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LABORATORY 8: GLOBAL CONVEXITY TESTS

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POZNAŃ 2025

1 Problem Description

The problem is to select exactly 50% of the nodes (from n available) and build a Hamiltonian cycle through the selected nodes. The objective is to minimize the sum of two components:

1. The total length of the Hamiltonian cycle (calculated as the sum of Euclidean distances between consecutive nodes in the cycle).
2. The total cost of the selected nodes (the sum of the cost attributes for each selected node).

All distances are rounded to the nearest integer.

2 Methodology

To understand the geometry of the problem's search space, we conducted a fitness-distance correlation analysis for both instances.

First, we generated 1,000 random local optima by running a Greedy Local Search, with edge swap as the intra neighbourhood, from random starting points.

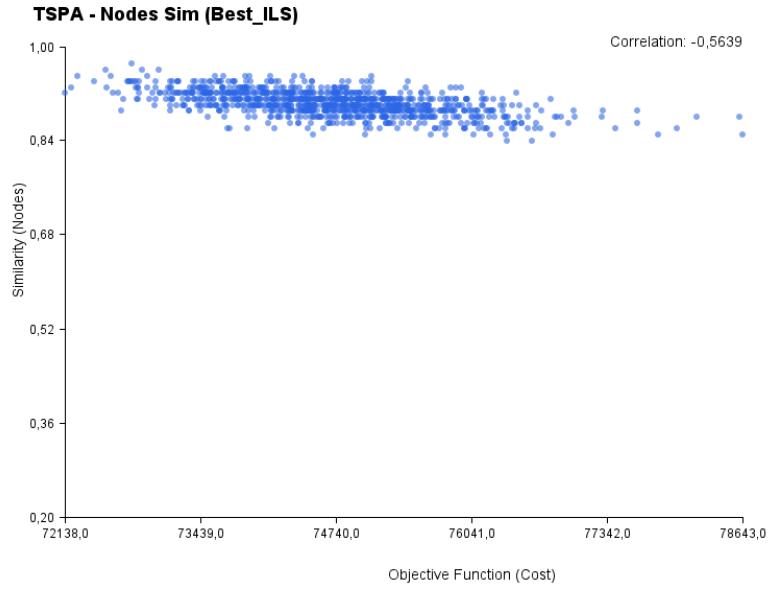
Next, to calculate similarity, we established three reference points: the best solution found within our 1000 random runs, the average similarity to all other local optima, and an external reference - the solution found by the Iterated Local Search (ILS), which in previous experiments yielded the best results.

We have used two distinct similarity metrics. Common Nodes measures how much the sets of selected cities overlap, indicating if better solutions tend to pick the same specific locations. Common Edges measures structural identity - it checks if the cities are connected in the same order (however, independently of the direction of the connection). This is a stricter measure, as two solutions might pick the same nodes but visit them in a completely different sequence.

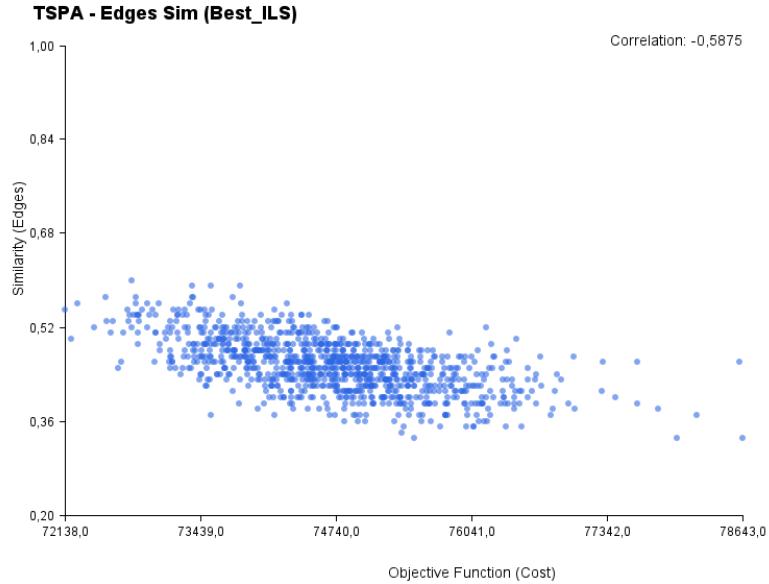
3 Experimental Results

The scatter plots below illustrate the relationship between solution quality (cost) and similarity. By calculating the Pearson correlation coefficient, we can statistically confirm if lower costs correlate with higher similarity to the best-known solutions.

3.1 TSPA: Fitness-Distance Correlation



(a) Similarity (Nodes) vs Cost (Ref: Best Known: ILS)



(b) Similarity (Edges) vs Cost (Ref: Best Known: ILS)

FIGURE 1: TSPA Correlations with Best Known Solution (ILS).

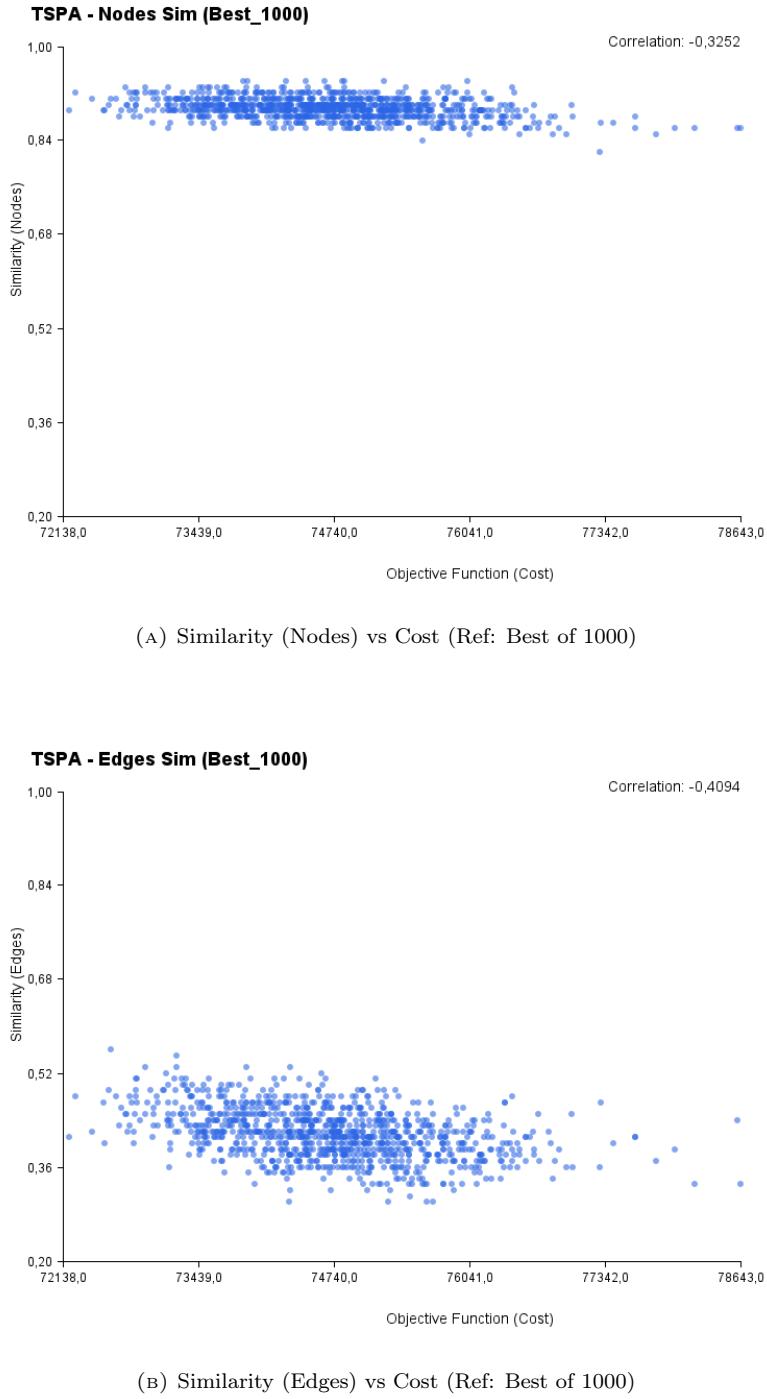


FIGURE 2: TSPA Correlations with Best of 1000 Random Optima.

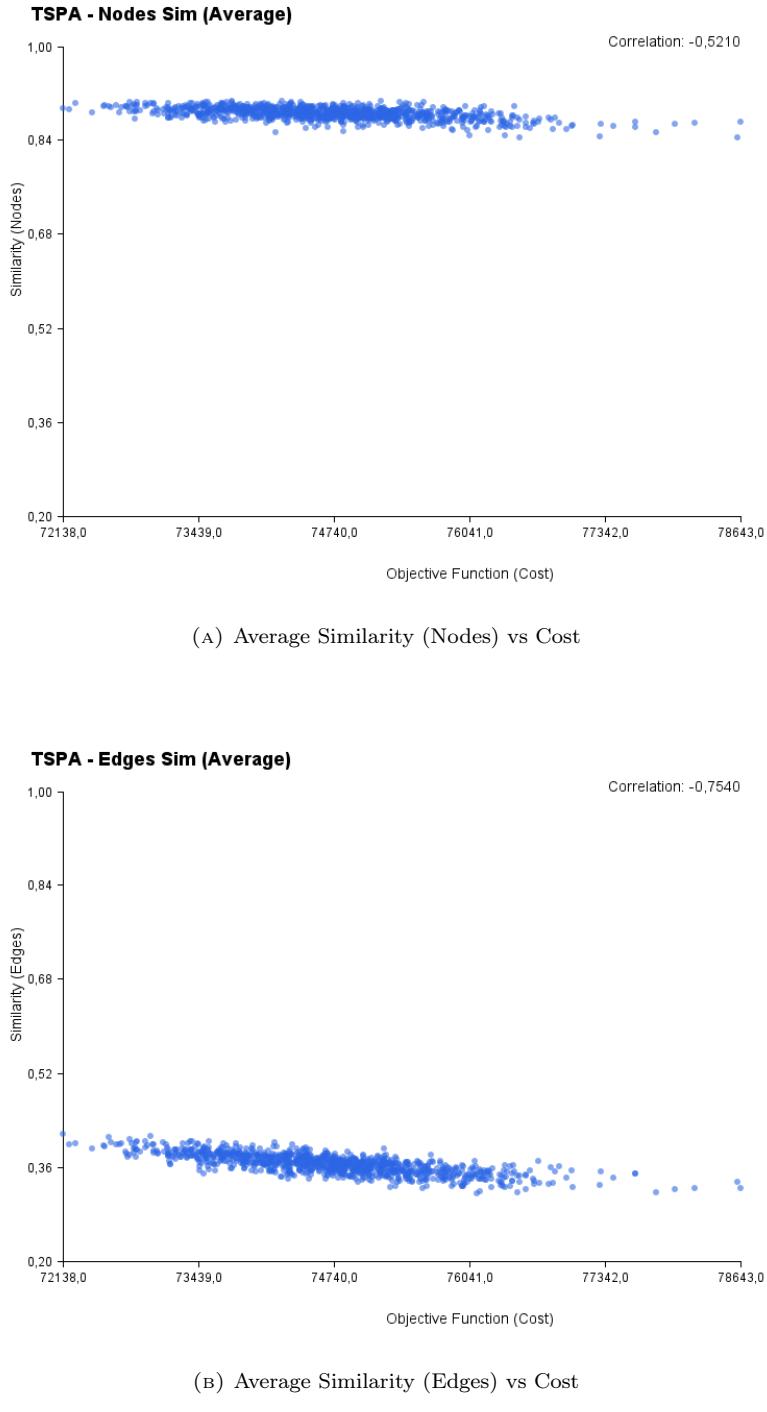
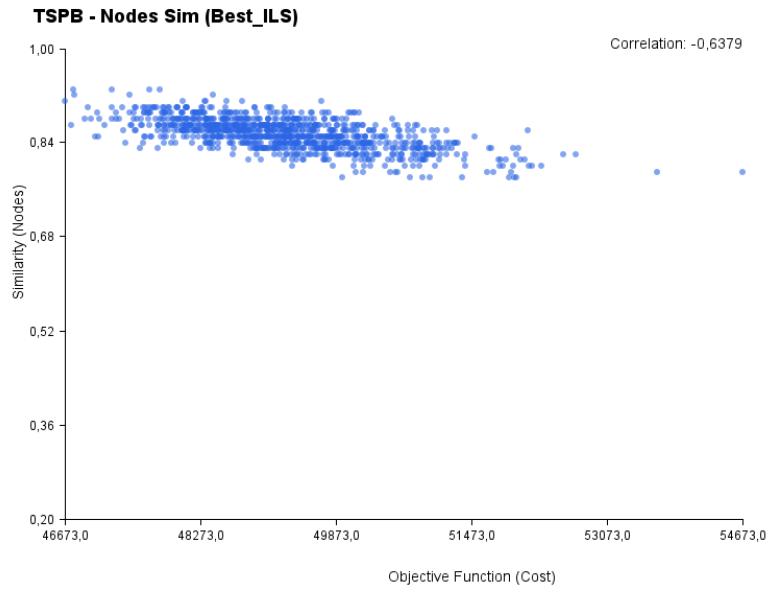
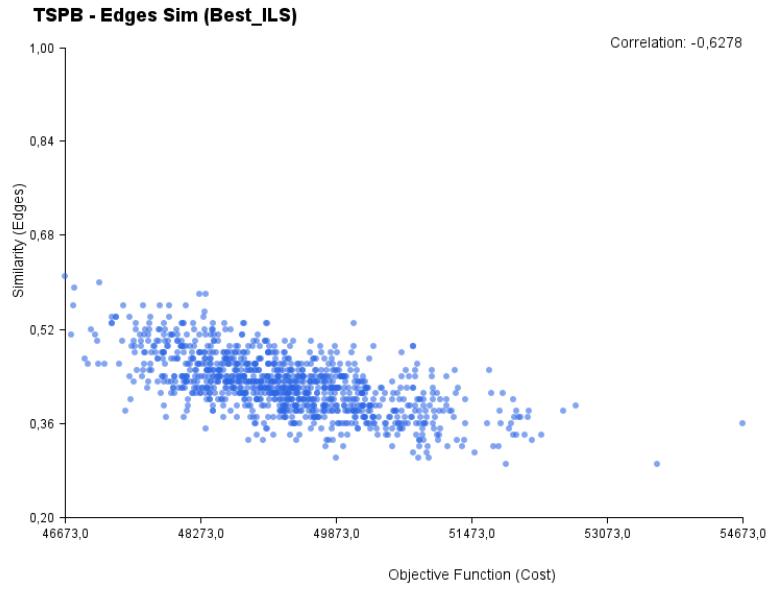


FIGURE 3: TSPA Average Similarity Correlations.

3.2 TSPB: Fitness-Distance Correlation



(a) Similarity (Nodes) vs Cost (Ref: Best Known: ILS)



(b) Similarity (Edges) vs Cost (Ref: Best Known: ILS)

FIGURE 4: TSPB Correlations with Best Known Solution.

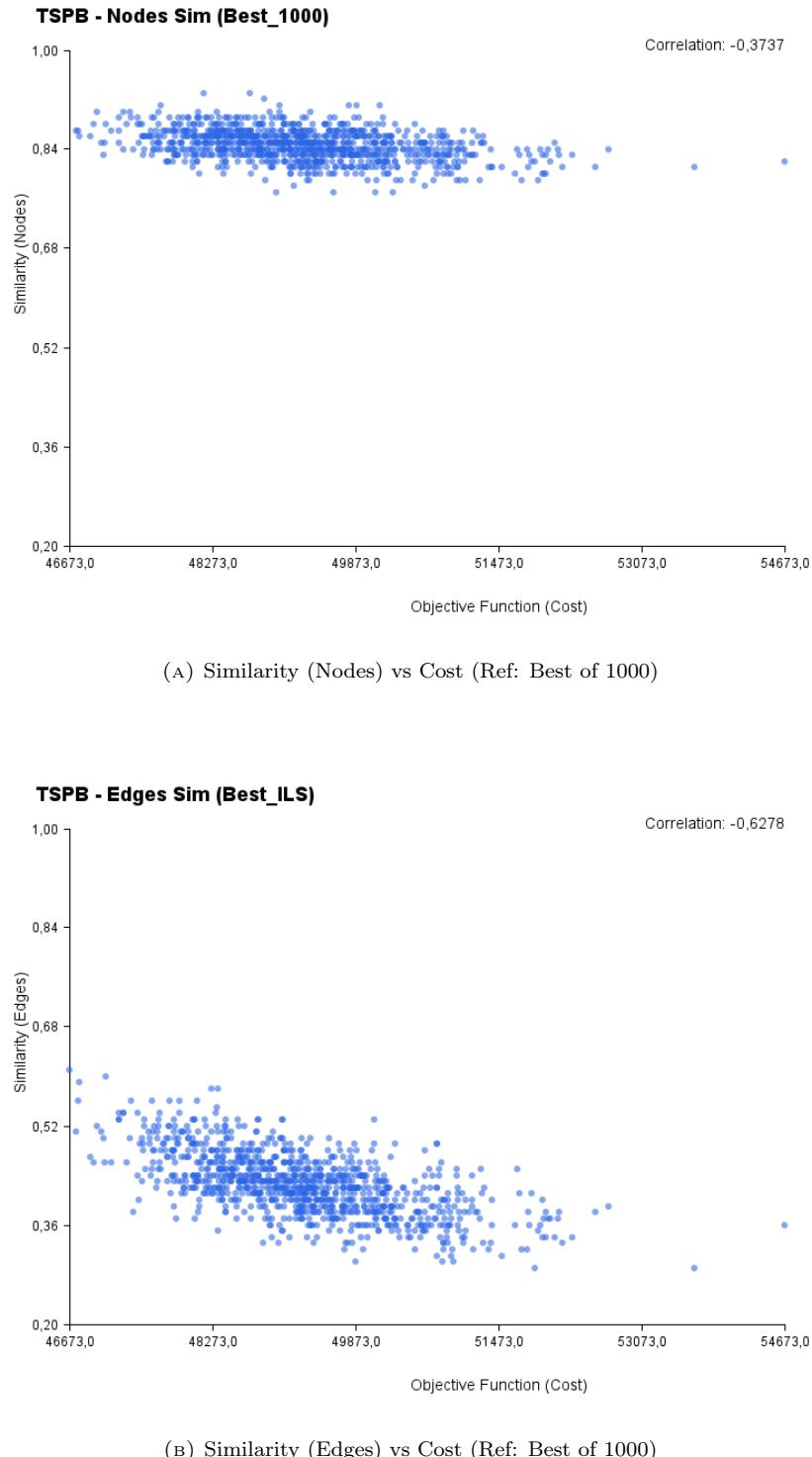


FIGURE 5: TSPB Correlations with Best of 1000 Random Optima.

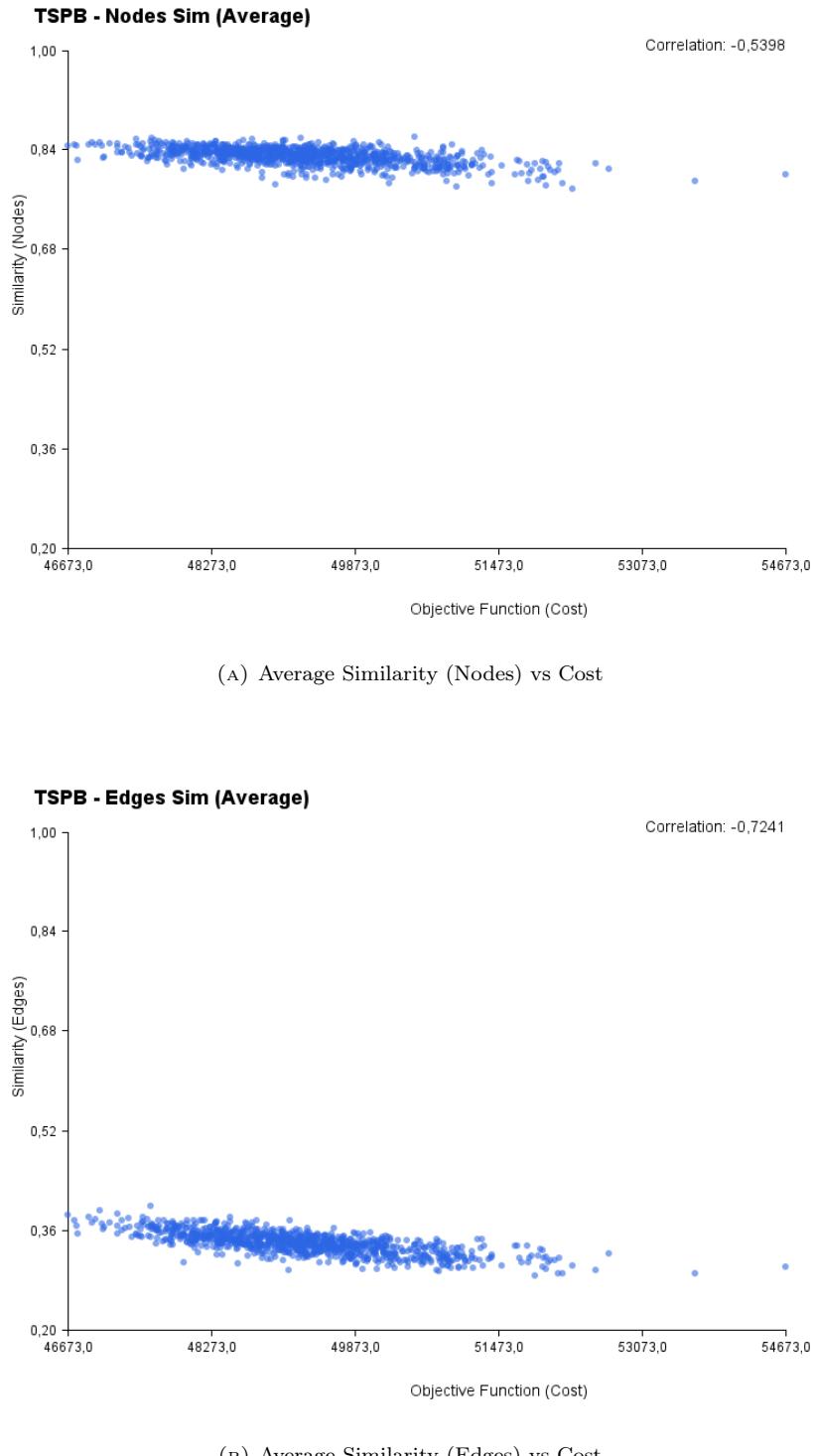


FIGURE 6: TSPB Average Similarity Correlations.

4 Conclusions

Based on the experimental analysis, we observe that comparing solutions based on common nodes yields high similarity scores, indicating that the set of "good" nodes is relatively stable and that high-quality solutions tend to select largely the same subset of nodes. In general, the correlation coefficients across the experiments are moderate. However, the average similarity for edges in both TSPA and TSPB presents a special case where correlations are notably high. Furthermore, the data suggests that edge correlations tend to be stronger than node correlations. This implies that the specific structural connections (the sequence of visits) are even more critical to the solution quality than the selection of nodes itself.

Source Code: <https://github.com/PBalewski/EvolutionaryComputation/tree/main/lab8>