

Evolutionary Computation Lab VI

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Contents

1	Problem description	2
2	Pseudocode	2
2.1	Perturbation	2
3	Results	3
3.1	Best solutions	4
4	Visualizations	5
4.1	TSPA.csv	5
4.2	TSPB.csv	6
4.3	TSPC.csv	7
4.4	TSPD.csv	8
5	Source code	9
6	Conclusions	9

1 Problem description

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.

1. Select exactly 50% of the nodes (if the number of nodes is odd we round the number of nodes to be selected up).
2. 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 Pseudocode

2.1 Perturbation

I define a perturbation as applying **10** uniformly random (with replacement) swaps (can be both intra- and inter-swaps).

This is the most important part of my algorithm that commences after the initial linear search (expressed in Python for ease of reading):

```
perturb_delta = -1;
anneal_temp = 600.0 * 1.2;
while perturb_delta < anneal_temp and clock() < deadline:
    score_before = evaluate(graph)
    perturb(graph);
    lsearch_steepest(graph);
    score_after = evaluate(graph)
    perturb_delta = score_after - score_before;
    anneal_temp /= 1.2;
```

Basically, I enter a loop where a perturbation is applied, linear search performed, and then if the delta is lower than some threshold, we continue. This threshold starts at **600.0** and is divided by **1.2** after every successful perturbation.

The parameters **10**, **600.0** and **1.2** were chosen experimentally.

3 Results

ALG.	TSPA TSPB	TSPC TSPD
ls-steepest-random	77,866 (75,315–81,017) 71,322 (68,623–76,002)	51,453 (49,257–53,785) 48,234 (45,351–51,534)
lsc-steepest-random	89,127 (82,350–101,152) 84,469 (74,393–96,069)	62,892 (55,074–74,956) 60,203 (51,897–67,824)
lsd-steepest-random	77,866 (75,315–81,017) 71,322 (68,623–76,002)	51,453 (49,257–53,785) 48,234 (45,351–51,534)
lscd-steepest-random	89,127 (82,350–101,152) 84,469 (74,393–96,069)	62,892 (55,074–74,956) 60,203 (51,897–67,824)
msls-steepest-random	75,048 (74,178–75,644) 68,211 (67,828–68,622)	49,128 (48,311–49,620) 45,649 (45,075–46,032)
ils-steepest-random	74,893 (74,137–75,593) 68,070 (67,676–68,496)	48,969 (48,662–49,308) 45,505 (45,016–46,114)

Table 1: Average, minimum and maximum scores of found solutions

ALG.	TSPA TSPB	TSPC TSPD
ls-steepest-random	85.737 (71.796–105.250) 88.181 (73.757–107.447)	85.470 (72.226–98.981) 87.450 (67.483–102.099)
lsc-steepest-random	21.973 (17.070–28.766) 22.002 (17.069–29.329)	20.936 (15.504–30.904) 21.179 (15.651–28.530)
lsd-steepest-random	43.684 (33.639–66.647) 43.794 (35.071–54.709)	42.885 (33.038–57.912) 43.747 (30.598–74.864)
lscd-steepest-random	28.267 (18.670–39.157) 28.695 (19.072–38.583)	27.632 (18.752–39.882) 27.669 (19.578–40.003)

Table 2: Average, minimum, maximum running times per instance (ms)

ALG.	TSPA TSPB	TSPC TSPD
msls-steepest-random	16.339 (15.744–16.838) 16.606 (16.074–17.191)	16.064 (15.530–16.725) 16.282 (15.941–16.693)
ils-steepest-random	16.335 (16.323–16.387) 16.333 (16.324–16.380)	16.342 (16.323–16.395) 16.342 (16.323–16.403)

Table 3: Average, minimum, maximum running times for MSLS and ILS (s)

ALG.	TSPA TSPB	TSPC TSPD
ils-steepest-random	1,149.3 (1,091–1,209) 1,117.7 (1,056–1,178)	1,207.8 (1,139–1,249) 1,150.0 (1,067–1,194)

Table 4: Average, minimum, maximum number of times linear search was run

3.1 Best solutions

All best solutions are available [in the repository](#), as always. I export them as *.graph files, which follow a very simple text encoding:

```

<no_vacant_nodes>;<no_active_nodes>
<x>;<y>;<cost>          \
<x>;<y>;<cost>          | vacant nodes
...                      /
<x>;<y>;<cost>          \
<x>;<y>;<cost>          | active nodes
...                      /

```

”Vacant” nodes are the nodes not used in the solution. ”active” nodes are the ones in the solution. Since all graphs consist of 200 nodes and all solutions are 50% active, to find the list of nodes in the solution, simply look at the last 100 lines of each *.graph file.

4 Visualizations

4.1 TSPA.csv

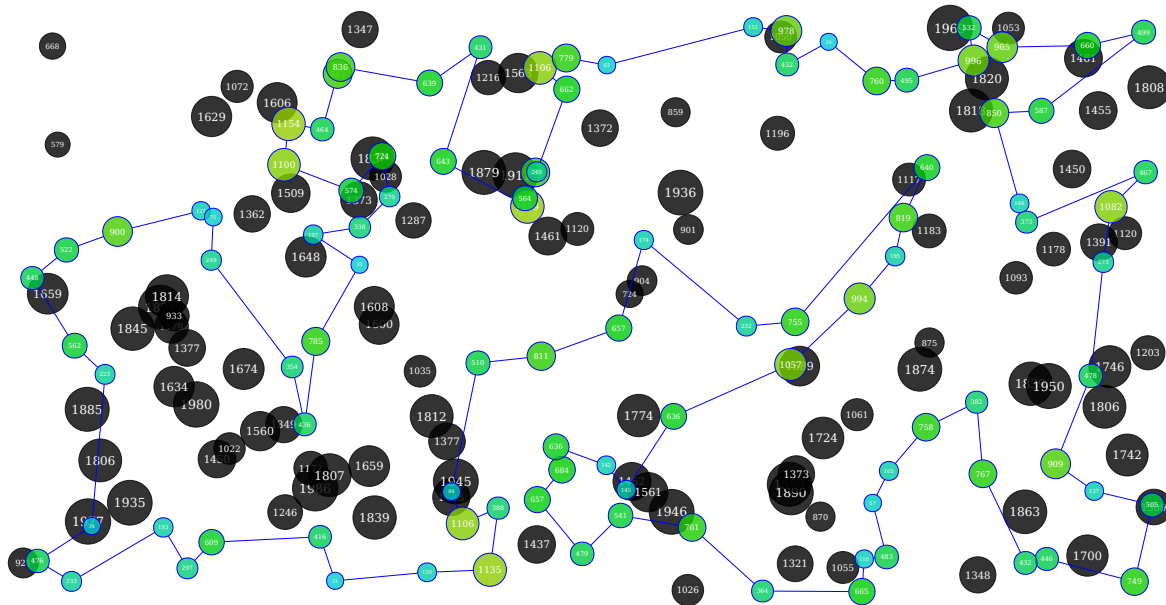


Figure 1: Best msls-steepest-random solution to TSPA (74,178)

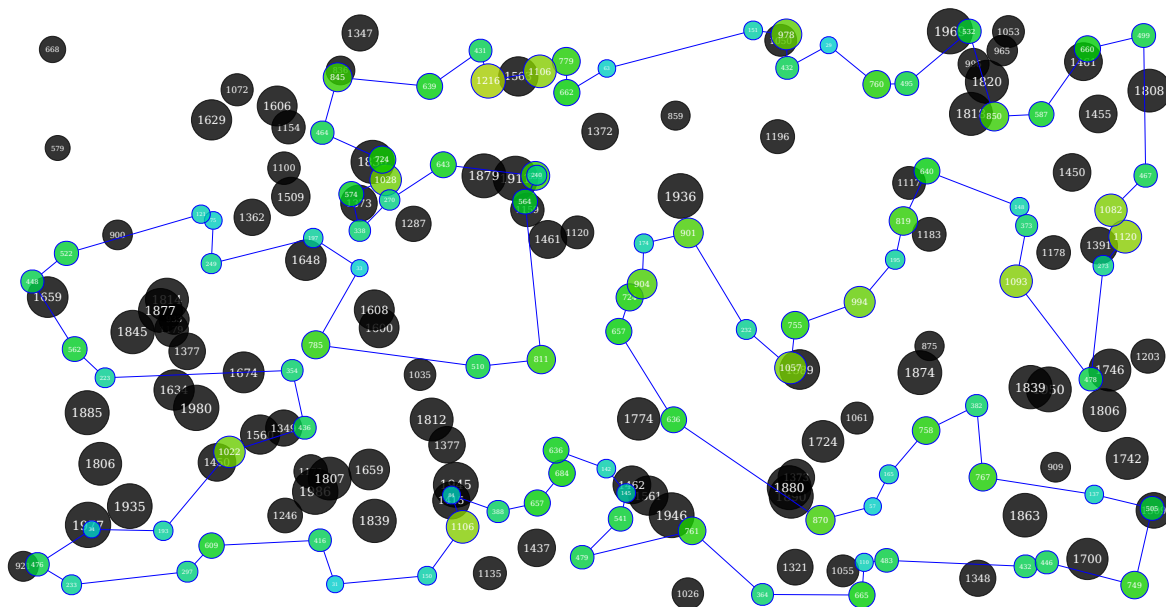


Figure 2: Best ils-steepest-random solution to TSPA (74,137)

4.2 TSPB.csv

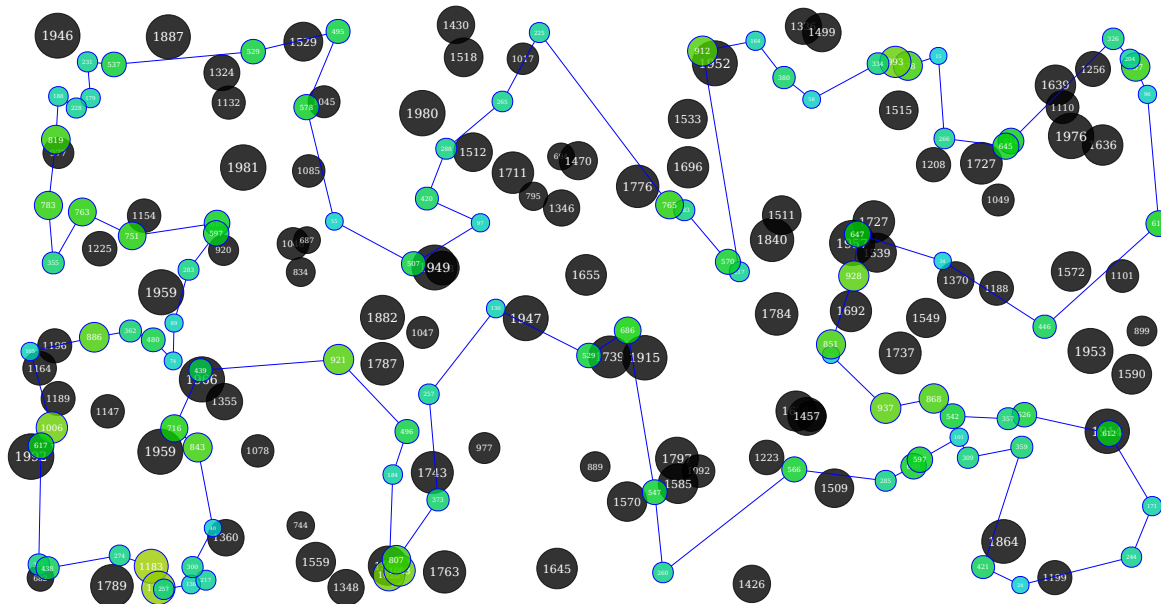


Figure 3: Best msls-steepest-random solution to TSPB (67.828)

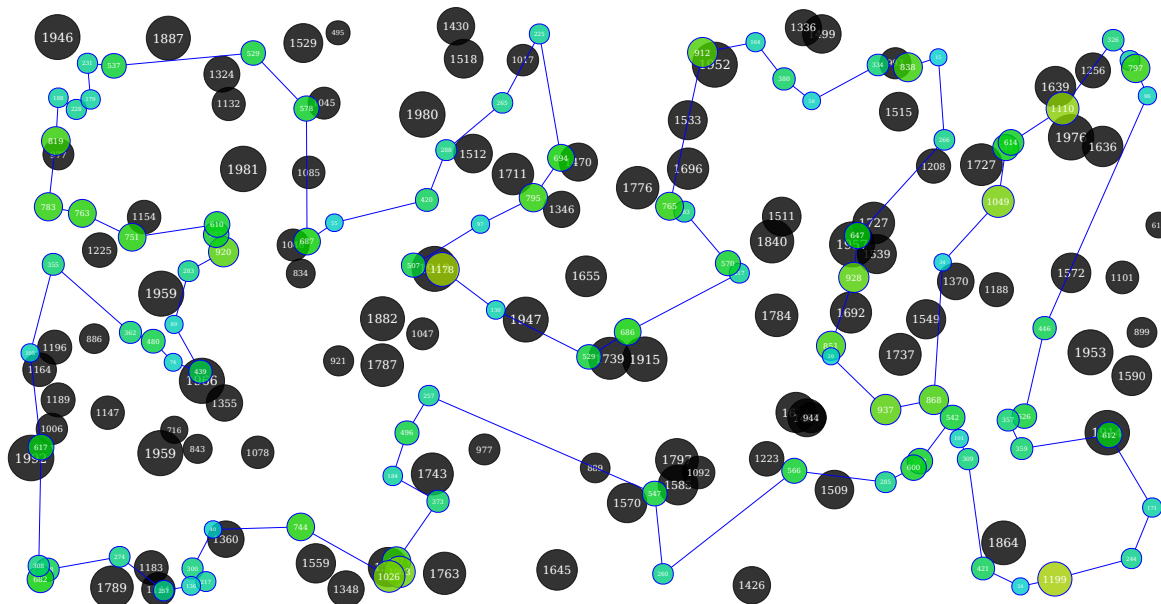


Figure 4: Best ils-steepest-random solution to TSPB (67,676)

4.3 TSPC.csv

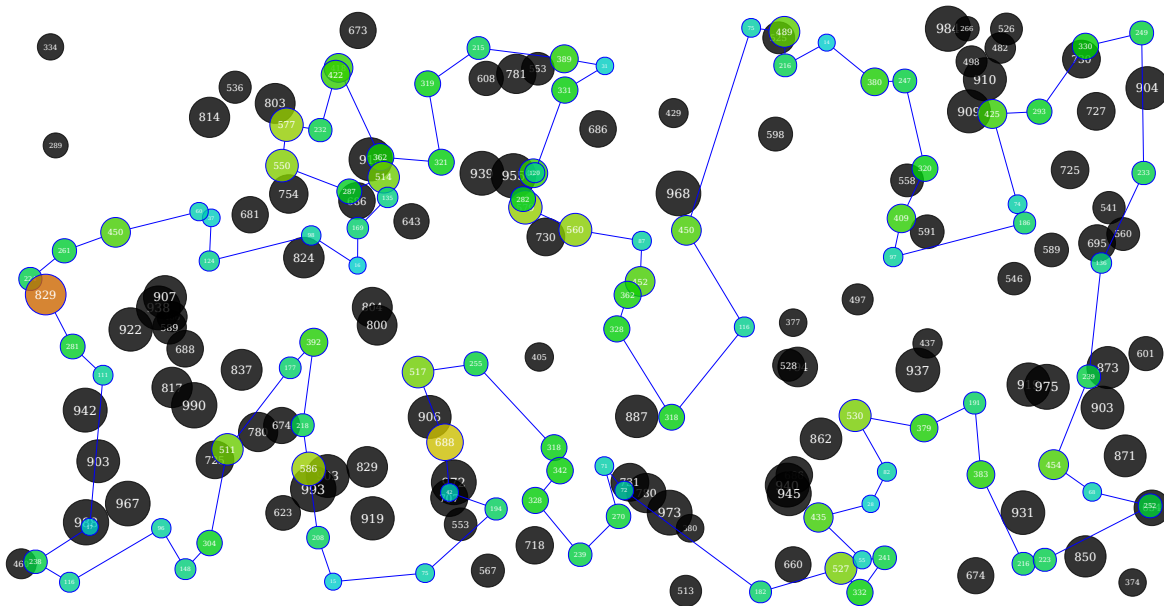


Figure 5: Best msls-steepest-random solution to TSPC (48,311)

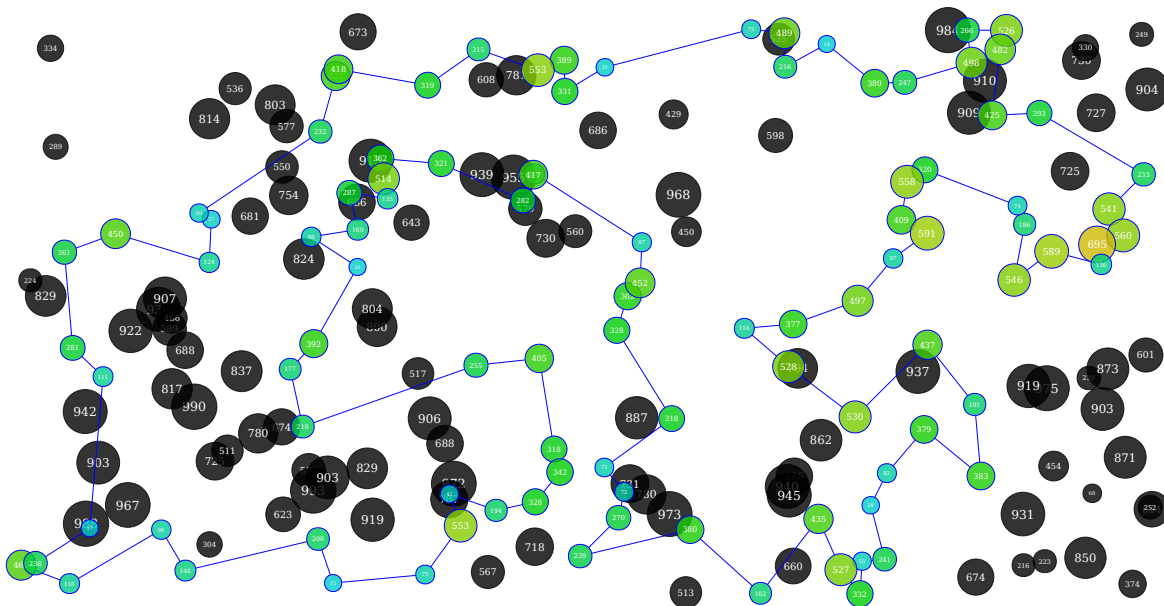


Figure 6: Best ils-steepest-random solution to TSPC (48,662)

4.4 TSPD.csv

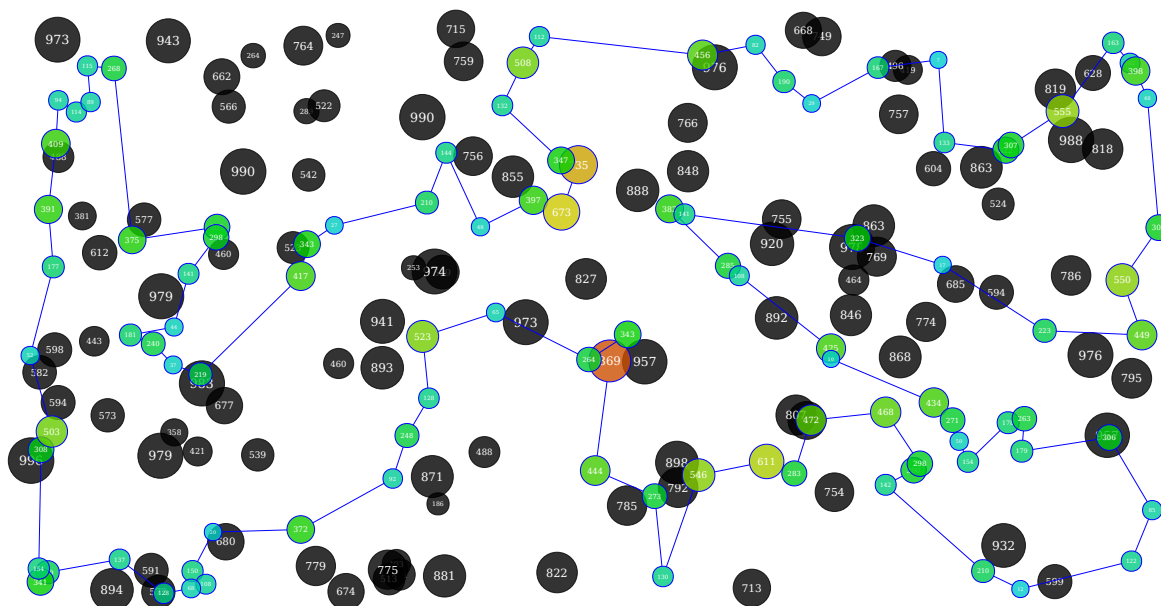


Figure 7: Best msls-steepest-random solution to TSPD (45,075)

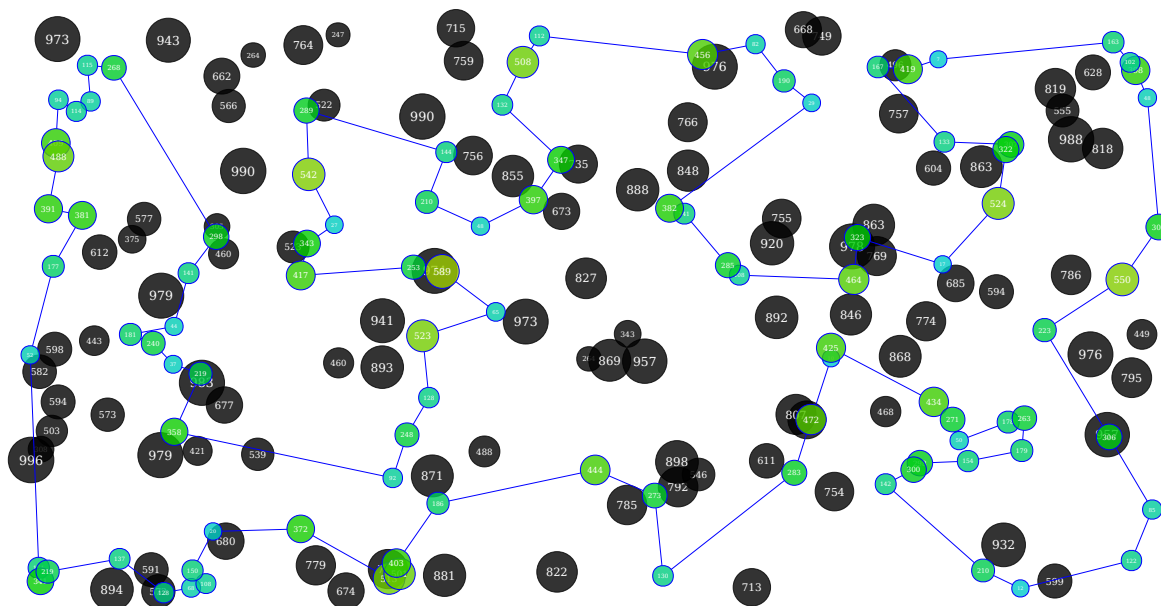


Figure 8: Best ils-steepest-random solution to TSPD (45,016)

5 Source code

The source code for all the experiments and this report is hosted on GitHub:
<https://github.com/RoyalDonkey/put-ec-tasks>

6 Conclusions

As expected, iterated linear search with perturbations outperformed the more naïve multiple-start local search. The margin isn't great, but considering the flexibility of ILS (tweakable perturbation function and timeout), it is a significantly more versatile approach, while still being very simple in its concept.

Despite their promising results, both MSLS and ILS can't really be compared with the previously tested techniques, due to the many times longer execution time that was given to them. In the case of ILS, this could of course be tweaked, but capping it at 1 linear search's time would make it identical to just linear search. Both MSLS and ILS are really only viable as extensions to linear search, with the assumption that we have enough time for many runs.