In [1]:
```
import json
import random
import sys

sys.path.insert(1, '../../src')

from ce.algorithms.greedy_heuristics import random_solution
from ce.algorithms.local_search import steepest_local_search, two_edges_ne
from ce.tsp_optimized import create_tsp, TSP
from ce.utils.experiments import run_all_experiments

random.seed(13)
```

Local Search

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In [2]:
```
problem_instance_A_path = '../../data/TSPA.csv'
problem_instance_B_path = '../../data/TSPB.csv'
problem_instance_C_path = '../../data/TSPC.csv'
problem_instance_D_path = '../../data/TSPD.csv'
```

In [3]:
```
tspa, tspb, tspc, tspd = create_tsp(problem_instance_A_path), create_tsp(p
```

Algorithms

Initial solution generation: random generation

Next solution generation (typical steepest)

For each of the methods we implemented three different functions to:

- generate all possible 'moves' that creates new solution
- calculate a cost difference for a given move
- construct new solution for a given move

Inter route

```
def inter_route_moves(solution: List[int], tsp: TSP):
    # replace any node of the solution with any node from the rest
    # return pair (position_to_replace, node_idx_to_insert)
    outer_nodes = [i for i in tsp.indexes if i not in solution]
    for i, _ in enumerate(solution):
        for n in outer_nodes:
            yield i, n


def inter_route_cost_delta(solution: List[int], move: Tuple[int, in
t], tsp: TSP) -> int:
    i, outer_node = move
    node_to_replace = solution[i]
    before, after = solution[(i - 1) % len(solution)], solution[(i +
1) % len(solution)]

    return (
            + tsp.nodes[outer_node].cost - tsp.nodes[node_to_replac
e].cost
            + tsp.distances[before, outer_node] + tsp.distances[outer
_node, after]
            - tsp.distances[before, node_to_replace] - tsp.distances
[after, node_to_replace]
    )


def inter_route_new_solution(solution: List[int], move: Tuple[int, in
t]) -> List[int]:
    i, outer_node = move
    return solution[:i] + [outer_node] + solution[i + 1:]ut``n[replac
```

2-nodes exchange

```
def two_nodes_moves(solution: List[int]):
    # exchange position of any two nodes
    # return pair (position_1, position_2)
    for i, _ in enumerate(solution):
        for j, _ in enumerate(solution):
            # first node is fixed to not generate different (but sam
e) neighbors
            if 0 < i < j:
                yield i, j


def two_nodes_cost_delta(solution: List[int], move: Tuple[int, int],
tsp: TSP) -> int:
    i, j = move
    node1, node2 = solution[i], solution[j]
    before1, after1 = solution[(i - 1) % len(solution)], solution[(i
+ 1) % len(solution)]
    before2, after2 = solution[(j - 1) % len(solution)], solution[(j
+ 1) % len(solution)]

    return (
            + tsp.distances[before1, node2] + tsp.distances[node2, af
ter1]
            + tsp.distances[before2, node1] + tsp.distances[node1, af
ter2]
            - tsp.distances[before1, node1] - tsp.distances[node1, af
```

2-edges exchange

```
def two_edges_moves(solution: List[int]):
    # exchange position of any two edges
    # return pair (position_of_edge_1, position_of_edge_2)
    # edge nr i connects nodes i and i+1
    for i, _ in enumerate(solution):
        for j, _ in enumerate(solution):
            # no point in exchanging adjacent edges
            if i < j and (j - i) > 1 and not (i == 0 and j == len(sol
ution) - 1):
                yield i, j
```

Steepest local search

```
def steepest_local_search(tsp: TSP, init_solution, neighborhood) -> L
ist[int]:
    solution = init_solution
    local_optimum = False

    while not local_optimum:
        best_neighbor = min(neighborhood(solution, tsp), key=lambda
x: get_cost_delta(x, solution, tsp))
        if get_cost_delta(best_neighbor, solution, tsp) < 0:
            solution = get_new_solution(best_neighbor, solution)
        else:
            local_optimum = True

    return solution
```

Introducing the candidate edges (calculated as follows:)

```
def get_candidate_edges_for_solution_vertex(tsp: TSP, vertex: int, n: int = 10):
    # outer nodes are nodes not in solution
    outer_nodes = [i for i in tsp.indexes if i != vertex]

    costs = []
    for outer_node in outer_nodes:
        # calculate cost of inserting outer node between previous and next vertex
        cost = tsp.distances[vertex, outer_node] + tsp.nodes[outer_node].cost
        costs.append((outer_node, cost))

        # get n best candidates
    costs.sort(key=lambda x: x[1])
    candidate_edges = set([(vertex, costs[i][0]) for i in range(n)])
    return candidate_edges

def calculate_candidate_endges(tsp: TSP):
    set_of_candidate_edges = set()
    for i, _ in enumerate(tsp.indexes):
        candidate_edges = tsp.get_candidate_edges_for_solution_vertex(i)
        # add candidate edges to set
        set_of_candidate_edges.update(candidate_edges)
    return set_of_candidate_edges
```

makes the neighborhood function change as follows:

```
def two_nodes_candidates_neighborhood(solution: List[int], tsp: TSP,
candidate_edges: set):
    neighborhood = (
            [('i', move) for move in inter_route_candidate_moves(solu
tion, tsp, candidate_edges)]
            + [('2n', move) for move in two_nodes_candidate_moves(sol
ution, candidate_edges)]
    )
    random.shuffle(neighborhood)
    return neighborhood


def two_edges_candidates_neighborhood(solution: List[int], tsp: TSP,
```

Experiments

In [4]:

```
experiments = [
    "S_r_2n",
    "S_r_2e",
    "S_r_2n_can n=5",
    "S_r_2e_can n=5",
    "S_r_2n_can n=10",
    "S_r_2e_can n=10",
    "S_r_2n_can n=15",
    "S_r_2e_can n=15",

]

def experiments_provider(tsp: TSP, random_inits):
    return [
        lambda x: steepest_local_search(tsp, random_inits[x], two_nodes_ne
        lambda x: steepest_local_search(tsp, random_inits[x], two_edges_ne
        lambda x: steepest_local_candidates_search(tsp, random_inits[x], t
        lambda x: steepest_local_candidates_search(tsp, random_inits[x], t
        lambda x: steepest_local_candidates_search(tsp, random_inits[x], t
        lambda x: steepest_local_candidates_search(tsp, random_inits[x], t
        lambda x: steepest_local_candidates_search(tsp, random_inits[x], t
        lambda x: steepest_local_candidates_search(tsp, random_inits[x], t
    ]
```

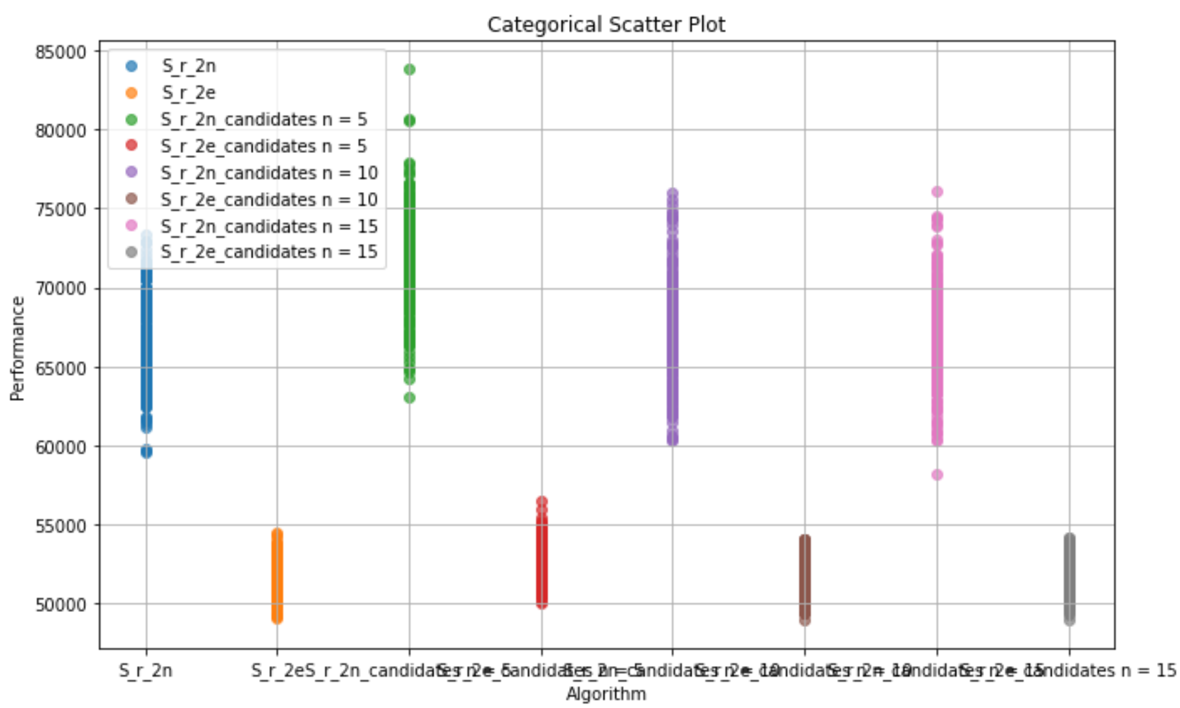
Instance C

In [5]:

```
random_inits_c = [random_solution(tspc) for i in range(200)]
```

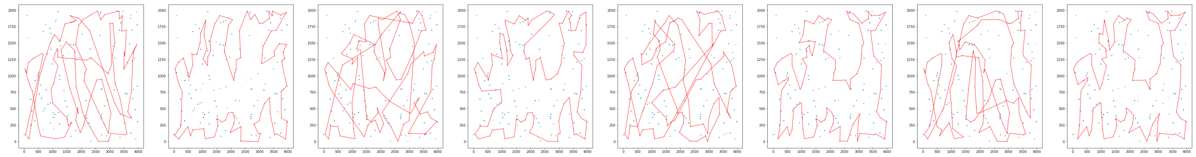
In [6]:
```
%%time
best_solutions_c, results_list_c = run_all_experiments(200, experiments_pr
```

```
****************************************************************************
********************
S_r_2n: cost: AVG 66453.05, (59607.00 - 73381.00)       time: AVG 7.07s, (5.5
2s - 11.93s)
S_r_2e: cost: AVG 51540.60, (49044.00 - 54523.00)       time: AVG 5.39s, (4.3
8s - 6.09s)
S_r_2n_candidates n = 5:        cost: AVG 71790.16, (63116.00 - 83833.00)
        time: AVG 3.46s, (2.64s - 4.87s)
S_r_2e_candidates n = 5:        cost: AVG 52682.30, (50052.00 - 56476.00)
        time: AVG 3.33s, (2.87s - 4.02s)
S_r_2n_candidates n = 10:       cost: AVG 67479.43, (60348.00 - 75988.00)
        time: AVG 4.26s, (3.31s - 6.32s)
S_r_2e_candidates n = 10:       cost: AVG 51554.19, (49009.00 - 54068.00)
        time: AVG 3.41s, (2.74s - 4.00s)
S_r_2n_candidates n = 15:       cost: AVG 66923.16, (58186.00 - 76040.00)
        time: AVG 4.37s, (3.31s - 6.32s)
S_r_2e_candidates n = 15:       cost: AVG 51542.99, (48937.00 - 54189.00)
        time: AVG 3.83s, (3.04s - 5.99s)
****************************************************************************
********************
```




```
Wall time: 1h 57min 7s
```

In [7]:
```
tspc.plot(best_solutions_c)
```



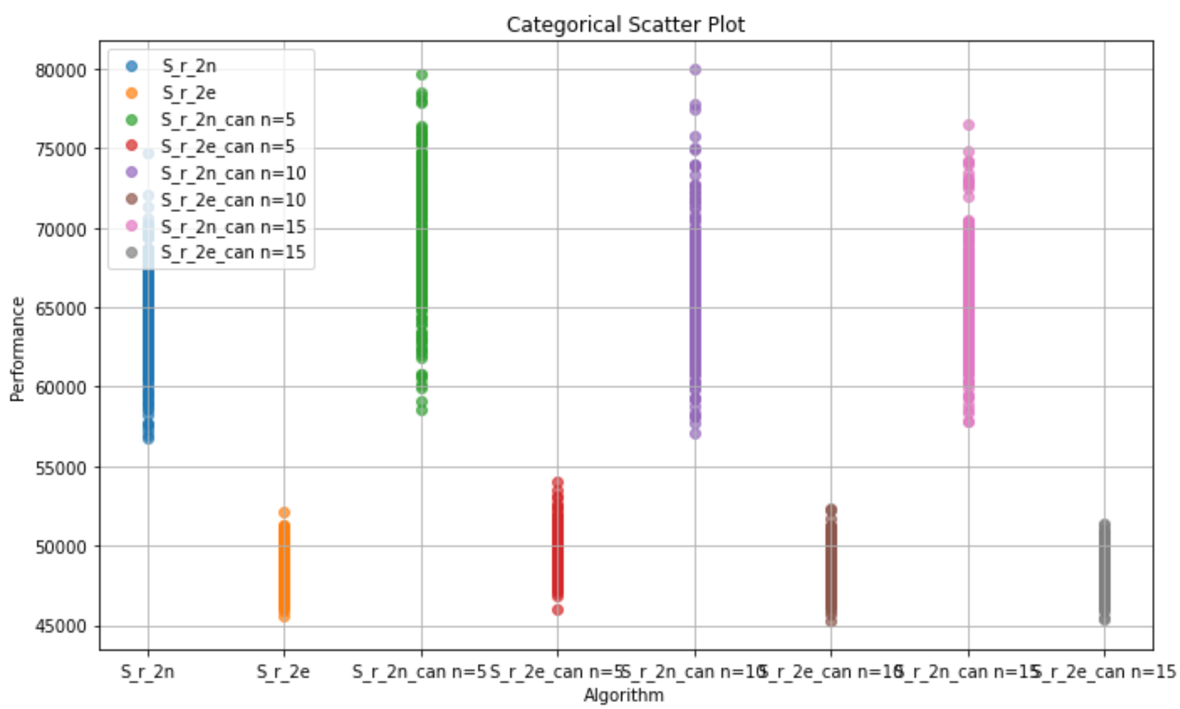
Instance D

In [5]:
```
random_inits_d = [random_solution(tspd) for i in range(200)]
```

In [6]:

```
%%time
best_solutions_d, results_list_d = run_all_experiments(200, experiments_pr
```

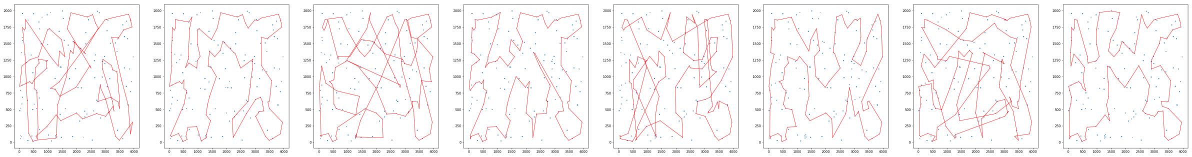
```
********************************************************************************************
S_r_2n: cost: AVG 64358.35, (56808.00 - 74771.00)       time: AVG 6.96s, (5.09s - 24.75s)
S_r_2e: cost: AVG 48355.54, (45583.00 - 52112.00)       time: AVG 14.14s, (7.27s - 29.53s)
S_r_2n_can n=5: cost: AVG 69353.79, (58580.00 - 79702.00)       time: AVG 5.38s, (3.96s - 7.31s)
S_r_2e_can n=5: cost: AVG 49544.68, (45983.00 - 54083.00)       time: AVG 5.17s, (4.42s - 9.06s)
S_r_2n_can n=10:        cost: AVG 66071.00, (57095.00 - 80019.00)       time: AVG 5.07s, (3.34s - 29.86s)
S_r_2e_can n=10:        cost: AVG 48278.38, (45228.00 - 52383.00)       time: AVG 3.49s, (3.12s - 4.06s)
S_r_2n_can n=15:        cost: AVG 65512.42, (57806.00 - 76559.00)       time: AVG 4.34s, (3.54s - 5.47s)
S_r_2e_can n=15:        cost: AVG 48158.49, (45393.00 - 51375.00)       time: AVG 3.68s, (3.27s - 4.10s)
********************************************************************************************
```




```
Wall time: 2h 40min 49s
```

In [7]:

```
tspd.plot(best_solutions_d)
```



In [10]:

```
with open('results_c.json', 'w', encoding='utf-8') as f:
    json.dump(results_list_c, f, ensure_ascii=False, indent=4)
with open('best_solutions_c.json', 'w', encoding='utf-8') as f:
    json.dump(best_solutions_c, f, ensure_ascii=False, indent=4)
```

In [8]:

```
with open('results_d.json', 'w', encoding='utf-8') as f:
    json.dump(results_list_d, f, ensure_ascii=False, indent=4)
with open('best_solutions_d.json', 'w', encoding='utf-8') as f:
    json.dump(best_solutions_d, f, ensure_ascii=False, indent=4)
```

Conclusions

- The 2-edge neighborhood outperformed the 2-node neighborhood similarly as in the previous report.
- What is interesting the n-candidate parameter outperformed the original solution in the 2-node approach, which might be interpreted as not only a heurestic parameter, but also a regularization parameter, that has prevented stepping into local optima (in this case), overall it yelds results which are a bit worse than the original solution
- Experiments for the 2-egde neighborhood showed better performance indicating that the candidate-heuristic is well-cut for it - which makes sence because the heuristic is edge-based not vertex-based, and in the 2-node neighborhood method might lead (and probably did lead) to not picking the optimal vertex since the two edges leading to it were not an obvious choice (they might be not that good separatly but they might form a good match together).