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Pareto Front Grid Guided Multi-objective Optimization in Dynamic Pickup and Delivery Problem Considering Two-Sided Fairness

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MSc. Do Tuan Anh

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Outline

1. Introduction
2. Related works
3. Problem formulation
4. Proposed algorithm
5. Experiments and results
6. Conclusion

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Logistics has grown rapidly due to rising global demand.

Optimization plays a critical role in improving transportation efficiency.

Helps companies **reduce costs** and **enhance operational effectiveness**.

Figure 1. AI in Logistics: Transforming Transportation.

Vehicle Routing Problem

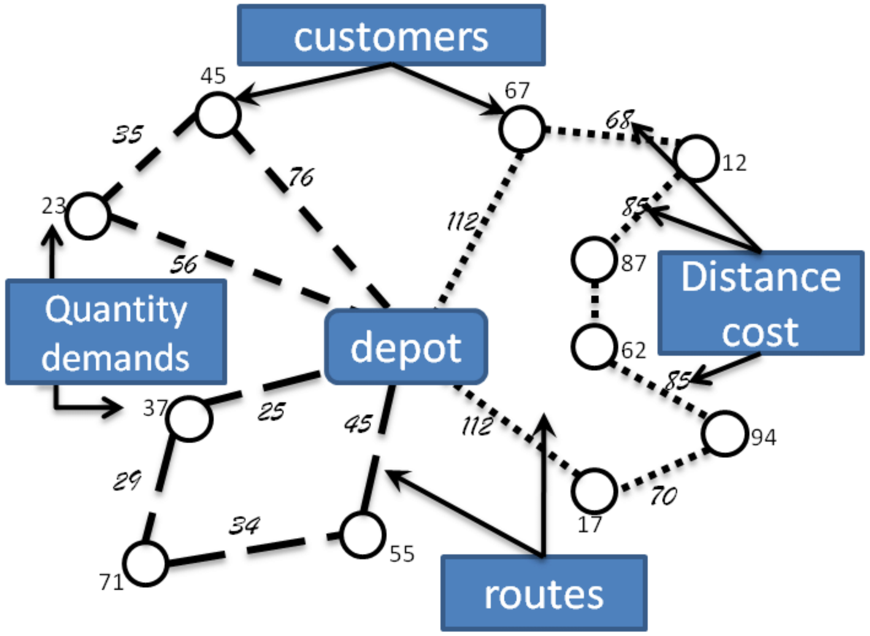

Figure 2. Traditional Vehicle Routing Problem (VRP) [1].

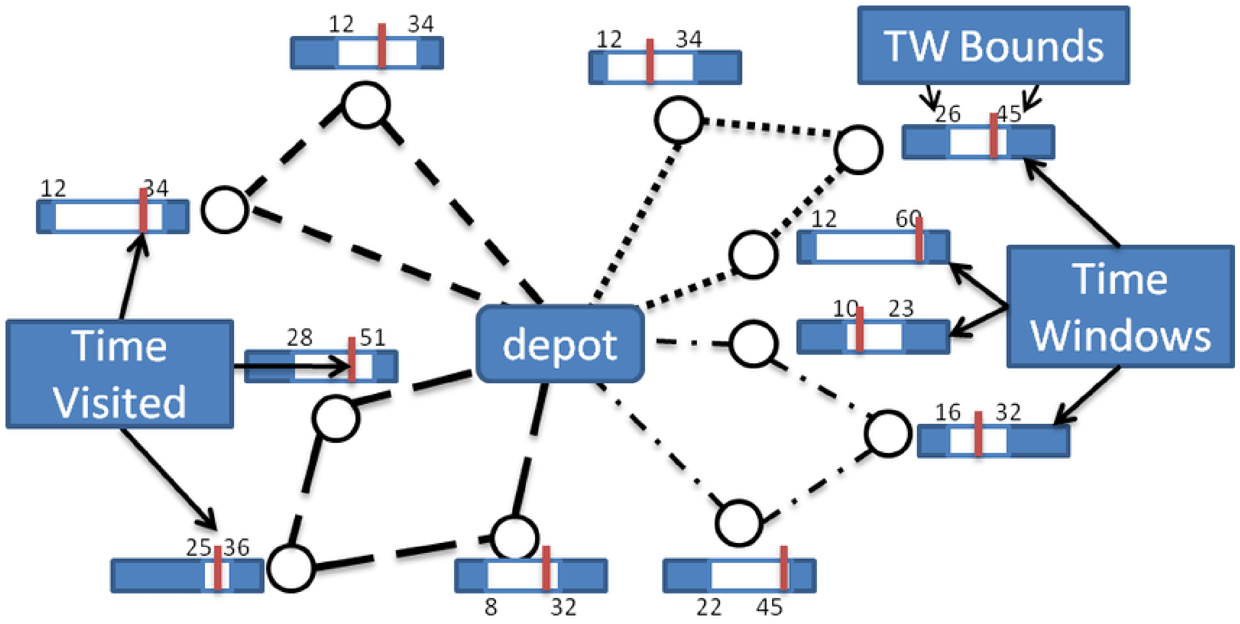

Figure 3. Vehicle Routing Problem with Time Windows (VRPTW) [2].

Inflexible for environments with uncertain demand, real-time changes.

[1] Dantzig, G.B., & Ramser, J.H. "Truck Dispatching Problem" Management Science, 1959.
[2] Solomon, Marius M. "A Sequential Insertion Algorithm for the Vehicle Routing Problem with Time Windows" Operations Research, 1987.

Vehicle Routing Problem

Figure 4. Pickup and delivery services.

Figure 5. An example of taxi system.

Vehicle Routing Problem

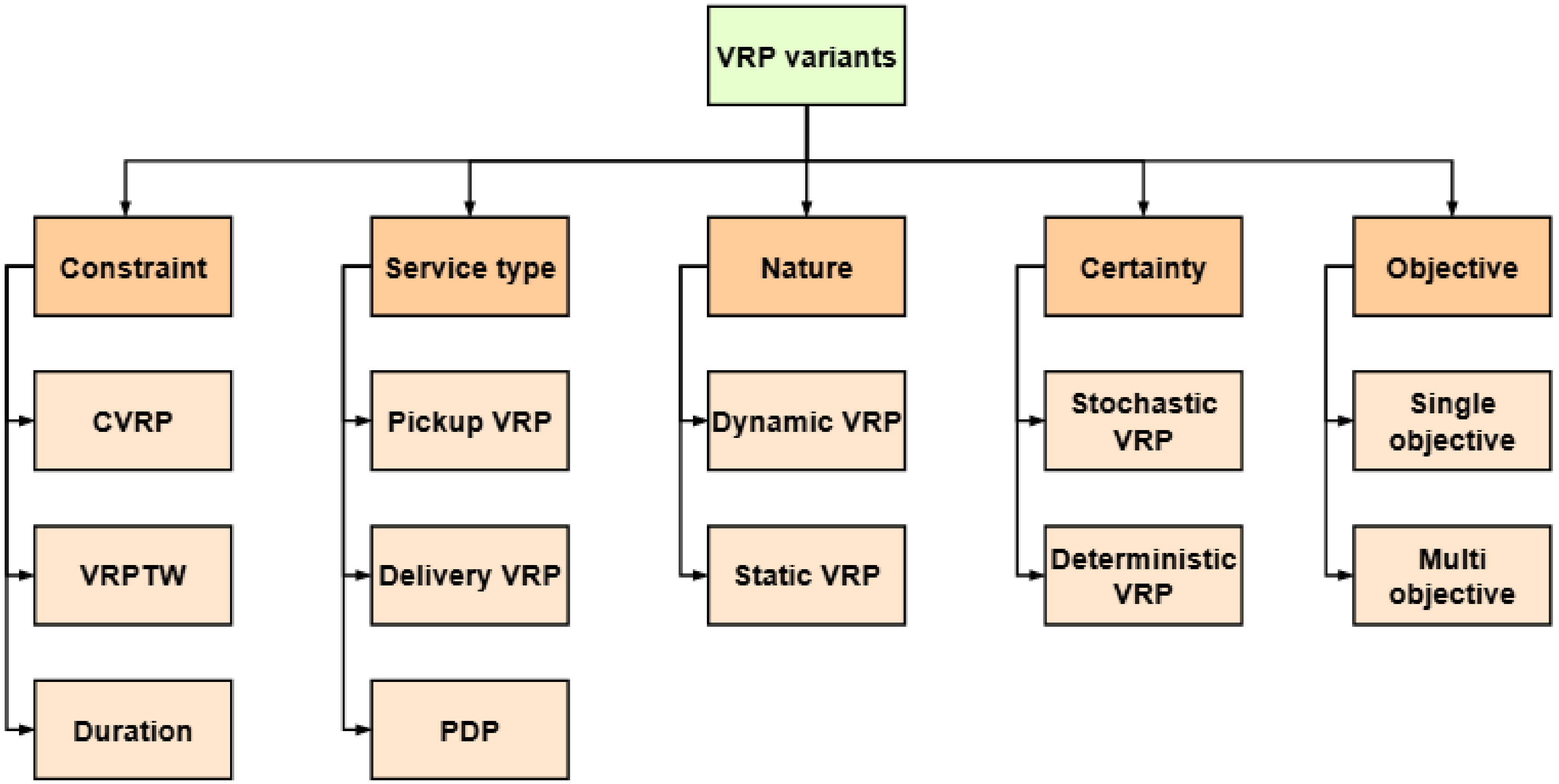

Figure 6. Survey on VRPs.

[1] Dantzig, G.B., & Ramser, J.H. "Truck Dispatching Problem" Management Science, 6(1), pp 80-91, 1959

[2] Solomon, Marius M. "A Sequential Insertion Algorithm for the Vehicle Routing Problem with Time Windows" Operations Research, 35(2), pp 254-265 1987

[3] Psaraftis "A dynamic programming solution to the single vehicle many-to-many immediate request dial-a-ride problem." Transportation Science, 1980.

[4] Cai et al. A survey of dynamic pickup and delivery problems. Neurocomputing, 554, 126631, 2023.

Dynamic Pickup and Delivery Problem (DPDP)

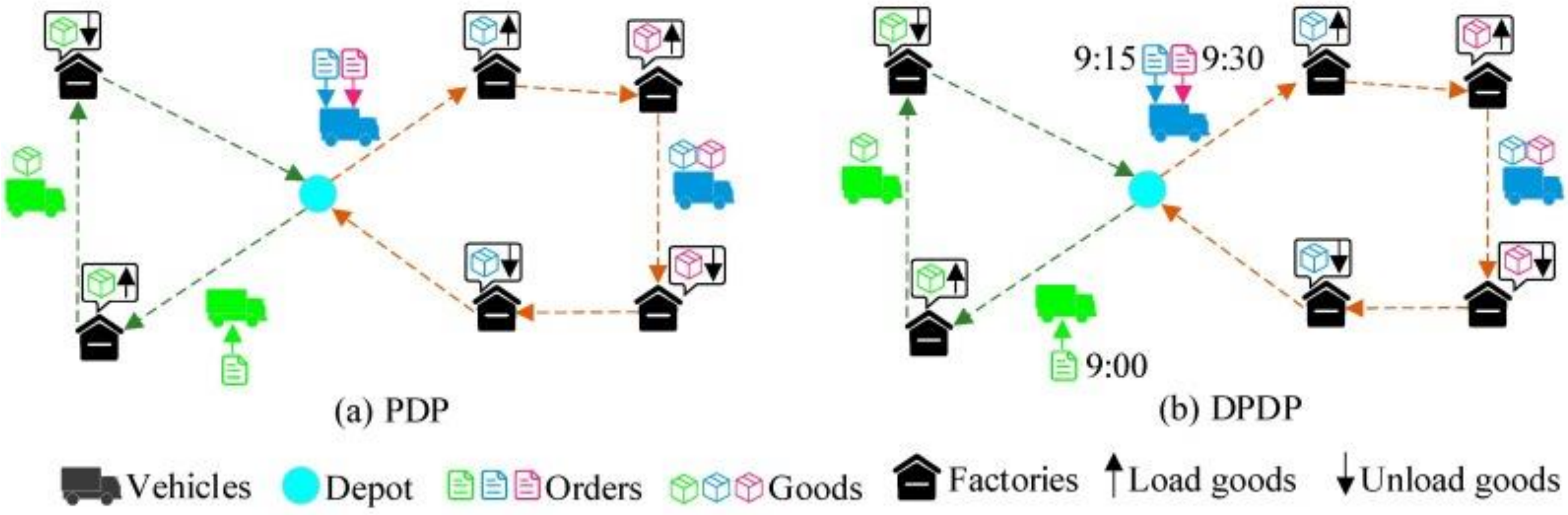

Figure 7. Overview on Dynamic Pickup and Delivery Problem [4].

[4] Cai et al. A survey of dynamic pickup and delivery problems. Neurocomputing , 554, 126631, 2023.

Introduction

- Fairness has been introduced to improve **longevity and consistency** of the provider-customer service system [6], [7].

Figure 8. Unfairness between service providers.

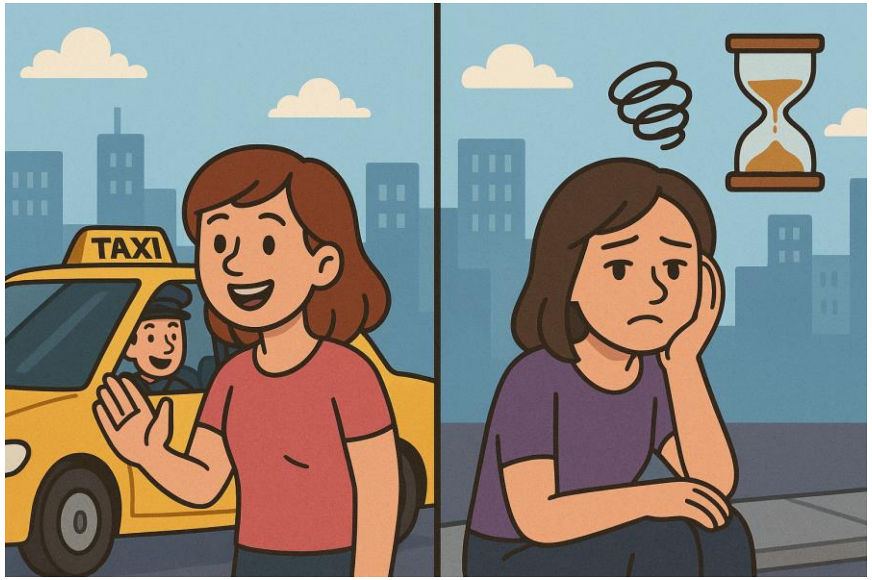

Figure 9. Unfairness between customers.

[5] Gupta et al. FairFoody: Bringing In Fairness in Food Delivery. AAAI 2022, pp 11900 – 11907.
[6] Kang et al. Promoting Two-sided Fairness in Dynamic Vehicle Routing Problems. GECCO 2024, pp 759 – 767.

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Related works

Table 1. Related works on real-world VRPs.

Related Works	Categories	Methods	Drawbacks
MOEA/D [4]	Multi-objective, dynamic, DPDP	MOEA based decomposition Time slot optimization	Inferior performance
VNSME [7]	Single-objective, dynamic, DPDP	VNS, re-optimization	Single-objective problem
FairFoody [5]	Fairness optimization	Matching algorithm	Considering fairness one sided
FairGA [6]	Fairness, DVRP	GA, time slot optimization	Single-objective problem

[4] Cai et al. A survey of dynamic pickup and delivery problems. Neurocomputing, 554, 126631, 2023;
[5] Gupta et al. FairFoody: Bringing In Fairness in Food Delivery. AAAI 2022, pp 11900 – 11907;
[6] Kang et al. Promoting Two-sided Fairness in Dynamic Vehicle Routing Problems. GECCO 2024, pp 759 – 767;
[7] Cai et al. Variable neighborhood search for a new practical dynamic pickup and delivery problem. Swarm and Evolutionary Computation 75, 101182, 2022.

Related works

The limitations of the existing studies:

- Addressed fairness from single perspective, cause losing the balance and longevity of the system.
- Considered two-sided fairness, but still in single objective approaches.

Thesis contributions:

➢ **Multi-objective Dynamic Pickup and Delivery Problem with Time Windows (MODPDPTW)**

- Incorporate energy consumption, waiting time, customer fairness and provider fairness.
- Consider to optimize four objective at the same time.

➢ **Pareto Front Grid guided MOEAs considering two-sided fairness (PFG-2F)** for MODPDPTW

- More efficiency compared to state-of-the-art multi-objective algorithms.
- Outperform single-objective specific designed for problem in all objectives.

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MODPDPTW

Input:

- Directed graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$.
- V set of vehicles.
- Set of customer requests R^t arrives randomly at time t.
- A request includes information about sender and receiver locations, time windows, load capacity.

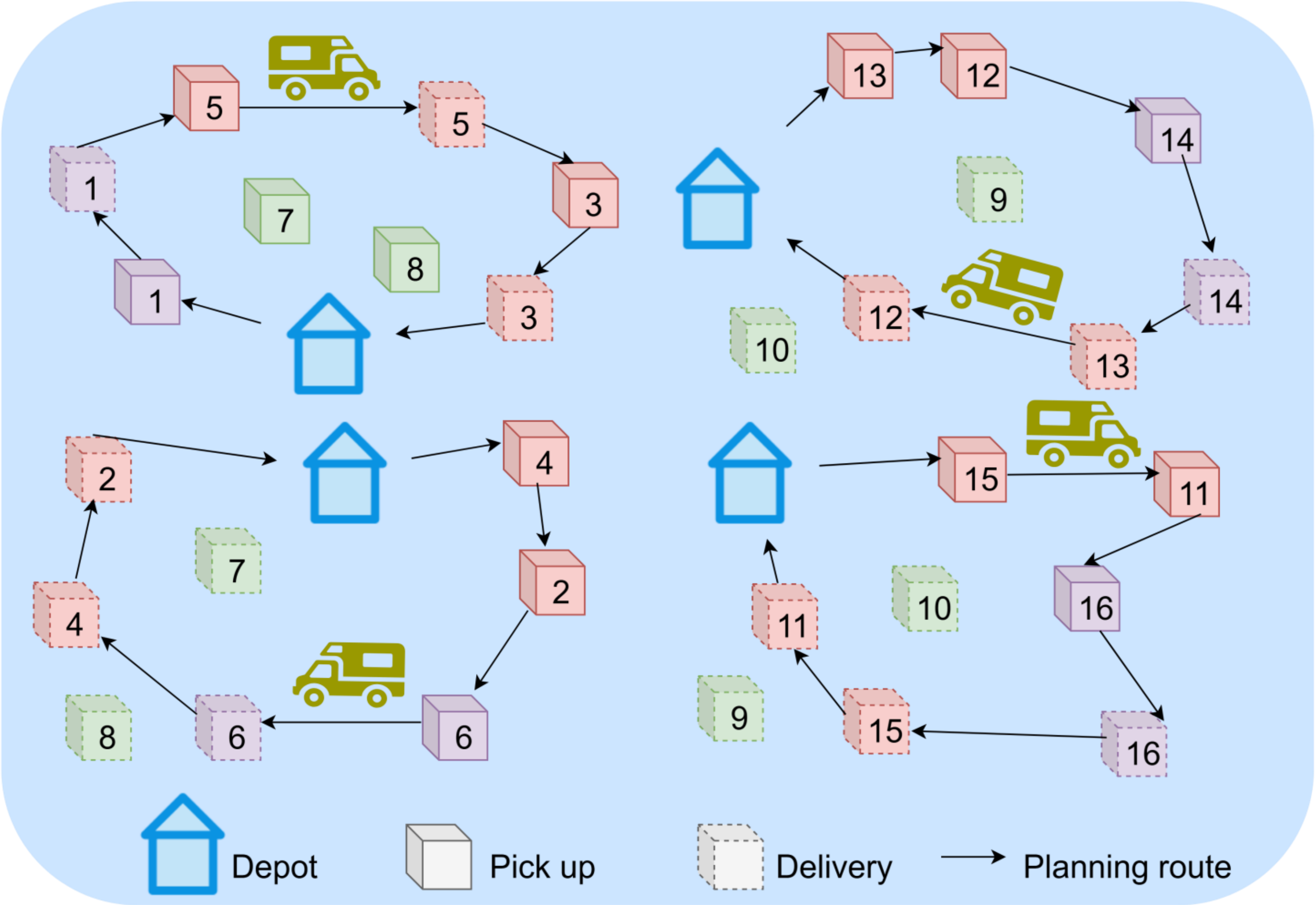

Figure 10. Example solution of MODPDPTW.

Objectives:

- *Energy consumption:*

$$EC = \sum_{t \in T} \sum_{r \in R^t} \sum_{v \in V} \sum_{(i,j) \in \mathcal{E}} y_{r,ij}^v \, L_{ij}^v$$

where

$$L_{ij}^v = \frac{\xi}{\kappa\psi}\left(\omega R + \frac{P_{ij}^v}{\eta}\right)\frac{d_{ij}}{\gamma},$$

$$p_{ij}^v = \frac{1}{2} c_d . \rho . S . \gamma$$

Objectives

- *Waiting time:*

$$MWT = \max_{r \in R^t, t \in T} WT_r,$$

where

$$WT_r = \max\left(\tau_r^p - sp_r^e, 0\right) + \max\left(\tau_r^d - sd_r^e, 0\right), \forall r \in R^t, t \in T$$

Objectives

- *Customer-based Fairness:*

$$CF = \sqrt{\frac{1}{n}\sum_{t\in T}\sum_{r\in R^t}\left(WT_r - \frac{1}{n}\sum_{t\in T}\sum_{r\in R^t} WT_r\right)^2}$$

where

$$n = \sum_{t\in T}|R^t|$$

Objectives

- *Vehicle-based Fairness:*

$$VF = \sqrt{\frac{1}{K}\sum_{v\in V}(D_v - \frac{1}{K}\sum_{v\in V} D_v)^2}$$

where

$$DT_v = \sum_{t\in T}\sum_{r\in R^t}\sum_{(i,j)\in\mathcal{E}} y^v_{r,ij}\, d_{ij}, \forall v \in V$$

Variables and parameters

Table 2. Variables and parameters of MODPDPTW.

x_r^v	$= 1$ if demand r served by v, 0 otherwise
$y_{r,ij}^v$	$= 1$ if v traverses (i,j) while serving r
τ_r^p	Time when r is picked up
τ_r^d	Time when r is delivered
c_d	Aerodynamic drag coefficient
c_r	Rolling friction coefficient
ρ	Air density
S	Frontal area of a vehicle
m_v	Curb weight of a vehicle

g	Gravitational constant
γ	Speed of a vehicle
$\widetilde{Q_{ij}^v}$	Load of vehicle v in edge (i,j)
ξ	Fuel-to-air mass ratio
κ	Heating value of fuel
ψ	Fuel rate conversion factor
ω	Engine friction factor
R	Technical parameter of engine efficiency
η	Technical parameter of drive train efficiency

ILP formulation

MODPDPTW is modeled as follows:

$$minimize\ \{EC, MWT, CF, VF\}$$

subject to

$$\sum_{v \in V} x_r^v = 1, \forall r \in R^t, t \in T$$

$$y_{r,ij}^v \leq x_r^v, \forall\ (i,j) \in \mathcal{E}, r \in R^t, t \in T, v \in V$$

$$\tilde{q}_{ij}^{v,t} \leq Q, \forall\ (i,j) \in \mathcal{E}, t \in T, v \in V$$

$$\tau_r^p \geq sp_r^b, \forall r \in R^t, t \in T$$

$$\tau_r^d \geq sd_r^b, \forall r \in R^t, t \in T$$

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Overview

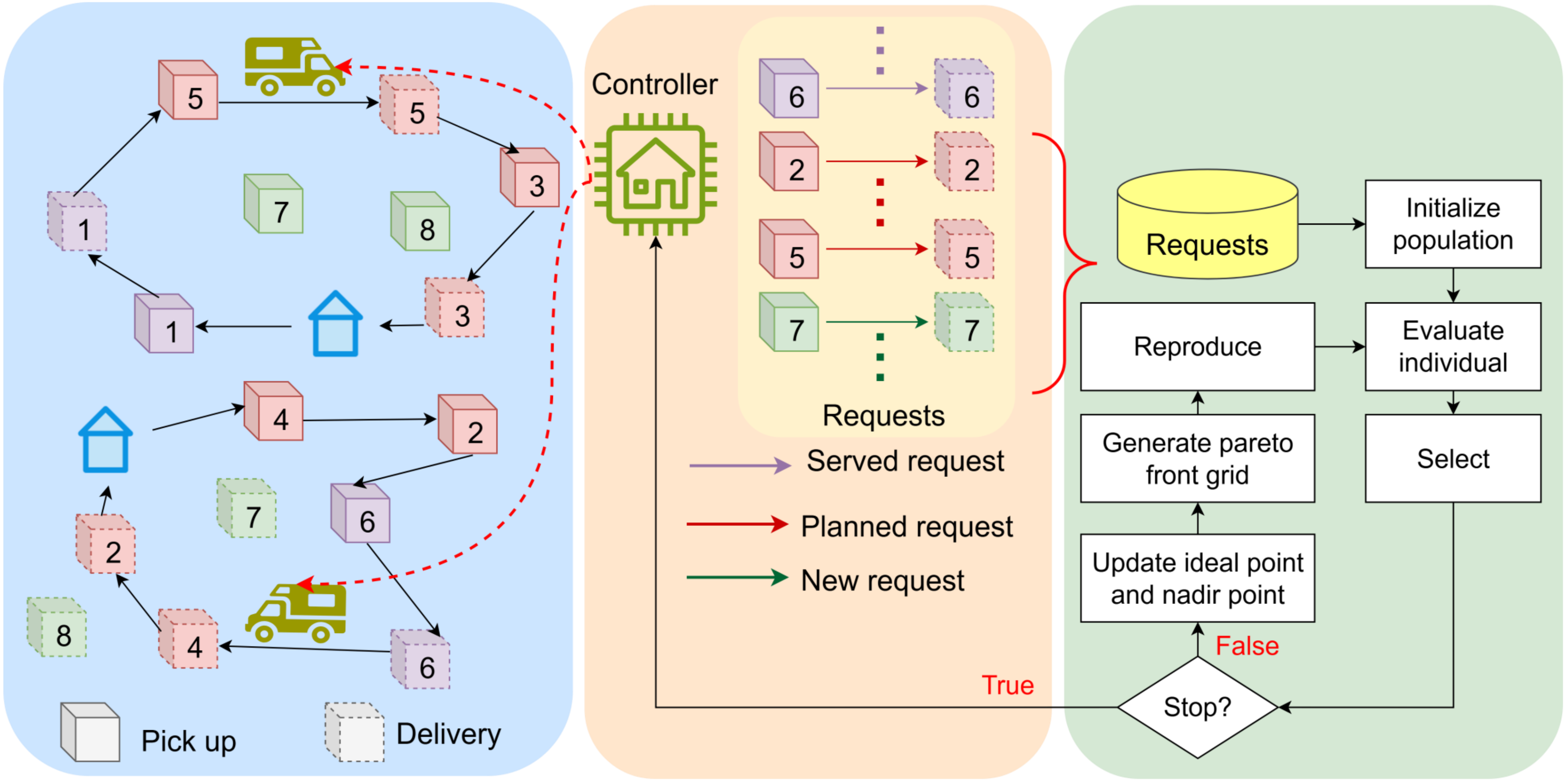

Figure 11. Overview of proposed algorithm.

Pareto front grid generation

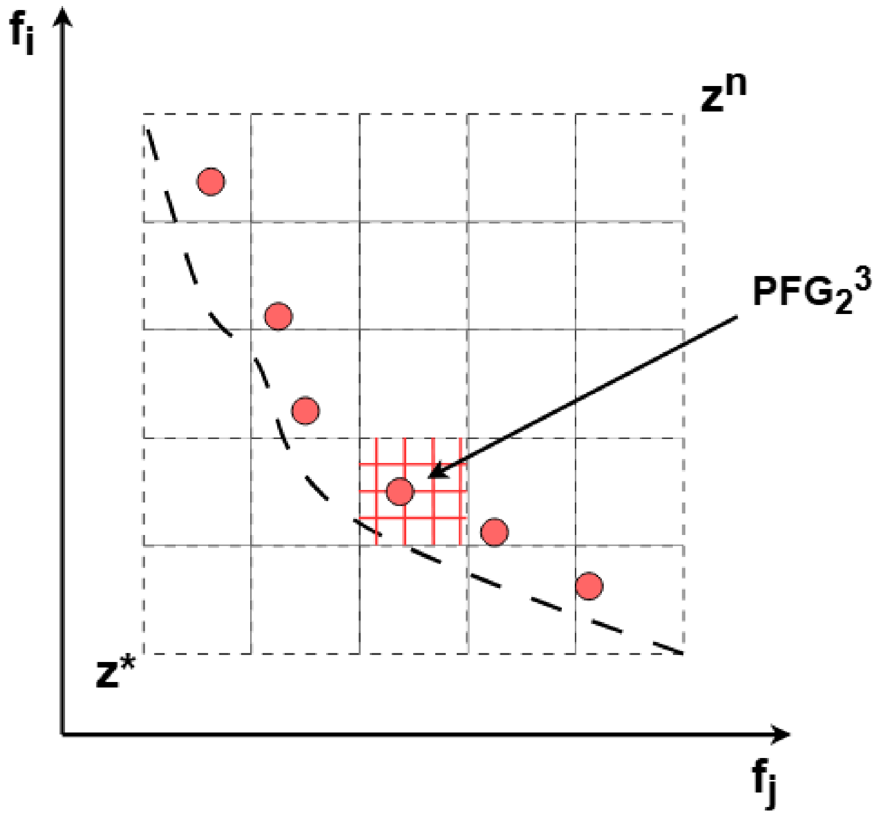

Figure 13. Pareto Front Grid generation.

Algorithm 1 Generate PFG

Require: population, the number of segments GK, the number of objectives m, the idea point $z^* = [z_1^*, ..., z_m^*]$, the nadir point $z^n = [z_1^n, ..., z_m^n]$, a small positive value σ;

Ensure: Pareto front grid $\{PFG_j^i\}, \forall j = 1, ..., GK, i = 1, ..., m$;

for $j \leftarrow 1$ to m **do**
    $d_j \leftarrow \left(z_j^n - z_j^* + 2\sigma\right) / \mathrm{GK}$
end for
for all $x \in$ Pop **do**
    for $j \leftarrow 1$ to m **do**
        $\mathrm{Grid}_j(x) \leftarrow \left\lceil \frac{f_j(x) - z_j^* + \sigma}{d_j} \right\rceil$
    end for
end for
for $i \leftarrow 1$ to m **do**
    for $j \leftarrow 1$ to GK **do**
        $S_i(j) \leftarrow$ individuals depending on the j–th segment of the i-th objective;
        $g_{\min} \leftarrow \min\{\mathrm{Grid}(S_i(j))\}$
        for all $x \in S_i(j)$ **do**
            if $\mathrm{Grid}_j(x) = g_{\min}$ **then**
                $PFG_j^i \leftarrow PFG_j^i \cup \{x\}$
            end if
        end for
    end for
end for

[8] Xu et al. A Pareto Front grid guided multi-objective evolutionary algorithm. Applied Soft Computing 2023

Individual representation

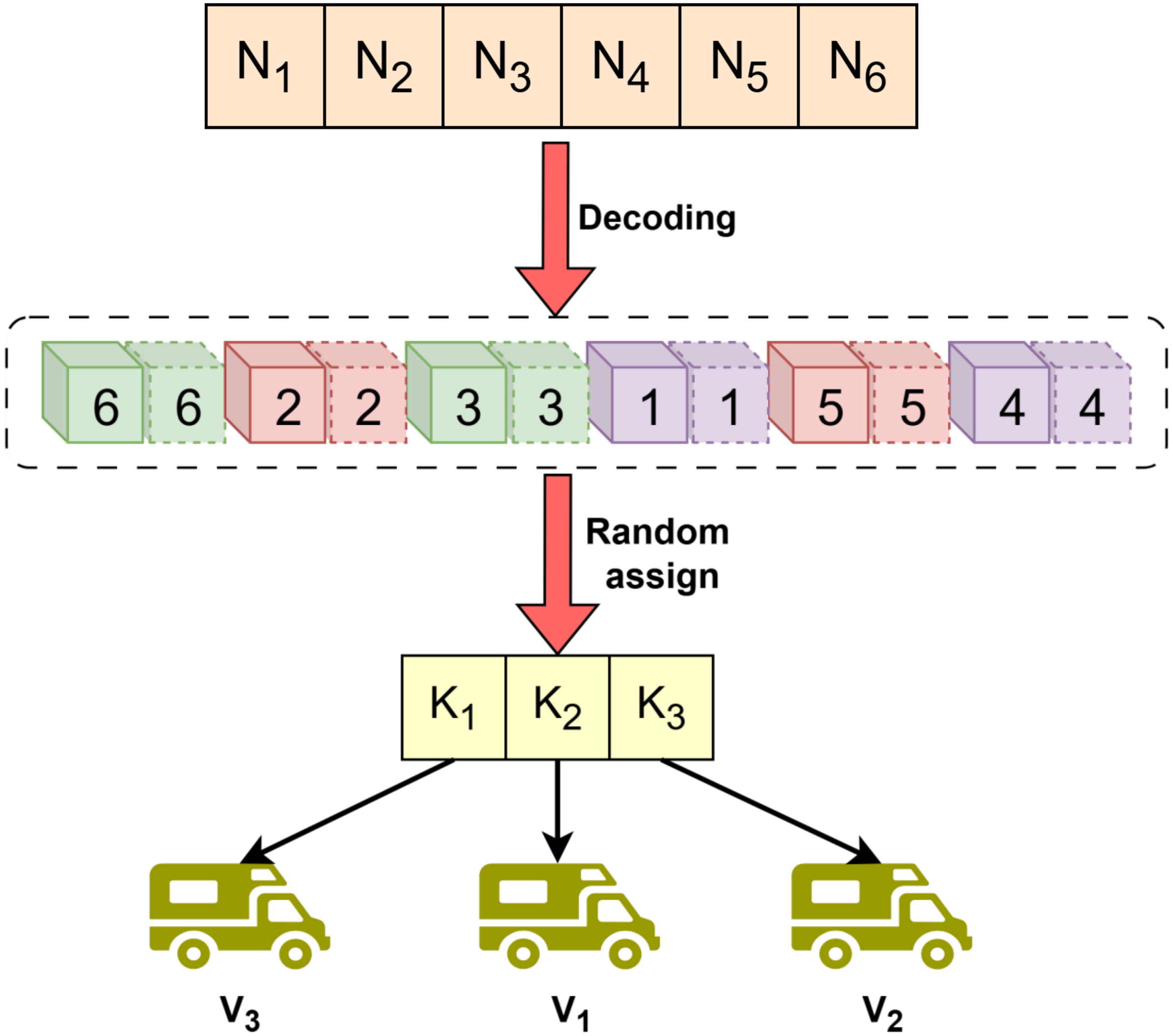

Figure 12. Individual representation.

Individual representation

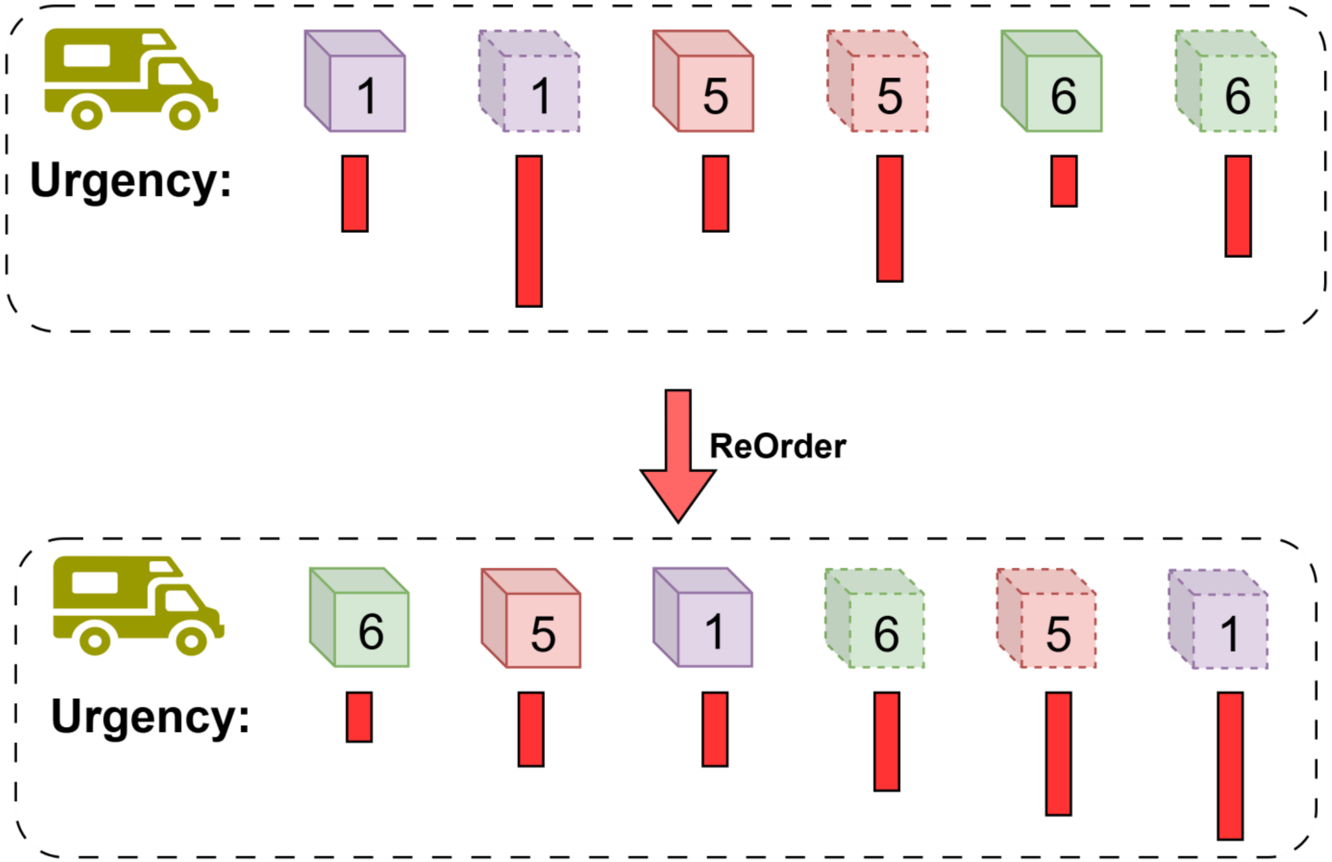

Figure 14. Urgent time ordering heuristics.

Reproduction

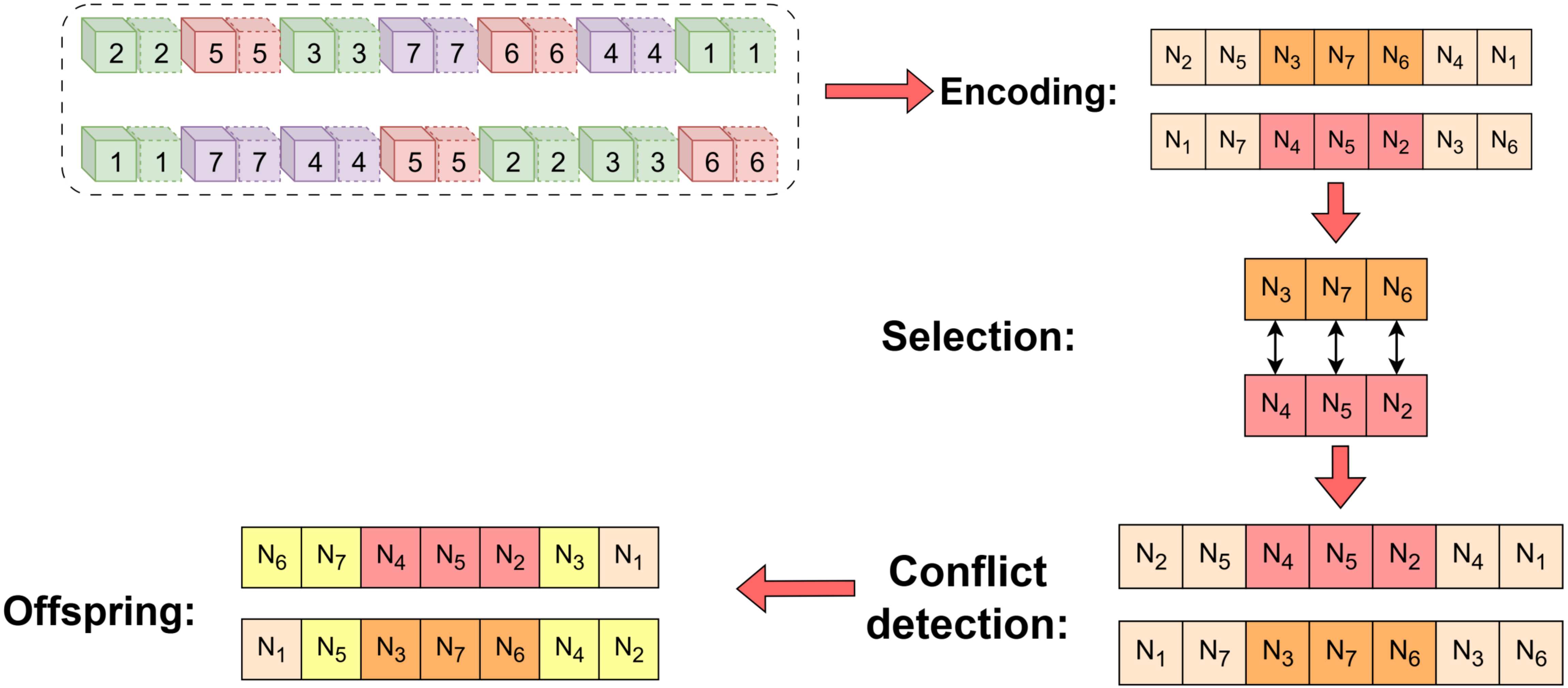

Figure 15. Partially mapped crossover.

Reproduction

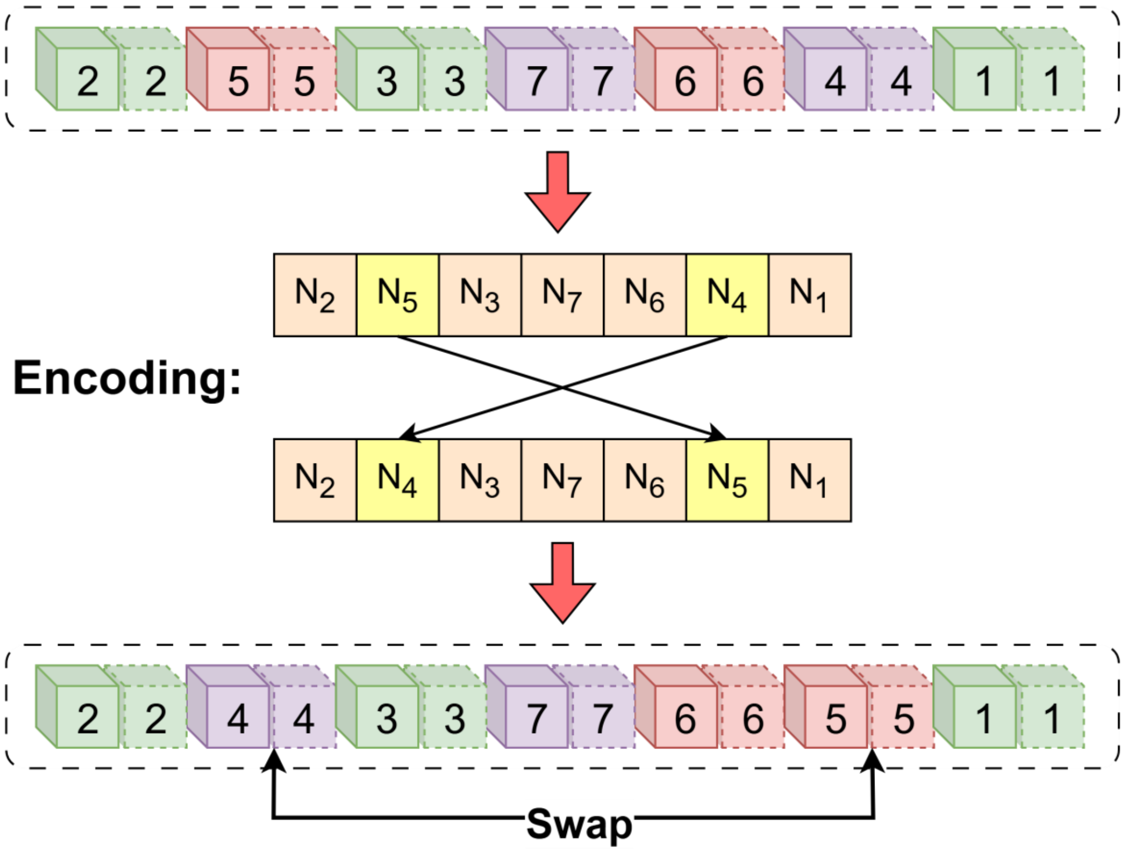

Figure 16. Swap mutation.

Outline

Experiments and Results

Dataset is developed from PDP [9] with format:

$$[dis][cat]\_[type]\_[index],$$

Where:

- dis: $random, clustered, combined$
- cat: $narrow, wide$
- $type$: 100, 200, 400 requests
- $index$: order of instances

Table 3. Detail settings of MODPDPTW follows [9] [10].

c_d	0.7
c_r	0.01
ρ	$1.20\ kg/m^3$
S	$3.912\ m^2$
m_v	$3.2\ tons$
g	$9.81\ m/s^2$
γ	$40\ km/h$
ξ	1
κ	$44\ kJ/gram$
ψ	$737\ liters/gram$
ω	$0.2\ kJ/(rev.liter)$
R	$165\ liter.rev/s$
η	0.36
p_1	$1.098\ USD/liter$
p_2	$0.094\ USD/kWh$

[9] Li et al. A Metaheuristic for the Pickup and Delivery Problem with Time Windows. International Journal of Artificial Intelligence Tools, 12(02), pp 160-167 2001
[10] Chen et al. Green vehicle routing using mixed fleets for cold chain distribution. Expert Systems with Applications 223, 120979, 2023

Experiments and Results

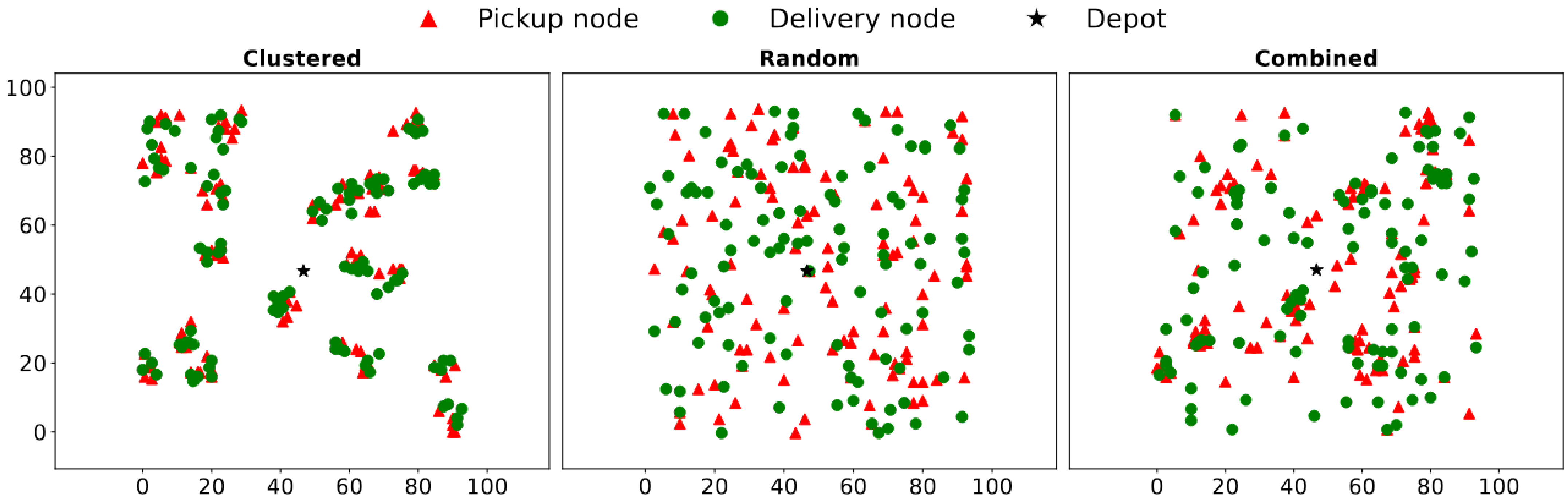

Figure 17. Different distributions of dataset.

Finetune parameters

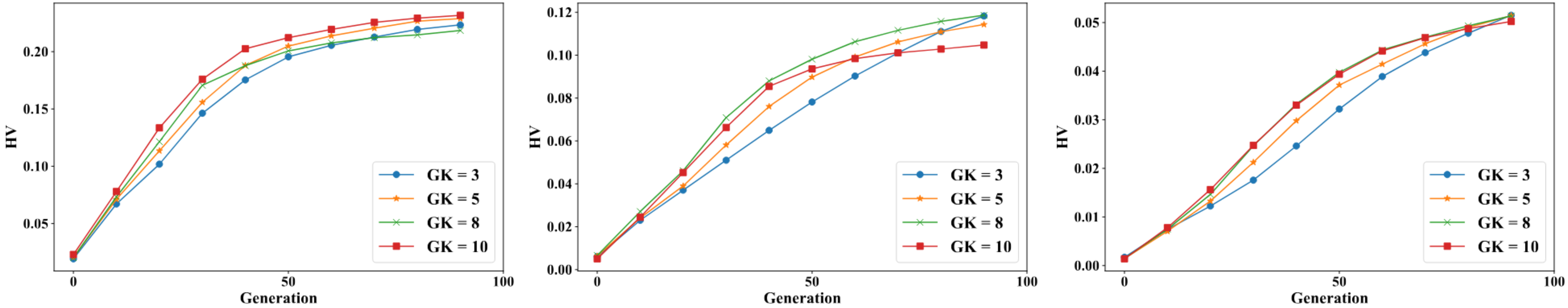

Figure 18. Finetune parameter GK in all instances.

Choose $GK = 5$ with best average results

Comparison with MOO algorithms

Metrics:

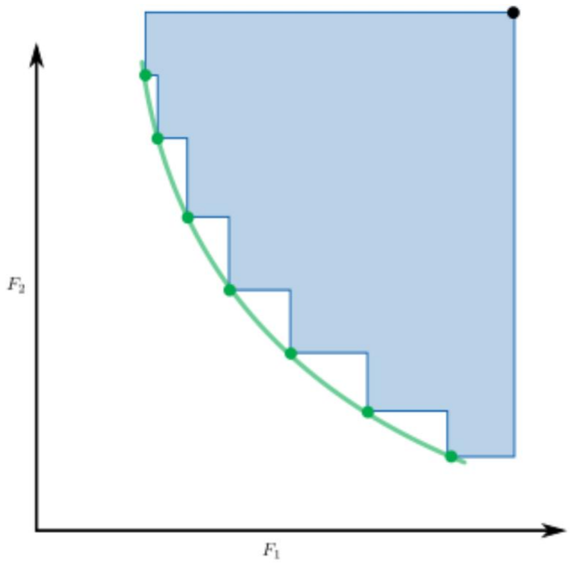

Figure 19. Hypervolume (HV).

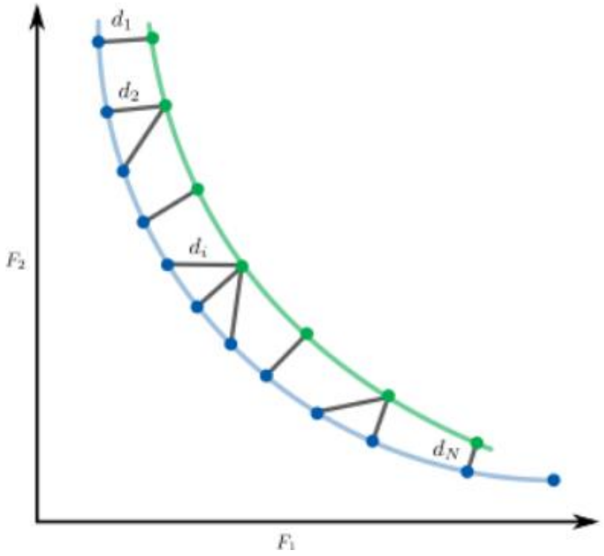

Figure 20. Inverted Generational Distance (IGD).

Compared algorithms: *NSGAII [11], MOEA/D [4], MOEA/D-DE [12], PFG-MOEA [8]*

[4] Cai et al. A survey of dynamic pickup and delivery problems. Neurocomputing 2023;
[8] Xu et al. A Pareto Front grid guided multi-objective evolutionary algorithm. Applied Soft Computing 2023;
[11] Tam et al. Multi-objective virtual network functions placement and traffic routing problem. IEEE CEC 2024;
[12] Li et al. Multiobjective Optimization Problems With Complicated Pareto Sets, MOEA/D and NSGA-II. IEEE Transactions on Evolutionary Computation 2009.

Comparison with MOO algorithms

Parameters settings

- Python programming language
- Kaggle Cloud Server

Table 4. The parameters setting of algorithms.

Parameter	Value
Number of populations	1
Population size	100
Number of generations	150
Crossover	0.9
Mutation	0.1
Parent selection	Random

Comparison with MOO algorithms

Table 5. Comparison of results between PFG-2F and other algorithms using the HV metric.

		NSGA-II	MOEA/D	MOEA/D-DE	PFG-MOEA	PFG-2F-PM	PFG-2F-RK
100	**C**	0.138 ± 0.03	0.077 ± 0.03	0.081 ± 0.02	0.209 ± 0.04	0.412 ± 0.05	**0.463 ± 0.06**
	R	0.081 ± 0.02	0.038 ± 0.01	0.038 ± 0.01	0.150 ± 0.03	0.287 ± 0.04	**0.325 ± 0.07**
	RC	0.043 ± 0.02	0.018 ± 0.01	0.020 ± 0.01	0.086 ± 0.02	0.212 ± 0.03	**0.223 ± 0.04**
200	**C**	0.113 ± 0.04	0.067 ± 0.03	0.064 ± 0.03	0.192 ± 0.05	0.331 ± 0.05	**0.370 ± 0.06**
	R	0.077 ± 0.02	0.037 ± 0.01	0.039 ± 0.01	0.132 ± 0.03	0.273 ± 0.03	**0.316 ± 0.02**
	RC	0.052 ± 0.02	0.018 ± 0.01	0.021 ± 0.01	0.074 ± 0.03	**0.211 ± 0.04**	0.203 ± 0.05
400	**C**	0.124 ± 0.04	0.066 ± 0.02	0.071 ± 0.02	0.209 ± 0.04	0.369 ± 0.06	**0.406 ± 0.06**
	R	0.070 ± 0.02	0.036 ± 0.01	0.036 ± 0.01	0.131 ± 0.03	0.271 ± 0.05	**0.324 ± 0.05**
	RC	0.057 ± 0.02	0.023 ± 0.01	0.022 ± 0.01	0.081 ± 0.03	0.215 ± 0.02	**0.231 ± 0.04**

PFG-2F-RK better than other algorithms for most instances with an average improvement of 10.18%

Comparison with MOO algorithms

Table 6. Comparison of results between SMOGP and other algorithms using the IGD metric.

		NSGA-II	MOEA/D	MOEA/D-DE	PFG-MOEA	PFG-2F-PM	PFG-2F-RK
100	**C**	0.353 ± 0.05	0.481 ± 0.07	0.468 ± 0.06	0.258 ± 0.04	0.039 ± 0.03	$\mathbf{0.020 \pm 0.02}$
	R	0.369 ± 0.06	0.517 ± 0.07	0.523 ± 0.07	0.241 ± 0.05	0.033 ± 0.04	$\mathbf{0.017 \pm 0.02}$
	RC	0.435 ± 0.09	0.586 ± 0.12	0.558 ± 0.10	0.298 ± 0.06	$\mathbf{0.006 \pm 0.01}$	0.026 ± 0.01
200	**C**	0.325 ± 0.08	0.450 ± 0.08	0.454 ± 0.09	0.201 ± 0.07	0.030 ± 0.03	$\mathbf{0.010 \pm 0.01}$
	R	0.372 ± 0.07	0.505 ± 0.08	0.504 ± 0.08	0.247 ± 0.07	0.024 ± 0.02	$\mathbf{0.018 \pm 0.01}$
	RC	0.401 ± 0.10	0.590 ± 0.11	0.541 ± 0.10	0.370 ± 0.09	$\mathbf{0.004 \pm 0.00}$	0.035 ± 0.02
400	**C**	0.350 ± 0.06	0.488 ± 0.07	0.470 ± 0.07	0.232 ± 0.05	0.038 ± 0.04	$\mathbf{0.017 \pm 0.02}$
	R	0.402 ± 0.06	0.513 ± 0.08	0.530 ± 0.09	0.265 ± 0.06	0.040 ± 0.03	$\mathbf{0.017 \pm 0.02}$
	RC	0.389 ± 0.09	0.551 ± 0.08	0.552 ± 0.09	0.335 ± 0.08	$\mathbf{0.008 \pm 0.01}$	0.026 ± 0.02

PFG-2F-PM better than other algorithms for all instances with an average improvement of 14.63%

Comparison with MOO algorithms

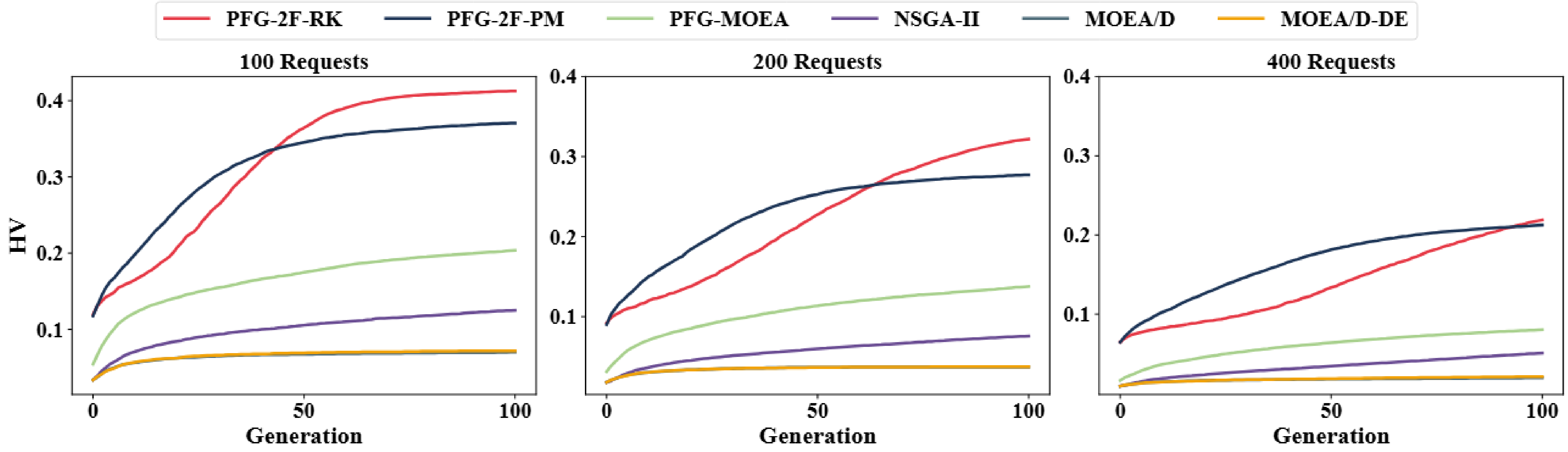

Figure 21. HV convergence trends of MOO algorithms.

Comparison with MOO algorithms

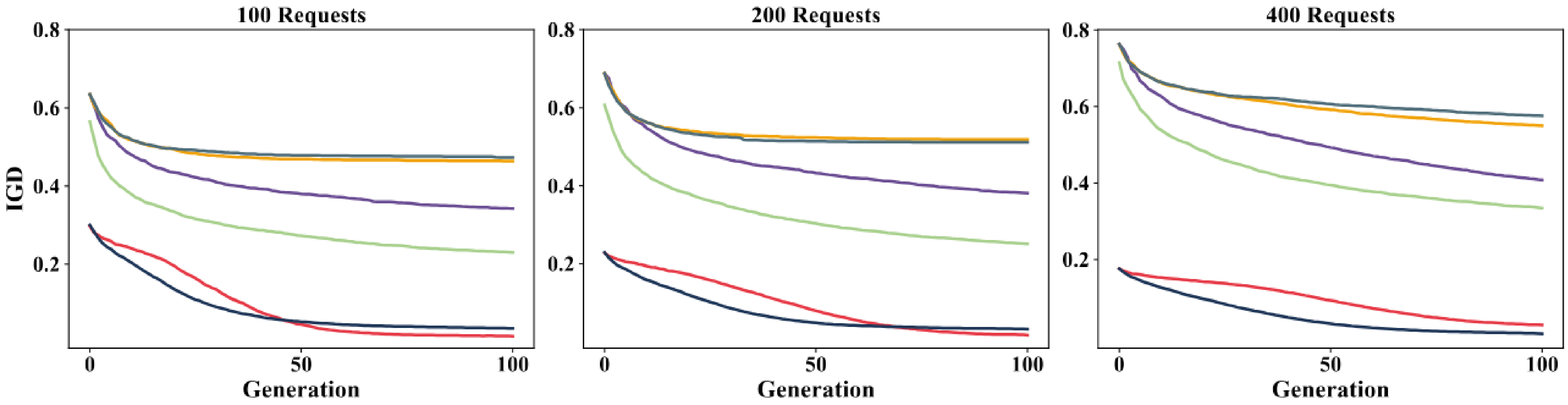

Figure 22. IGD convergence trends of MOO algorithms.

Comparison with MOO algorithms

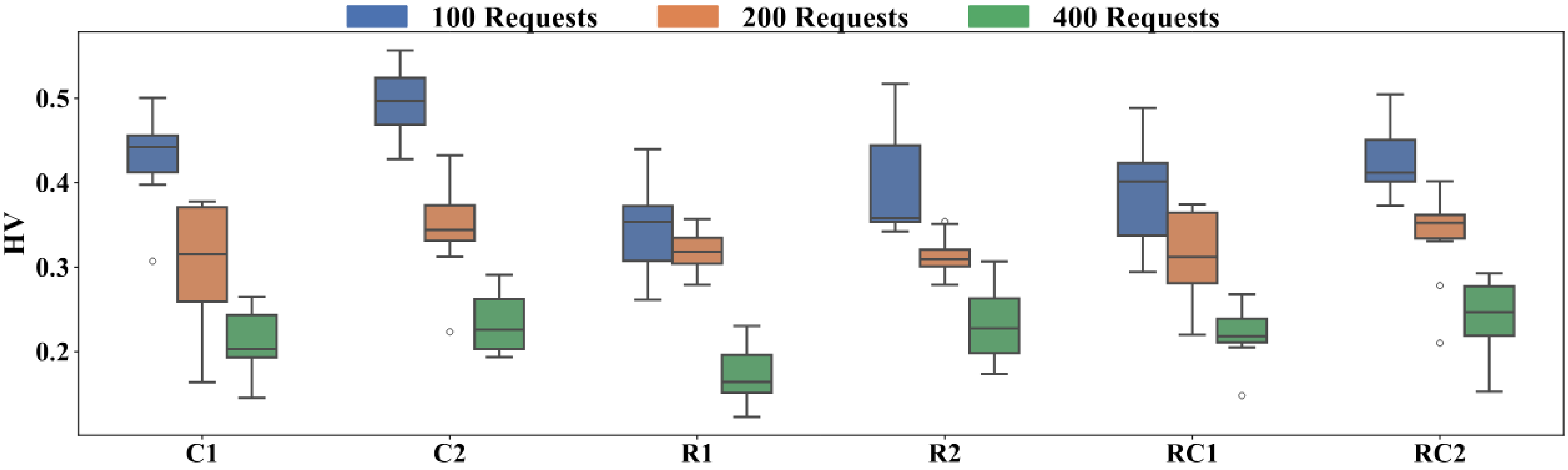

Figure 23. Effectiveness of PFG-2F across instances.

PFG-2F performs best on C2 with 100 requests

Comparison with SOO algorithms

Results is compared to *2FairGA [6]*, a SOO algorithm specific designed to problem.

Table 7. Improvement of PFG-2F compared to 2FairGA.

Dis	EC imp (%)	VF imp (%)	CF imp (%)	MWT imp (%)
C1	15.42	69.15	39.74	40.11
C2	18.74	58.04	45.75	36.18
R1	16.29	64.83	28.85	34.46
R2	14.56	59.95	58.11	49.19
RC1	17.62	64.90	31.35	33.60
RC2	15.85	64.40	58.87	52.21

PFG-2F have improvement from 15 – 69% compared to *2FairGA*

[6] Kang et al. Promoting Two-sided Fairness in Dynamic Vehicle Routing Problems. GECCO 2024, pp 759 – 767;

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Conclusion

Conclusions:

- Introduced a MODPDPTW, addressing complexities of dynamic logistics, minimizing energy consumption, reduce waiting time and ensuring fairness for both customers and service providers.
- Proposed a MO algorithm based on Pareto Front Grid generation named PFG-2F.
- Conducted experiments to evaluate the effectiveness of proposed method on HV and IGD.

Future Works:

- Incorporating machine learning-based method to improve efficiency and adaptability of dynamic routing system.
- Acquiring empirical data to enable realistic simulation of service systems.

Conclusion

Parts of this thesis have been published and awarded:

- **Phan Duc Hung**, Bui Trong Duc, Nguyen Thi Tam and Huynh Thi Thanh Binh, "Pareto Front Grid Guided Multiobjective Optimization In Dynamic Pickup And Delivery Problem Considering Two-Sided Fairness" in The Genetic and Evolutionary Computation Conference (**GECCO '25**), 2025. (accepted, full paper, **rank A**).
- Ha Minh Hieu, **Phan Hung**, Tran Duc Chinh, Van Duc Cuong, Dao Van Tung, and Huynh Thi Thanh Binh, "Alimentation Deep Multiple Optimal Ant Colony Optimization to solve Vehicle Routing Problem with Time Windows" in The Genetic and Evolutionary Computation Conference (**GECCO '24**), 2024. (poster, **rank A**).
- **Second prize** at The 42st Student Research Conference, Hanoi University of Science and Technology, in the field of AI Applications, Blockchain, and Big Data, academic year: 2024-2025.
- Second Prize at "SoICT Hackathon 2024: TIKI Container Shipping Route Coordination", 2024.

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Thank you for your attention!