Evolutionary Computation

Assignment 2

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Source code: https://github.com/JankowskiDaniel/evolutionary-computation/tree/main/assignment2

Problem description

The task involves analyzing three columns of integers, each row corresponding to a single node. The initial two columns designate the x and y coordinates, pinpointing the nodes' locations on a plane, while the third column specifies the cost associated with each node. The objective is to meticulously choose an exact half of the total nodes (in cases where the total node count is an odd number, the count of nodes to be selected is adjusted upward to the nearest whole number) to construct a Hamiltonian cycle, which is essentially a continuous loop that passes through each member of the selected set of nodes. The criterion for this selection is that the aggregate of the complete path's length and the cumulative cost of the chosen nodes should be as low as possible.

To quantify the distances between nodes, we employ the Euclidean distance formula, and the resulting figures are rounded off to the nearest integer in a standard mathematical fashion. Moreover, as part of the distance between nodes, we take into account the cost of the destination node. This ensures that cost has a significant impact on the final results.

We implement two heuristic methods based on the greedy cycle algorithm: greedy 2-regret heuristics and greedy heuristics with a weighted sum criterion.

Pseudocode of implemented algorithms

An additional method for calculating the distance matrix

```
Calculate_distance_matrix(coords, costs):
    dist_matrix = [][]
    FOR i in range(len(coords)):
        FOR j in range(len(coords)):
            dist_matrix[i][j] = round(sqrt((coords[i].x – coords[j].x)**2 + (coords[i].y – coords[j].y)**2) + costs[j]
    return dist_matrix
```

Greedy 2-regret heuristic

```
Generate_greedy_2regret_solution(dist_matrix,  start_node):
    num_nodes = dist_matrix.shape[0]
    num_select = (num_nodes + 1) // 2
    selected_nodes = [start_node]
    unselected_nodes = {num_nodes} \ {start_node}
    total_distance = 0
    WHILE len(selected_nodes) < num_select:
        regret_node = None
        regret_position = None
         best_regret= float('-inf')
        regret_best_increase = float('inf')
        FOR node in unselected_nodes:
            best_node = None
            best_position = None
            best_min_increase =infinity
            second_best_min_increase = infinitiy
            FOR i in range(len(selected_nodes):
                next_index = (i +1)% len(selected_nodes)
                 increase = (dist_matrix[selected_nodes[i], node] +
                        dist_matrix[node, selected_nodes[next_i]] -
                         dist_matrix[selected_nodes[i], selected_nodes[next_i]])
                // calculate the increase of distance if the node is inserted after the
          node of index i
                 IF increase < second_best_min_increase:
                    IF increase < best_min_increase:
                        best_min_increase = increase
                         best_node = node
                        best_position = next_i
                    ELSE:
                        second_best_min_increase = increase
            regret= second_best_min_increase - best_min_increase
            IF regret > best_regret:
                 best_regret = regret
                regret_node =  best_node
                regret_position = best_position
                regret_best_increase = best_min_increase

        ADD regret_node at the regret_position to selected nodes
        REMOVE regret_node from unselected_nodes
    total_distance += regret_best_increase

    total_distance +=  dist_matrix[selected_nodes[-1], selected_nodes[0]]
    return selected_nodes, total_distance
```

Greedy 2-regret with a weighted sum

```
Generate_greedy_2regret_weights_solution(dist_matrix, start_node, weight):
    num_nodes = dist_matrix.shape[0]
    num_select = (num_nodes + 1) // 2
    selected_nodes = [start_node]
    unselected_nodes = {num_nodes} \ {start_node}
    total_distance = 0
    WHILE len(selected_nodes) < num_select:
        regret_node = None
        regret_position = None
        best_regret= float('-inf')
        regret_best_increase = float('inf')
        FOR node in unselected_nodes:
            best_node = None
            best_position = None
            best_min_increase =infinity
            second_best_min_increase = infinitiy
            FOR i in range(len(selected_nodes):
                next_index = (i +1)% len(selected_nodes)
                increase = (dist_matrix[selected_nodes[i], node] +
                        dist_matrix[node, selected_nodes[next_i]] -
                        dist_matrix[selected_nodes[i], selected_nodes[next_i]])
                // calculate the increase of distance if the node is inserted after the
            node of index i
                IF increase < second_best_min_increase:
                    IF increase < best_min_increase:
                        best_min_increase = increase
                        best_node = node
                        best_position = next_i
                    ELSE:
                        second_best_min_increase = increase

            regret= second_best_min_increase - best_min_increase
            score = weight * regret - (1-weight)*best_min_increase
            IF score > best_score:
                best_score = score
                score_node = best_node
                score_position = best_position
                score_best_increase = best_min_increase

        ADD score_node at the score_position to selected nodes
        REMOVE score_node from unselected_nodes
    total_distance += score_best_increase
    total_distance += dist_matrix[selected_nodes[-1], selected_nodes[0]]
    return selected_nodes, total_distance
```

Results

Results from the previous report
The random solution

	Min	Max	Mean
Instance A	237,941	288,302	264,028.49
Instance B	243,288	295,269	266,655.16
Instance C	191,705	241,451	214,929.07
Instance D	191,218	242,515	219,678.85

The nearest neighbor algorithm

	Min	Max	Mean
Instance A	84,471	95,013	87,679.14
Instance B	77,448	82,631	79,282.58
Instance C	56,304	63,697	58,872.68
Instance D	50,335	59,846	54,290.68

The greedy cycle algorithm

	Min	Max	Mean
Instance A	75,136	80,025	76,711.19
Instance B	67,896	76,096	70,464.27
Instance C	53,020	58,499	55,859.31
Instance D	50,288	60,208	54,931.05

The greedy 2-regret algorithm

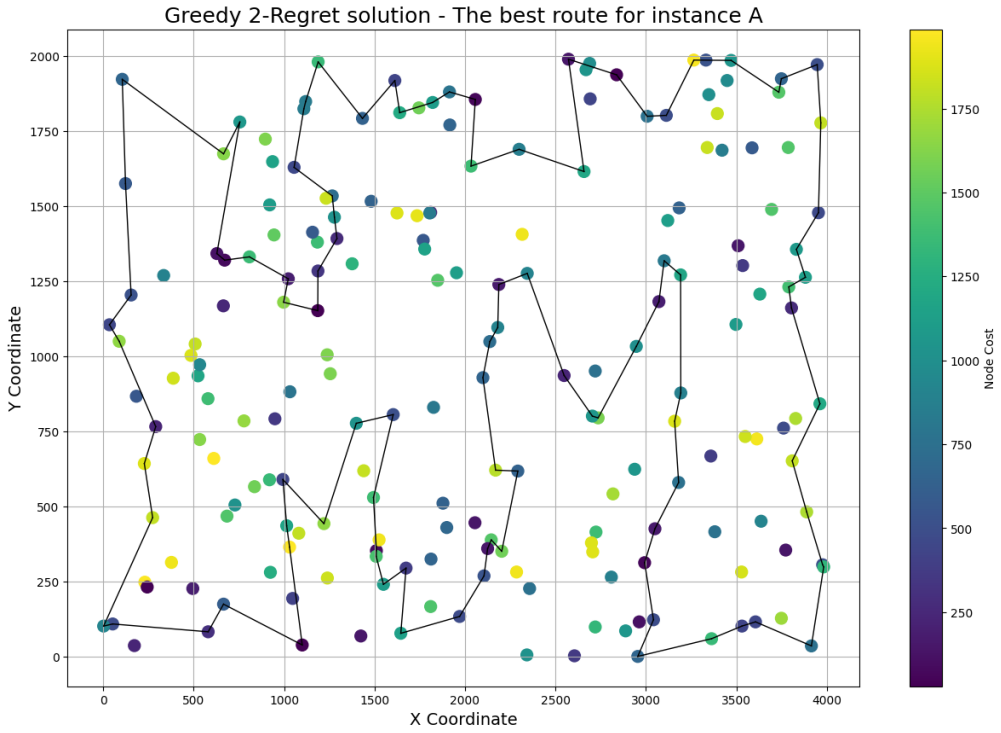
	Min	Max	Mean
Instance A	106,734	124,404	116,772.94
Instance B	104,997	125,925	116,871.66
Instance C	63,247	72,558	68,444.90
Instance D	62,852	74,184	68,585.68

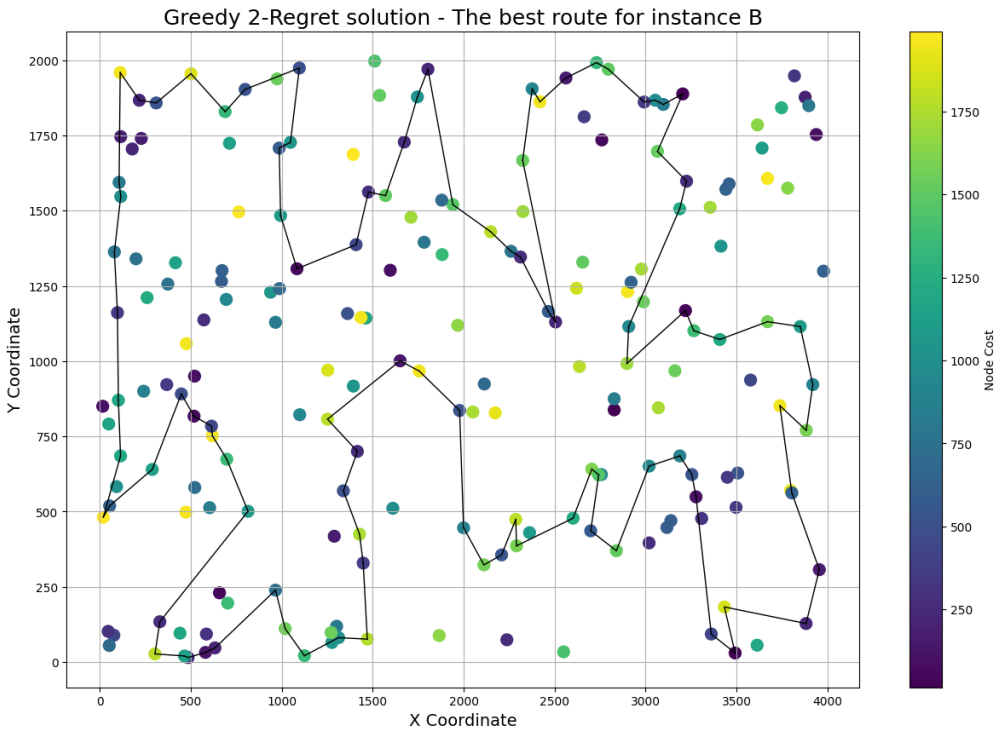
The greedy 2-regret with a weighted sum

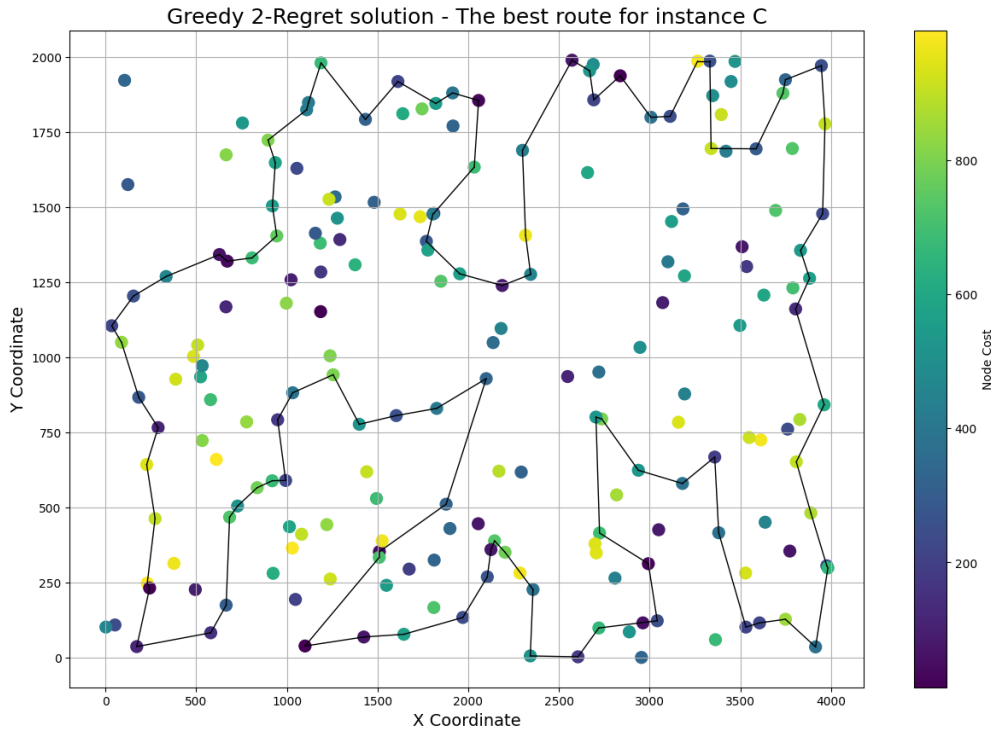
	Min	Max	Mean
Instance A	74,708	82,990	76,980.75
Instance B	67,490	80,001	73,067.76
Instance C	50,158	58,173	53,795.98
Instance D	46,549	62,321	52,930.70

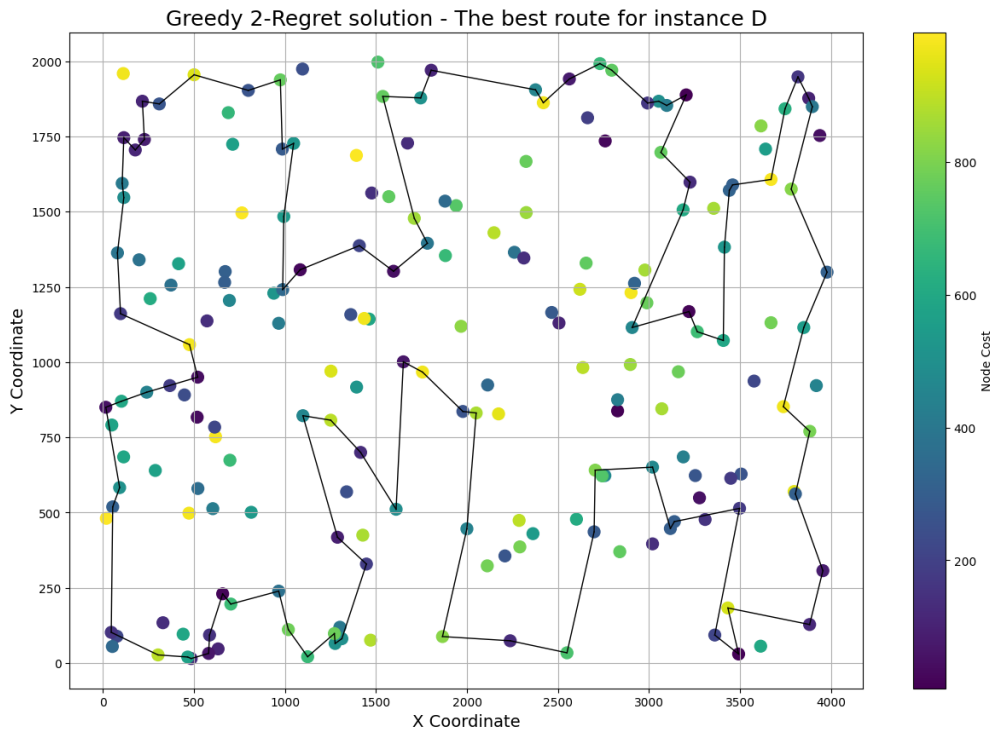
Visualizations

The greedy 2-regret algorithm

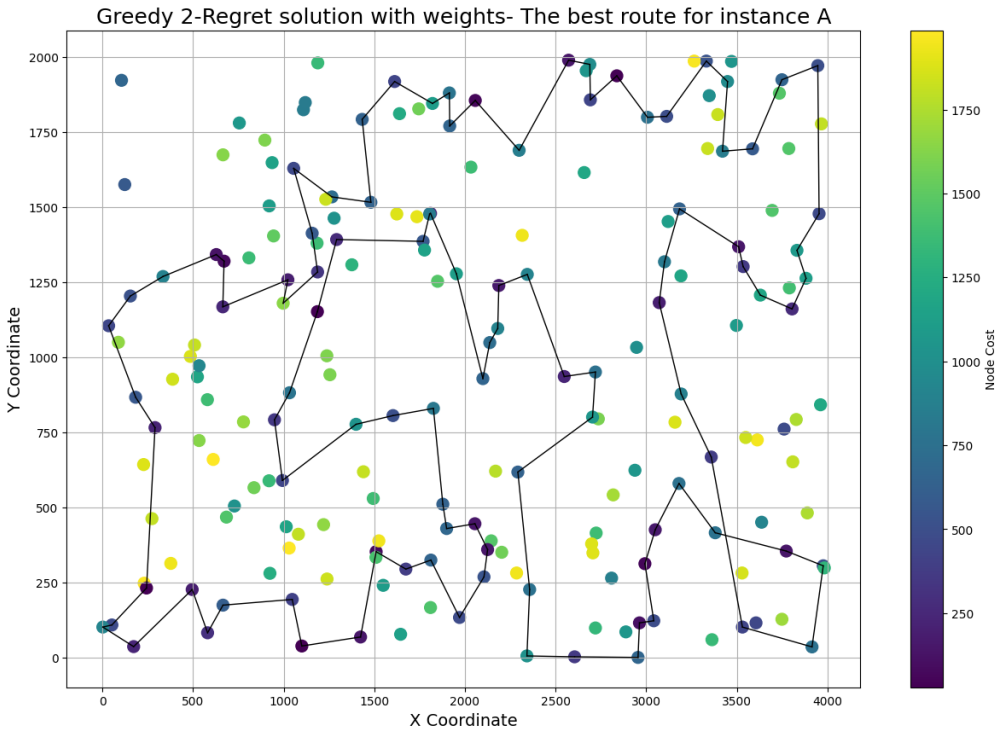


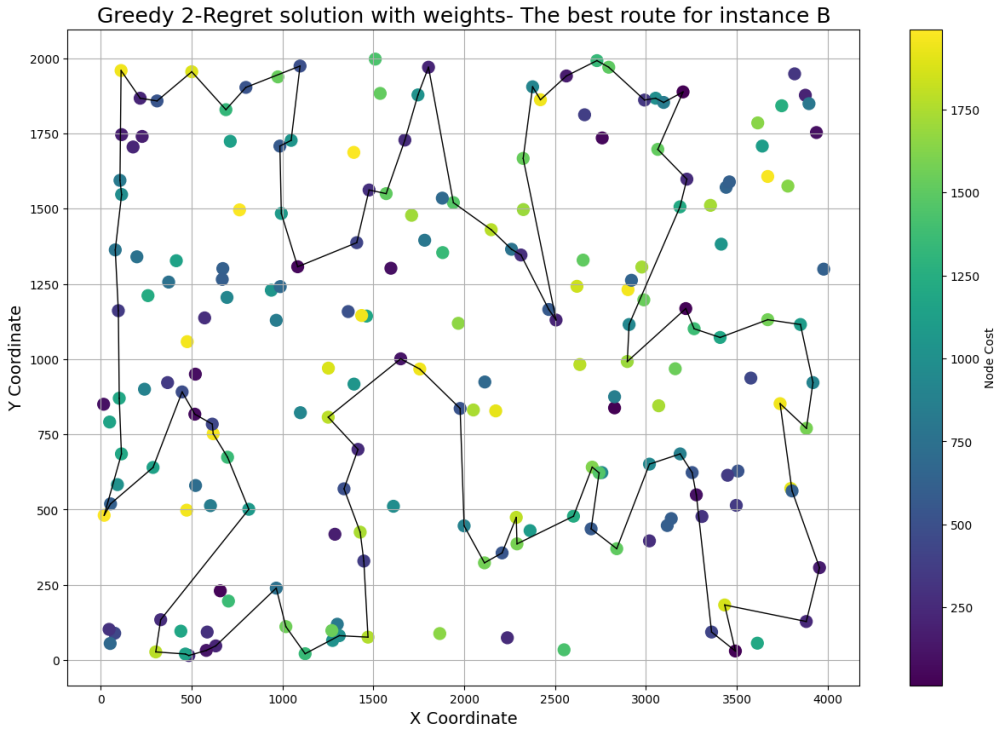

Greedy 2-Regret solution - The best route for instance B
Y Coordinate
X Coordinate
Node Cost
0
250
500
750
1000
1250
1500
1750
2000
2500
3000
3500
4000

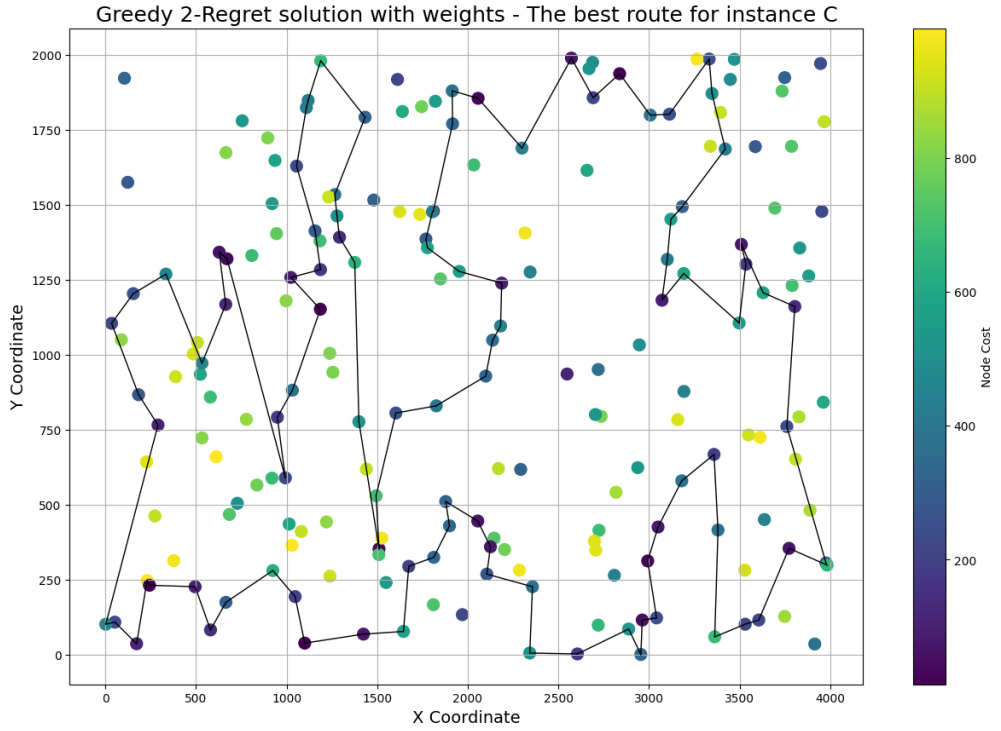

Greedy 2-Regret solution - The best route for instance C
Y Coordinate
X Coordinate
Node Cost
0
200
400
600
800
250
500
750
1000
1250
1500
1750
2000
2500
3000
3500
4000

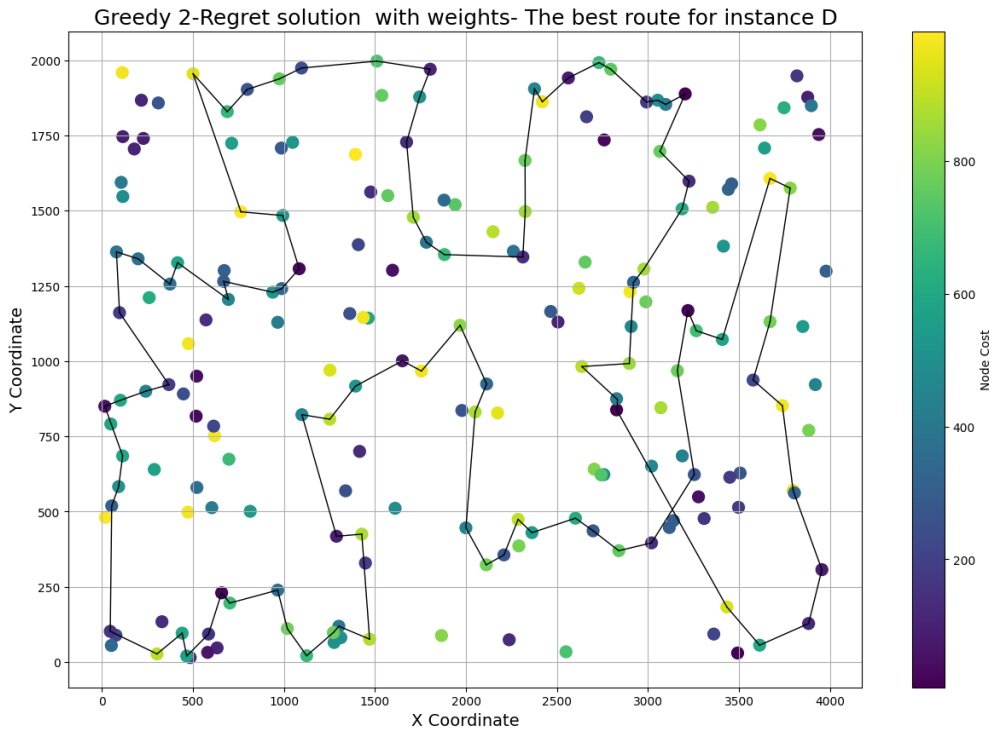


The greedy 2-regret with a weighted sum




Greedy 2-Regret solution with weights- The best route for instance B
Y Coordinate
X Coordinate
Node Cost
0
250
500
750
1000
1250
1500
1750
2000
2500
3000
3500
4000


Greedy 2-Regret solution with weights - The best route for instance C
Y Coordinate
X Coordinate
Node Cost
0
200
400
600
800
250
500
750
1000
1250
1500
1750
2000
2500
3000
3500
4000



Conclusions

The analysis of the heuristic algorithms applied to the Traveling Salesman Problem (TSP) reveals significant differences in performance, underscoring the importance of algorithm selection in obtaining efficient solutions. The Random Solution, devoid of any strategic path selection, resulted in the least efficient routes, emphasizing the necessity for heuristic logic in tackling such optimization problems. The Nearest Neighbor and Greedy Cycle algorithms demonstrated considerable improvements in comparison to the random algorithm. Especially the greedy cycle where paths started to cross each other much less than for NN and random algorithm.

Interestingly, the Greedy 2-Regret algorithm, despite its strategy to minimize future regret, didn't always yield shorter paths. This can be attributed to its inherent mechanism of considering not just the immediate distance but also potential future path restrictions, reflecting the trade-offs involved in decision-making during optimization problems. However, the most efficient paths were often produced by the Greedy 2-Regret algorithm with a weighted sum, indicating that a more holistic approach—incorporating additional factors like node costs into the decision metric—can lead to superior solutions. This algorithm's ability to balance immediate distance with overall route cost and regret resulted in paths that, while not always the shortest, were often the most cost-effective.

The visualizations presented above show more direct and less convoluted paths for the more advanced heuristics, especially the Greedy 2-Regret with a weighted sum. These findings highlight the critical role of sophisticated heuristics in solving complex optimization problems like the TSP, where multiple factors must be considered beyond mere distance. They also underscore the potential for even more advanced algorithms or hybrid approaches that could further enhance solution efficiency, especially in real-world scenarios where variables such as time, cost, and resource constraints are of paramount importance.