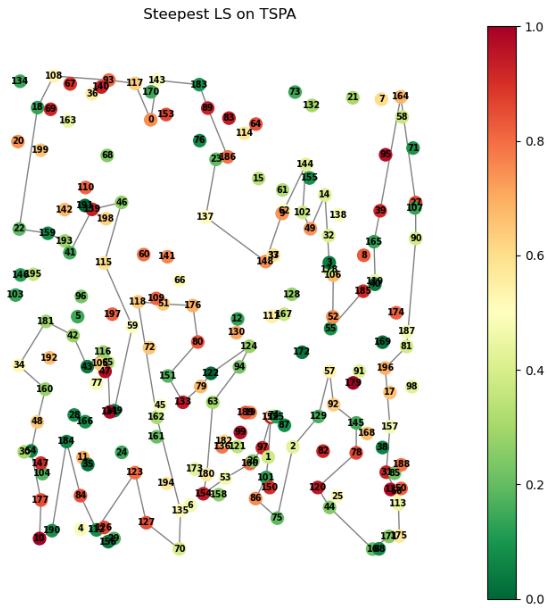
In [5]:
```
warnings.filterwarnings("ignore", category=MatplotlibDeprecationWarning)
cmap = plt.cm.get_cmap('RdYlGn_r')

for count, method in enumerate(methods):
    if count == len(best_solutions) // 2:
        break
    print(method)
    print('TSPA')
    print(best_solutions[count])
    print(count, count + len(best_solutions)//2)
    print('TSPB')
    print(best_solutions[count + len(best_solutions)//2])

    fig, axs = plt.subplots(1, 2, figsize=(14, 7))

    for count, sol in enumerate([best_solutions[count], best_solutions[count + len(
        if count == 0:
            df_temp = dfTSPA
            ax = axs[0]
            instance = 'TSPA'
        else:
            df_temp = dfTSPB
            ax = axs[1]
            instance = 'TSPB'

        G = nx.Graph()
        positions = {}

        for idx in sol:
            G.add_node(idx, size=df_temp.loc[idx, 'Normalized_Cost'])
            positions[idx] = (df_temp.loc[idx, 'X'], df_temp.loc[idx, 'Y'])

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

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


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

        nx.draw(G, pos=positions, with_labels=True, node_color=node_colors, node_si
            font_size=7, edge_color='gray', linewidths=1, font_weight='bold', ax=ax

        sm = ScalarMappable(cmap=cmap, norm=norm)
        sm.set_array([])
```

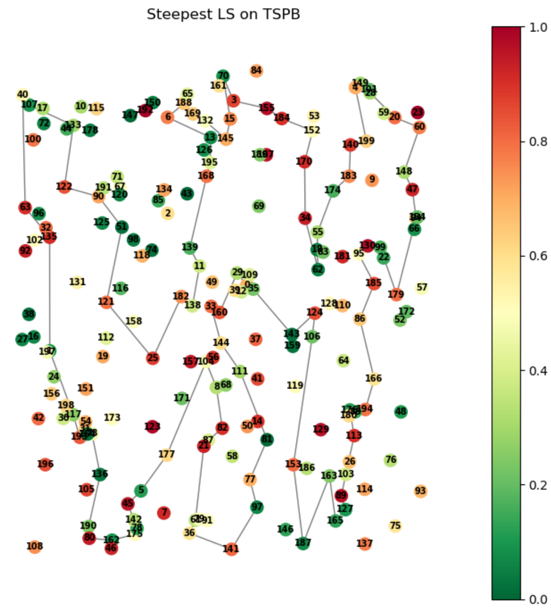
```
        cbar = plt.colorbar(sm, ax=ax)
        cbar.set_label('Normalized Cost')

        ax.set_title(f" {method} on {instance}")

    plt.tight_layout()
    plt.show()
```

```
LS with delta moves evaluation
TSPA
[48, 54, 177, 10, 4, 112, 123, 149, 65, 116, 59, 118, 51, 151, 133, 162, 194, 127, 7
0, 135, 154, 180, 158, 53, 26, 86, 75, 101, 1, 97, 152, 2, 129, 120, 44, 25, 16, 171
, 175, 113, 56, 31, 157, 196, 81, 90, 165, 119, 40, 185, 179, 145, 78, 92, 57, 55, 5
2, 106, 178, 3, 14, 144, 49, 102, 62, 9, 148, 94, 63, 122, 79, 80, 176, 137, 23, 89,
183, 143, 0, 117, 93, 140, 108, 18, 22, 146, 181, 159, 193, 41, 139, 68, 46, 198, 11
5, 42, 43, 184, 160, 34]
0 3
TSPB
[61, 91, 141, 77, 81, 153, 187, 163, 103, 89, 127, 137, 114, 113, 176, 194, 166, 86,
185, 179, 94, 47, 148, 60, 20, 28, 149, 140, 183, 152, 170, 34, 55, 18, 62, 128, 124
, 106, 143, 35, 109, 0, 29, 160, 33, 144, 111, 82, 21, 8, 104, 138, 168, 195, 145, 1
5, 3, 70, 13, 132, 169, 188, 6, 147, 191, 90, 125, 51, 98, 118, 25, 158, 121, 131, 1
22, 135, 63, 38, 27, 16, 1, 156, 198, 117, 193, 31, 54, 164, 73, 136, 190, 80, 162,
175, 78, 142, 45, 5, 177, 36]
```

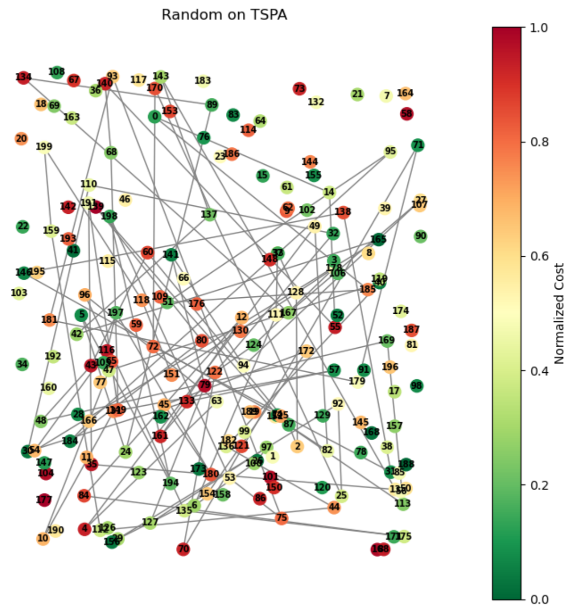


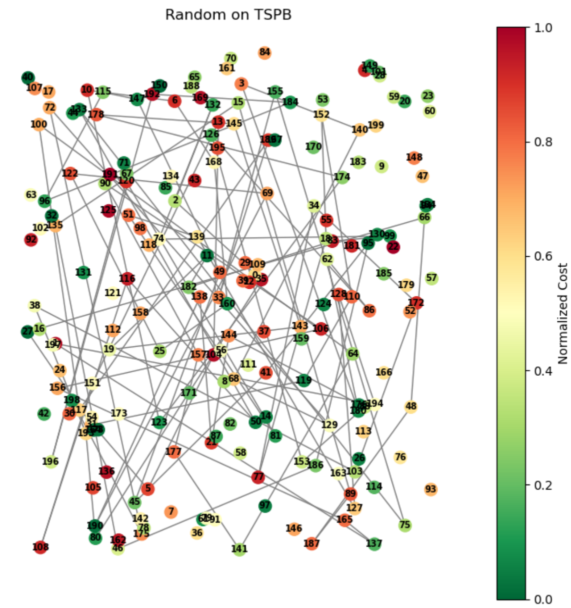
Steepest LS
TSPA
[44, 16, 171, 175, 113, 56, 31, 157, 196, 81, 90, 27, 164, 39, 165, 119, 40, 185, 55
, 52, 106, 178, 3, 14, 49, 102, 144, 62, 9, 148, 137, 23, 186, 89, 183, 143, 0, 117,
93, 108, 18, 22, 159, 193, 41, 139, 46, 115, 59, 149, 131, 65, 116, 43, 42, 181, 34,
160, 48, 54, 177, 10, 190, 184, 84, 112, 123, 127, 70, 135, 162, 118, 51, 176, 80, 1
51, 133, 79, 122, 124, 94, 63, 180, 154, 53, 100, 26, 97, 152, 1, 101, 86, 75, 2, 12
9, 57, 92, 145, 78, 120]
1 4
TSPB
[136, 190, 80, 162, 175, 78, 142, 45, 5, 177, 104, 8, 82, 87, 21, 61, 36, 141, 97, 7
7, 81, 111, 144, 33, 160, 29, 0, 109, 35, 143, 124, 106, 153, 187, 163, 165, 127, 89
, 103, 113, 176, 194, 166, 86, 185, 95, 130, 99, 179, 94, 47, 148, 60, 20, 28, 149,
4, 199, 140, 183, 174, 55, 18, 62, 34, 170, 152, 184, 155, 3, 70, 15, 145, 132, 169,
188, 6, 13, 195, 168, 139, 11, 138, 182, 25, 121, 51, 90, 122, 133, 107, 40, 63, 135
, 1, 117, 193, 31, 54, 73]





Random
TSPA
[48, 169, 113, 152, 82, 49, 4, 63, 96, 135, 175, 84, 12, 161, 32, 110, 30, 133, 57,
131, 10, 47, 40, 136, 44, 112, 159, 199, 118, 151, 178, 124, 122, 70, 71, 179, 181,
93, 75, 53, 198, 194, 5, 24, 89, 134, 167, 27, 94, 141, 79, 127, 97, 26, 100, 6, 111
, 37, 166, 184, 80, 139, 74, 146, 138, 31, 72, 170, 25, 92, 29, 154, 172, 45, 180, 1
97, 116, 54, 165, 42, 137, 143, 13, 35, 191, 149, 68, 140, 55, 14, 0, 185, 51, 95, 3
3, 128, 2, 87, 60, 43]
2 5
TSPB
[11, 182, 83, 99, 74, 132, 2, 35, 80, 193, 38, 103, 172, 34, 77, 18, 152, 110, 119,
31, 27, 66, 48, 187, 89, 15, 135, 46, 186, 95, 41, 45, 49, 147, 115, 96, 184, 192, 1
96, 120, 81, 51, 139, 127, 128, 194, 1, 137, 165, 156, 106, 90, 157, 177, 141, 64, 1
00, 117, 189, 33, 155, 75, 133, 50, 116, 108, 151, 13, 104, 5, 198, 175, 72, 129, 68
, 140, 3, 180, 62, 86, 126, 153, 88, 144, 21, 138, 190, 69, 122, 25, 160, 168, 6, 10
, 123, 174, 178, 145, 143, 19]





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 Lab5 folder.

Conclusions

The use of deltas from previous iterations was successfully able to lower the time of the Local Search algorithm by approximately 5 times, while loosing very minimal objective function score. The time savings result from leveraging previously computed deltas and updating them incrementally, rather than recalculating the objective function for all candidate moves in every iteration.

Authors

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