ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

ΣΧΟΛΗ ΔΙΟΙΚΗΣΗΣ ΕΠΙΧΕΙΡΗΣΕΩΝ
SCHOOL OF BUSINESS

ΤΜΗΜΑ ΔΙΟΙΚΗΤΙΚΗΣ ΕΠΙΣΤΗΜΗΣ & ΤΕΧΝΟΛΟΓΙΑΣ
DEPARTMENT OF MANAGEMENT SCIENCE & TECHNOLOGY

An adaptive memory matheuristic for the SOP

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Presentation Outline

01

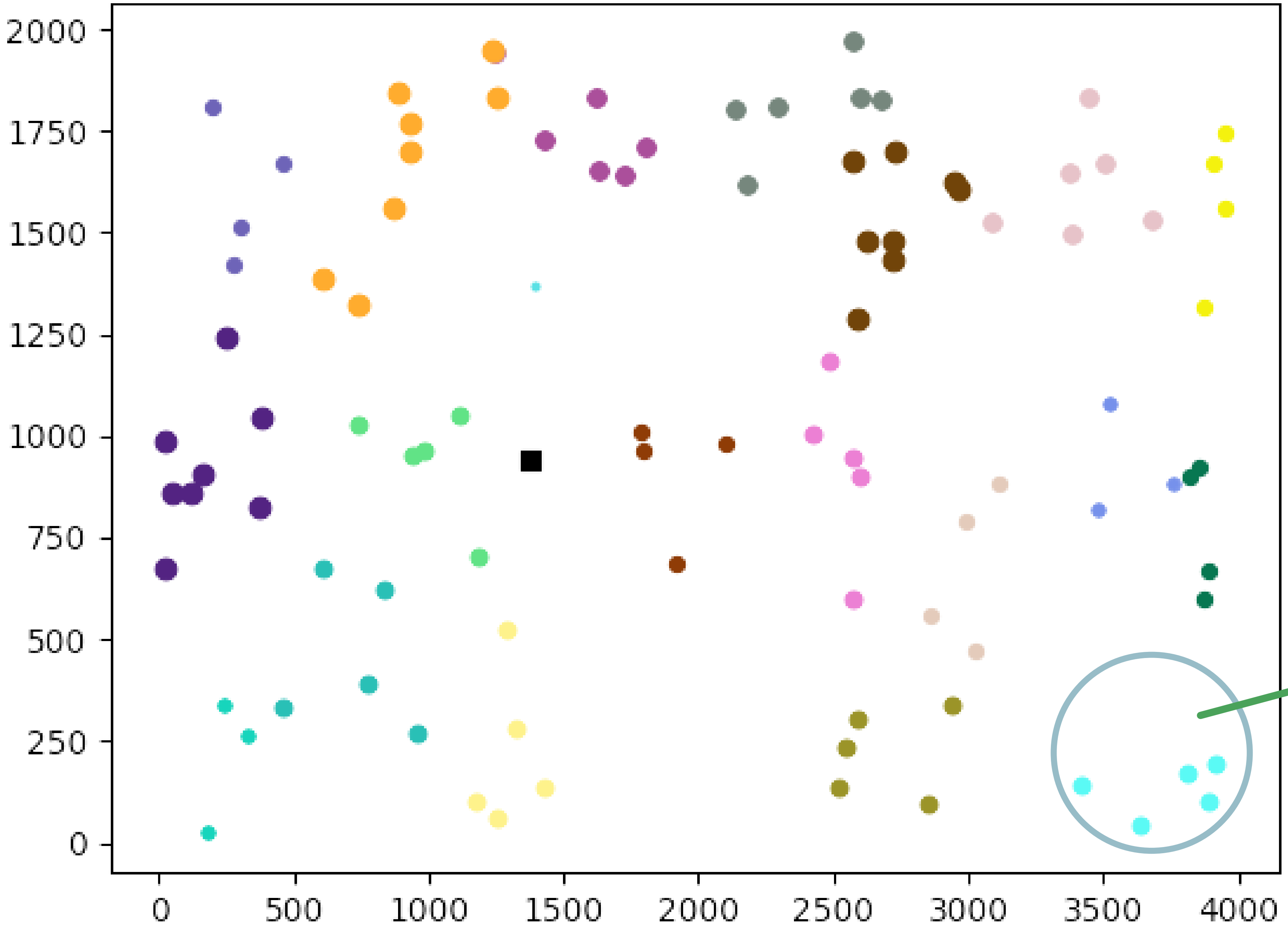
The Set Orienteering Problem

Problem Description

Objective: Maximize the profit of visited clusters

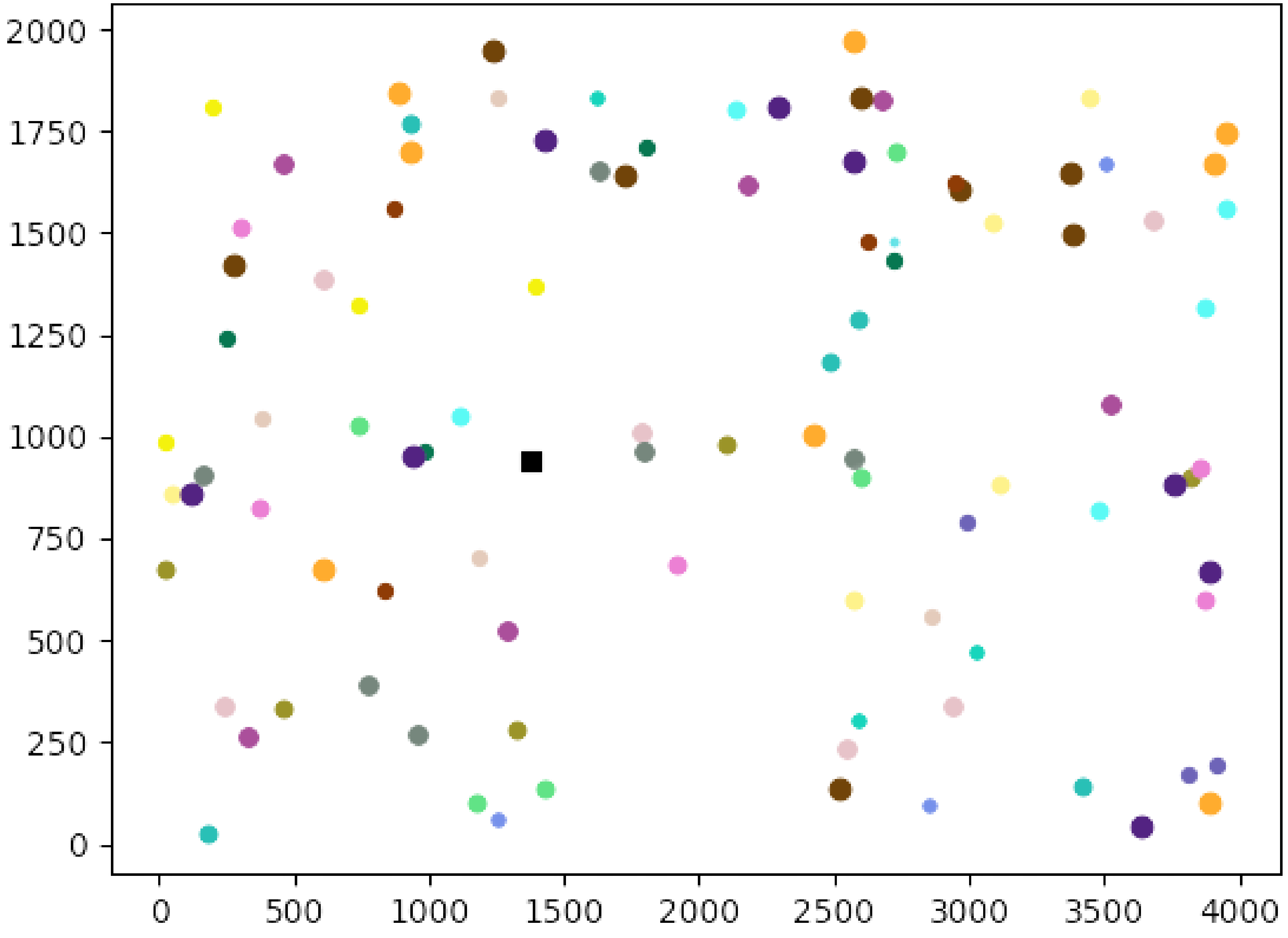
- **Single** vehicle routing.
- Each customer is associated with a **profit** value and is part of a set of customers (cluster).
- Route length cannot exceed a specified **time limit** (Tmax).
- It takes **only one customer** visit to collect the **total profit** associated with the **cluster**.
- Route must start from **depot** and return back to it.

Problem Visualization

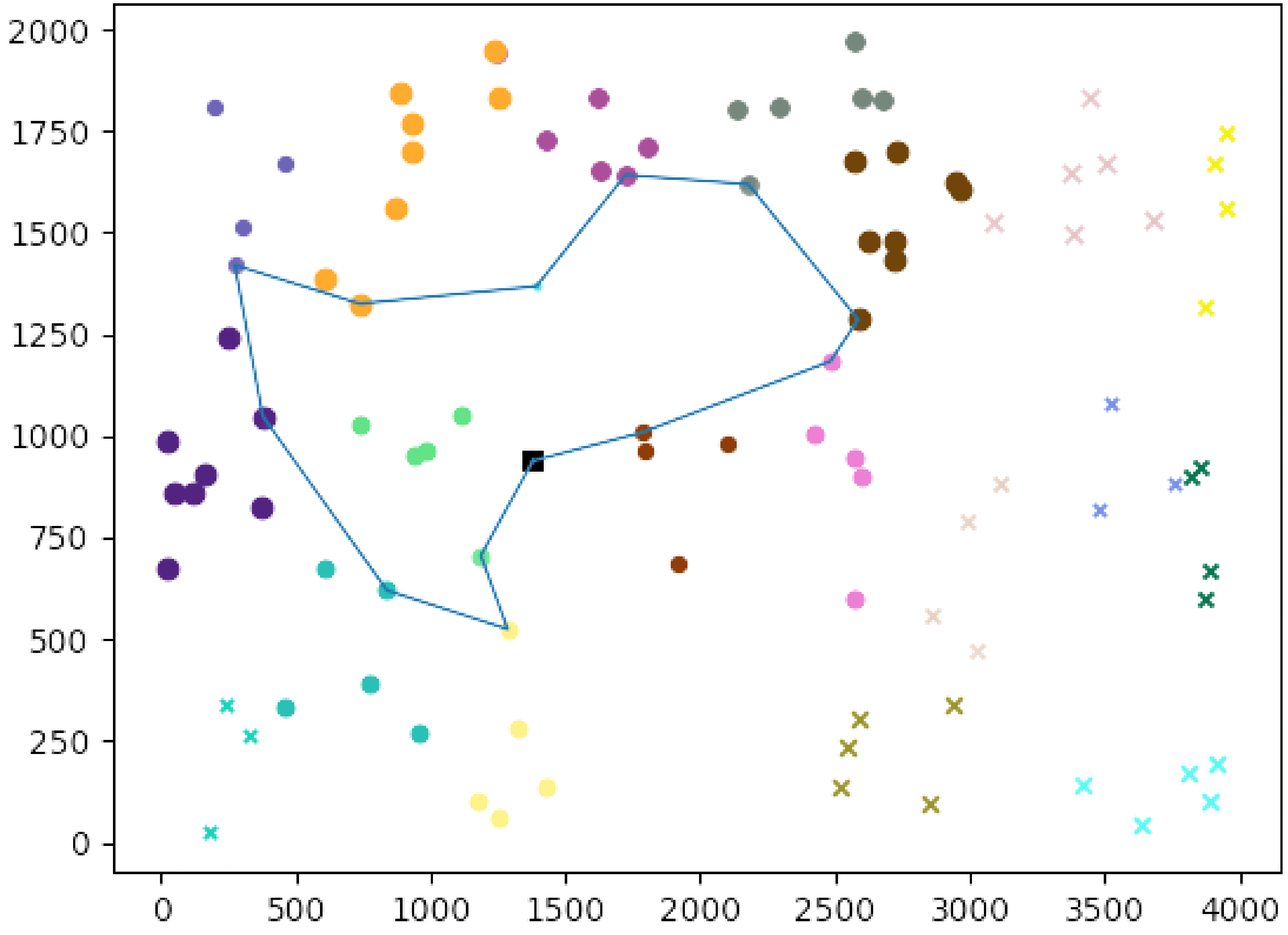


Customer cluster

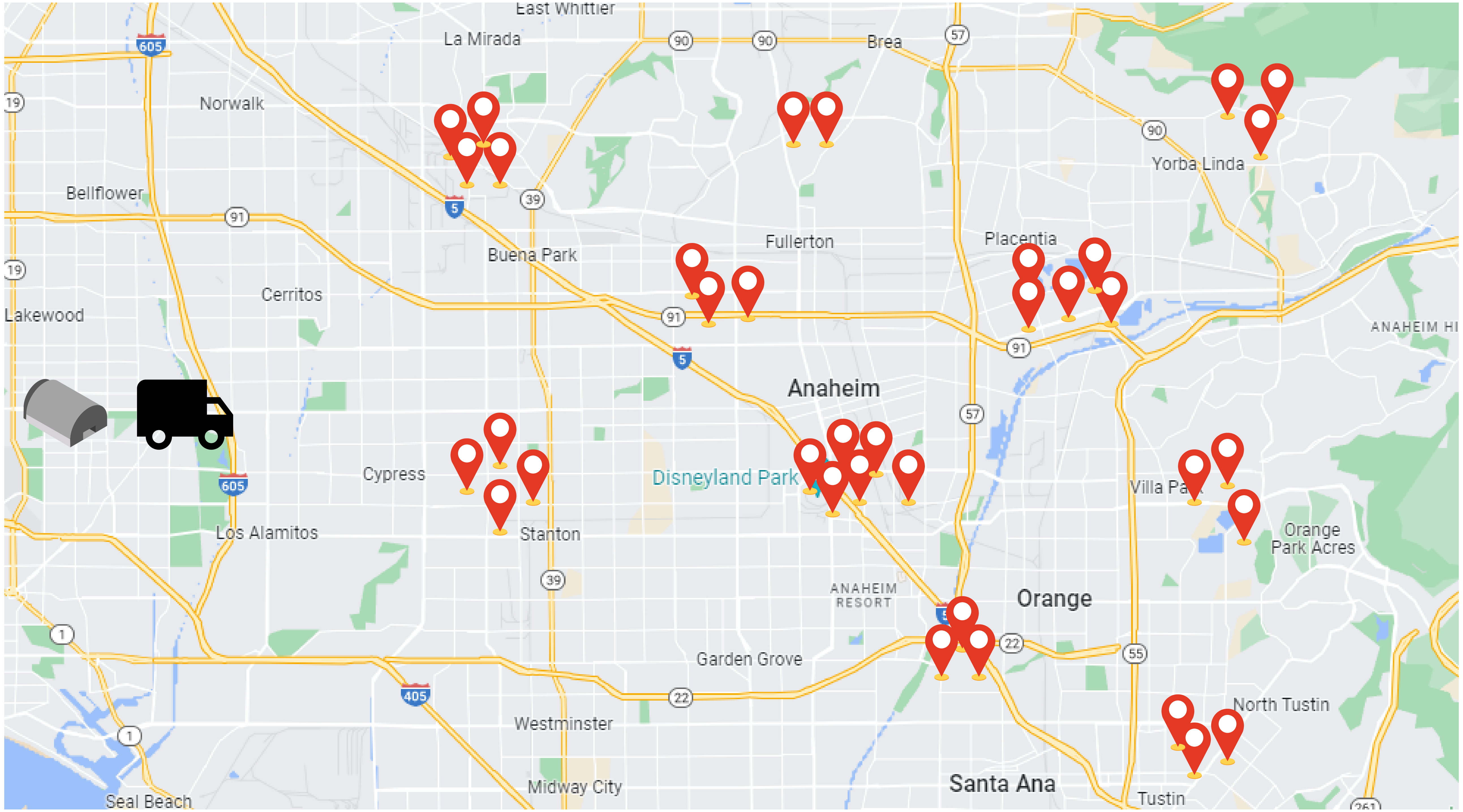
Visualization - Random Dataset



Feasible Solution



Practical Application



02

The AMMH Algorithm

Overall Scheme

Algorithm 1 *Overall Scheme*

$S \leftarrow ConstructInitialSol()$, $S^* \leftarrow \emptyset$ → Initial Solution Construction
for $r \leftarrow 1$ to $RESTARTS$ **do**
    $S \leftarrow LocalSearch(S)$ → Neighborhood Exploration
    if $Z(S) > Z(S^*)$ **then**
        $S^* \leftarrow S$
    end if
    $S \leftarrow SR\text{-}2()$ → Solution Reconstruction
end for
return S^*

Solution Construction Algorithm

Solution Construction

Algorithm 2 *ConstructInitialSol*

```
S_unvisited ← P, S ← [depot, depot]
do
    feasible_insertions ← []
    for set in S_unvisited do
        for node in set do
            for pos ← 1 to |S| − 1 do
                c ← CalculateCost(node, S, pos)
                if C(S) + c <= t_max then
                    feasible_insertions.Insert([node, set, pos, c])
                end if
            end for
        end for
    end for
    if |feasible_insertions| > 0 then
        OrderDescending(feasible_insertions, Z)
        selected_move ← SelectRandom(feasible_insertions, l)
        UpdateSolution(S, selected_move)
        S_unvisited.Remove(selected_move[1])
    end if
while |feasible_insertions| > 0
return S
```

Minimum Inertions logic

Criterion: added_profit/added_cost

Use of **Restricted Candidate List**

Neighborhood Exploration

01

Operators

02

Tabu Policy

03

Intensification procedure

Neighborhood Exploration

01

Operators

02

Tabu Policy

03

Intensification procedure

Local Search Operators

Outer Insertion

Introduce a node into the solution

In-Out Swap

Interchange between an outer and an inner node

Inner Relocation

Move an inner node to a new position in the solution.

Customer Removal

Remove a node from the solution

Selection criterion:

M*profit + cost

Neighborhood Exploration

01

Operators

02

Tabu Policy

03

Intensification procedure

Tabu policy - Promises

Promises-based policy is a
variation of the Tabu Search

Whenever a **set** is removed from the solution, a new promise is defined - equal to the solution's **objective**.

Restriction:
The set will be re-accessible to the operators **only** if current solution's objective is greater than the promise.

Promises are **reinitialized** after a certain number of iterations.

Neighborhood Exploration

01

Operators

02

Tabu Policy

03

Intensification procedure

Intensification Procedure

Basic Intuition

In depth exploration of high quality regions, by applying **exact** and **powerful heuristic** methods.

Aim

Improvement of elite or promising solutions.

Intensification Procedure - Outline

Customer Insertion-Deletion (CID)

Optimal insertions-deletions

Profit Increase

Shortest Path Problem

Optimal node selection given set sequence

TSP Heuristic

Optimal set sequence given node selection

Cost Reduction

Customer Insertion-Deletion (CID)

Parameters

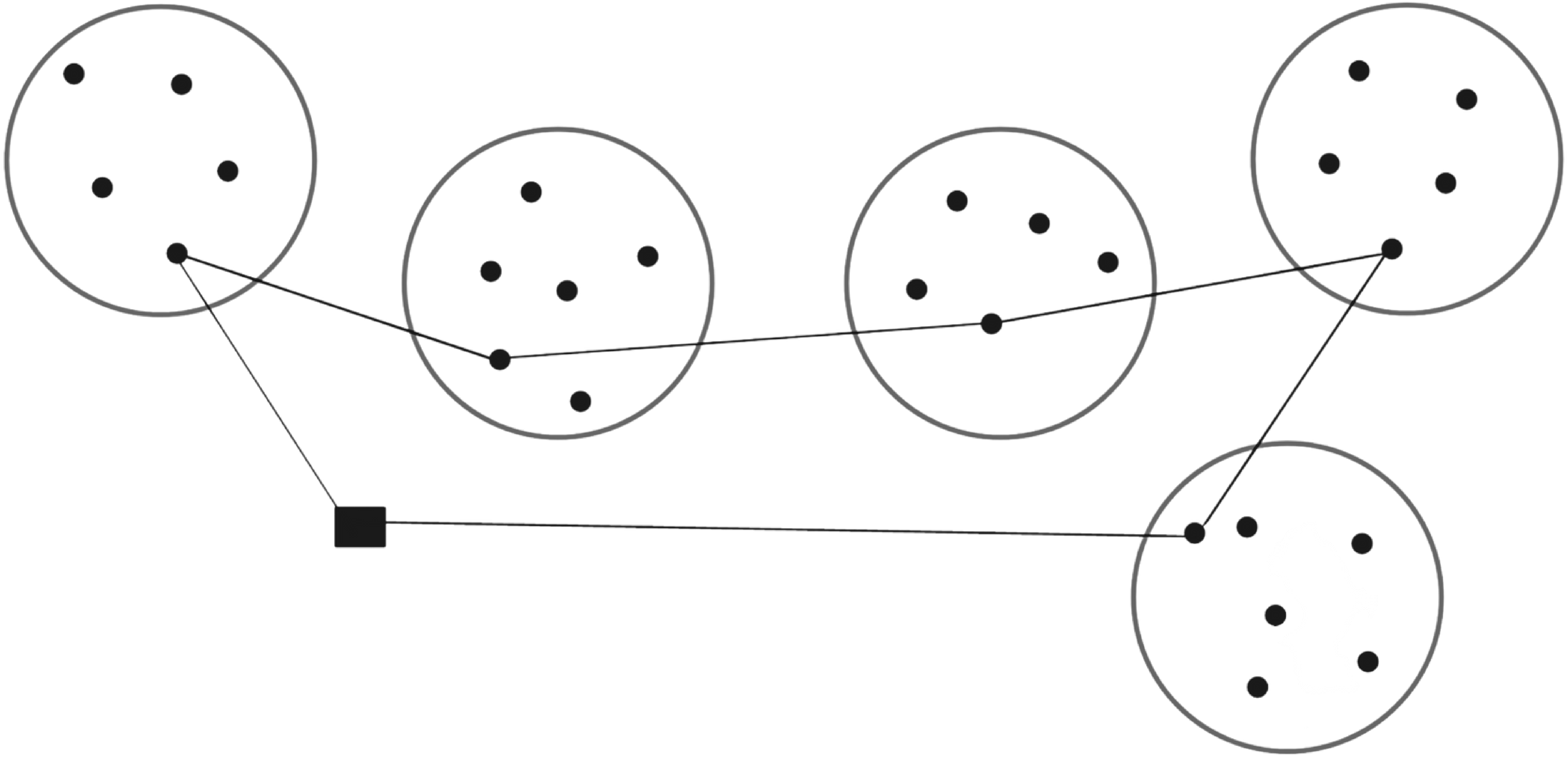
i: max number of insertions
d: max number of deletions

Matheuristic Method

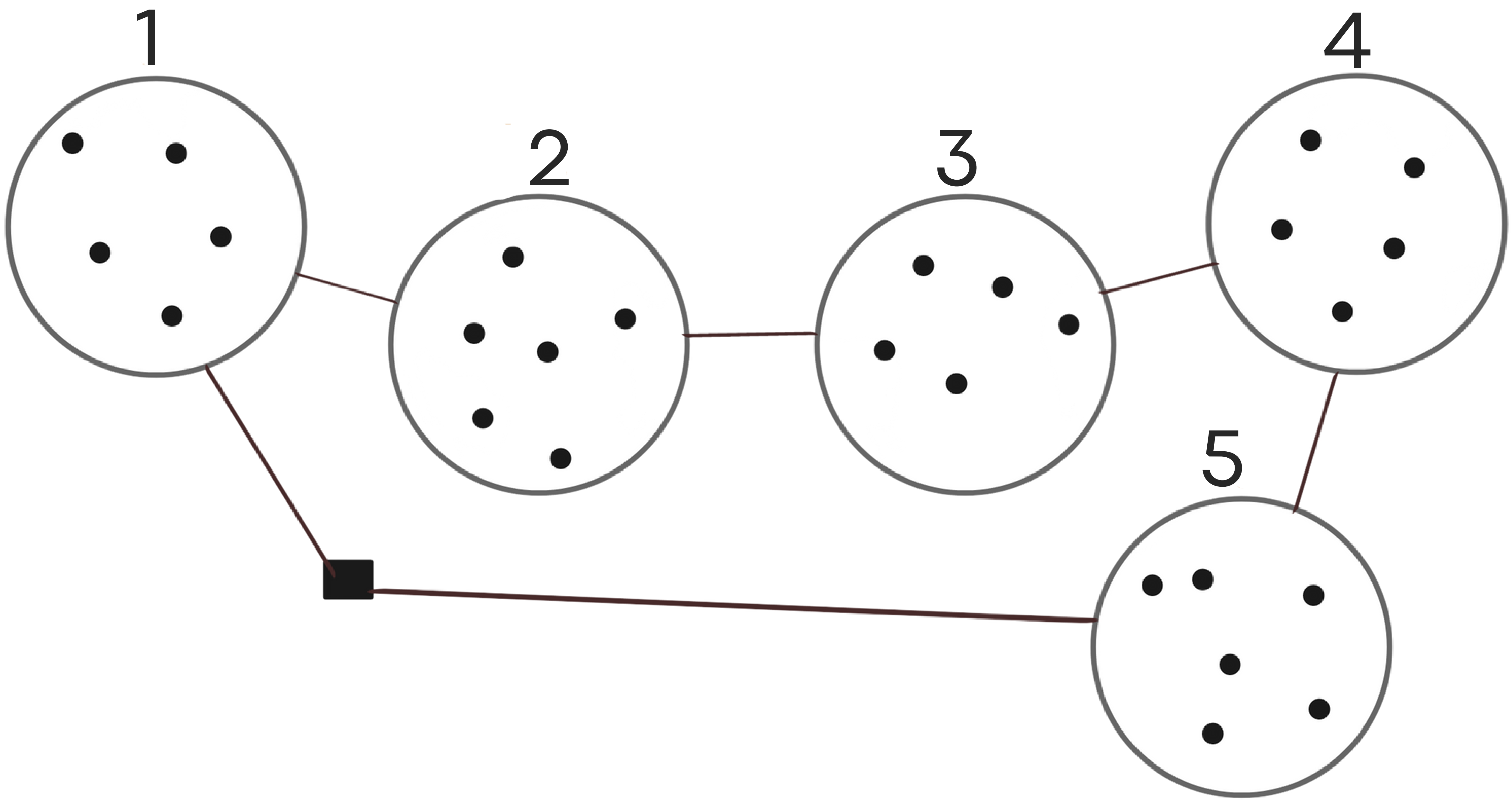
Process

Solve the problem of **simultaneous** insertions and deletions to **optimality**, aiming at **profit maximization**.

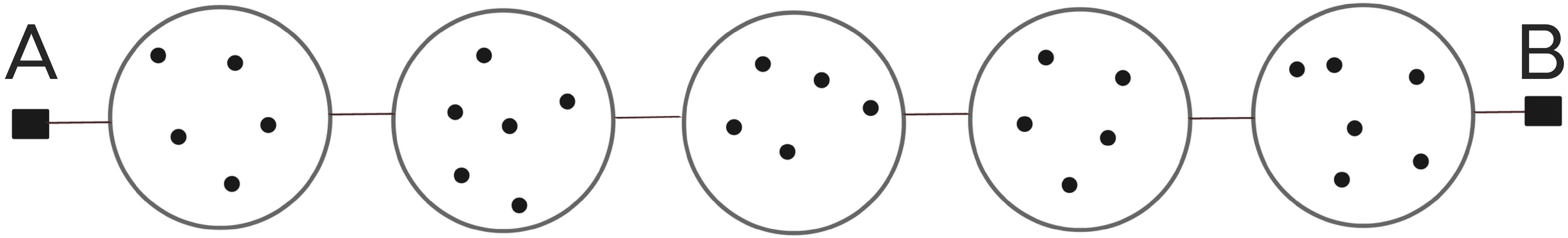
Shortest Path Problem



Shortest Path Problem



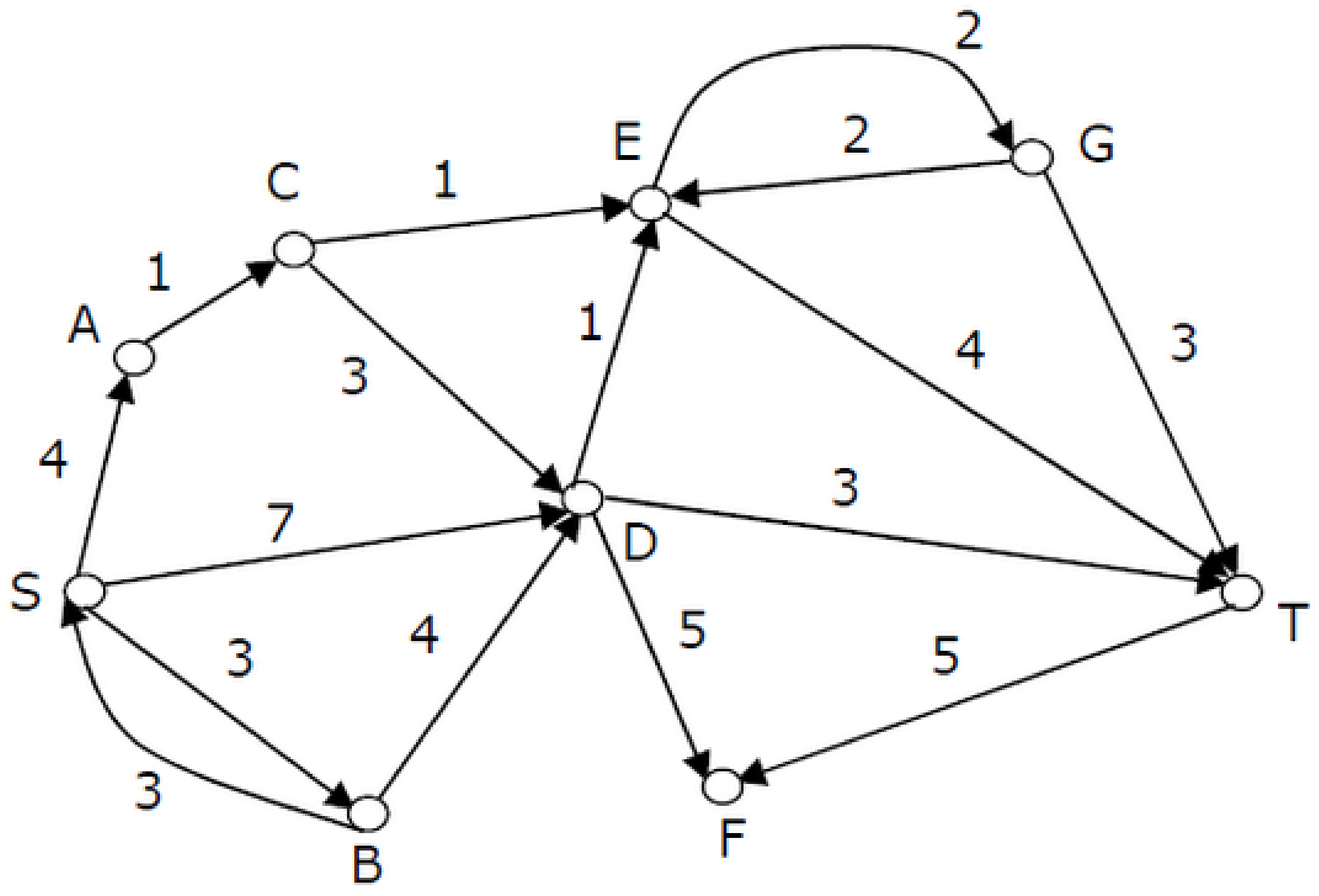
Shortest Path Problem



Shortest Path Problem

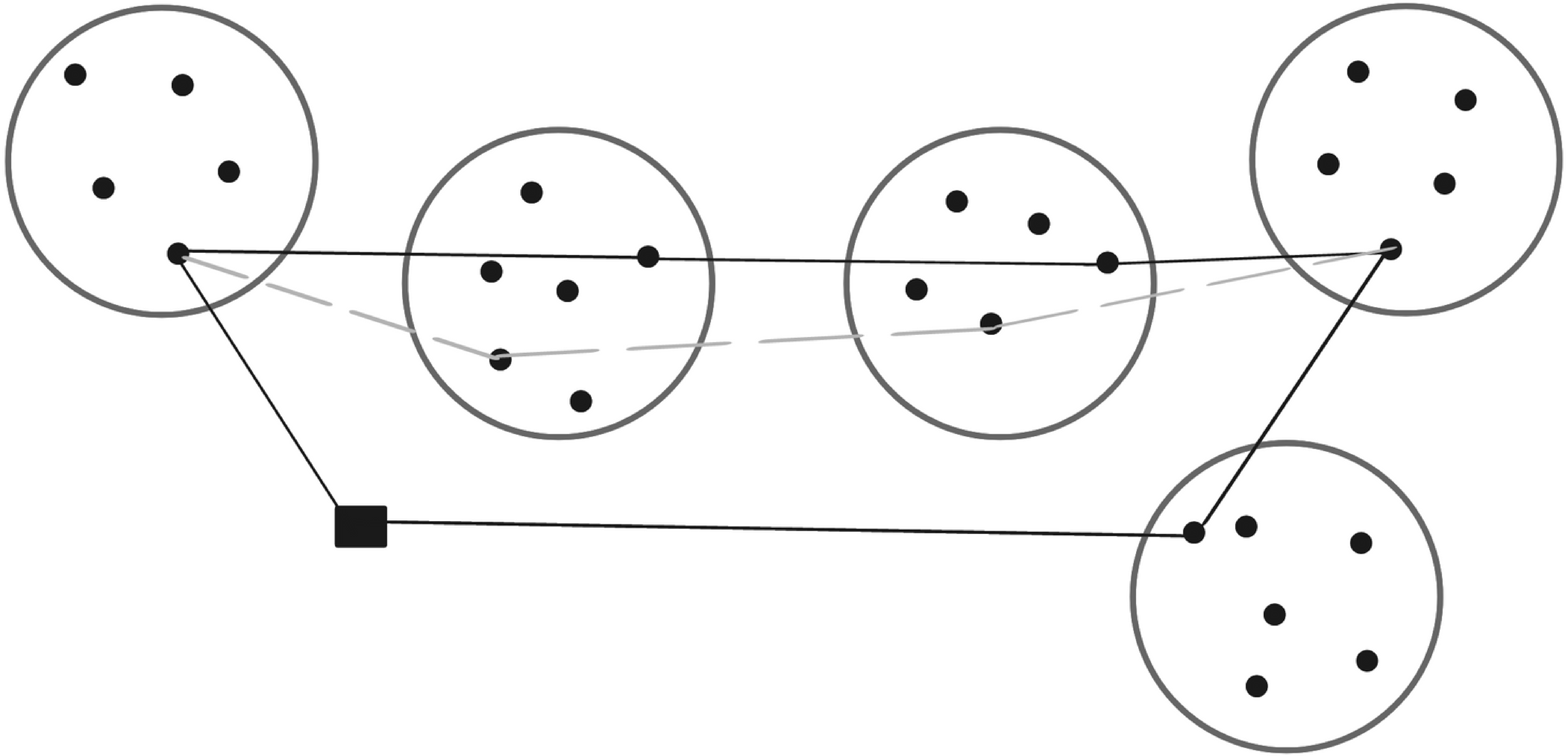
Suitable Algorithms

- **Bellman-Ford** - O(VE)
- **Dijkstra** - O(E+VlogV)
- **Directed Acyclic Graph Shortest Path** (using Topological Sorting) - O(V+E)

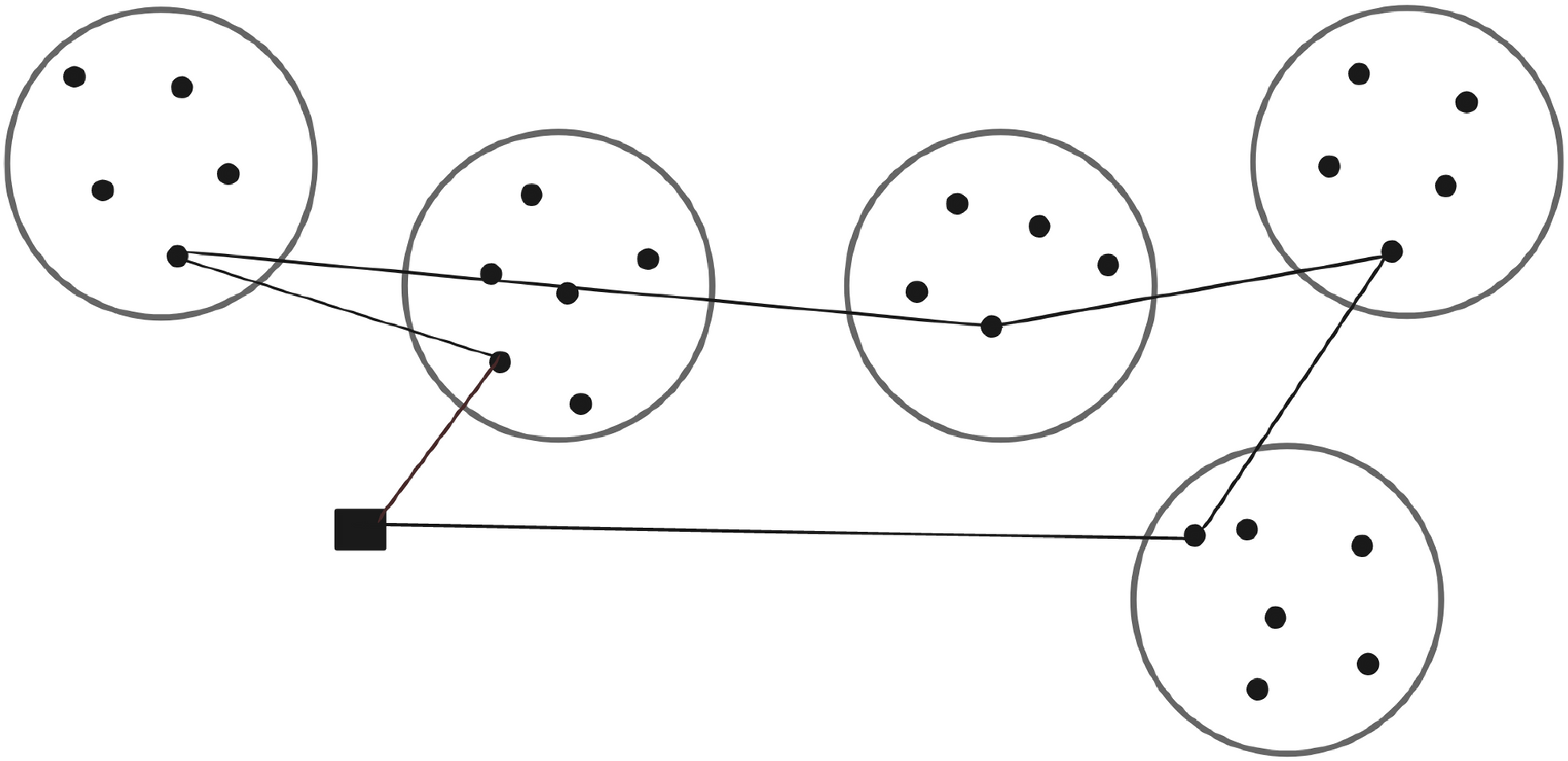


Shortest Path Problem

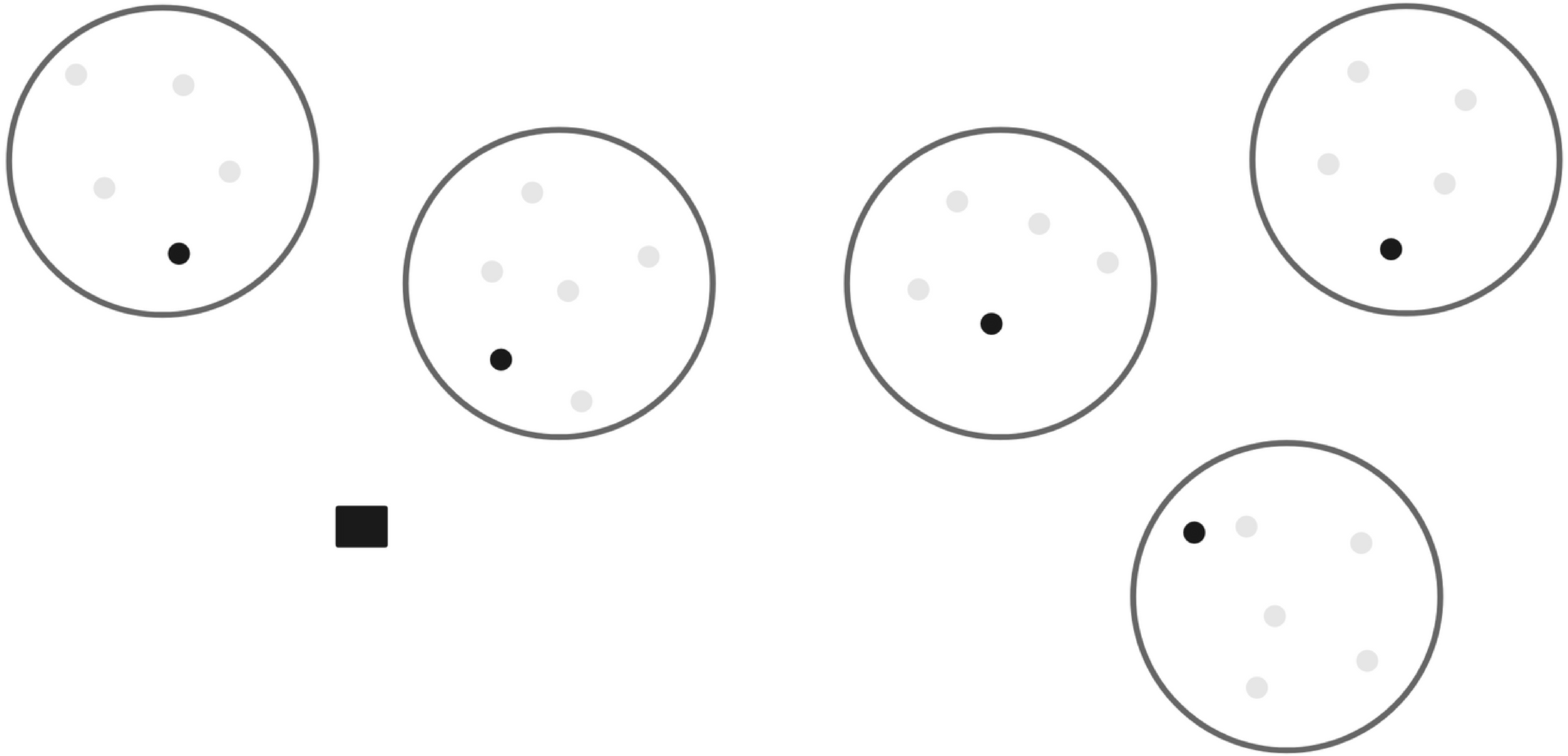
Enhanced Solution



Traveling Salesman Problem



Traveling Salesman Problem



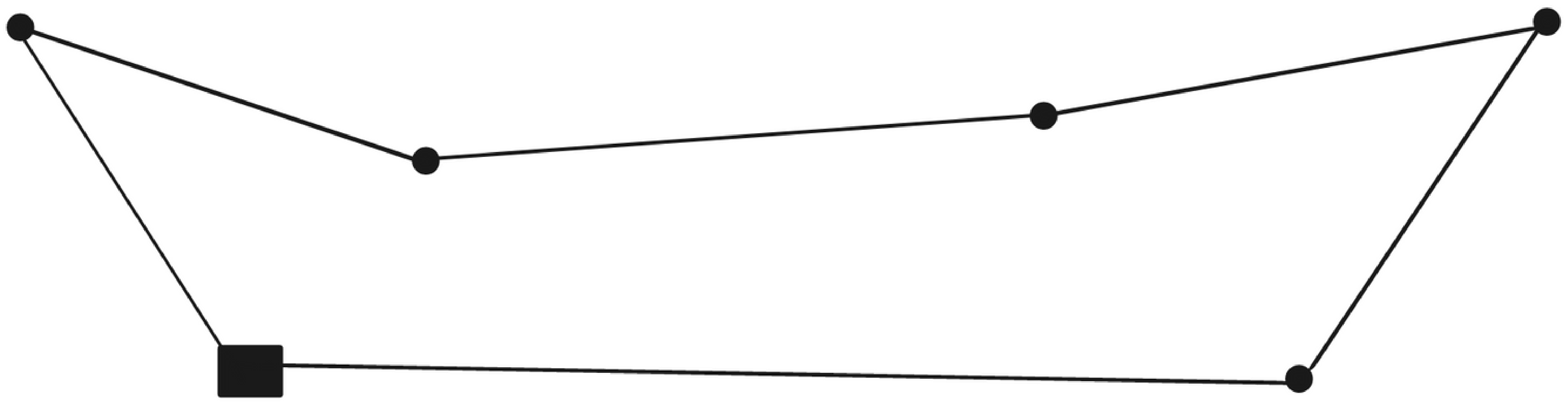
Traveling Salesman Problem

Traveling Salesman Problem

Heuristic: **Lin-Kernighan-Helsgaun Solver**

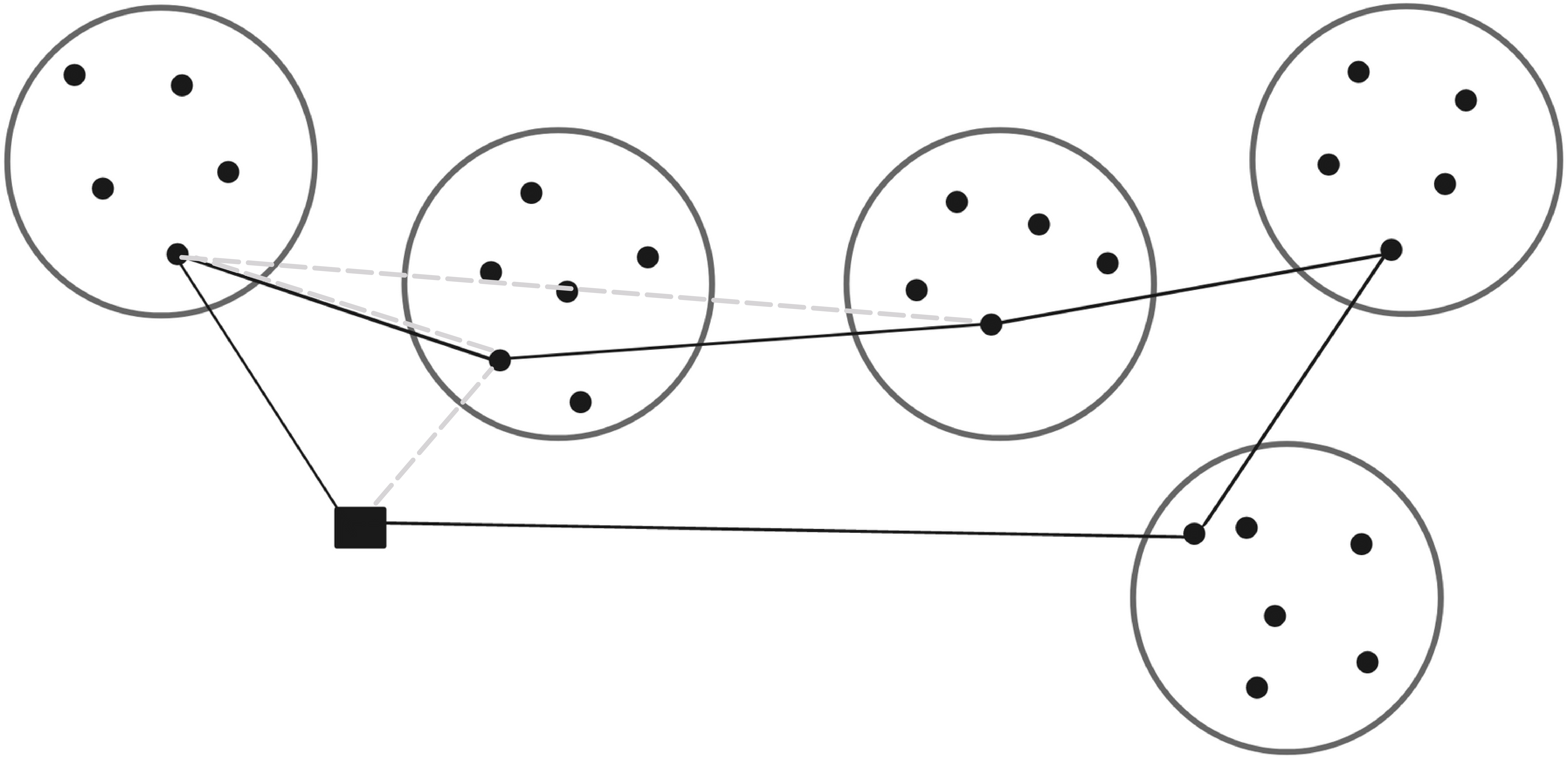
- Very effective heuristic capable of solving to **optimality** problems with up to a million nodes
- For the problem scale of our test cases - a few hundreds of nodes - LKH usually obtains the optimal solutions **very fast** (less than a CPU second)

TSP heuristic



TSP heuristic

Enhanced Solution



Intensification Procedure - Outline

Customer Insertion-Deletion (CID)

Optimal insertions-deletions

Shortest Path Problem

Optimal node selection given set sequence

TSP Heuristic

Optimal set sequence given node selection

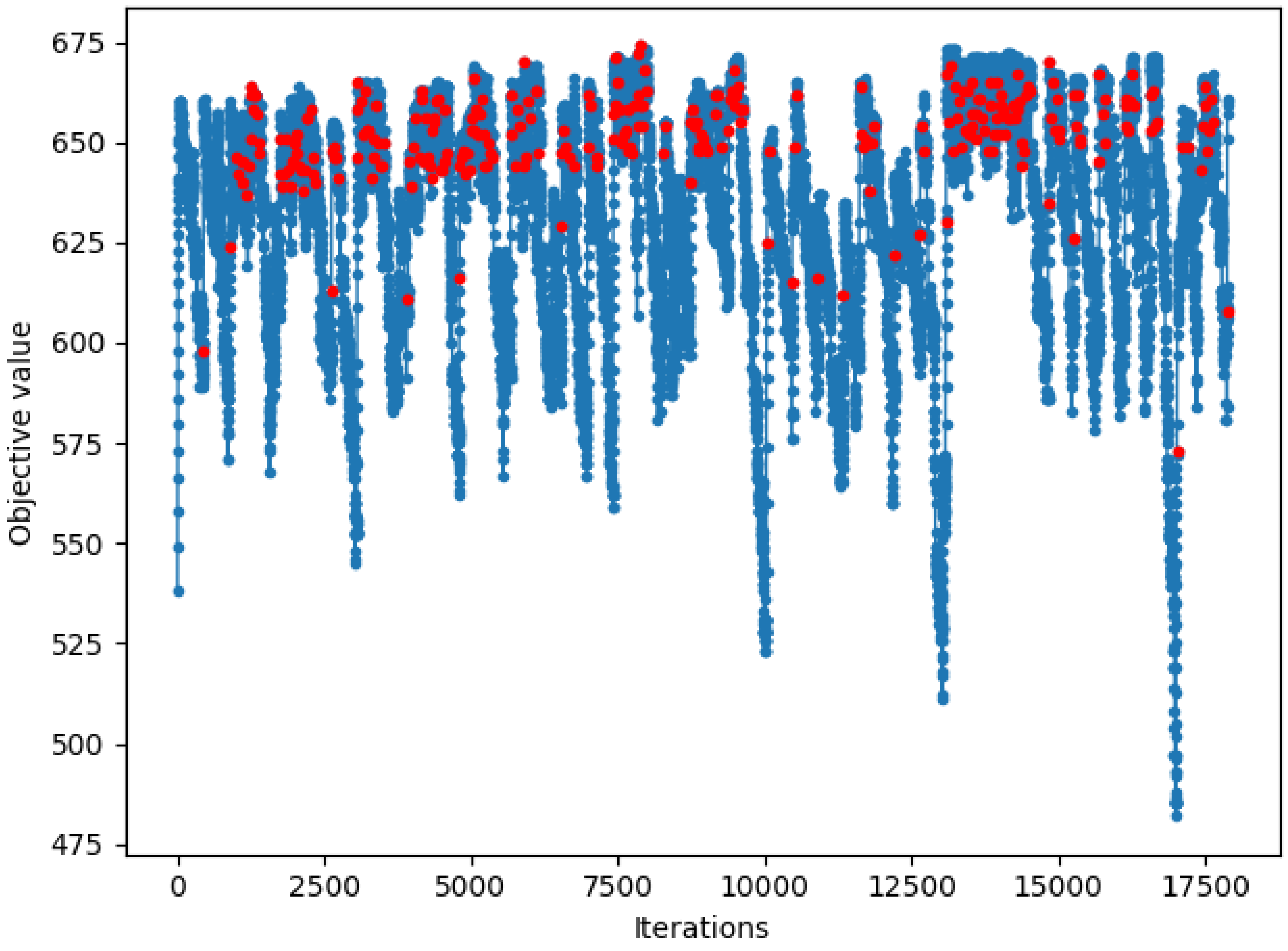
Profit Increase

Cost Reduction

Intensification Procedure

When is it executed?

- When a **new best** solution is found.
- When the **gap** between the current and the best solution is **smaller than a threshold g**.
- When **promises** are **reinitialized**.



Overall Scheme

Algorithm 1 *Overall Scheme*

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for $r \leftarrow 1$ **to** $RESTARTS$ **do**

  $S \leftarrow LocalSearch(S)$ → Neighborhood Exploration

  if $Z(S) > Z(S^*)$ **then**

    $S^* \leftarrow S$

  end if

  $S \leftarrow SR\text{-}2()$ → Solution Reconstruction

end for

return S^*

Solution Reconstruction

Adaptive Logic

- The algorithm uses a **memory-based** structure that takes advantage of **previous Local Search states**.
- This structure is a **pool of high quality solutions**.
- These solutions are stored during the Local Search iterations and are used in the **Solution Reconstrucion** stage.

Adaptive Logic

Solution Pool: A collection of elite solutions, sorted by their value of the objective function.

The **decision** of whether a solution will be inserted to the Pool depends on:

- The **objective** of the solution
- The non-violation of an **upper similarity bound** with the solutions currently present in the Pool.

Goal: Discovery of features that distinguish high quality solutions.

Solution Reconstruction

- The exploitation of Pool solutions begins with the extraction of **frequent chains of nodes**.
- **Chains**: sequences of 3 to 6 nodes
- The most frequently appearing node chains are encountered applying a **pattern matching** procedure.

Chains Collection Procedure

Solution Pool

```
Sol 1: 0 -> 49 -> 89 -> 30 -> 103 -> 67 -> 22 -> 66 -> 42 ->
96 -> 109 -> 48 -> 32 -> 130 -> 16 -> 84 -> 45 -> 81 -> 31 ->
104 -> 82 -> 90 -> 6 -> 105 -> 72 -> 76 -> 37 -> 40 -> 97 ->
15 -> 54 -> 108 -> 64 -> 41 -> 123 -> 63 -> 17 -> 99 -> 29 ->
73 -> 125 -> 115 -> 10 -> 92 -> 0

Sol 2: 0 -> 5 -> 89 -> 30 -> 103 -> 67 -> 22 -> 66 -> 42 ->
96 -> 109 -> 48 -> 32 -> 130 -> 16 -> 127 -> 50 -> 55 -> 82 ->
27 -> 90 -> 6 -> 86 -> 43 -> 105 -> 72 -> 85 -> 19 -> 113 ->
40 -> 97 -> 15 -> 54 -> 108 -> 64 -> 41 -> 123 -> 17 -> 99 ->
73 -> 125 -> 115 -> 10 -> 92 -> 0

Sol 3: 0 -> 49 -> 89 -> 30 -> 103 -> 67 -> 22 -> 66 -> 42 ->
96 -> 109 -> 48 -> 32 -> 130 -> 16 -> 127 -> 50 -> 55 -> 82 ->
27 -> 90 -> 6 -> 105 -> 72 -> 76 -> 37 -> 113 -> 40 -> 97 ->
15 -> 54 -> 108 -> 64 -> 41 -> 123 -> 63 -> 17 -> 99 -> 29 ->
125 -> 73 -> 115 -> 10 -> 92 -> 0
```

Chains Collection Procedure

Solution Pool

```
Sol 1: 0 -> 49 -> 89 -> 30 -> 103 -> 67 -> 22 -> 66 -> 42 ->
96 -> 109 -> 48 -> 32 -> 130 -> 16 -> 84 -> 45 -> 81 -> 31 ->
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125 -> 73 -> 115 -> 10 -> 92 -> 0
```

Chain frequency: 3

Chains Collection Procedure

Solution Pool

```
Sol 1: 0 -> 49 -> 89 -> 30 -> 103 -> 67 -> 22 -> 66 -> 42 ->
96 -> 109 -> 48 -> 32 -> 130 -> 16 -> 84 -> 45 -> 81 -> 31 ->
104 -> 82 -> 90 -> 6 -> 105 -> 72 -> 76 -> 37 -> 40 -> 97 ->
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27 -> 90 -> 6 -> 105 -> 72 -> 76 -> 37 -> 113 -> 40 -> 97 ->
15 -> 54 -> 108 -> 64 -> 41 -> 123 -> 63 -> 17 -> 99 -> 29 ->
125 -> 73 -> 115 -> 10 -> 92 -> 0
```

Text Representation

```
0-49-89-30-103-67-22-66-42-96-109-48-32-130-16-84-45-81-31-104
-82-90-6-105-72-76-37-40-97-15-54-108-64-41-123-63-17-99-29-73
-125-115-10-92-0-0-5-89-30-103-67-22-66-42-96-109-48-32-130-16
-127-50-55-82-27-90-6-86-43-105-72-85-19-113-40-97-15-54-108-6
4-41-123-17-99-73-125-115-10-92-0-0-49-89-30-103-67-22-66-42-9
6-109-48-32-130-16-127-50-55-82-27-90-6-105-72-76-37-113-40-97
-15-54-108-64-41-123-63-17-99-29-125-73-115-10-92-0
```

Chains Collection Procedure

Input 67-22-66 (string to match)

```
0-49-89-30-103-67-22-66-42-96-109-48-32-130-16-84-45-81-31-104
-82-90-6-105-72-76-37-40-97-15-54-108-64-41-123-63-17-99-29-73
-125-115-10-92-0-0-5-89-30-103-67-22-66-42-96-109-48-32-130-16
-127-50-55-82-27-90-6-86-43-105-72-85-19-113-40-97-15-54-108-6
4-41-123-17-99-73-125-115-10-92-0-0-49-89-30-103-67-22-66-42-9
6-109-48-32-130-16-127-50-55-82-27-90-6-105-72-76-37-113-40-97
-15-54-108-64-41-123-63-17-99-29-125-73-115-10-92-0
```

(Text)

Process String matching algorithm (Boyer-Moore-Horspool)

Output Frequency: 3

Chains Collection Procedure

- This procedure is executed for every **unique** chain of nodes, and those that appear **at least twice** are **collected**.
- Out of all accumulated chains, the **50% most frequent** sequences are qualified and used at the next stage.
- At the final step, the chosen chains will be employed by the **Reconstruction Algorithms**.

Reconstrucion Algorithms

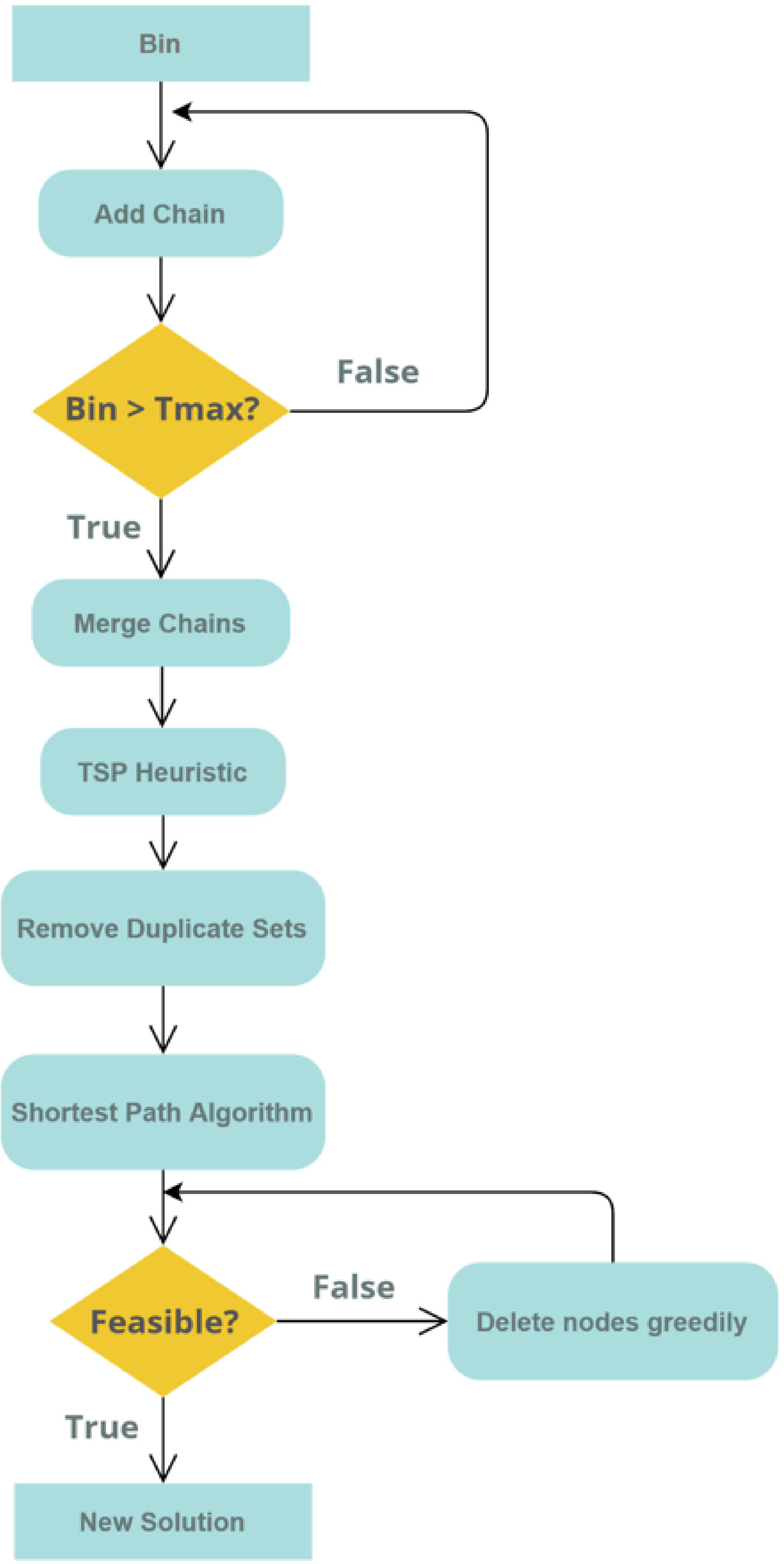
- SR-1
- SR-2
- SR-3

Reconstruction Algorithm SR-1

- Exactly same logic as the construction algorithm.
- But, it only takes into account the nodes that appear in the top 50% of the most frequent chains.

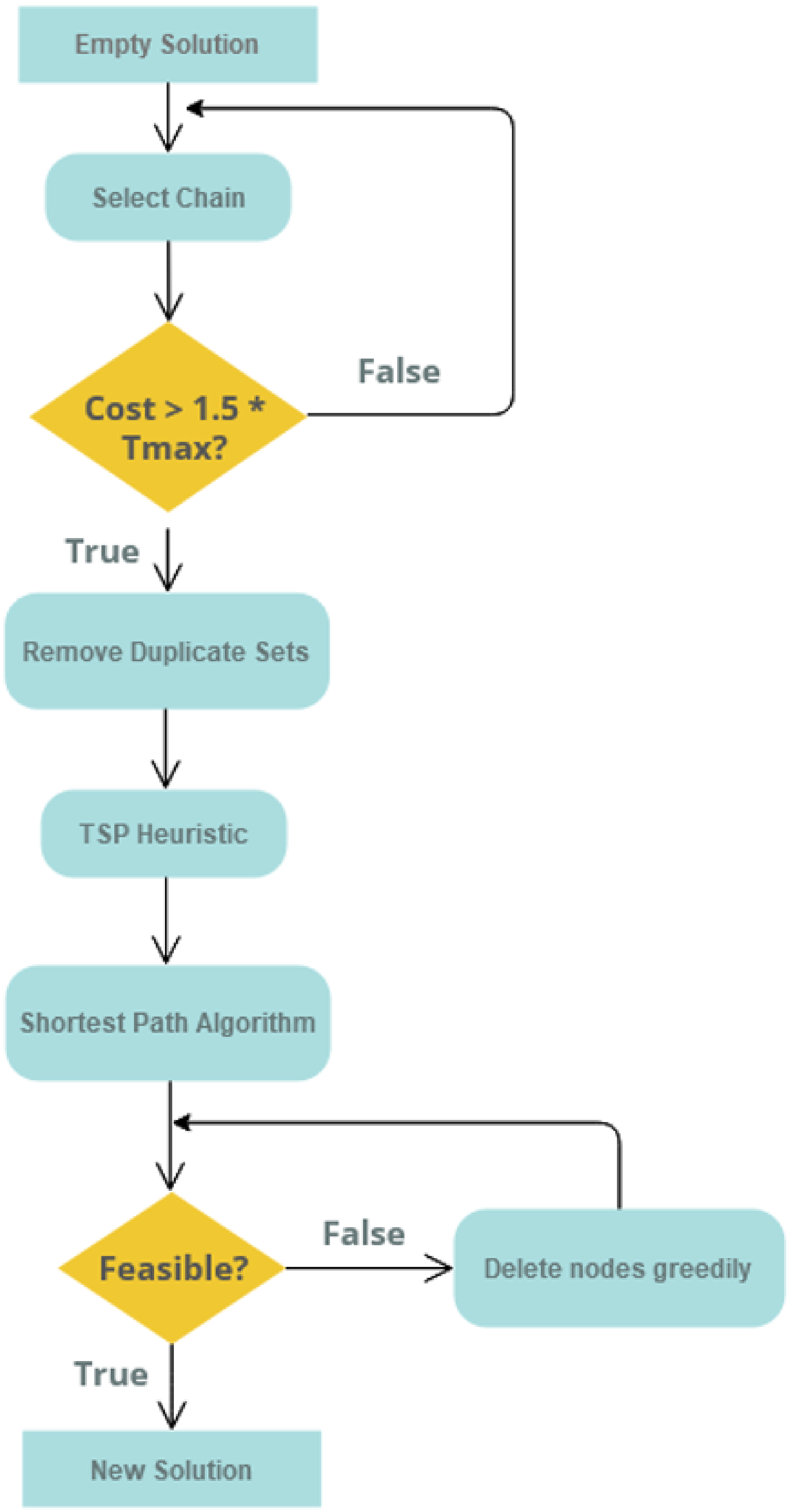
Reconstruction Algorithm SR-2

- **Bin** of Tmax capacity.
- Chains are **inserted** into the bin until it is full.
- The chains are **connected** to a single sequence.
- **TSP** heuristic is applied to this sequence.
- Nodes of **duplicate sets** are serially **removed**.
- **Shortest path** algorithm is applied, reducing the cost of the created solution.
- In case of **infeasibility**, nodes are deleted following a **greedy** criterion.



Reconstruction Algorithm SR-3

- **Minimum Insertions logic**
- Insertions are performed at a **chain level**.
- To do that, a **center** is assigned to each chain.
- Upper cost bound for the solution is set to **Tmax' = 1.5 * Tmax**.
- A single node of each set is stochastically selected, to be kept into the solution.
- **TSP** and **Shortest Path** algorithms are applied.
- In case of **infeasibility**, nodes are deleted following a **greedy** criterion.



03

AMMH Results

Intensification Procedure value

Instance	n	ω	pg	Diff_{sol}	$\text{Diff}_{sol.avg}$	Diff_{time}
115rat575_RND	575	0.4	g1	0.47	0.24	1.18
115rat575_RND	575	0.6	g1	0.00	0.55	3.25
115u574	574	0.6	g2	0.69	1.82	1.80
132d657_RND	657	0.4	g2	0.00	0.65	1.70
132d657	657	0.4	g2	0.44	1.27	0.35
132d657	657	0.8	g1	1.35	1.36	4.18
145u724	724	0.6	g2	1.20	3.62	0.96
157rat783_RND	783	0.4	g2	1.10	1.37	1.20
157rat783	783	0.6	g2	1.14	3.55	0.62
157rat783	783	0.8	g1	1.35	1.97	1.33
201pr1002_RND	1002	0.6	g1	0.40	0.71	4.00
201pr1002	1002	0.6	g2	1.52	3.86	0.56
212u1060_RND	1060	0.4	g1	0.10	0.62	1.95
212u1060_RND	1060	0.6	g2	0.15	0.16	3.55
212u1060	1060	0.4	g1	-0.37	2.08	0.25
212u1060	1060	0.8	g1	0.90	1.51	2.04
217vm1084	1084	0.4	g1	0.45	2.99	-0.08
217vm1084	1084	0.6	g2	0.92	4.67	0.81
217vm1084	1084	0.8	g2	1.46	1.62	3.08
53gil262_RND	262	0.6	g2	0.00	0.07	12.75
80rd400_RND	400	0.4	g2	0.00	0.54	2.79
80rd400	400	0.8	g1	0.82	0.83	3.97
89pcb442_RND	442	0.4	g1	-0.26	0.00	2.95
89pcb442_RND	442	0.4	g2	0.00	0.26	3.29
99d493	493	0.8	g2	0.63	0.85	7.50
Average				0.58	1.49	2.64

Enhancement of best solution: 0.58%

Enhancement of average solution: 1.49%

Increase in computational time: 2.64%

SR algorithms comparison

Instance	Best	No pool	SR1	SR2	SR3
		Gap	Gap	Gap	Gap
1187rl5934_T40_p1	2953	0.038	0.058	0.000	0.018
200E1k.0_T80_p1	911	0.001	0.002	0.000	0.001
235pcb1173_RND_T60_p2	58877	0.028	0.000	0.072	0.009
259d1291_T40_p2	29520	0.103	0.061	0.111	0.000
261rl1304_T60_p2	48198	0.005	0.057	0.012	0.000
265rl1323_T80_p2	61850	0.000	0.139	0.084	0.043
276nrw1379_RND_T60_p1	1367	0.001	0.001	0.001	0.000
280fl1400_T40_p1	884	0.000	0.000	0.000	0.000
287u1432_T60_p1	1052	0.000	0.002	0.001	0.001
316fl1577_T80_p1	1398	0.001	0.001	0.001	0.000
331d1655_RND_T40_p2	64684	0.141	0.195	0.259	0.000
350vm1748_RND_T60_p2	88203	0.000	0.000	0.000	0.000
364u1817_T80_p2	82443	0.067	0.178	0.109	0.000
378rl1889_T40_p2	49869	0.821	0.646	0.000	0.335
421d2103_T60_p1	1410	0.002	0.001	0.000	0.001
431u2152_T80_p2	96430	0.600	0.587	0.000	0.098
464u2319_RND_T40_p1	1569	0.007	0.007	0.001	0.000
479pr2392_RND_T60_p2	120627	0.255	0.125	0.034	0.000
49usa1097_RND_T40_p1	1096	0.000	0.000	0.000	0.000
608pcb3038_T80_p1	2709	0.012	0.003	0.000	0.000
633E3k.0_T40_p1	1578	0.015	0.023	0.000	0.008
759fl3795_T60_p2	140880	1.908	1.640	0.000	0.222
893fnl4461_T80_p1	3804	0.001	0.006	0.000	0.001
Average	-	0.174	0.162	$\boxed{0.030}$	0.032

SR2 and **SR3** algorithms produced the best results with **SR2** being the best.

Summarized final results

Table 3: Algorithms comparison on data set

Clustering Type	ω	pg	MASOP			VNS			BRKGA			AMMH			
			#Bst	t	Gap	#Bst	t	Gap	#Bst	t	Gap	#New	# Bst	t	Gap
Original	0.4	g1	41	73.04	0.18	41	20.9	0.7	41	12.39	0.23	5	**48**	10.38	0.09
		g2	36	89.98	0.54	39	20.4	0.8	40	12.57	0.24	7	**49**	13.61	0.07
	0.6	g1	37	45.32	0.24	35	35.2	1.0	36	20.60	0.44	12	**51**	20.91	0.00
		g2	37	51.04	0.15	34	35.2	0.9	39	20.67	0.32	11	**50**	21.08	0.00
	0.8	g1	37	35.66	0.20	34	52.0	0.7	35	28.29	0.64	10	**51**	22.95	0.00
		g2	37	39.27	0.12	36	52.5	0.6	33	28.30	0.61	11	**49**	29.85	0.01
Random	0.4	g1	31	97.83	1.29	33	85.8	0.7	34	46.04	1.05	13	**51**	19.72	0.00
		g2	31	121.85	0.86	33	87.4	0.8	32	45.78	0.80	16	**51**	29.90	0.00
	0.6	g1	42	84.48	0.13	35	147.6	0.5	31	64.96	0.76	9	**51**	27.52	0.00
		g2	39	84.96	0.17	31	145.3	0.4	31	63.30	0.52	11	**50**	32.58	0.00
	0.8	g1	51	136.21	0.00	51	230.8	0.0	43	69.24	0.07	0	51	21.56	0.00
		g2	51	148.92	0.00	51	233.4	0.0	44	67.78	0.06	0	51	21.36	0.00
Total/Average			470	84.05	0.32	453	95.52	0.60	439	39.99	0.48	105	**603**	22.62	0.01

603/612 (98%) best

102/612 (17%) new best

Large Datasets

- The available SOP datasets were **relatively small**.
- The **high efficiency of AMMH** even at the largest of them, led us to create **new and even bigger datasets**.
- The new instances contain up to **3038 nodes** and **633 sets**.

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