Evolutionary Computation

Assignment 5

Antoni Lasik 148287
Daniel Jankowski 148257
https://github.com/JankowskiDaniel/evolutionary-computation/tree/AL/assignment5

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.

In this report we implement the steepest version of a local search with deltas from previous iteration. While the results should be almost the same, the purpose of the modification is to reduce the runtime of a classical algorithm version.

Pseudocode of implemented algorithms

```
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)
        RETURN dist_matrix

objective_function(solution, dist_matrix, costs):
        total_score = 0
        n = len(solution)
        FOR x in range(n):
                        total_score += dist_matrix[solution[x - 1]][solution[x]]
                        total_score += costs[solution[x]]
        RETURN total_score
```

The methods for checking the applicability of a given move. The methods returns the following values:

- -1 if a move is not applicable and should be removed from LM
- 0 if a move is not applicable now, but shouldn't be removed from LM
- 1 if a move is applicable and will be accepted

```
is_intra_move_applicable(solution, move):
      # for the intra moves changes affects only nodes that are inside a given solution,
      # therefore first we check if all nodes in edges, that a move introduced, are
      # present in the current solution
      FOR edge IN move.added_edges:
            IF edge.source_node NOT IN solution OR
               edge.dest_node NOT IN solution:
                  RETURN -1
      # check if all edges that a move removed are present in a solution
      all_edges_match = True
      FOR edge IN move.removed_edges:
            reversed_edge = edge[-1] # reverse the edge
            IF edge NOT IN solution AND reversed_edge NOT IN solution:
                  RETURN -1
            IF edge NOT IN solution AND reversed_edge IN solution:
                  all_edges_match = False
      RETURN 1 IF all_edges_match ELSE 0


is_inter_move_applicable(solution, move):
      # added edges by a move have shape:(old_node_1, NEW_NODE),(NEW_NODE, old_node_2)
      # therefore first we check if all old nodes are present in the current solution
      IF move.added_edges[0].source_node NOT IN solution OR
         move.added_edges[1].dest_node NOT IN solution:
            RETURN -1
      # if the node that will be inserted is not in the list of currently unselected
      # nodes, a move can't be applied
      IF move.added_edges[0].dest_node NOT IN unselected_nodes:
            RETURN -1
      # check if all edges that a move removed are present in a solution
      all_edges_match = True
      FOR edge IN move.removed_edges:
            reversed_edge = edge[-1] # reverse the edge
            IF edge NOT IN solution AND reversed_edge NOT IN solution:
                  RETURN -1
            IF edge NOT IN solution AND reversed_edge IN solution:
                  all_edges_match = False
      RETURN 1 IF all_edges_match ELSE 0
```

To control moves that has been already discovered and evaluated the heap has been implemented using built-in python package. The heap stores information about discovered moves and their delta score, always sorted in a descending order by the score. We have used two basic methods:

- `heap.add_move()` – add a new move to the heap
- `heap.heappop()` – take the first element from the heap (with the best score)

```
two_edges_exchange(solution, heap, dist_matrix, nodes_to_check):
       n = len(solution)
       nodes_indices = [solution.index(i) FOR i IN nodes_to_check]
       FOR i IN nodes_indices:
              FOR j IN RANGE(n):
                     x, y = i, j
                     IF y < x:
                            x, y = y, x
                     IF abs(x-y) >= 2:
                            score_delta = (
                              -dist_matrix[solution[x]][solution[x+1]]
                              -dist_matrix[solution[y]][solution[(y+1)%n]]
                              +dist_matrix[solution[x]][solution[y]]
                              +dist_matrix[solution[x+1]][solution[(y+1)%n]]
                            IF score_delta < 0:
                              added_edges = ((solution[x], solution[y]),
                                             (solution[x+1], solution[(y+1)%n]))
                              removed_edges = ((solution[x], solution[x+1]),
                                               (solution[y], solution[(y+1)%n]))
                              # Add a move to the LM
                              heap.add_move((score_delta, (added_edges, removed_edges)))
```

```
inter_route_exchange(solution, unselected, heap, dist_matrix, nodes_to_check):
       n_unselected = len(unselected)
       index_pairs = [(solution.index(i), j) FOR i IN nodes_to_check FOR j IN
                                                       RANGE(n_uselected)]
       FOR i, j IN index_pairs:
              selected_node = solution[i]
              new_node = unselected[j]
              new_solution = solution.copy()
              new_solution[i] = new_node
              prev_node_index = (i-1)% len(solution)
              next_node_index = (i+1)% len(solution)

              removed_edges = ((solution[prev_node_index], selected_node),
                                (selected_node, solution [next_node_index]))
              added_edges = ((solution[prev_node_index], new_node),
                              (new_node, solution[next_node_index]))
              score_delta = (
                -dist_matrix[solution[prev_node_index]][selected_node]
                -dist_matrix[selected_node][solution[next_node_index]]
                +dist_matrix[solution[prev_node_index]][new_node]
                +dist_matrix[new_node][solution[next_node_index]]
                -selected_node.cost
                +new_node.cost
              IF score_delta < 0:
                     heap.add_move((score_delta, (added_edges, removed_edges)))
```

```
apply_edge_move(solution, added_edges):
       # indices of first nodes of edges that are exchanged
       x = solution.index(added_edges[0][0])
       y = solution.index(added_edges[0][1])
       IF y < x:
              X, y = y, x
       # update class parameter that holds current solution
       new_solution = solution[:x + 1] + solution[x+1:y+1][::-1] + solution[y+1:]
       # return new solution and all nodes that has been affected by a move, and should
       # be checked in the next iteration
       RETURN new_solution, added_edges[0] + added_edges[1]
```

```
apply_inter_move(solution, added_edges, removed_edges):
       new_node = added_edges[0][1]
       index_old_node = solution.index(removed_edges[0][1])
       # update changed node in the solution
       solution[index_old_node] = new_node
       self.unselected_nodes.remove(new_node)
       self.unselected_nodes.append(removed_edges[0][1])
       # return all nodes that has been affected by a move, and should be checked in the
       # next iteration
       RETURN solution, (added_edges[0] +  added_edges[1])


run_algorithm(start_solution, dist_matrix, costs, moves)
       current_score = objective_function(start_solution, dist_matrix, costs)
       LM = []
       solution = start_solution
       # Call both moves methods to add the whole neighborhood in the first iteration to
       # the LM
       inter_route_exchange(solution, unselected, LM, dist_matrix)
       two_edges_exchange(solution, LM, dist_matrix)

       progress = True
       WHILE(progress):
              progress = False
              moves_to_restore = []
              WHILE(LM):
                     delta_score, (move_type, added_edges, removed_edges) = LM.heappop()
                     # call move applicability w.r.t. to its type
                     IF is_move_applicable(solution, added_edges, removed_edges) == 1:
                        # a move is applicable and will be accepted:
                        new_solution, affected_nodes = apply_move(solution,added_edges)
                        solution = new_solution
                        current_score += delta_score
                            progress = True
                            BREAK
                     ELIF is_move_applicable(solution, added_edges, removed_edges) == 0:
                            moves_to_restore.append((delta_score, (move_type, added_edges,
                                                                            removed_edges)))
                     ELSE:
                            # a move is not applicable and it's okay to keep it deleted
                            CONTINUE
              FOR move IN moves_to_restore:
                     LM.add_move(move)
              IF progress:
                     # performs new moves, and add them to the LM
                     inter_route_exchange(solution, LM, dist_matrix, affected_nodes)
                     two_edges_exchange(solution, LM, dist_matrix, affected_nodes)
       RETURN solution, current_score
```

Results

Method	Instance A	Instance B	Instance C	Instance D
Random solution	264,028(237,941-288,302)	266,665(243,288-295,269)	214,929(192,705-241,451)	219,678(191,218-242,515)
Nearest Neighbor	87,679(84,471-95,013)	79,282(77,448-82,631)	58,290(56,304-63,697)	54,290.68(50,335-59,846)
Greedy Cycle	76,711(75,136-80,025)	70,464(67,896-76,096)	55,859(53,020-58,499)	54,931(50,288-60,208)
2-regret GC	116,772(106,734-124,404)	116,871(104,997-125,925)	68,444(63,247-72,558)	68,585(62,852-74,184)
2-regret with weighted sum	76,980(74,708-82,990)	73,067(67,490-80,001)	53,795(50,158-58,173)	52,930(46,549-62,321)
Greedy LS, random solution, two-edges + inter route	77,014(74,663-79,803)	69,990(67,877-74,141)	50,998 (49,340-53,141)	48,068 (45,336-51,629)
Greedy LS, random solution, two-nodes + inter route	90,940(84,816-99,390)	85,570(77,908-97,299)	63,929 (58,135-70,886)	62,175 (54,310-71,108)
Greedy LS, best solution from 2-regret with weighted sum, two-edges + inter route	75,792 (74,221-79,688)	**71,266 (67,384-77,120)**	**52350,15(48,931-55,758)**	51,013 (45,212-59,478)
Greedy LS, best solution from 2-regret with weighted sum, two-nodes + inter route	75,932(74,344-79,315)	**71,839 (67,384-77,565)**	52,638 (49,649-56,472)	51,248(45,097-60,185)
Steepest LS, best solution from 2-regret with weighted sum, two-edges + inter route	**75,728(74,091-79,220)**	**71,233 (67,384-77,057)**	52,299 (49,098-5,5665)	**50,977(45,097-59,478)**
Steepest LS, best solution from 2-regret with weighted sum, two-nodes + inter route	75,880(74,280-79,220)	**71,894(67,384-77,420)**	52,607 (49,460-56,472)	**51,247 (45,097-60,185)**
Candidates LS, random solution, two-edges + inter route	81,129(76,609-86,447)	73,977(69,300-80,189)	51,588(49,120-54,801)	48,429(45,385-51,392)
Steepest LS, random solution, two-nodes + inter route	92,714(84,218-103,034)	87,666(79,356-97,895)	65,679(59,604-73,386)	64,162(54,716-75,351)
Steepest LS, random solution, two-edges + inter route	78,017 (74,874-82,619)	71,337(67,909-76,199)	51,485 (49,235-53,755)	48,225 (45,673-51,639)
Deltas from previous iteration, random solution, two-edges + inter route	78,192(75,149-82,556)	71,709(68,307-76,210)	51,940(49,347-55,591)	48,509(45,966-52,016)

**the structure of values in the table: avg(min-max)*
***in bold there are the best minimal solutions founded by a given method*

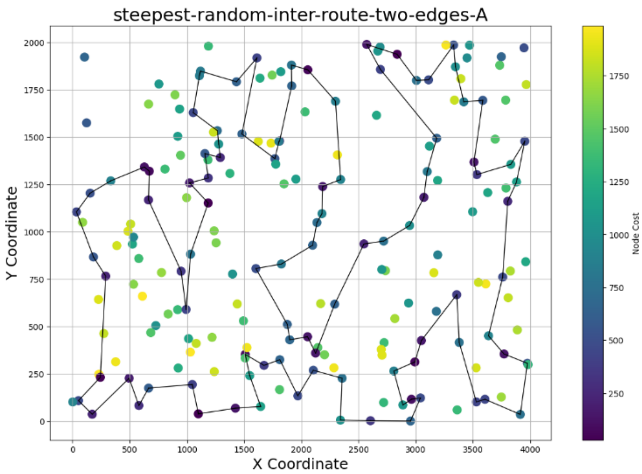
Runtimes

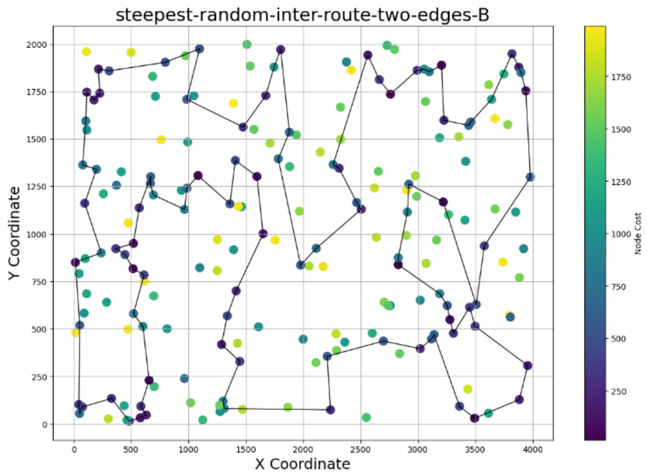
Method	Instance A	Instance B	Instance C	Instance D
Greedy LS, random solution, two-edges + inter route	1.56(1.06-2.63)	1.95(1.19-3.48)	1.25(0.77-2.28)	1.18(0.72-1.99)
Greedy LS, random solution, two-nodes + inter route	1.68(1.03-2.98)	1.95(0.81-6.66)	1.38(0.79-2.21)	1.37(0.77-2.36)
Greedy LS, best solution from 2-regret with weighted sum, two-edges + inter route	0.67(0.51-0.97)	0.7(0.5-1.18)	0.66(0.5-0.93)	0.65(0.51-0.89)
Greedy LS, best solution from 2-regret with weighted sum, two-nodes + inter route	0.63(0.46-0.89)	0.69(0.53-1.15)	0.68(0.49-1.24)	0.67(0.54-1.18)
Steepest LS, best solution from 2-regret with weighted sum, two-edges + inter route	0.85(0.55-1.53)	0.95(0.53-1.78)	0.94(0.57-1.6)	1(0.58-1.38)
Steepest LS, best solution from 2-regret with weighted sum, two-nodes + inter route	0.88(0.58-1.71)	0.83(0.53-1.57)	0.89(0.5-1.58)	1.03(0.67-1.5)
Candidate LS, random solution, two-edges + inter route	4.43(3.95-6.41)	4.52(3.99-5.70)	4.53(3.83-6.44)	4.58(4.06-5.88)
Steepest LS, random solution, two-nodes + inter route	6.82(5.46-8.96)	6.63(4.89-10.51)	6.8(5.41-9.2)	0.69(0.5-1.18)
Steepest LS, random solution, two-edges + inter route	5.46(4.47-7.46)	5.64(4.51-7.16)	5.41(4.72-6.54)	5.64(4.76-6.88)
Deltas from previous iteration, random solution, two-edges + inter route	1.34(1.06-2.13)	1.80(0.80-2.31)	1.82 (1.05-2.51)	1.88(1.23-2.44)

**the format is: avg(min-max)*
***all runtimes are provided in seconds.*

Below we've written down best paths found for the Candidate Local Search that were missing in the previous report.

TSPA: [43, 121, 50, 149, 0, 19, 178, 164, 37, 159, 143, 59, 96, 147, 27, 116, 185, 64, 20, 71, 163, 74, 113, 132, 128, 36, 55, 195, 22, 18, 53, 93, 62, 180, 81, 154, 144, 87, 141, 24, 170, 21, 79, 194, 171, 108, 15, 117, 28, 76, 91, 114, 4, 175, 153, 88, 127, 186, 45, 6, 156, 172, 66, 98, 190, 72, 94, 111, 14, 80, 8, 169, 95, 31, 73, 112, 51, 196, 135, 101, 167, 126, 109, 119, 26, 92, 48, 106, 198, 160, 11, 152, 130, 189, 75, 1, 177, 41, 199, 77]
TSPB: [153, 80, 157, 145, 79, 136, 61, 73, 33, 29, 18, 132, 81, 185, 189, 170, 181, 147, 159, 64, 129, 89, 58, 85, 114, 67, 91, 70, 51, 174, 188, 140, 148, 141, 130, 142, 192, 196, 117, 150, 162, 44, 71, 119, 59, 97, 107, 12, 52, 16, 8, 63, 82, 115, 40, 2, 133, 75, 182, 163, 172, 95, 190, 198, 135, 169, 66, 128, 167, 5, 34, 183, 197, 92, 122, 143, 179, 127, 24, 121, 31, 101, 38, 103, 131, 152, 50, 43, 99, 57, 146, 137, 37, 165, 154, 25, 36, 88, 55, 4]
TSPC: [108, 15, 53, 62, 32, 180, 81, 154, 144, 141, 87, 79, 194, 21, 88, 127, 186, 45, 24, 6, 156, 172, 66, 98, 190, 72, 94, 12, 73, 31, 80, 124, 8, 169, 95, 112, 51, 196, 135, 99, 101, 167, 60, 126, 109, 119, 92, 48, 106, 160, 11, 152, 1, 41, 137, 177, 75, 189, 174, 199, 192, 4, 114, 77, 43, 50, 121, 91, 161, 76, 145, 36, 132, 128, 40, 0, 149, 69, 19, 178, 164, 143, 59, 147, 27, 96, 185, 64, 20, 71, 61, 113, 163, 74, 138, 195, 55, 22, 117, 171]
TSPD: [171, 129, 64, 147, 159, 89, 58, 72, 114, 158, 162, 150, 44, 117, 196, 192, 67, 3, 156, 91, 70, 51, 174, 188, 140, 148, 141, 130, 142, 53, 82, 63, 8, 16, 172, 95, 163, 182, 5, 128, 66, 34, 183, 197, 179, 143, 122, 127, 24, 121, 31, 101, 38, 103, 131, 50, 94, 112, 23, 154, 134, 25, 36, 194, 123, 165, 37, 102, 99, 137, 88, 55, 153, 157, 80, 57, 0, 135, 198, 190, 19, 6, 33, 29, 18, 73, 136, 185, 132, 65, 52, 12, 107, 139, 193, 119, 59, 71, 166, 85]


steepest-random-inter-route-two-edges-A
Y Coordinate
X Coordinate
Node Cost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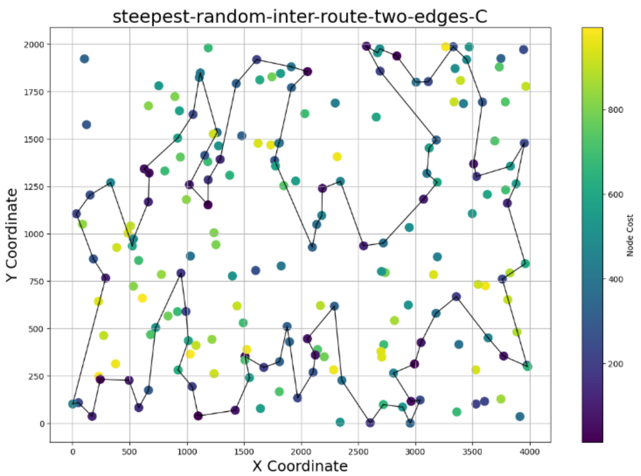
Node Cost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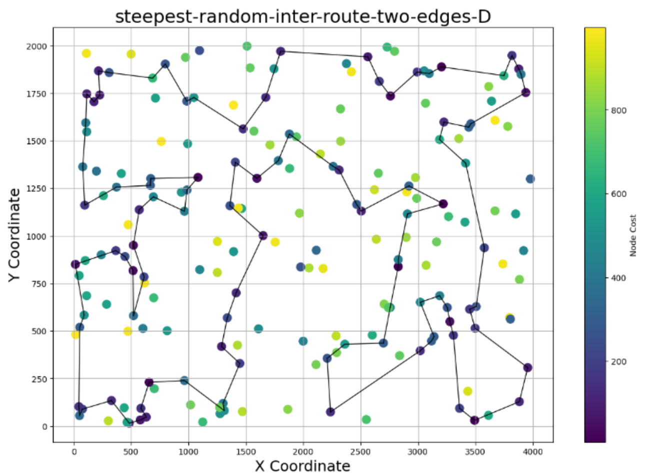
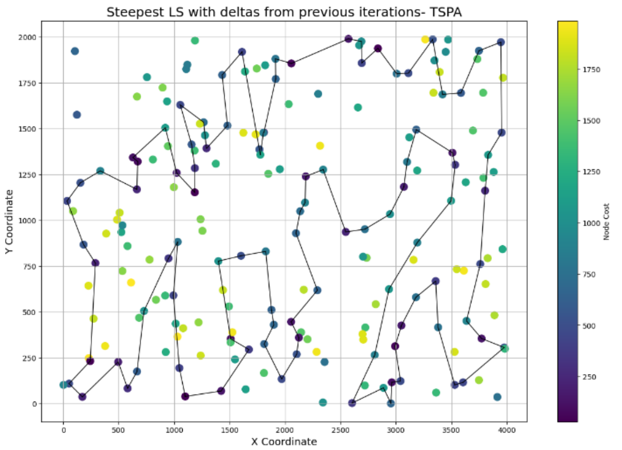
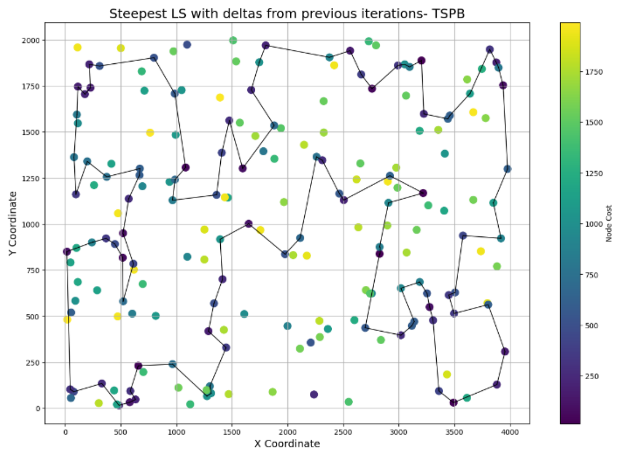
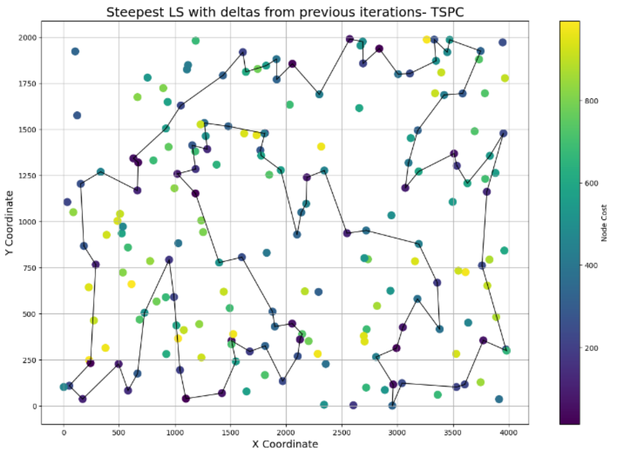
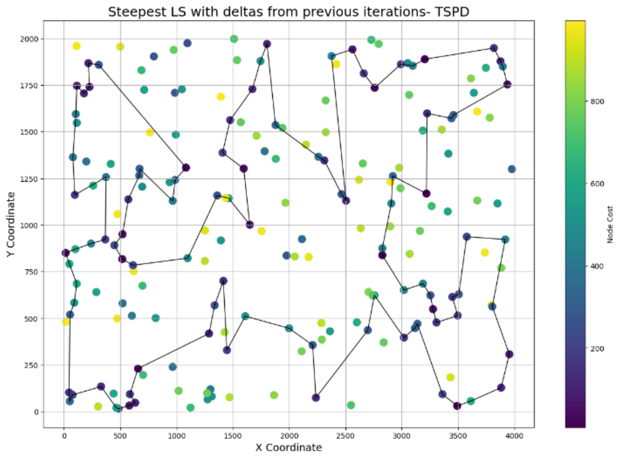
Y Coordinate
X Coordinate
Node Cost


steepest-random-inter-route-two-edges-D
Y Coordinate
X Coordinate
Node Cost









TSPA: [22, 53, 62, 108, 15, 117, 171, 81, 154, 21, 157, 194, 79, 87, 144, 141, 6, 156, 66, 98, 190, 72, 94, 73, 31, 111, 14, 80, 124, 8, 26, 92, 48, 106, 11, 152, 130, 119, 109, 189, 75, 1, 177, 41, 137, 199, 174, 126, 134, 139, 169, 95, 112, 51, 135, 99, 101, 167, 45, 186, 127, 88, 153, 175, 114, 4, 77, 43, 50, 121, 91, 161, 76, 145, 0, 149, 19, 178, 164, 128, 36, 132, 37, 159, 143, 59, 147, 27, 96, 185, 64, 20, 71, 61, 113, 74, 163, 155, 195, 55]

TSPB: [53, 32, 113, 69, 115, 82, 63, 8, 14, 16, 172, 95, 19, 190, 198, 135, 57, 99, 0, 169, 66, 5, 34, 183, 197, 26, 92, 122, 143, 179, 31, 101, 38, 103, 131, 121, 127, 24, 50, 152, 94, 112, 154, 134, 25, 36, 123, 165, 37, 137, 88, 55, 4, 153, 80, 157, 145, 79, 136, 61, 73, 33, 18, 185, 132, 52, 139, 107, 12, 189, 181, 147, 159, 64, 129, 89, 58, 72, 114, 85, 166, 59, 119, 71, 44, 196, 192, 117, 150, 162, 158, 67, 91, 51, 174, 140, 148, 141, 130, 142]

TSPC: [24, 6, 156, 66, 98, 190, 72, 12, 94, 89, 42, 111, 31, 73, 112, 51, 135, 196, 95, 169, 110, 124, 80, 8, 26, 106, 198, 48, 11, 152, 1, 41, 177, 174, 75, 189, 109, 130, 119, 134, 101, 167, 45, 186, 127, 88, 153, 170, 157, 21, 79, 194, 171, 108, 117, 53, 22, 195, 55, 145, 76, 91, 121, 114, 2, 4, 77, 43, 50, 149, 0, 69, 19, 178, 164, 128, 132, 37, 159, 143, 59, 147, 27, 96, 185, 64, 71, 61, 113, 74, 163, 155, 62, 81, 154, 133, 102, 144, 87, 141]

TSPD: [57, 99, 137, 37, 165, 154, 134, 25, 36, 88, 55, 153, 80, 157, 145, 79, 135, 198, 190, 19, 33, 136, 61, 73, 185, 132, 18, 16, 65, 52, 84, 196, 117, 150, 44, 71, 119, 59, 139, 107, 12, 147, 159, 64, 129, 89, 58, 72, 114, 166, 162, 158, 126, 67, 45, 78, 3, 156, 91, 70, 51, 174, 188, 140, 148, 141, 130, 142, 82, 63, 8, 115, 40, 163, 182, 2, 5, 128, 34, 183, 197, 31, 101, 42, 38, 103, 131, 152, 50, 24, 127, 121, 179, 143, 122, 92, 26, 66, 169, 0]

Conclusions

Results obtained by the modified version of a Steepest Local Search, where we store deltas from previous iterations, are very similar to the classical version of the algorithm. It was expected, since the main idea for finding a best solution didn’t changed. The size of the neighborhood was the same, however, the way how we explore it was different. Instead of evaluating each move, we were computing delta score only for new moves, and considering only those, that provided improvement with respect to the current solution.

The purpose of this change was to reduce the runtime in comparison to the classical version of the Steepest Local Search. As the provided results showed, the implementation with deltas from previous iteration was approximately 3-4x faster than the original approach. The most positive impact on runtime was primarily due to different way of browsing the neighborhood. We haven’t anymore iterating in each iteration through all moves that are possible, but instead we were only checking solutions that were new. It was achieved, by creating new moves only for parts of the solution, that has been modified in the previous iteration. For example, if in the previous iteration, a move has introduced two new edges to the solution, in the next epoch we were only iterating trough all moves, that contains these edges (or their neighbor edges), since all other moves has been already evaluated and potentially stored in the LM previously.