Evolutionary Computation - Assignment 6 Report

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Imports

In [16]:
```
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 [17]:
```
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 two new methods of LS - Multiple start local search and Iterated local search.

- **Multiple start local search**

    - **Input:**
        - `nodes` : An array of available nodes
        - `costDistanceInfo` : A symmetric matrix of distances and costs between nodes
        - `iterations` : A number of iterations that the algorithm is to be run
    - **Output:**
        - An array of new `cycle` node IDs
    - **Function:**

```
FUNCTION generateCycle(start_pos)
    INITIALIZE bestCycle AS an empty array
    INITIALIZE bestFuncValue TO -1
    # Create an initial cycle generator
    INITIALIZE initialGenerator AS RandomHamiltonianCycleGenerator(costDistanceInfo, nodesInCycle, start_pos * iters)
    FOR i FROM 0 TO iters - 1 DO
        # Generate an initial cycle
        INITIALIZE cycle AS initialGenerator.generateCycle(i)
        # Perform local search optimization on the cycle
        INITIALIZE localSearchGenerator AS LocalSearchGenerator(costDistanceInfo, cycle)
        INITIALIZE optimizedCycle AS localSearchGenerator.generateCycle(i)
        # Calculate the objective value of the optimized cycle
        INITIALIZE currFuncValue AS localSearchGenerator.calculateCycleCost(optimizedCycle)
        # Update the best cycle if a better one is found
        IF currFuncValue < bestFuncValue OR bestFuncValue == -1 THEN
            SET bestFuncValue TO currFuncValue
            SET bestCycle TO optimizedCycle
        END IF
    END FOR
    RETURN bestCycle
END FUNCTION
```

- **Iterated local search**
    - **Input:**
        - `nodes` : An array of available nodes
        - `costDistanceInfo` : A symmetric matrix of distances and costs between nodes
        - `time` : A duration for which the algorithm is to be run
        - `perturbation_moves` : A number of perturbation moves to be performed between iterations
    - **Output:**

    ◦ An array of new `cycle` node IDs

- **Function:**

```
FUNCTION generateCycle(start_pos)
    # Generate an initial random cycle
    GENERATE currentCycle BY RandomHamiltonianCycle
    # Perform local search on the initial cycle
    INITIALIZE localSearchGenerator AS
LocalSearchGenerator(costDistanceInfo, currentCycle)
    SET currentCycle TO
localSearchGenerator.generateCycle(start_pos)
    INITIALIZE bestFuncValue AS
localSearchGenerator.calculateCycleCost(currentCycle)
    INITIALIZE bestCycle AS currentCycle
    INITIALIZE startTime AS current time
    INITIALIZE currTime AS current time
    CALCULATE timePassed AS currTime - startTime
    WHILE timePassed < maxRuntime DO
        # Apply perturbation to the current cycle
        CALL perturbCycle(currentCycle)
        # Perform local search on the perturbed cycle
        INITIALIZE localSearchGeneratorCur AS
LocalSearchGenerator(costDistanceInfo, currentCycle)
        SET currentCycle TO
localSearchGeneratorCur.generateCycle(start_pos)
        INITIALIZE currFuncValue AS
localSearchGeneratorCur.calculateCycleCost(currentCycle)
        # Update the best cycle if a better one is found
        IF currFuncValue < bestFuncValue THEN
            SET bestCycle TO currentCycle
            SET bestFuncValue TO currFuncValue
        ELSE
            # Revert to the best cycle if no improvement
            SET currentCycle TO bestCycle
        END IF
        # Update time and iteration count
        SET currTime TO current time
        CALCULATE timePassed AS currTime - startTime
        INCREMENT iterationsDone
    END WHILE
    RETURN bestCycle
END FUNCTION
FUNCTION perturbCycle(currentCycle)
    # Apply perturbations
    FOR i FROM 0 TO perturbationMoves - 1 DO
        # Determine move type (inter or intra)
        INITIALIZE isInterMove AS moveType(rng) == 0
        IF isInterMove THEN
            GENERATE ALL POSSIBLE interMoves
            INITIALIZE move AS RANDOM CHOICE FROM interMoves
            CALL move.performMove(currentCycle, NULL)
        ELSE
```

```
                GENERATE ALL POSSIBLE intraMoves
                INITIALIZE move as RANDOM CHOICE FROM intraMoves
                CALL Move.performMove(currentCycle, NULL)
            END IF
        END FOR
    END FUNCTION
```

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 [18]:
```python
file_paths = ['.\\TSPA_IteratedLocalSearch.csv', '.\\TSPA_MultistartLocalSearch.csv
              '.\\TSPB_IteratedLocalSearch.csv', '.\\TSPB_MultistartLocalSearch.csv
methods = ['Iterated LS', 'Multiple start LS']
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[18]:

	TSPA	TSPB
Method		
Iterated LS	69256.11 (69095 - 69614)	43634.53 (43448 - 44215)
Multiple start LS	71250.74 (70684 - 71957)	45795.84 (45108 - 46295)

Information regarding running time of Multiple start LS and number of local searches in Iterated LS.

In [19]:
```python
times_files = ['.\\times.csv', '.\\ILSruns.csv']
```

```
results_times = []
for counter_main, file in enumerate(times_files):
    df_temp = pd.read_csv(file, header=None).iloc[:, :-1]
    for count, column in enumerate(df_temp.columns):
        min_value = df_temp[column].min()
        max_value = df_temp[column].max()
        avg_value = df_temp[column].mean()
        if counter_main < 1:
            if count < 1:
                results_times.append(('Multiple start LS', 'TSPA', f"{round(avg_val
            else:
                results_times.append(('Multiple start LS', 'TSPB', f"{round(avg_val
        else:
            if count < 1:
                results_times.append(('Iterated LS', 'TSPA', f"{round(avg_value, 4)
            else:
                results_times.append(('Iterated LS', 'TSPB', f"{round(avg_value, 4)

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[19]:

Method	TSPA	TSPB
Iterated LS	2602.95 (2358 - 2823) runs	2611.65 (2416 - 2886) runs
Multiple start LS	36404.82 (33524.3 - 38601.8) ms	34441.575 (33030.7 - 38215.2) ms

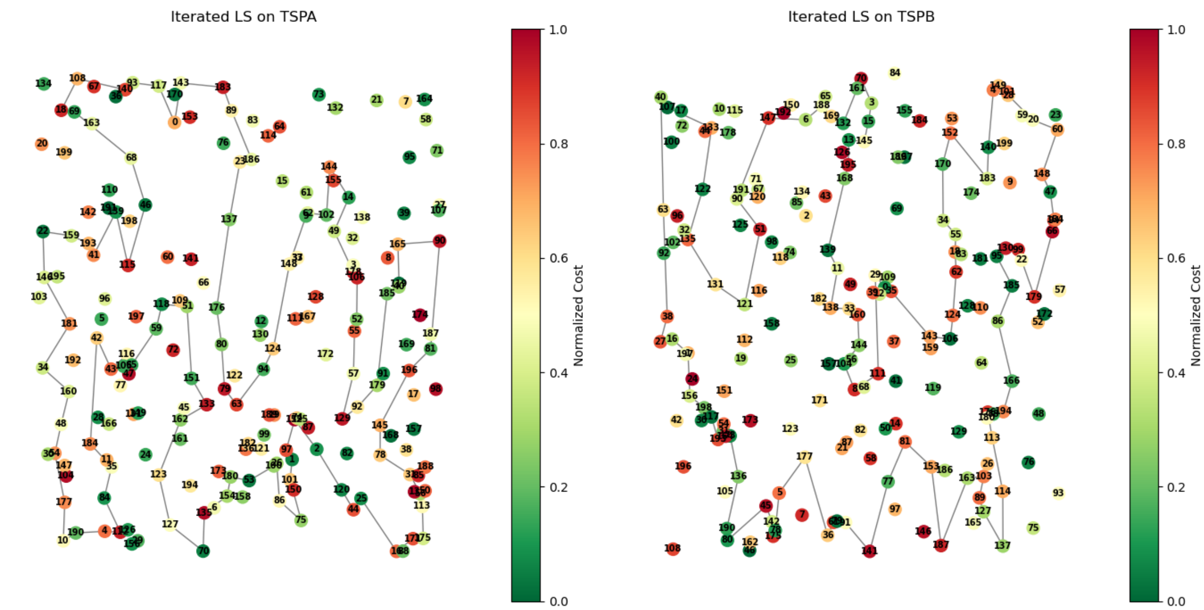
Visualization of the best path for each method

Additionally, a list of node indices is presented.

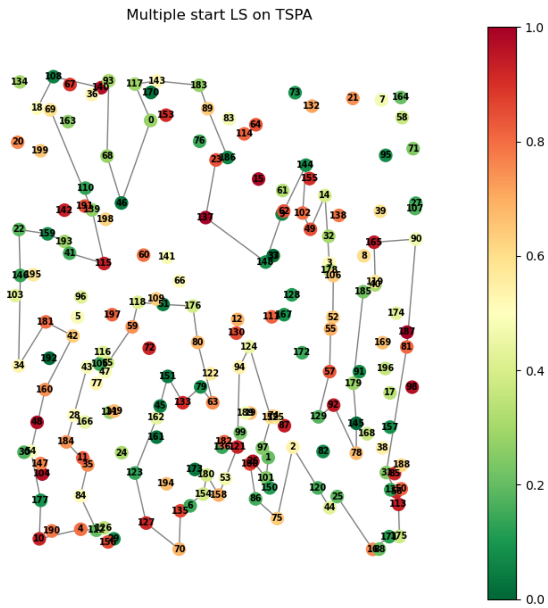
In [20]:
```
warnings.filterwarnings("ignore", category=MatplotlibDeprecationWarning)
cmap = plt.cm.get_cmap('RdYlGn_r')

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
```

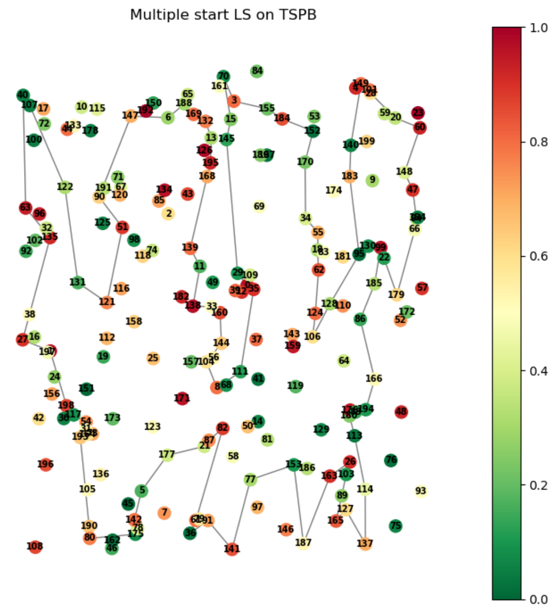
```
        ax = axs[0]
        instance = 'TSPA'
    else:
        df_temp = dfTSPB
        ax = axs[1]
        instance = 'TSPB'

    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()
```

Iterated LS
TSPA
[80, 176, 137, 23, 186, 89, 183, 143, 0, 117, 93, 140, 108, 18, 69, 68, 46, 115, 139
, 41, 193, 159, 22, 146, 181, 34, 160, 48, 54, 177, 10, 190, 4, 112, 84, 35, 184, 42
, 43, 116, 65, 59, 118, 51, 151, 133, 162, 123, 127, 70, 135, 154, 180, 53, 100, 26,
86, 75, 101, 1, 97, 152, 2, 120, 44, 25, 16, 171, 175, 113, 56, 31, 78, 145, 196, 81
, 90, 165, 119, 40, 185, 179, 92, 129, 57, 55, 52, 106, 178, 49, 14, 144, 102, 62, 9
, 148, 124, 94, 63, 79]
0 2
TSPB
[139, 168, 195, 13, 145, 15, 3, 70, 132, 169, 188, 6, 147, 90, 51, 121, 131, 135, 12
2, 133, 107, 40, 63, 38, 27, 16, 1, 156, 198, 117, 193, 31, 54, 73, 136, 190, 80, 45
, 142, 175, 78, 5, 177, 36, 61, 91, 141, 77, 81, 153, 187, 163, 103, 89, 127, 137, 1
14, 113, 176, 194, 166, 86, 185, 95, 130, 99, 22, 179, 66, 94, 47, 148, 60, 20, 28,
149, 4, 140, 183, 152, 170, 34, 55, 18, 62, 124, 106, 143, 35, 109, 0, 29, 111, 8, 1
04, 144, 160, 33, 138, 11]



Multiple start LS
TSPA
[101, 1, 97, 152, 124, 94, 121, 53, 158, 180, 154, 135, 70, 127, 123, 162, 151, 133,
79, 63, 80, 176, 51, 118, 59, 65, 116, 43, 184, 35, 84, 112, 4, 10, 177, 54, 160, 42
, 181, 34, 146, 22, 159, 193, 41, 115, 139, 69, 18, 108, 140, 93, 68, 46, 0, 117, 14
3, 183, 89, 186, 23, 137, 148, 9, 62, 144, 102, 49, 14, 3, 178, 106, 52, 55, 57, 129
, 92, 78, 145, 179, 185, 40, 119, 165, 90, 81, 31, 56, 113, 175, 171, 16, 25, 44, 12
0, 2, 75, 86, 100, 26]
1 3
TSPB
[113, 180, 176, 194, 166, 86, 185, 99, 22, 179, 66, 94, 47, 148, 60, 20, 28, 149, 14
0, 183, 95, 128, 106, 124, 62, 18, 55, 34, 170, 152, 184, 155, 3, 70, 15, 145, 29, 0
, 109, 35, 111, 8, 104, 144, 160, 33, 138, 11, 139, 168, 195, 13, 132, 169, 188, 6,
147, 90, 51, 121, 131, 122, 107, 40, 63, 135, 38, 27, 1, 198, 117, 54, 73, 31, 193,
190, 80, 175, 78, 142, 5, 177, 21, 87, 82, 61, 36, 91, 141, 77, 153, 187, 163, 26, 1
03, 89, 165, 127, 137, 114]





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 Lab6 folder.

Conclusions

Multiple Start Local Search allows exploration of the solution space but lacks the ability to refine solutions further, leading to worse results in both problem instances. In contrast, Iterated Local Search balances exploration with refinement of the current solution, enabling it to achieve higher-quality results.

Interestingly, while Multiple Start Local Search took the same amount of time to perform 200 iterations of Local Search, Iterated Local Search managed to complete 13x as many iterations. This is because Multiple Start Local Search performs Local Search from a newly generated random solution in each iteration, which often requires significant changes to reach a local optimum. Conversely, Iterated Local Search begins each iteration (after the first) with a solution from the previous iteration, perturbed only slightly, thereby requiring far fewer changes and allowing for much faster iterations.

Authors

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