07-large-neighborhood-search

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Github

1 Description of a problem

We are given three columns of integers with a row for each node. The first two columns contain x and y coordinates of the node positions in a plane. The third column contains node costs. The goal is to select exactly 50% of the nodes (if the number of nodes is odd we round the number of nodes to be selected up) and form a Hamiltonian cycle (closed path) through this set of nodes such that the sum of the total length of the path plus the total cost of the selected nodes is minimized.

The distances between nodes are calculated as Euclidean distances rounded mathematically to integer values. The distance matrix should be calculated just after reading an instance and then only the distance matrix (no nodes coordinates) should be accessed by optimization methods to allow instances defined only by distance matrices.

2 LNS

2.1 Pseudocode

Algorithm: LargeNeighborhoodSearch

1. start_time ← current_time()
2. num_iterations ← 0
3. best_s ← LocalSearch(InitRandomSolution(ds, dm))
4. best_cost ← Cost(best_s)
5. while current_time() - start_time < max_runtime:
   1. num_iterations ← num_iterations + 1
   2. s' ← Repair(ds, dm, w_cost, w_regret, Destroy(best_s))
   3. if apply_local_search: s' ← LocalSearch(s')
   4. if Cost(s') < best_cost: best_s, best_cost ← s', Cost(s')
6. return best_s, num_iterations

Destroy Operation

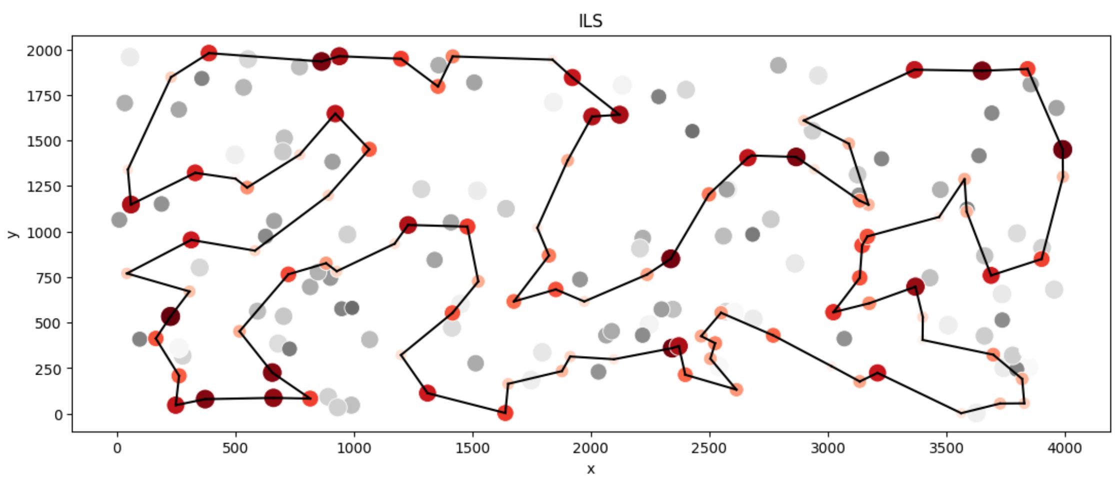
1. (segment_length, k_segments) ← `GenerateRandomSegmentsParams(length(solution), min_percentage=0.2, max_percentage=0.3)`
2. longest_segments ← `FindKLongestSegments(dm, solution, segment_length, k_segments)`

3. destroyed_solution ← `EliminateSegments(solution, longest_segments)`
4. return destroyed_solution

2.2 Results with LS

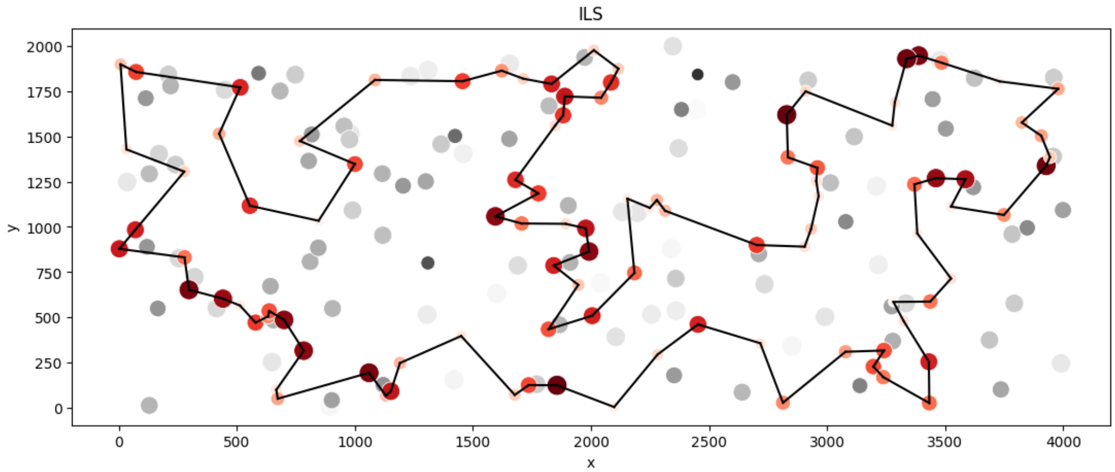
2.2.1 Dataset A

```
Best solution: [144, 14, 106, 178, 49, 102, 62, 9, 148, 124, 94, 63, 79, 133,
80, 176, 137, 23, 186, 89, 183, 143, 0, 117, 93, 140, 108, 18, 22, 146, 159,
193, 41, 139, 68, 46, 115, 42, 181, 34, 160, 48, 54, 177, 10, 190, 4, 112, 84,
184, 43, 116, 65, 59, 118, 51, 151, 162, 123, 127, 70, 135, 154, 180, 53, 100,
26, 86, 75, 101, 1, 97, 152, 2, 120, 44, 25, 16, 171, 175, 113, 31, 78, 145,
179, 92, 129, 57, 55, 52, 185, 165, 40, 196, 81, 90, 27, 164, 7, 21]
Objective function statistics:
minimum.cost = 69474
mean = 70179.05
maximum.cost= 71022
Mean Number of sucessfull perturbations: 3027.2
```



2.2.2 Dataset B

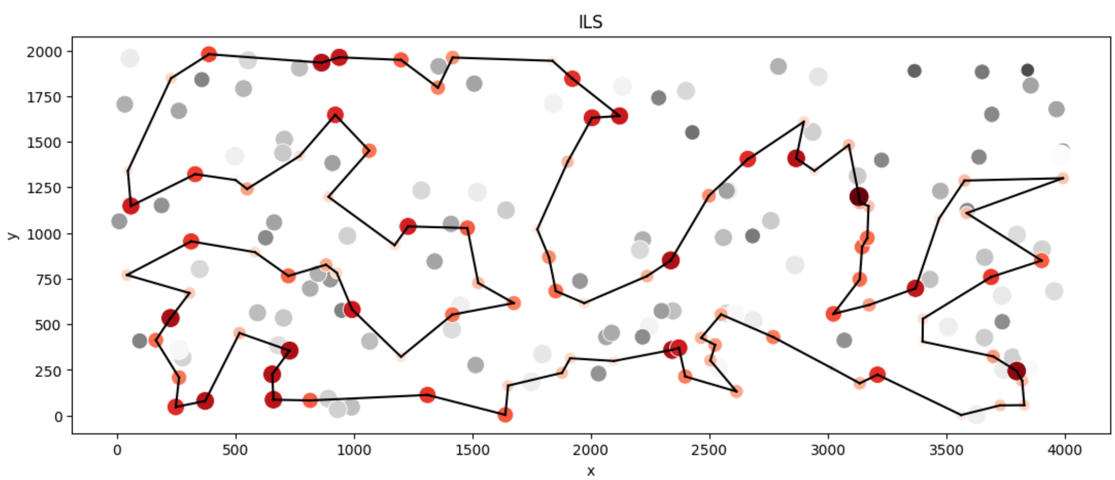
```
Best solution: [11, 139, 168, 195, 13, 145, 15, 3, 70, 132, 169, 188, 6, 147,
90, 51, 121, 131, 122, 133, 107, 40, 63, 135, 38, 27, 1, 156, 198, 117, 193, 31,
54, 73, 136, 190, 80, 45, 175, 78, 5, 177, 36, 61, 91, 141, 77, 81, 153, 187,
163, 103, 89, 127, 137, 114, 113, 176, 194, 166, 86, 95, 130, 99, 185, 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, 82, 21, 8, 104, 144, 160, 33, 138, 182]
Objective function statistics:
minimum.cost = 43568
mean = 44290.55
maximum.cost= 45011
Mean Number of sucessfull perturbations: 3058.25
```



2.3 Results without LS

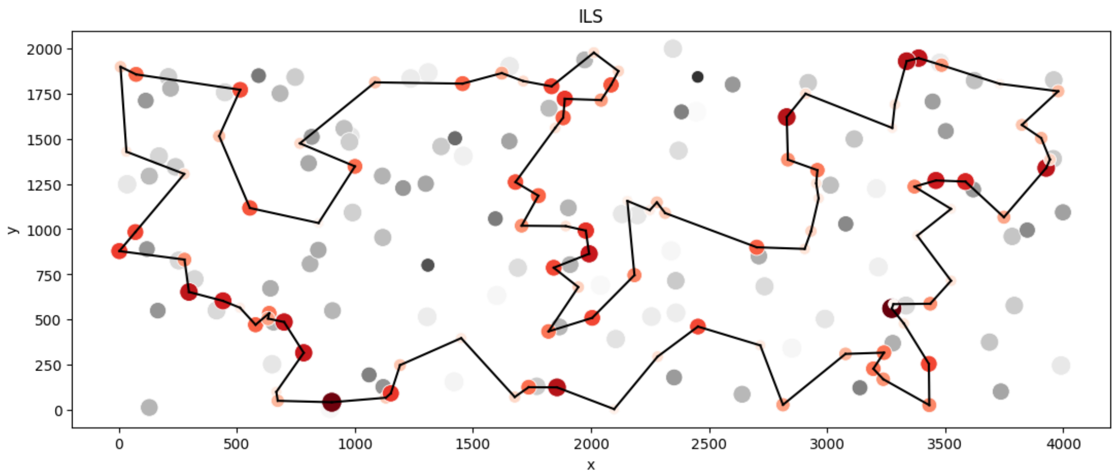
2.3.1 Dataset A

Best solution: [116, 43, 42, 181, 34, 160, 48, 54, 177, 10, 190, 184, 35, 84, 4, 112, 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, 40, 90, 165, 185, 179, 92, 129, 57, 55, 52, 106, 178, 3, 14, 49, 102, 144, 62, 9, 148, 124, 94, 63, 79, 80, 176, 137, 23, 186, 89, 183, 143, 0, 117, 93, 140, 108, 18, 22, 146, 159, 193, 41, 139, 68, 46, 115, 59, 118, 51, 151, 133, 162, 123, 149, 65]
Objective function statistics:
minimum.cost = 69657
mean = 70494.5
maximum.cost= 71452
Mean Number of sucessfull perturbations: 6705.1



2.3.2 Dataset B

Best solution: [193, 54, 31, 73, 136, 190, 80, 162, 175, 78, 5, 177, 36, 61, 91, 141, 77, 81, 153, 187, 163, 103, 89, 127, 137, 114, 113, 180, 176, 194, 166, 86, 185, 95, 130, 99, 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, 82, 21, 8, 104, 144, 160, 33, 138, 11, 139, 168, 195, 13, 145, 15, 3, 70, 132, 169, 188, 6, 147, 90, 51, 121, 131, 122, 133, 107, 40, 63, 135, 38, 27, 1, 156, 198, 117]
Objective function statistics:
minimum.cost = 43595
mean = 44507.05
maximum.cost= 45558
Mean Number of sucessfull perturbations: 6717.85



3 Summary

	Dataset A				\
	min	mean	max	seconds/instance	
ILS	69107.0	69326.150	69765.0	2223.00	
LNS with LS	69474.0	70179.050	71022.0	2223.00	
LNS without LS	69657.0	70494.500	71452.0	2223.00	
MLSM	70662.0	71267.400	71693.0	2223.00	
Greedy weighted cycle	71057.0	72218.320	73587.0	0.40	
Steepest edge LS	72046.0	74033.715	78801.0	9.54	

		Dataset B			\
	iterations	min	mean	max	
ILS	1106.2	43493.0	43783.050	44312.0	
LNS with LS	3027.2	43568.0	44290.550	45011.0	
LNS without LS	6705.1	43595.0	44507.050	45558.0	

MLSM	200.0	45321.0	45751.250	4613.0
Greedy weighted cycle	1.0	45453.0	46252.105	47884.0
Steepest edge LS	1.0	45393.0	48264.780	50697.0

	seconds/instance	iterations
ILS	2218.00	1114.80
LNS with LS	2218.00	3058.25
LNS without LS	2218.00	6717.85
MLSM	2218.00	200.00
Greedy weighted cycle	0.40	1.00
Steepest edge LS	9.02	1.00

4 Conclusion

We didn't manage to achieve better results with LNS than we achieved with ILS. However, our results of LNS with and without LS are almost similar, meaning that 2 times more destroy and repair operations have +- same effect as polishing with local seacrh. Nevertheless, LNS, despite having the same time budget as MLSM resulted in smaller costs.