MATHÉMATIQUES ET INFORMATIQUE
Sciences
Université de Paris

LGI2A

UNIVERSITÉ D'ARTOIS

# COST OPTIMIZATION IN PI CROSS-DOCK NETWORKS USING GENETIC ALGORITHMS

**Master 2 Réseaux et systèmes autonomes, paris cité**

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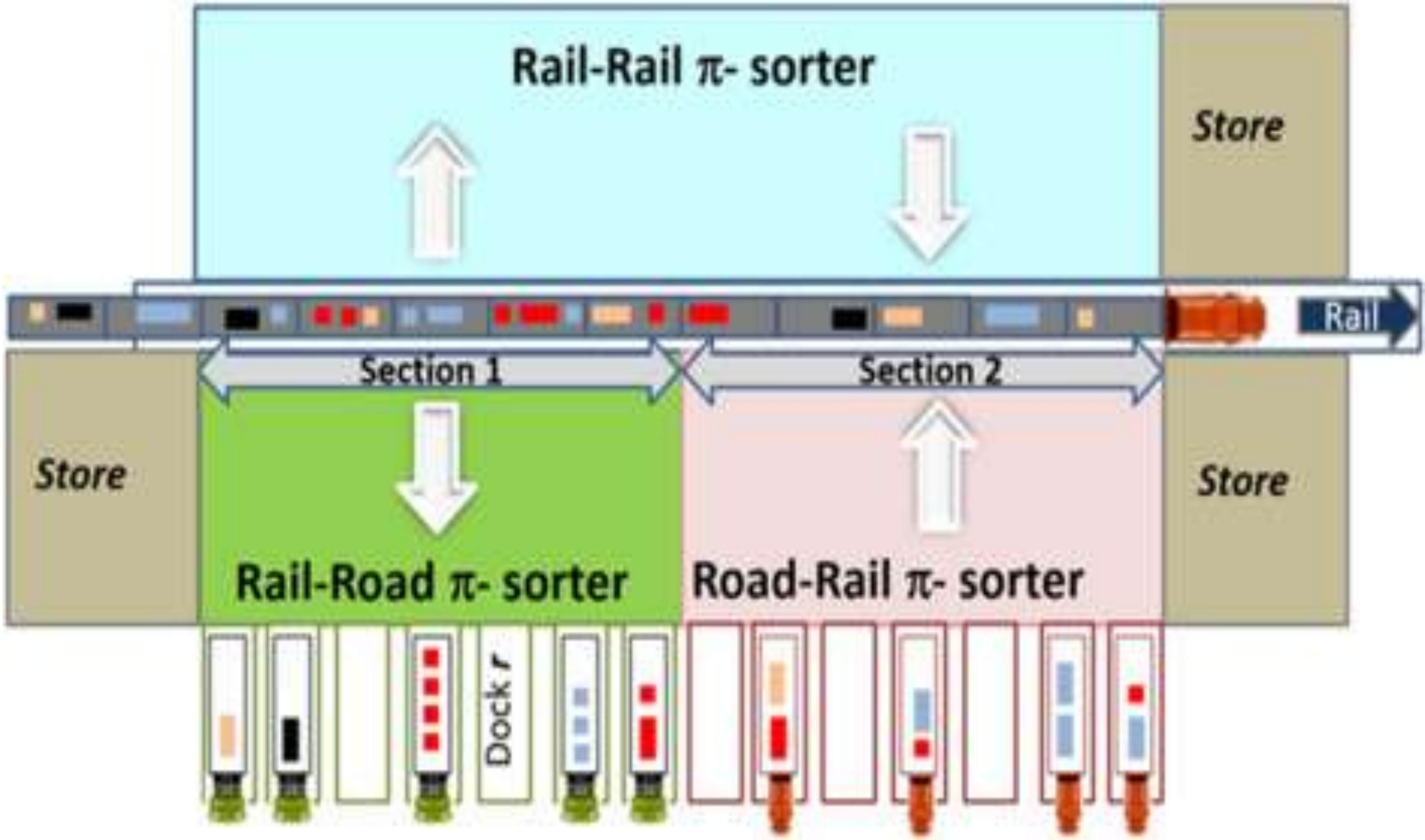
**Definition**

Cross-docking is a logistics approach that enables fast transshipment of goods between inbound and outbound transportation modes with minimal storage. Due to the involvement of multiple docks, modes, and constraints, optimizing cross-dock operations is a challenging problem that requires efficient scheduling and assignment strategies.

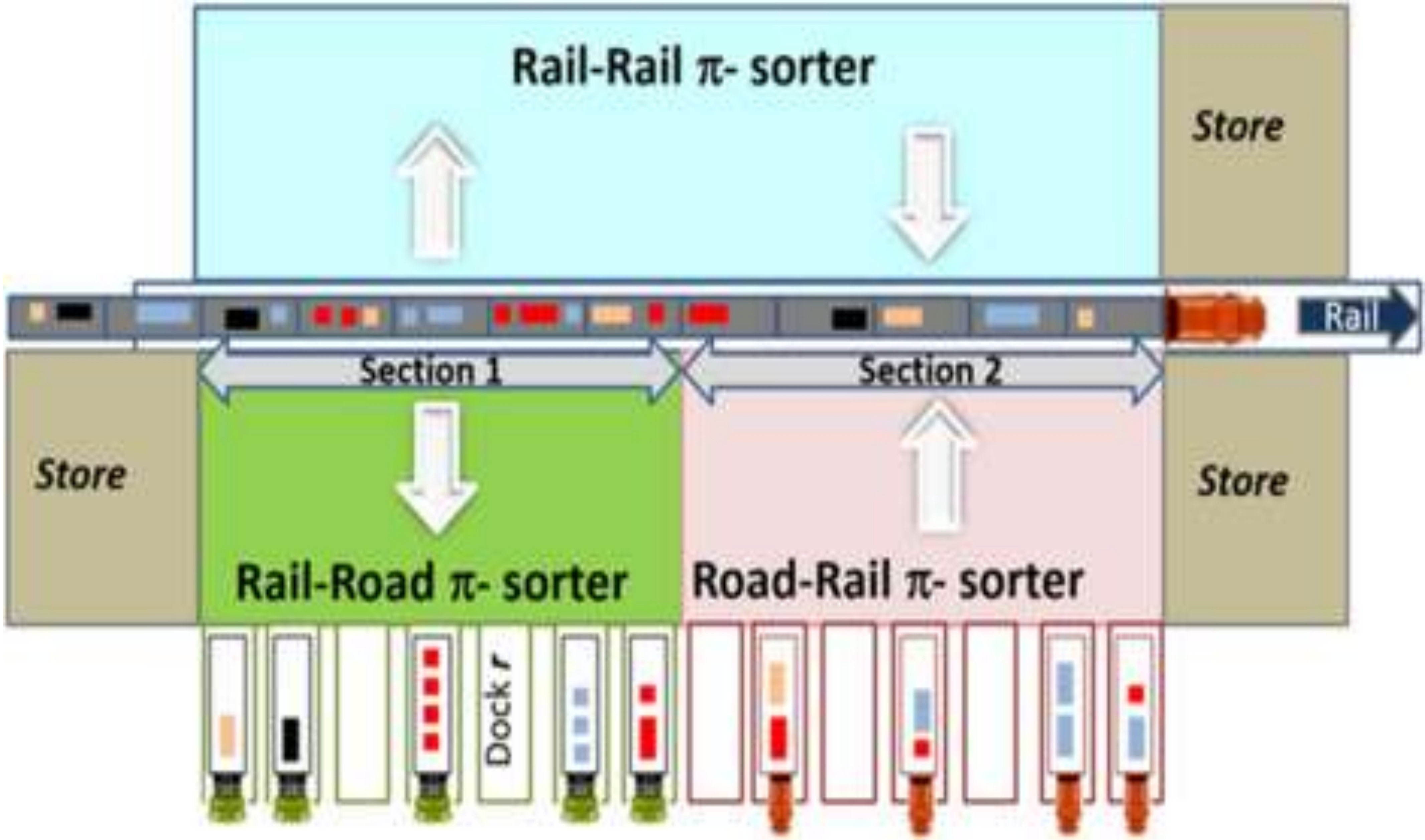


Physical Internet cross dock sorter [1]

[1] : Tran-Dang et al , (2021

**Problem statement**

How to efficiently schedule and assign containers, vehicles, and docks in a cross-docking platform so as to minimize cost and energy consumption under strict operational constraints and limited computational time?



Physical Internet cross dock sorter [1]

| Reference | Objective Function | Methods |
|---|---|---|
| **Chargui, et al. (2019) Truck Scheduling in a Rail–Road PI cross-dock Considering Energy Consumption** | Min energy consumption + vehicle costs | Hybrid metaheuristic (Variable Neighborhood Search+ Tabu Search) |
| **Shahram, et al. (2019)Trucks scheduling in cross-docking with energy consumption consideration and trucks queuing** | Min costs of holding products in a cross-dock + energy consumption of forklift in a cross-doc | Multi objective imperialist competitive algorithm (MOICA) + multi objective grey wolf optimizer (MOGWO) |
| **Aberka, et al. (2024) Sustainable Multi-Objective Truck Scheduling in a Rail-Road Physical Internet Cross-Docking Hub with Internal Storage** | Min storage cost and energy consumption | Multi-objective Mixed Integer Programming Model (MO MIP) SEPLEX (exact method) |
| **Madani-Isfahani, et al. (2014), Multiple cross-docks scheduling using two meta-heuristic algorithms** | Min operation time | Simulated Annealing(SA) + Firefly Algorithm |
| **Yu, et al. (2021), Hybrid GA Truck Scheduling and Product Routing on the Cross-Docking System** | Min completion time | Hybrid GA |
| **Mohtashami.A (2015) Scheduling Trucks in Cross Docking Systems with Temporary Storage and Repetitive Pattern for Shipping Trucks** | Min completion | Genetic Algorithm |
| **Maxim A. Dulebenets (2018), A Diploid Evolutionary Algorithm for Sustainable Truck Scheduling at a Cross-Docking Facility** | Min total cost | Evolutionary Algorithm |

**Research gap**

Some works focus on:

- Energy consumption (Chargui et al. (2019), Shahram et al. (2019))
- Completion time (Madani-Isfahani et al ,(2014), Yu, Mohtashami et al , (2014))
- Total cost only Dulebenets (2018)

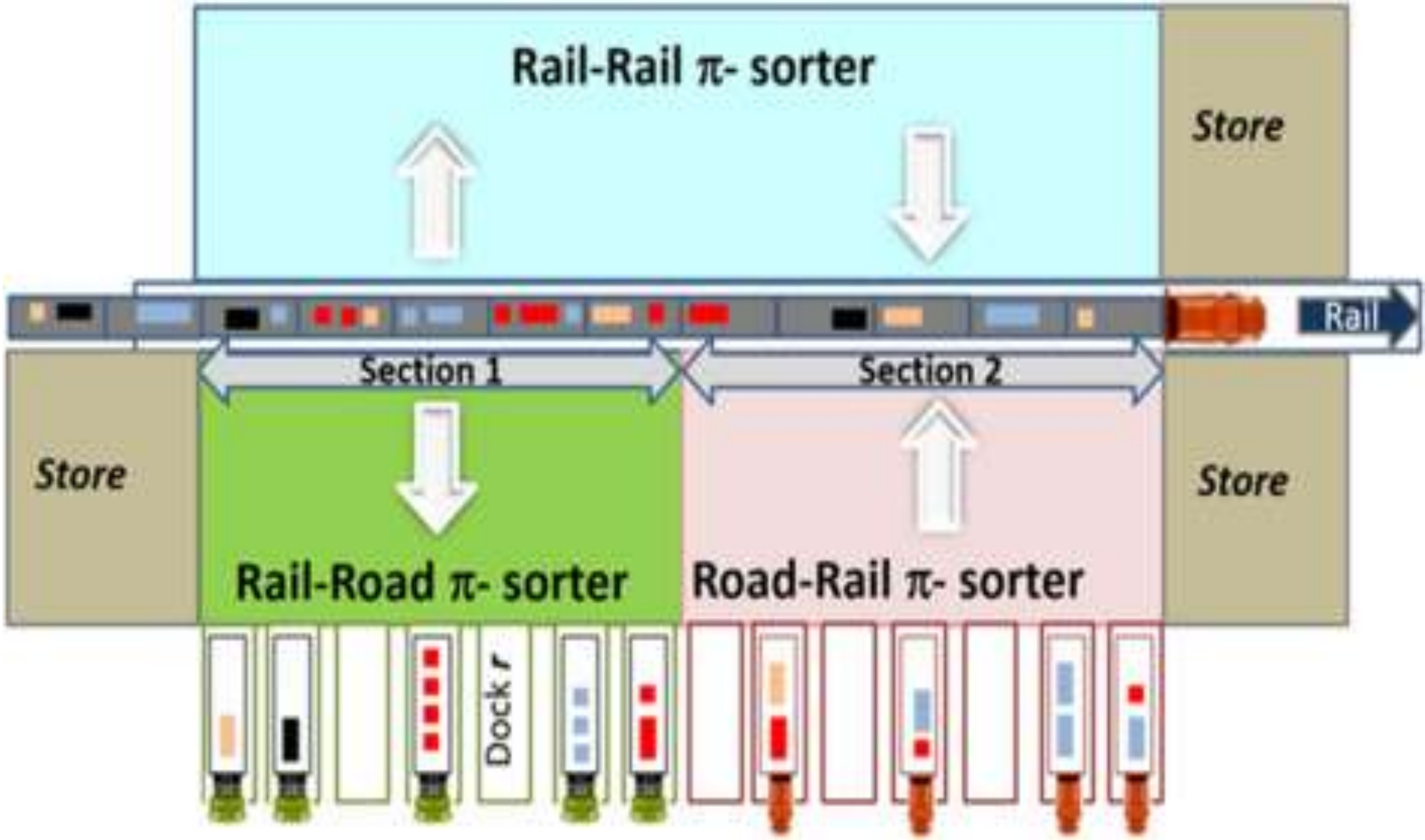
**Research gap**

Few studies joined

❌Truck cost

❌Energy consumption

In a rail–road π-hub layout



Optimizing : Completion Time And/or Cost While : Real world constraints

- NP-hard problem

  Finding the optimal solution in a reasonable time is very difficult.

- Find a near optimal solution with approximative methods
- Explore the search space to find the global optimal solution

# WHY GA FOR CROSS DOCK OPTIMIZATION?

- **Objectif**

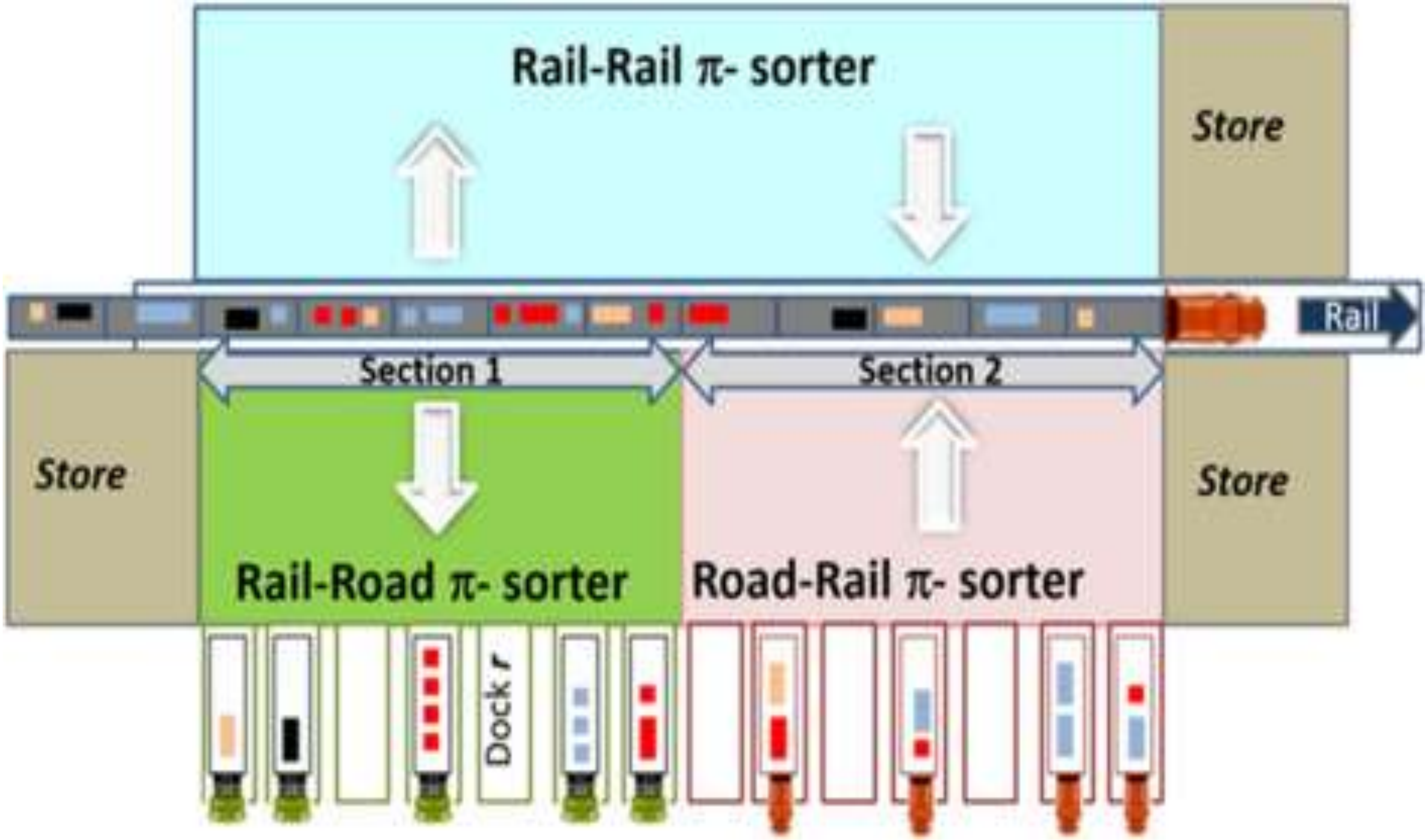
  We aim to optimize container-truck assignments to minimize transport cost and energy cost

- **NP-hard**

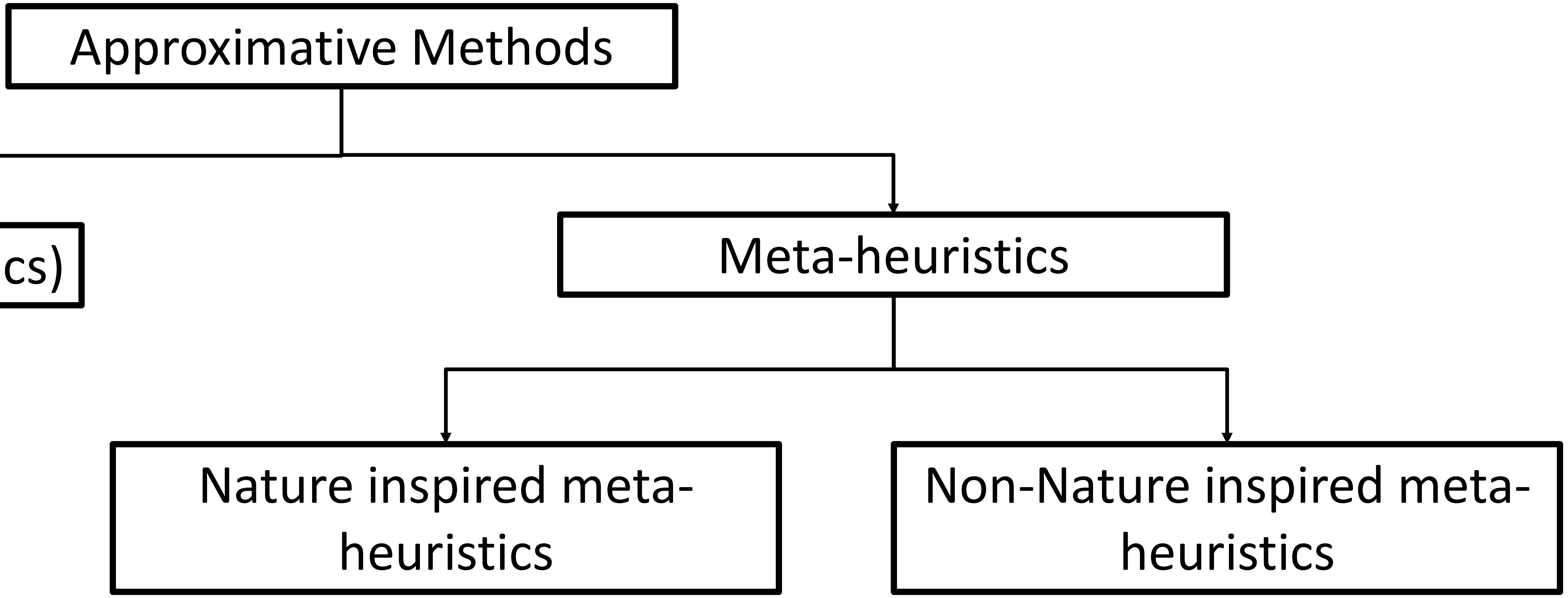
  Optimization of this kind of problems is NP-hard

- **Why Genetic algorithms?**

  Robustness, Adaptability, Flexibility(hybridization)



Physical Internet cross dock sorter [1]



Approximative Methods

Problem specific (heuristics)

Meta-heuristics

Nature inspired meta-heuristics

Non-Nature inspired meta-heuristics

- Evolutionary based algorithm
- Swarm Intelligence based algorithm
- Physical/chemical based algorithm

- Tabu search
- Local search
- Large neighbourhood

ADVANTAGE Not Prolem specific

ADVANTAGE Scalability

ADVANTAGE Hybridization

ADVANTAGE Flexibility and adaptability

ADVANTAGE Integer data representation

**Objective**

$$Minimize\ F1 = \sum_{h=1}^{H}\sum_{d=1}^{D} CT_d \times a_{hd}$$

And

$$Minimize\ F2 = CE \times \sum_{i=1}^{N}\sum_{h=1}^{H} z_{ih}$$

[2]

- $F1 : The\ cost\ of\ using\ trucks\ H\ for\ destinations\ D$
- $F2 : Energy\ cost\ to\ assign\ container\ i\ to\ truck\ h$

**Parameters :**

$CT_d : the\ cost\ of\ using\ truck\ h\ for\ destination\ d$

$CE : the\ cost\ of\ one\ energy\ unit\ to\ transport\ container\ i\ to\ truck\ h$

$P_i : the\ container's\ i\ position\ in\ the\ rail\ area$

$R_k : the\ truck's\ h\ position\ in\ the\ road\ area$

$\gamma : vertical\ length\ of\ the\ cross\ dock\ system$

$L_i : Length\ of\ the\ container\ i$

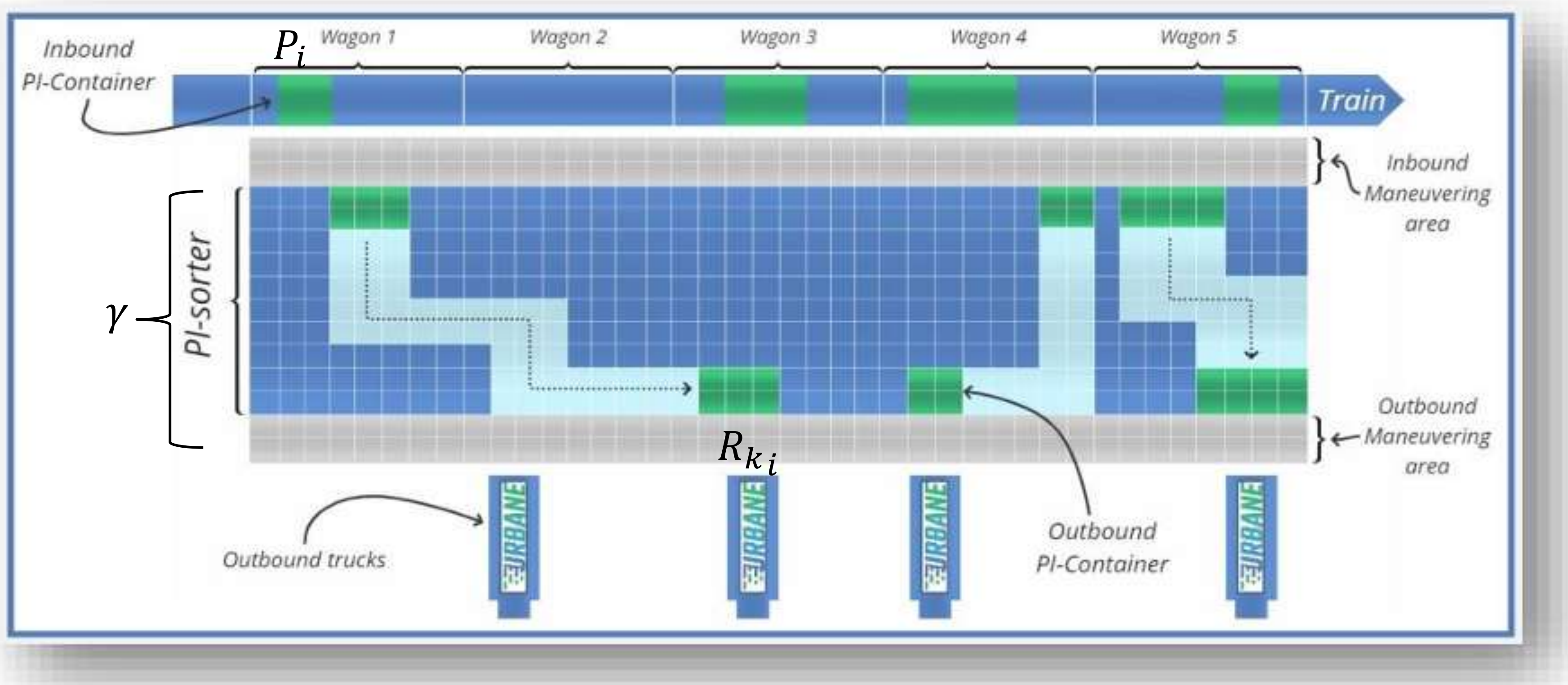
$M : large\ number$

**Decision variables :**

$a_{hd} : binary\ variable, 1\ if\ truck\ h\ is\ assigned\ to\ destination\ d, 0\ otherwise$

$P_{ih} : binary\ bariable, 1\ if\ container\ i\ is\ assigned\ to\ truck\ h$

$x_{hk} : binary\ variable, 1\ if\ truck\ h\ is\ assigned\ to\ dock\ k$



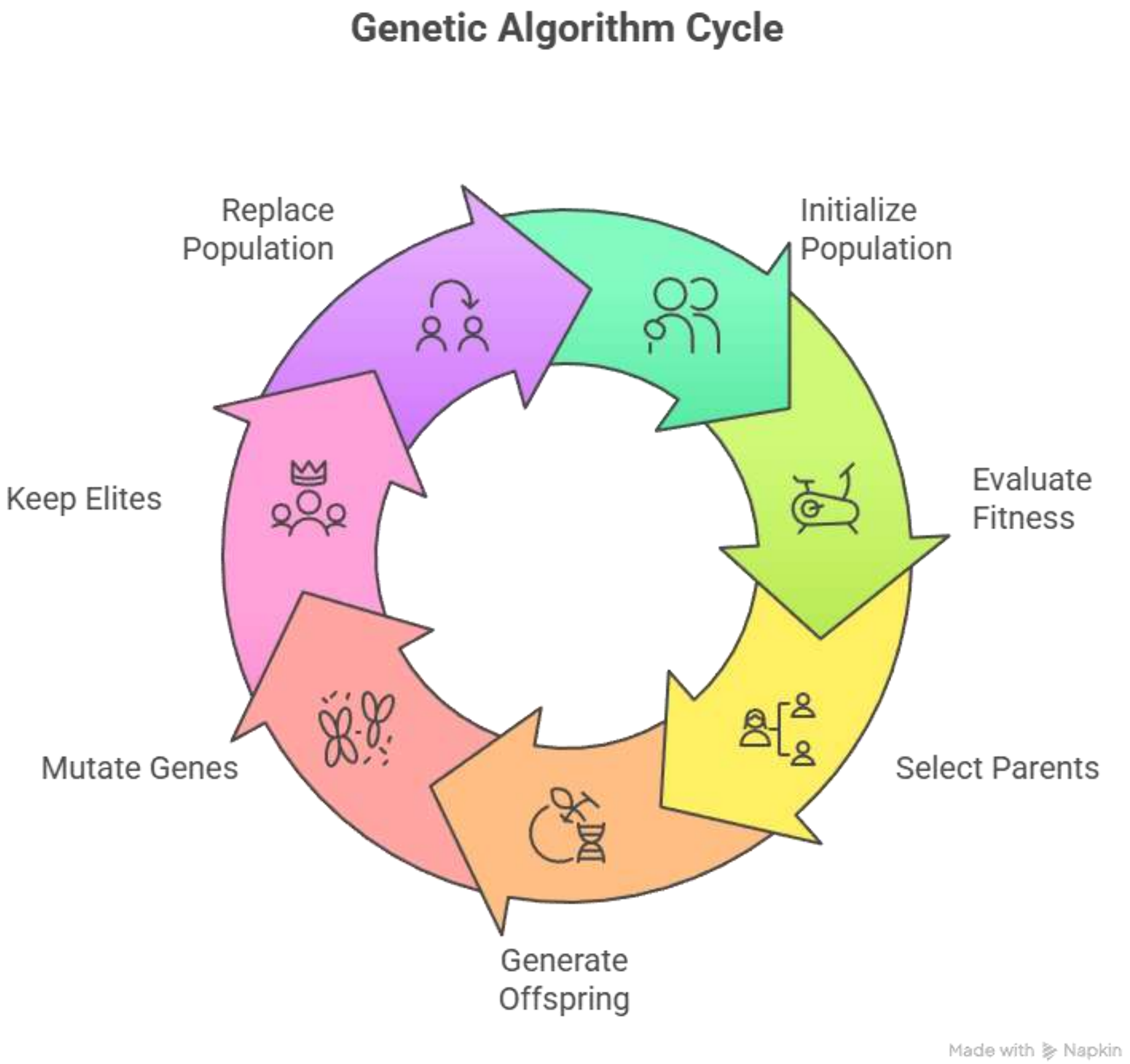
Physical Internet cross dock sorter [2]

$$z_{ih} = 2|P_i - R_k| + \gamma \times L_i - M\big(2 - (p_{ih} + x_{hk})\big)\ \forall\, i, k, h$$

- $z_{ih} : the\ area\ swept\ by\ the\ container\ i\ to\ reach\ the\ truck\ h\ at\ the\ k\ position\ in\ the\ cross\ dock$

$if\ container\ i\ is\ assigned\ to\ truck\ h\ and\ truck\ h\ is\ assigned\ to\ dock\ k\ in\ the\ road\ s$

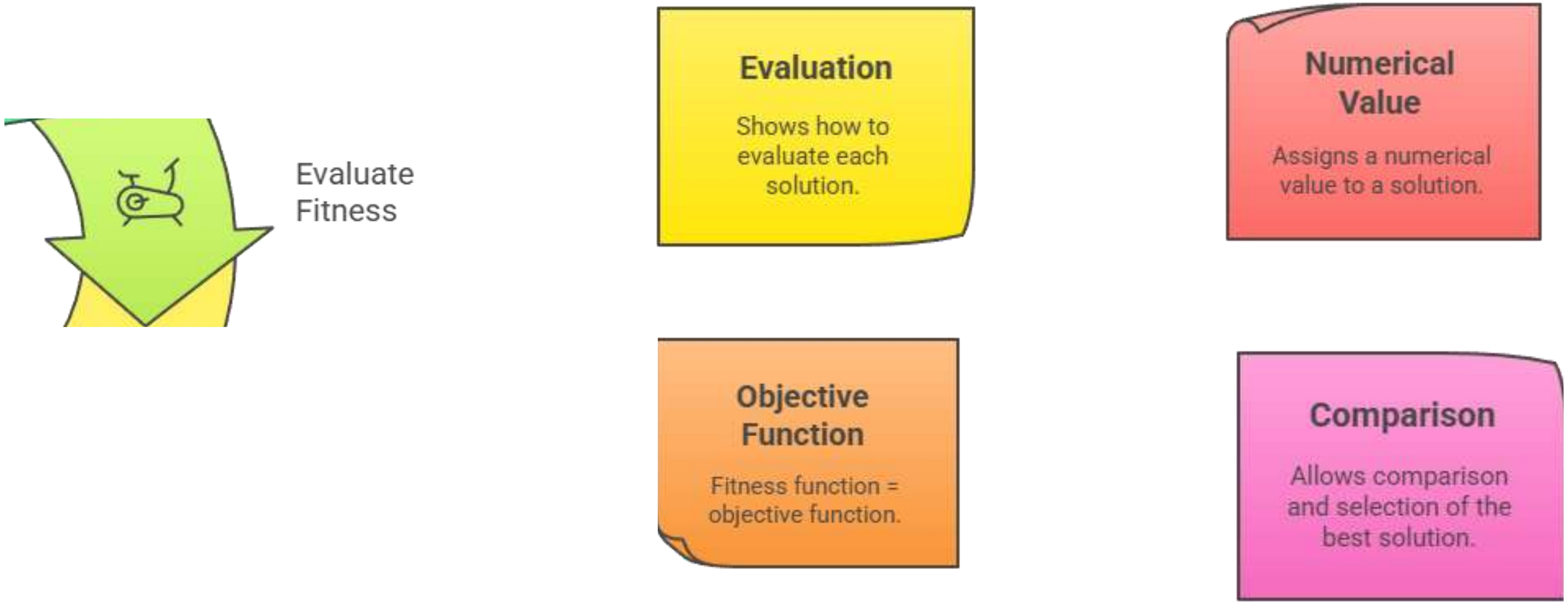
[2] : Chargui et al , (2019



Key step in the Genetic Algorithm loop

Inspired by natural selection process in Evolutionary therory

Evaluation tool



Evaluate Fitness

**Evaluation**
Shows how to evaluate each solution.

**Numerical Value**
Assigns a numerical value to a solution.

**Objective Function**
Fitness function = objective function.

**Comparison**
Allows comparison and selection of the best solution.

How can we evaluate the fitness of individuals based on two different objectives?

One optimal solution for an objective does not necessarily represent an optimal solution for the second objective.

How can a multi-objective optimization problem (with more than two objectives) be effectively transformed into a single-objective formulation that remains representative of all objectives and suitable for evaluation by a genetic algorithm?

## Approach: Weighted-Sum Fitness Function

$$Fitness = W_1 \times F_1 + W_2 \times F_2 + \ ... + W_n \times F_n$$

$$With \sum W_i = 1$$

$$Fitness = W_1 \times F_{1_{Truck\ cost}} + W_2 \times F_{2_{Energy\ cost}}$$

$$W_1 = 0{,}5 \ , W_2 = 0{,}05$$

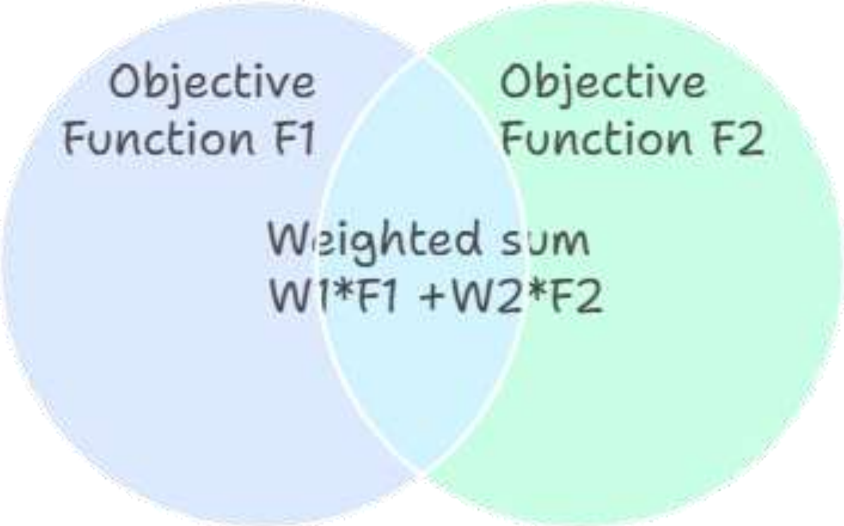
ADVANTAGE

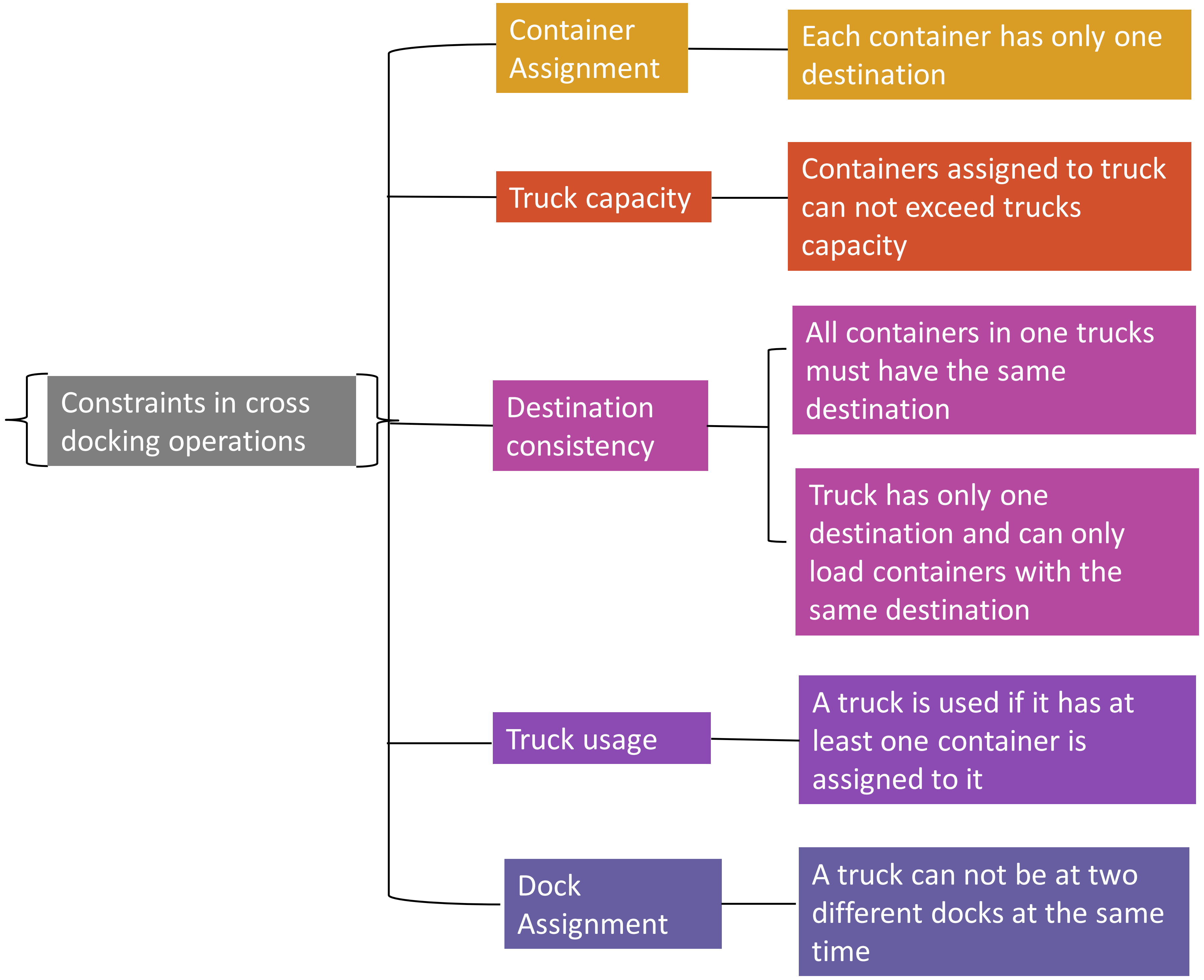
Reduces computational complexity

ADVANTAGE

Equal weights = equal influance of F1 and F2 on the total cost

Balancing Multiple Objectives in Optimization





Constraints in cross docking operations

Container Assignment: Each container has only one destination

$$\sum_{h=1}^{H} p_{ih} = 1, \forall i = 1 \dots N \quad , N\ the\ number\ of\ containers$$

Truck capacity: Containers assigned to truck can not exceed trucks capacity

$$\sum_{i=1}^{N} p_{ih} \times L_i \leq Q, \forall h = 1 \dots H$$

, H the number of trucks, Q capacity of truck h , $L_i$ the length of container i

Destination consistency:

All containers in one trucks must have the same destination

$$p_{ih} + p_{jh} \leq \sum_{d=1}^{D} G_{di} \times G_{dj} + 1, G_{di}\ and\ G_{dj}\ destination\ matrix,$$

*for container and destination*

Truck has only one destination and can only load containers with the same destination

$$v_h = \sum_{d=1}^{D} a_{hd}, a_{hd} :\ binary\ variable, 1\ if\ truck\ h\ is\ assigned\ to\ destination\ d$$

$$v_h :\ binary\ variable, 1\ if\ truck\ h\ is\ used$$

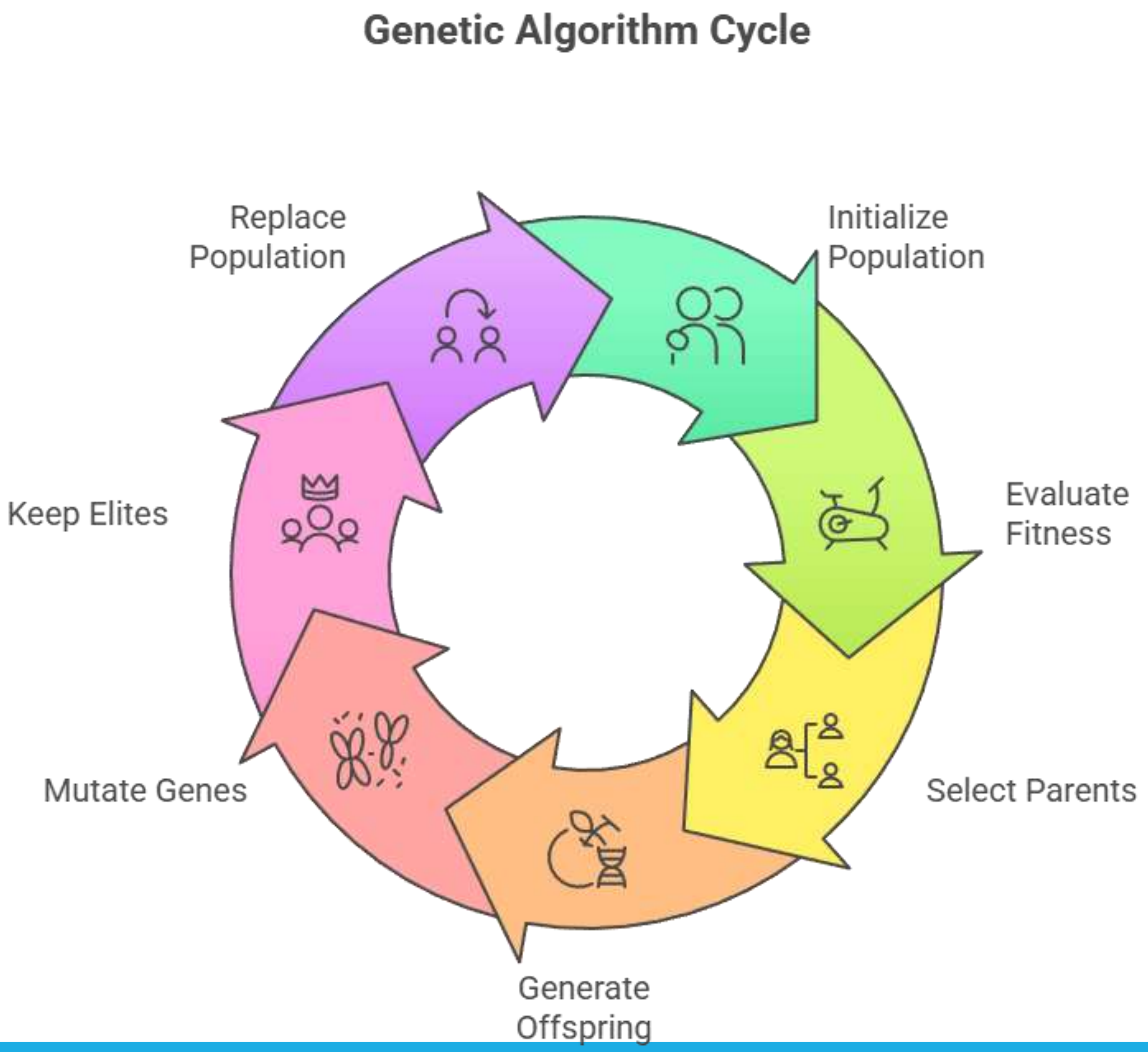
$$a_{hd} \leq G_{di} + 1 + p_{ih},$$

Truck usage: A truck is used if it has at least one container is assigned to it

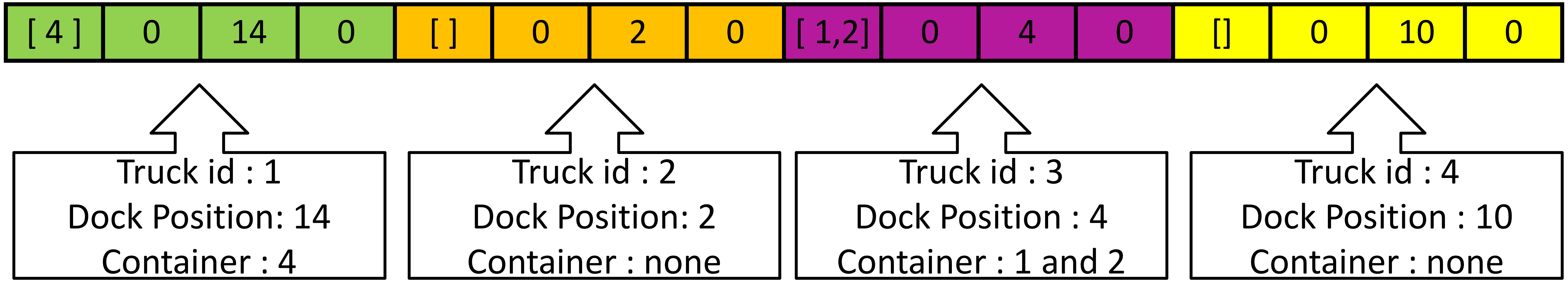
$$p_{ih} \leq v_h, v_h\ is\ binary\ variable, 1\ if\ truck\ h\ is\ used\ 0\ otherwise$$

Dock Assignment: A truck can not be at two different docks at the same time

$$\sum_{k=1}^{K} x_{hd} = v_h, \ \forall k = 1 \ \dots K, x_{hd}:\ binary\ variable, 1\ if\ truck\ h\ is\ assigned\ to\ dock\ k,$$


Genetic Algorithm Cycle
Initialize Population
Evaluate Fitness
Select Parents
Generate Offspring
Mutate Genes
Keep Elites
Replace Population

A **chromosome** represents a **solution**, each block represents a truck and its assignments.



| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [ 4 ] | 0 | 14 | 0 | [ ] | 0 | 2 | 0 | [ 1,2] | 0 | 4 | 0 | [] | 0 | 10 | 0 |

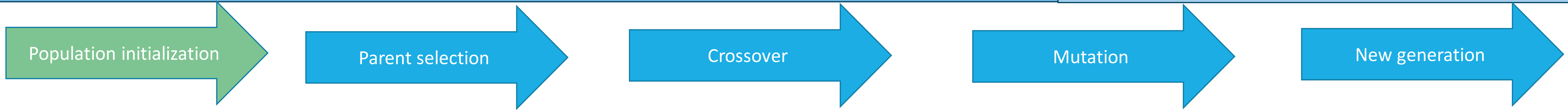
Truck id : 1
Dock Position: 14
Container : 4

Truck id : 2
Dock Position: 2
Container : none

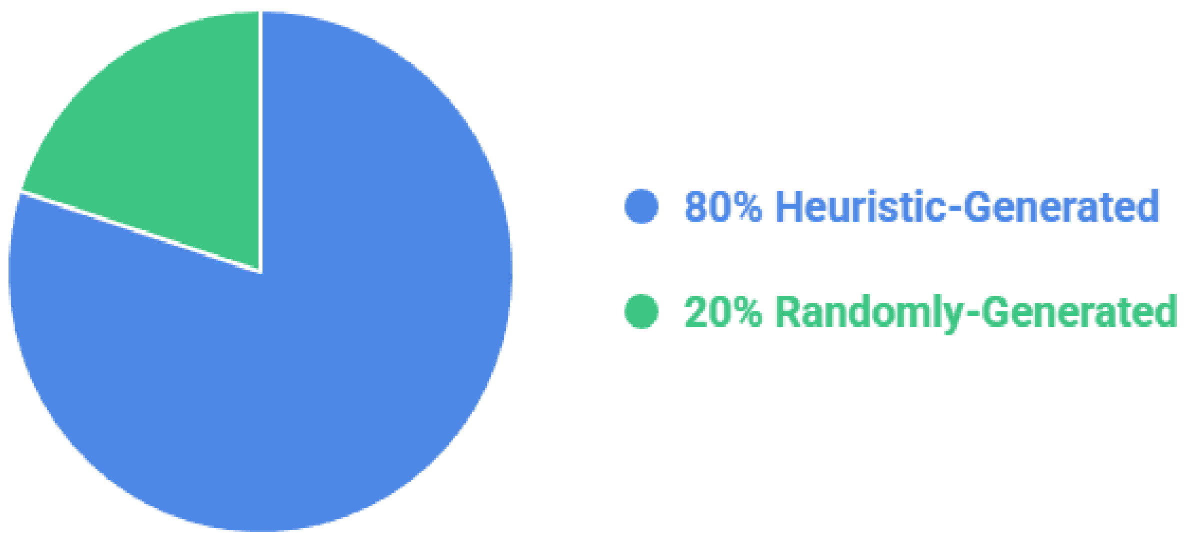
Truck id : 3
Dock Position : 4
Container : 1 and 2

Truck id : 4
Dock Position : 10
Container : none

- Truck id : Number to identify a truck
- Dock position : Position of the truck in the Road part of the cross dock hub
- Container : the container id assigned to the truck



Hybrid Population Initialization Strategy

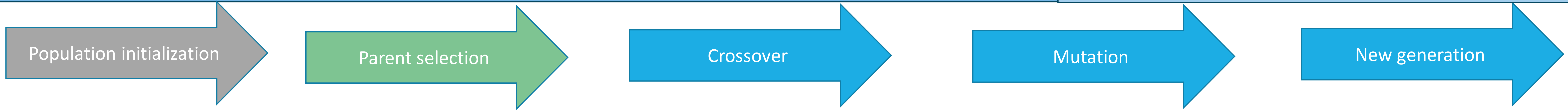


Heuristic population initialization : Binpacking

- Group containers by destination and sort by decreasing length
- For each destination group:
  - If truck is new , assign destination to truck
  - Else assign container to truck with same destination and enough capacity
  - Move to next container

Best fit decreasing, fills the trucks to maximum capacity, no truck waste

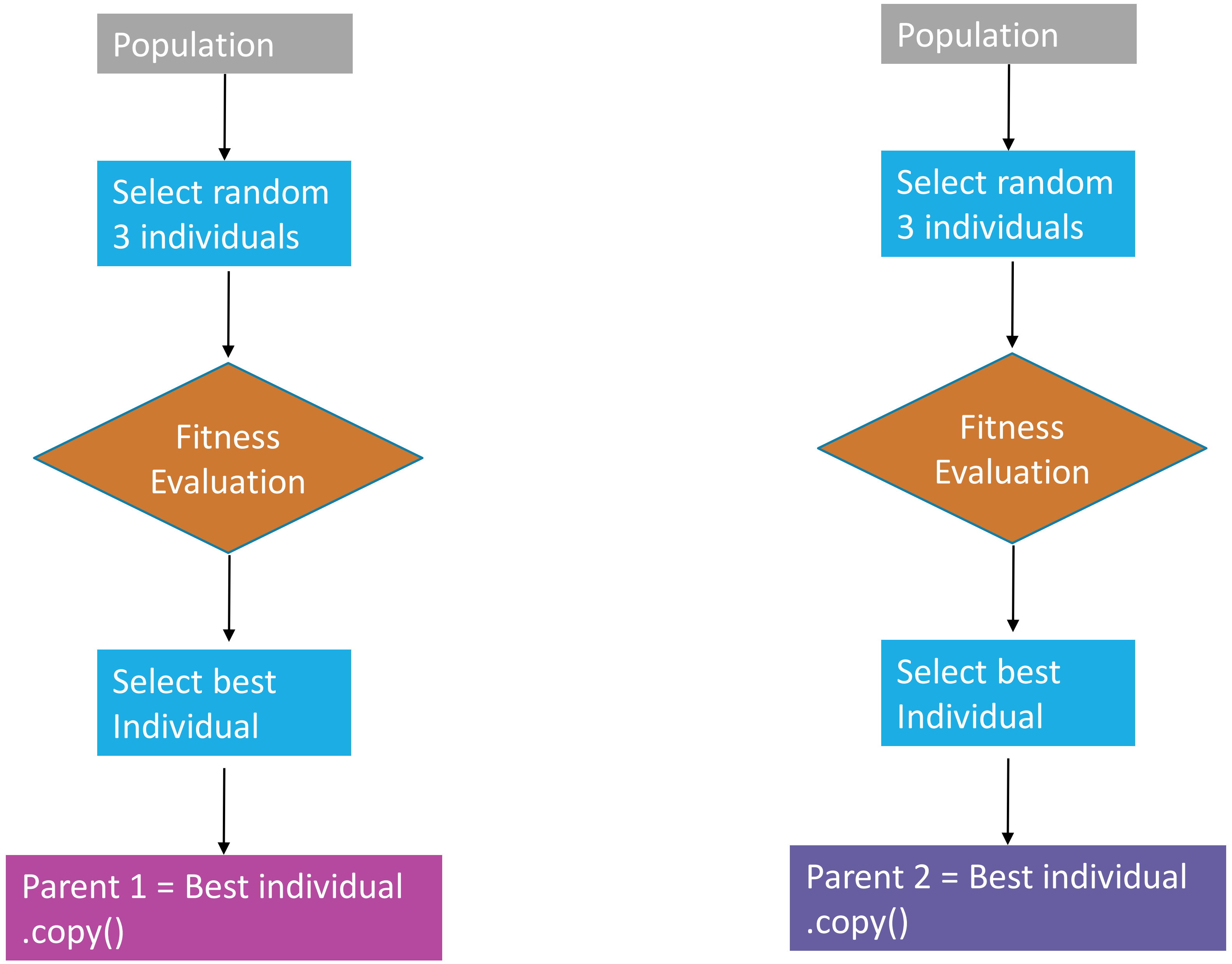
Fast and less computational time

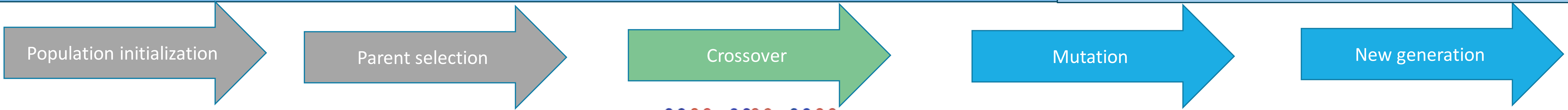


**Tournament selection**

- Select a group of k individuals from population
- For each individual :
    - Calculate fitness
    - Best_individual = best_fitness

Return Best_individual.copy()


Population
Select random 3 individuals
Fitness Evaluation
Select best Individual
Parent 1 = Best individual .copy()
Population
Select random 3 individuals
Fitness Evaluation
Select best Individual
Parent 2 = Best individual .copy()



**Parent 2 :** [ [3,7],0,4 ,0,{Crossover point} [],0,7 ,0,[2],0, 6, 0 ]

**Parent 1 :** [ [4,6],0,3,0, {Crossover point}[1],0, 5 ,0,[],0, 1 ,0 ]

**Offspring 1 :** [ [4,6],0,3,0, [],0,7 ,0,[2],0, 6, 0 ]

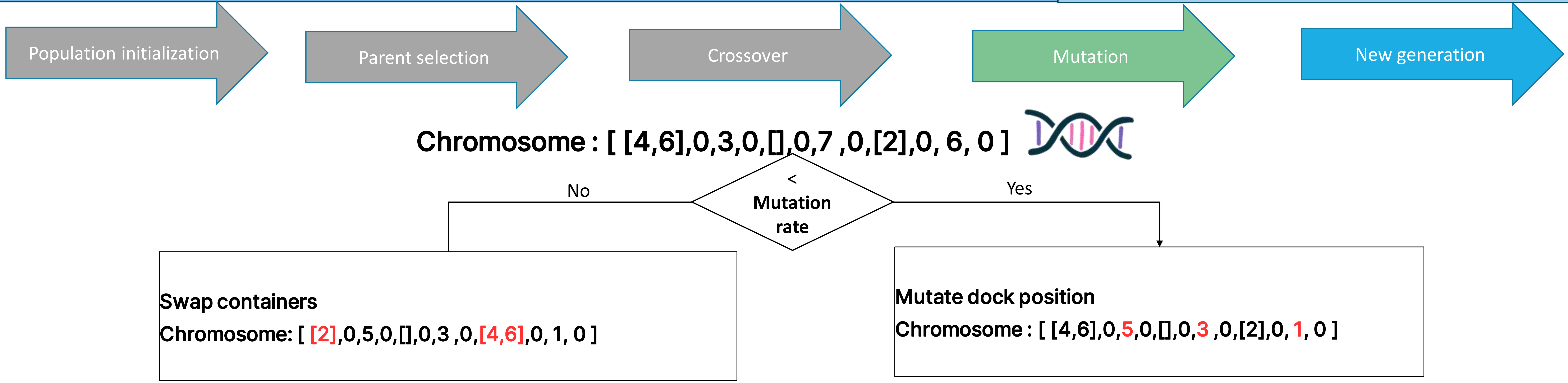
**Offspring 2 :** [ [3,7],0,4 ,0, [1],0, 5 ,0,[],0, 1 ,0 ]

**One point Crossover**

- Generate random float number [0, 1[:
- If random number< **mutation rate**:
  - **One point cross over (Parent 1, Parent 2)**
- Else :
  - **Offspring 1, Offspring 2 = copy(Parent 1, Parent 2)**

**Crossover rate** : Probability for parents to crossover

**One point crossover** : Preserves the chromosome structure



Population initialization → Parent selection → Crossover → Mutation → New generation

**Chromosome : [ [4,6],0,3,0,[],0,7 ,0,[2],0, 6, 0 ]**

< **Mutation rate**

No

Yes

**Swap containers**
**Chromosome: [ [2],0,5,0,[],0,3 ,0,[4,6],0, 1, 0 ]**

**Mutate dock position**
**Chromosome : [ [4,6],0,5,0,[],0,3 ,0,[2],0, 1, 0 ]**

**Container swap**

- Generate random float number [0, 1[:
- If random number < **Mutation rate**:
  - Chose two random indexes ; indx1, indx2
  - **Swap containers in index1 and index2**
- **Return chromosome**

**Dock mutation**

- Generate random float number [0, 1[:
- If random number > **Mutation rate**:
  - **replace all docks of chromosome with random generated docks**
  - **Return chromosome**

**Mutation rate** : Probability for parents to Mutate

**Dock mutation**: Changes dock numbers of chromosome

**Swap containers**: Exchange containers between trucks

## Mutation & Crossover can generate unfeasible solutions

**Example**

| Chromosome | Violation of the constraints |
|---|---|
| [ [3,2,1],0,3,0, [4,2],0, 5 ,0,[],0, 1 ,0 ,[1,2],0,10,0,[],0,1,0 ] | - **Multiple destination** in truck 1<br>- Container **duplicated**: 1,2<br>- Truck 1 :[3,2,1] → destination : 1, container 2 →destination :2<br>→**destination mismatch** |
| [ [],0,14,0, [],0, 2 ,0,[],0, 1 ,0 ,[],0,11,[],0,10,0 ] | - **Empty trucks** |
| [ [4,2,3,1,5],0,14,0, [],0, 4 ,0,[],0, 1 ,0 ,[],0,13,[],0,10,0 ] | - **Truck 1 capacity exceeded**, length(4,2,3,1,5) = 15> truck's capacity(13) |

| Truck id | Destination | Capacity |
|---|---|---|
| 1 | 1 | 13 |
| 2 | 2 | 13 |
| 3 | 1 | 13 |
| 4 | 2 | 13 |

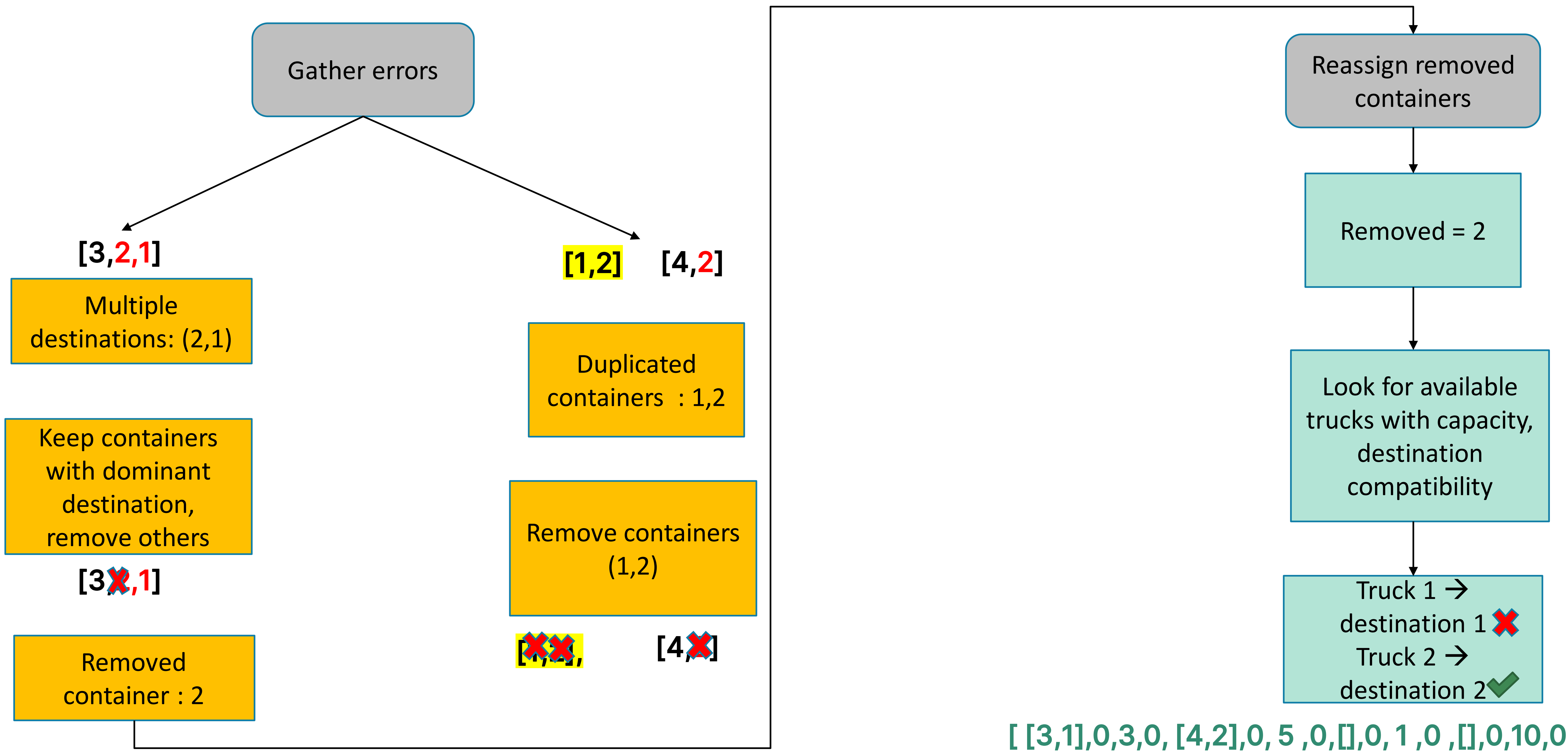
| Container id | Destination | Length |
|---|---|---|
| 1 | 2 | 3 |
| 2 | 2 | 5 |
| 3 | 1 | 2 |
| 4 | 3 | 3 |
| 5 | 4 | 4 |

Score very low fitness = considered "good solution" for the GA ⇒ "good solutions" survive to the next generation

**Good new !** Prevent unfeasible solutions from propagating by a simple strategy

## Strategy: repair wrong chromosomes, implemented in the correct_chrom function

[ [3,2,1],0,3,0, [4,2],0, 5 ,0,[],0, 1 ,0 ,[1,2],0,10,0,[],0,1,0 ]



Gather errors

[3,2,1]

Multiple destinations: (2,1)

Keep containers with dominant destination, remove others

[3~~2~~,1]

Removed container : 2

[1,2] [4,2]

Duplicated containers : 1,2

Remove containers (1,2)

~~[1,2]~~, [4,~~2~~]

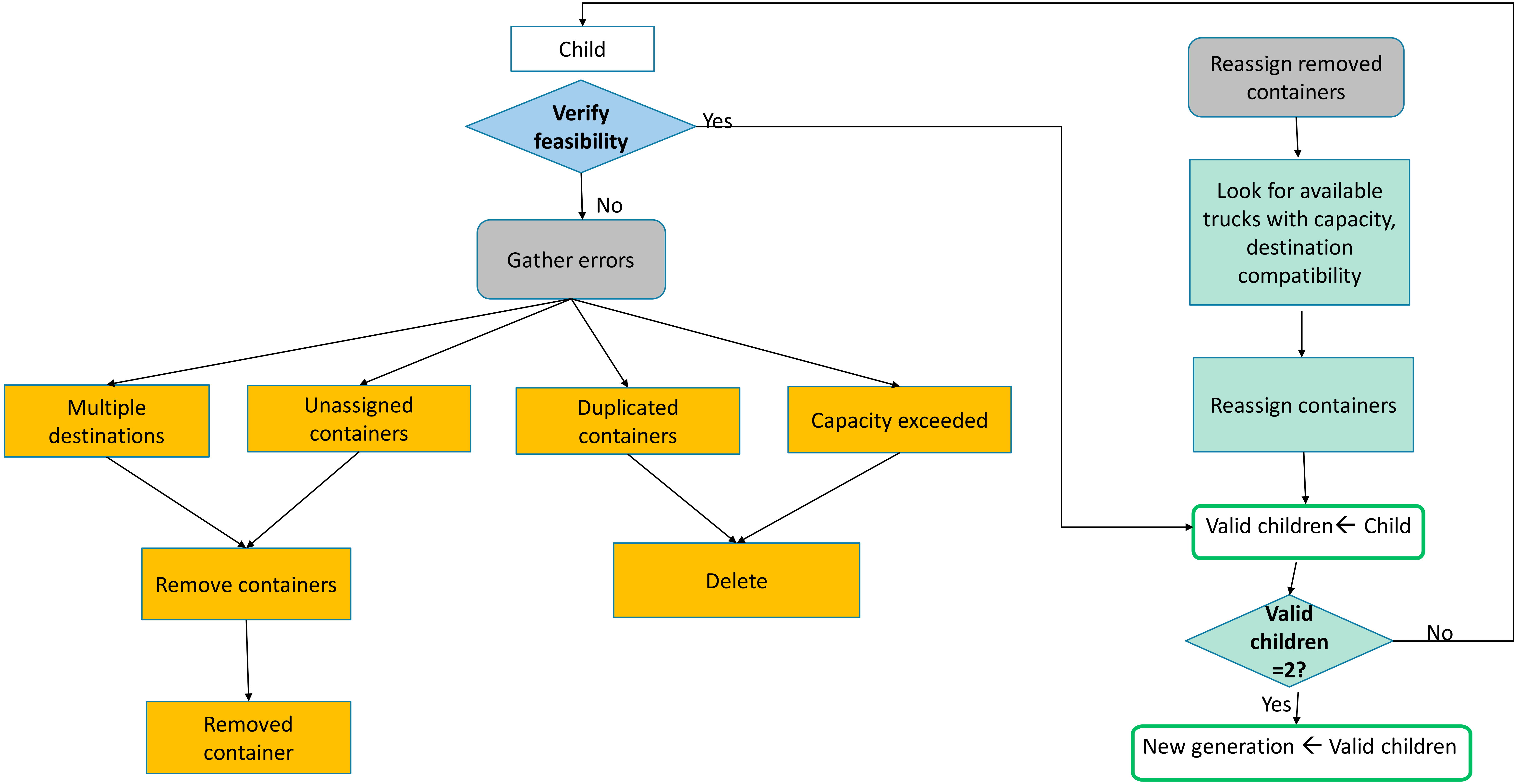
Reassign removed containers

Removed = 2

Look for available trucks with capacity, destination compatibility

Truck 1 → destination 1 ✗
Truck 2 → destination 2 ✓

[ [3,1],0,3,0, [4,2],0, 5 ,0,[],0, 1 ,0 ,[],0,10,0,[],0,1,0 ]


Child
Verify feasibility
Yes
No
Gather errors
Multiple destinations
Unassigned containers
Duplicated containers
Capacity exceeded
Remove containers
Delete
Removed container
Reassign removed containers
Look for available trucks with capacity, destination compatibility
Reassign containers
Valid children← Child
Valid children =2?
No
Yes
New generation ← Valid children

**Objective:**

**Compare the performance of different approaches on the same dataset using benchmark_set_for_sustainability_2019 by Chargui**

**Implementation method :**

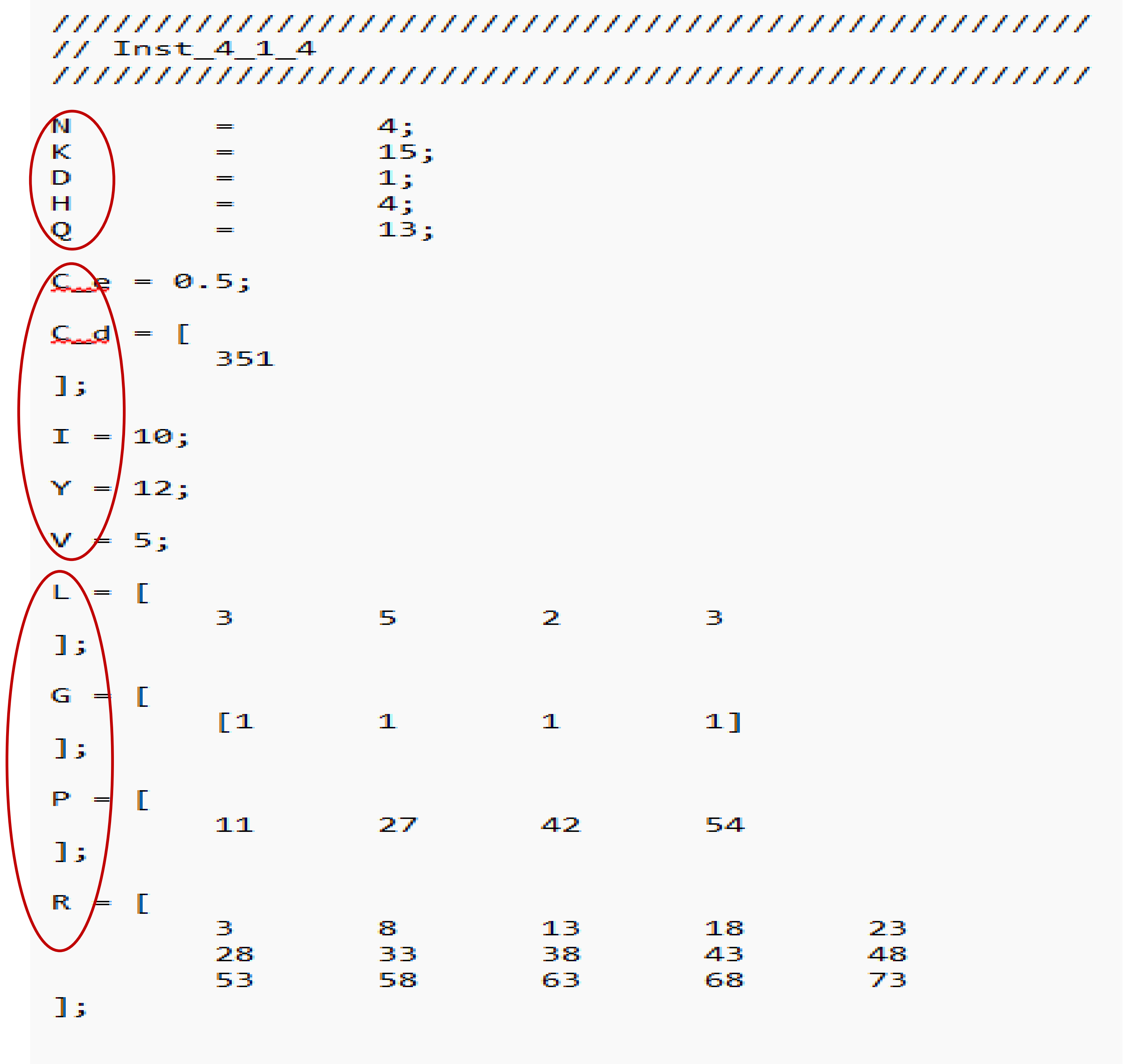
- **GA (Controlled + Random Population): mix of random and guided initialization.**
- **Exact Method: used as a benchmark for optimal results.**

**Evaluation method :**

- All  methods executed on the same set of instances
- Measured cost per instance to evaluate performance.
- Results presented in plots comparing cost for three methods

**Instances taken from benchmark available in the link:** https://www.researchgate.net/publication/333592362_Multi-Objective_Sustainable_Truck_Scheduling_in_a_Rail-Road_Physical_Internet_Cross-Docking_Hub_Considering_Energy_Consumption

| Symbol | Description | Meaning |
|---|---|---|
| **N** | Number of containers | Total number of containers to be handled |
| **D** | Number of destinations | Total number of distinct destinations |
| **H** | Number of trucks | Total number of available trucks |
| **K** | Number of docks | Number of loading/unloading docks |
| **Q** | Truck capacity | Maximum capacity of each truck |
| **$C_e$** | Energy cost per unit | Energy cost per unit of distance |
| **Cdt** | Truck cost for destination *d* | Fixed cost of using a truck assigned to destination *d* |
| **Y** | Vertical length of the cross-dock | Vertical dimension of the cross-dock layout |
| **L** | Container length | Length (or size) of containers |
| **P** | Container positions | Positions of containers inside the cross-dock |
| **R** | Truck positions | Positions of trucks at the docks |
| **G** | Destination–container matrix | Binary matrix indicating the destination of each container |



```
////////////////////////////////////////////////////////////
// Inst_4_1_4
////////////////////////////////////////////////////////////

N        =        4;
K        =        15;
D        =        1;
H        =        4;
Q        =        13;

C_e = 0.5;

C_d = [
         351

];

I = 10;

Y = 12;

V = 5;

L = [
         3        5        2        3

];

G = [
         [1       1        1        1]

];

P = [
         11       27       42       54

];

R = [
         3        8        13       18       23
         28       33       38       43       48
         53       58       63       68       73
];
```

**Instances taken from benchmark available in the link:** https://www.researchgate.net/publication/333592362_Multi-Objective_Sustainable_Truck_Scheduling_in_a_Rail-Road_Physical_Internet_Cross-Docking_Hub_Considering_Energy_Consumption

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**Table 1 : Description of instance data**

| Instance | file Name | containers | Destinations | Docks |
|---|---|---|---|---|
| 4 | inst_4_3_4.txt | 4 | 1-2-3 | 15 |
| 5 | inst_5_2_4.txt | 5 | 1-2-3 | 15 |
| 6 | inst_6_3_5.txt | 6 | 1-2-3 | 15 |
| 7 | inst_7_1_5.txt | 7 | 1-2-3 | 15 |
| 8 | inst_8_1_5.txt | 8 | 1-2-3 | 15 |
| 9 | inst_9_2_7.txt | 9 | 1-2-3 | 15 |
| 10 | inst_10_1_7.txt | 10 | 1-2-3 | 15 |
| 11 | inst_11_2_7.txt | 11 | 1-2-3 | 15 |
| 12 | inst_12_3_7.txt | 12 | 1-2-3 | 15 |
| 20 | inst_20_7_15.txt | 20 | 7 | 15 |
| 20 | inst_20_10_15.txt | 20 | 10 | 15 |
| 30 | inst_30_7_20.txt | 30 | 7 | 15 |
| 30 | inst_30_10_20.txt | 30 | 10 | 15 |
| 30 | inst_30_15_20.txt | 30 | 15 | 15 |

Model is **NP-hard** → requires **higher computational time and resources**

**LGI2A provided access to a HPC(High-performance Computing) cluster for running complicated calculations without disruption**

Why Computational cluster ?

Mixed Integer models and iterative algorithms require significant CPU time

32 large instances, complicated calculations lead high computational complexity

HPC : scalable and high computational power, stable long execution without interruptions

**Table 2 : Description of Cluster Tech3E**

| Company | Name | Access | Usage | CPU | Memory | Link |
|---|---|---|---|---|---|---|
| HPE Hewlett-Packard Enterprise | Tech3E (LGI2A _ Université d'Artois) | Slurm Workload manager, Linux | Batch execution of large experiments | 2 x AMD EPYC 9224 CPU , 24 cores , 2 threads per core | 640 Go theory, 629 Go available | https://www.hpe.com/emea_europe/en/hpe-proliant-dl385-gen11.html |

Gurobipy: A gurobi python interface, version : python3.12-gurobi

Gurobi is a Mathematical solver , for decision making problems

## Optimize :

$$Minimize\ F1 = \sum_{h=1}^{H}\sum_{d=1}^{D} CT_d \times a_{hd}$$

And

$$Minimize\ F2 = CE \times \sum_{i=1}^{N}\sum_{h=1}^{H} z_{ih}$$

- $F1 : The\ cost\ \ of\ using\ trucks\ H\ for\ destinations\ D$
- $F2 : Energy\ cost\ to\ assign\ container\ i\ to\ truck\ h$

**Unified Objective function: Weighted Sum, W1=0.5 W2= 0.5**

$$Fitness = W_1 \times F_{1_{Truck\ cost}} + W_2 \times F_{2_{Energy\ cost}} \quad W_1 = 0{,}5\ , W_2 = 0{,}05$$

### Exact method code structure

```
//Set Parameters
N_list # list of containers
H_list # list of trucks
K_list # list of docks
D_list # destinations

W1, W2 = 0.5, 0.5
Y = 12 # length of cross dock system

// initialize model

m = Model(f"Instance_{instance_id}_Transport_Energie« )
# Time limit: 2 hours
m.setParam("TimeLimit", 7200)

//Add decision variables
a : binary d is destination of the truck h
X : binary truck h is assigned to dock k
P : binary container n is assigned to truck h
v_used : binary truck is used ,
n : binary same dock for two trucks
Z : continous area swept by the container

//Add constraints
m.addConstrs
.
.
//Solve
m.optimize()

//Save results in csv
df_results = pd.DataFrame(results)
df_results.to_csv("results_exact_summary_with_chargui_instances_time
_limit_2_h.csv", index=False)
```

Benchmark_instances_set_for_Sustainability_2019,zip

**Table 3 : Exact method parameters**

| Technical setup | Data | Time limit | Gurobi license |
|---|---|---|---|
| ClusterTech3E | Chargui's benchmark "Benchmark_instances_set_for_sustainability (2019) | Time limits 7200s (2h) | Free academic license, version 12 |

**Table 4 : Approximative method parameters (GA)**

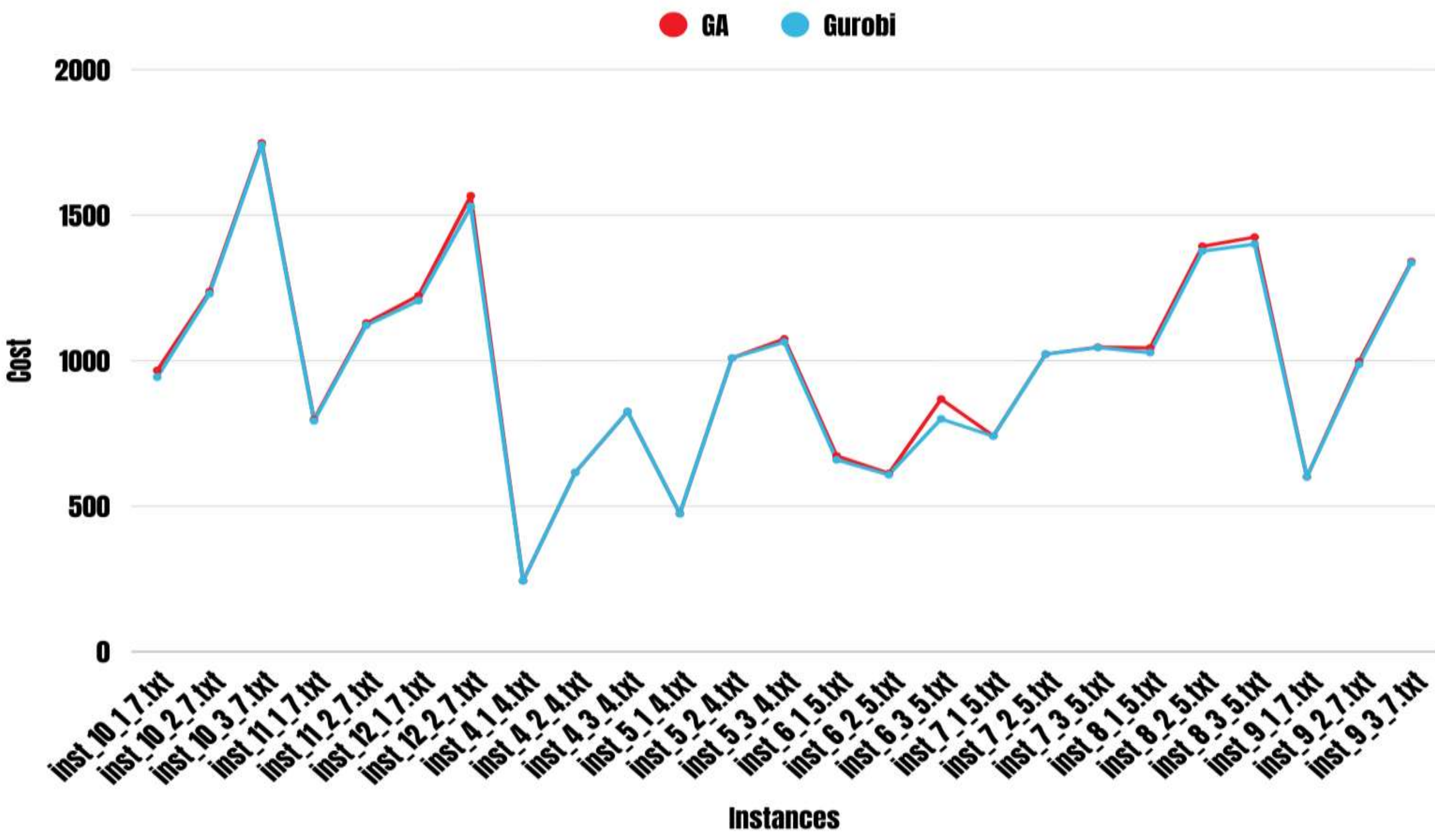
| Technical setup | Data | Population size | Mutation rate | Crossover rate | Number generations | Heuristic ratio binpacking |
|---|---|---|---|---|---|---|
| Desktop PC | Chargui's benchmark "Benchmark_instances_set_for_sustainability (2019) | 50 | 0,03 | 0,9 | 100 | 0,8 |

## GAP

| Instances | Small instances<br>(4 – 5) trucks /containers | Medium instances<br>(6 – 8) trucks /containers | Bigger instances<br>(8 – 12) trucks /containers |
|---|---|---|---|
| GAP | 0% | <1% | 2-2.5% |
| interpretation | GA reaches optimal value | GA near optimal value | GAP remains low, GA close to optimal value |

**Table 5 : Gap (Exact method vs Genetic algorithm)**

| File Name | Approximative_cost(Truck_cost + Energy_cost) | Exact_cost(truck_cost+energy_cost) | Gap(%) | Computational Time(s)_GA | Computational Time(s)_Exact |
|---|---|---|---|---|---|
| inst_4_1_4.txt | 243,0 | 243,0 | 0 | 27 | 0 |
| inst_4_2_4.txt | 616,0 | 616,0 | 0 | 27 | 0 |
| inst_4_3_4.txt | 825,0 | 825,0 | 0 | 25 | 1 |
| inst_5_1_4.txt | 474,0 | 474,0 | 0 | 31 | 0 |
| inst_5_2_4.txt | 1009,0 | 1009,0 | 0 | 33 | 0 |
| inst_5_3_4.txt | 1 074,0 | 1064,0 | 0.9868421053 | 42 | 0 |
| inst_6_1_5.txt | 673,0 | 659,0 | 2.124430956 | 37 | 4 |
| inst_6_2_5.txt | 612,0 | 608,0 | 0.7401315789 | 38 | 0 |
| inst_6_3_5.txt | 868,0 | 800,0 | 8.5 | 40 | 0 |
| inst_7_1_5.txt | 741,0 | 740,0 | 0.1350438893 | 42 | 0 |
| inst_7_2_5.txt | 1 022,0 | 1022,0 | 0.0489236791 | 43 | 0 |
| inst_7_3_5.txt | 1 046,0 | 1045,0 | 0.1435406699 | 45 | 0 |
| inst_8_1_5.txt | 1 043,0 | 1 027,0 | 1.557177616 | 55 | 1 |
| inst_8_2_5.txt | 1393,0 | 1 376,0 | 1.198692336 | 51 | 7 |
| inst_8_3_5.txt | 1 424,0 | 1 400,0 | 1.713673688 | 49 | 6 |
| inst_9_1_7.txt | 600,0 | 600,0 | 0 | 59 | 2 |
| inst_9_2_7.txt | 997,0 | 987,0 | 1.013171226 | 59 | 48 |
| inst_9_3_7.txt | 1 340,0 | 1 336,0 | 0.2992891882 | 60 | 46 |
| inst_10_1_7.txt | 966,0 | 943,0 | 2.437731849 | 81 | 7 |
| inst_10_2_7.txt | 1 237,0 | 1230,0 | 0.6097560976 | 83 | 6 |
| inst_10_3_7.txt | 1748,0 | 1 741,0 | 0.3732414585 | 75 | 232 |
| inst_11_1_7.txt | 797,0 | 793,0 | 0.5674653216 | 77 | 6 |
| inst_11_2_7.txt | 1129,0 | 1 121,0 | 0.6687472136 | 73 | 93 |
| inst_12_1_7.txt | 1 223,0 | 1206,0 | 1.451077944 | 1 240 | 17 |
| inst_12_2_7.txt | 1 566,0 | 1 529,0 | 2.419091206 | 68 | 6 |


● GA
● Gurobi
2000
1500
1000
500
0
Cost
inst_10_1_7.txt
inst_10_2_7.txt
inst_10_3_7.txt
inst_11_1_7.txt
inst_11_2_7.txt
inst_12_1_7.txt
inst_12_2_7.txt
inst_4_1_4.txt
inst_4_2_4.txt
inst_4_3_4.txt
inst_5_1_4.txt
inst_5_2_4.txt
inst_5_3_4.txt
inst_6_1_5.txt
inst_6_2_5.txt
inst_6_3_5.txt
inst_7_1_5.txt
inst_7_2_5.txt
inst_7_3_5.txt
inst_8_1_5.txt
inst_8_2_5.txt
inst_8_3_5.txt
inst_9_1_7.txt
inst_9_2_7.txt
inst_9_3_7.txt
Instances

- **Truck cost (benchmark H1)** : numerical results given by Chargui et , al (2019), using heuristic (H1) : «  Multi-Objective Variable Neighborhood Search hybridized with Simulated Annealing (MO-VNSSA) "
- **Energy cost (benchmark H2)** : numerical results given by Chargui et , al (2019), using heuristic (H2) : «  Multi-Objective Variable Neighborhood Search hybridized with Tabu Search (MO-VNSTS) "

Truck cost → for all instances, **Cost(GA)= Cost (benchmark) H1 and H2**

Energy cost → for all instances, **Cost(GA)= Cost (benchmark) H1 and H2**

**Table 6 : Numerical results on benchmark instances**

| Instances | | Truck cost (F1) | | | Energy cost (F2) | | |
|---|---|---|---|---|---|---|---|
| Instance | file name | Truck cost (GA) | Truck cost (benchmark H1) | Truck cost(benchmark H2) | Energy cost (GA) | Energy cost (benchmark H1) | Energy cost (benchmark H2) |
| 4 | inst_4_1_4.txt | 351 | 351 | 351 | 136 | 136 | 136 |
| 4 | inst_4_2_4.txt | 1096 | 1096 | 1096 | 136 | 136 | 136 |
| 4 | inst_4_3_4.txt | 1542 | 1542 | 1542 | 108 | 111 | 111 |
| 5 | inst_5_1_4.txt | 750 | 1835 | 1835 | 199 | 194 | 194 |
| 5 | inst_5_2_4.txt | 1835 | 750 | 750 | 183 | 199 | 199 |
| 5 | inst_5_3_4.txt | 1923 | 1923 | 1923 | 226 | 214 | 214 |
| 6 | inst_6_1_5.txt | 1166 | 1166 | 1166 | 180 | 192 | 192 |
| 6 | inst_6_2_5.txt | 1033 | 1033 | 1033 | 192 | 183 | 183 |
| 6 | inst_6_3_5.txt | 1440 | 1440 | 1440 | 296 | 160 | 160 |
| 7 | inst_7_1_5.txt | 1263 | 1263 | 1263 | 220 | 282 | 287 |
| 7 | inst_7_2_5.txt | 1792 | 1792 | 1792 | 253 | 306 | 306 |
| 7 | inst_7_3_5.txt | 1797 | 1797 | 1797 | 296 | 293 | 293 |
| 8 | inst_8_1_5.txt | 1821 | 1821 | 1821 | 266 | 273 | 273 |
| 8 | inst_8_2_5.txt | 2510 | 2510 | 2510 | 276 | 283 | 283 |
| 8 | inst_8_3_5.txt | 2520 | 2520 | 2520 | 329 | 281 | 281 |
| 9 | inst_9_1_7.txt | 891 | 891 | 891 | 310 | 357 | 360,2 |
| 9 | inst_9_2_7.txt | 1650 | 1650 | 1650 | 344 | 355,8 | 366 |
| 9 | inst_9_3_7.txt | 2331 | 2331 | 2331 | 350 | 372,8 | 374,8 |
| 10 | inst_10_1_7.txt | 1588 | 1588 | 1588 | 345 | 431 | 436 |
| 10 | inst_10_2_7.txt | 2098 | 2098 | 2098 | 377 | 392 | 394,2 |
| 10 | inst_10_3_7.txt | 3102 | 3102 | 3102 | 394 | 422,6 | 425,6 |
| 11 | inst_11_1_7.txt | 1276 | 1276 | 1276 | 319 | 406 | 406 |
| 11 | inst_11_2_7.txt | 1876 | 1876 | 1876 | 382 | 400 | 406,2 |
| 11 | inst_11_3_7.txt | 2042 | 3699 | 3699 | 401 | 495 | 498,6 |
| 12 | inst_12_1_7.txt | 2035 | 2035 | 2035 | 412 | 494 | 495 |
| 12 | inst_12_2_7.txt | 2688 | 2688 | 2688 | 445 | 499 | 499 |
| 12 | inst_12_3_7.txt | 4387 | 3699 | 3699 | 607 | 495 | 498,6 |
| 20 | inst_20_10_15.txt | 9595 | 7338 | 7338 | 1070 | 801,2 | 776 |
| 20 | inst_20_7_15.txt | 5001 | 5001 | 5001 | 760 | 772,6 | 750 |
| 30 | inst_30_10_20.txt | 6401 | 6401 | 6401 | 1209 | 1284,8 | 1201 |
| 30 | inst_30_15_20.txt | 9529 | 9529 | 9529 | 1104 | 1220,4 | 1182 |
| 30 | inst_30_7_20.txt | 5081 | 5081 | 5081 | 1250 | 1279,8 | 1216 |

**Table 5 : Exact method results for big instances**

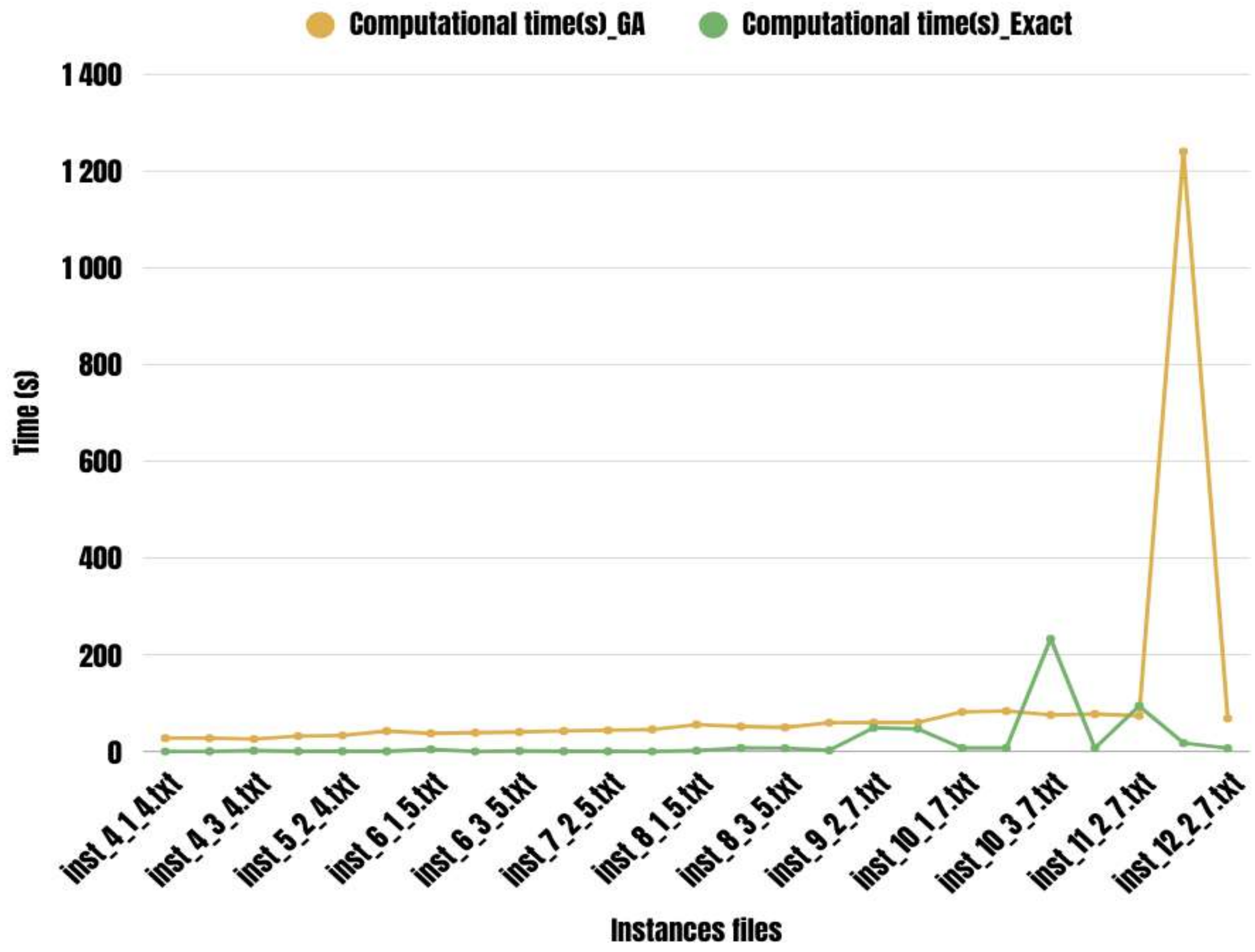
| File Name | Lower bound | Status | MipGap | Computational Time(s) |
|---|---|---|---|---|
| inst_11_3_7.txt | 1219,5 | TimeLimit | 0.0340303403 | 7200,031 |
| inst_12_3_7.txt | 2063,5 | TimeLimit | 0.0193845408 | 7200,029 |
| inst_20_7_15.txt | 2865 | TimeLimit | 0.1178010471 | 7200,034 |
| inst_20_10_15.txt | 4027 | TimeLimit | 0.0737521728 | 7200,026 |
| inst_30_7_20.txt | 3108,5 | TimeLimit | 0.2115168088 | 7200,082 |
| **inst_30_10_20.txt** | | **Infeasible** | | **0,141** |
| inst_30_15_20.txt | 5316,5 | TimeLimit | 0.0958337252 | 7200,032 |

**Table 6 : Approximative method results for big instances**

| File Name | Approximative cost | Computational Time(s) | Population size | Generations |
|---|---|---|---|---|
| inst_11_3_7.txt | 1221,5 | 73,379 | 50 | 100 |
| inst_12_3_7.txt | 2497 | 69,433 | 50 | 100 |
| inst_20_7_15.txt | 2880,5 | 124,687 | 50 | 100 |
| inst_20_10_15.txt | 5332,5 | 130,171 | 50 | 100 |
| inst_30_7_20.txt | 3165,5 | 180,866 | 50 | 100 |
| **inst_30_10_20.txt** | **3805** | **179,821** | **50** | **100** |
| inst_30_15_20.txt | 5316,5 | 191,094 | 50 | 100 |

● Instance_30_10_20 : **Infeasible** for Gurobi, **GA** found **approximative** total cost = 3805

- Instances (**inst_11_3_7, inst_12_3_7, inst_20_7_15, inst_20_10_15, inst_30_7_20, inst_30_15_20**): **Reached time limit = 7200 (2h**) for Gurobi
Gurobi found **lower bound** (theorical value with constraints relaxation**) < GA approximative values for the instances**


● Computational time(s)_GA
● Computational time(s)_Exact
Time (s)
1 400
1 200
1 000
800
600
400
200
0
inst_4_1_4.txt
inst_4_3_4.txt
inst_5_2_4.txt
inst_6_1_5.txt
inst_6_3_5.txt
inst_7_2_5.txt
inst_8_1_5.txt
inst_8_3_5.txt
inst_9_2_7.txt
inst_10_1_7.txt
inst_10_3_7.txt
inst_11_2_7.txt
inst_12_2_7.txt
Instances files

Three distinct difficulty regions:

Eazy region

[**4** to **7**] trucks and [**5** to **10**] containers, the solver found optimal solutions easily

Transition region

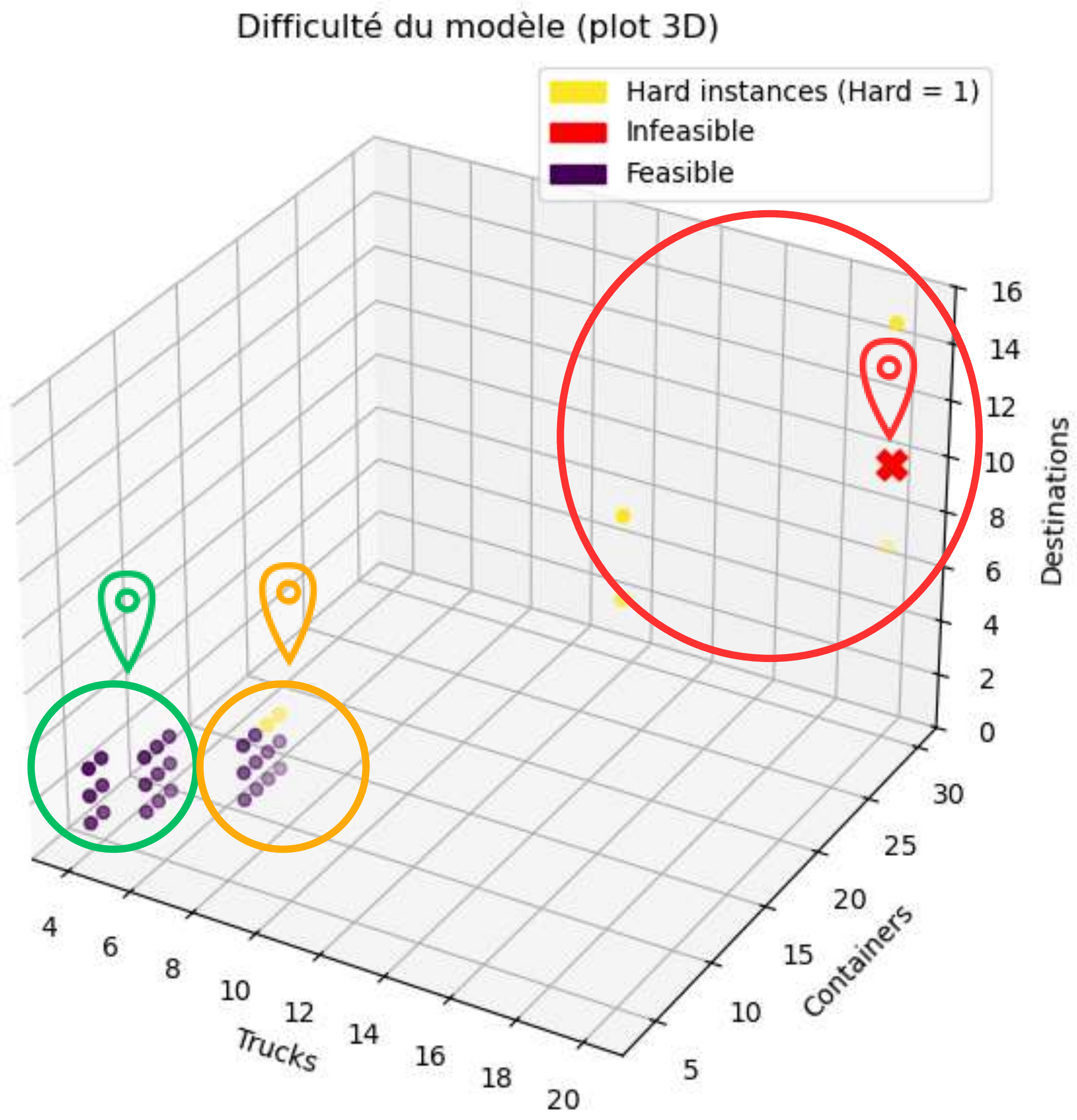
Starting from **7** trucks and **10** to **12** containers, approximately **33%** of instances reach the time limit; the model is still solvable but demands more computational power.

Difficult region (large instances)

**15** trucks, **20** trucks, and **7-10** destinations; all instances reached the time limit

**20** trucks, **30** containers, **7-15** destinations; **67%** hit time limit.

**20** trucks, **30** containers, and **10** destinations; the instance is unfeasible.



# Conclusion, improvements & future work

**Work addressed**

**Sustainable cross-dock optimization problem** in a **rail road P-hub context**, focusing on **truck cost** and **energy consumption**

**A Genetic Algorithm to solve this NP-hard problem, with adapted chromosome representation and repair mechanism to handle unfeasibility**

**Numerical results on benchmark has shown**

- **GA reaches optimal or near optimal solutions for small instances**
- **For large instances, GA provides high quality solutions with lower computational time compared to exact method**

**Future work**

- **Investigate other genetic operators (adaptive mutation, fitness sharing, random immigration) to improve diversity and convergence.**
- **Explore a True multi-objective Genetic Algorithm NSGA II (Non Dominated Sorting Genetic Algorithm II)**
- **Use other hybrid meta-heuristics**

Thank you