TÉCNICO LISBOA

UNIVERSIDADE D COIMBRA

Optimization-based Heuristics vs. Metaheuristics to solve the Smart Waste Collection Routing Problem

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OpLog Research Group

WSMARTROUTE

EURO 2019

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WSmartRoute Project

WSMARTROUTE

Waste Collection Based on a Real Time Route Planning System

Aims to explore a new paradigm that relies on smart waste management, where real-time data plays a central role in changing the way operations are managed today, moving from static to dynamic routes.

The tool to be developed will integrate technology with management concerns contributing to improve the companies' operations decision-making process.

http://wsmartroute.tecnico.ulisboa.pt/

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Agenda

Introduction

The Smart Waste Collection Routing Problem

Objectives

Optimization-based Heuristic Approach

Hybrid Simulated-Annealing/Local-Search Metaheuristic

Results for real-case instance

Conclusions

Future Work

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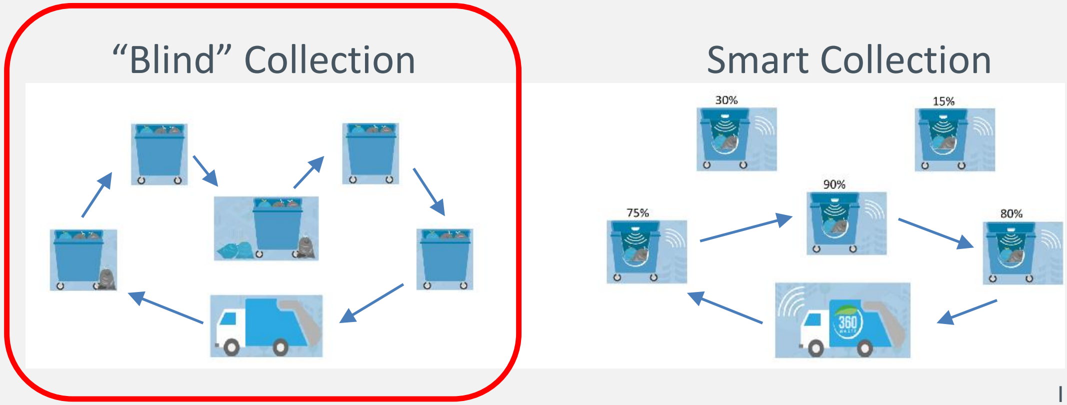
Introduction

Amount of municipal solid waste is highly variable and its accumulation is difficult to forecast[1]: high uncertainty.

Waste management operations are often related to high inefficiency: high transportation costs and high pollutant emissions.

"Blind collection": static routes and vehicles visiting partially full bins.



[1](Nuortio *et al.*, 2006)

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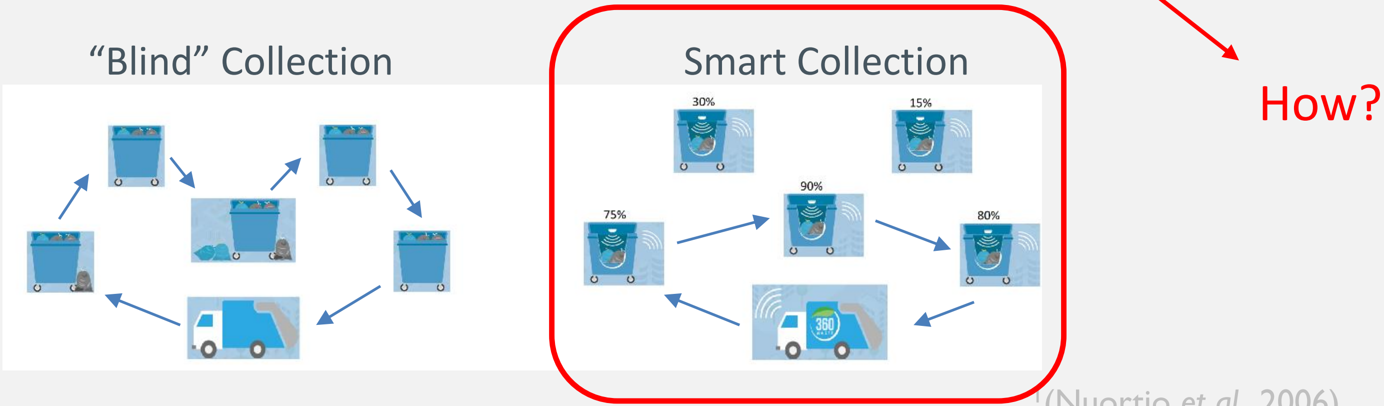
Introduction

Amount of municipal solid waste is highly variable and its accumulation is difficult to forecast[1]: high uncertainty.

Waste management operations are often related to high inefficiency: high transportation costs and high pollutant emissions.

Smart Collection: reduction of uncertainty and increase of collection operations' efficiency.



[1](Nuortio *et al.*, 2006)

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The Smart Waste Collection Routing Problem

Use of real-time information on the bins' fill-level (transmitted by volumetric sensors placed inside the bins) to define smart collection routes that maximize operational profit[2];

Max PROFIT = revenues obtained from the recyclable waste collected - transportation costs of collecting that waste

Maximize waste collected while minimizing distance travelled

Rather than simply selecting the fullest bins to be visited, and then apply VRP models to minimize the distance travelled

[2](Ramos *et al.*, 2018)

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The Smart Waste Collection Routing Problem

Use of real-time information on the bins' fill-level (transmitted by volumetric sensors placed inside the bins) to define smart collection routes that maximize operational profit[2];

Max PROFIT = revenues obtained from the recyclable waste collected - transportation costs of collecting that waste

Decision: To select the waste bins to be visited (if any) and the optimal visiting sequence in each day *t* for each vehicle *k*, which will maximize the profit while satisfying the vehicles' fixed capacity and the bins' capacity.

[2](Ramos *et al.*, 2018)

The Smart Waste Collection Routing Problem

Decision: To select the waste bins to be visited (if any) and the optimal visiting sequence in each day *t* for each vehicle *k*, which will maximize the profit while satisfying the vehicles' fixed capacity and the bins' capacity

Defines when (in which day) the model should be run to maximize profit within a time horizon

Solution Approach:

Heuristic + VRP with Profit (VRPP) model[2]:

Model is solved at day t, in the morning, after receiving sensors' information on the bins' fill-level, when at least *H* waste bins are expected to overflow (to comply with the defined service level).

[2](Ramos *et al.*, 2018)

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The Smart Waste Collection Routing Problem

Decision: To select the waste bins to be visited (if any) and the optimal visiting sequence in each day *t* for each vehicle *k*, which will maximize the profit while satisfying the vehicles' fixed capacity and the bins' capacity

Solution Approach:
Heuristic + VRP with Profit (VRPP) model[2]:

KPI	Day 1	Day 7	Day 12	Day 18	Day 24	Day 25	Day 30	Total	Average
Profit (€)	261.0	131.2	154.1	143.6	131.6	-59.9	111.3	872.9	124.7
Weight (kg)	5158.4	2644.0	4019.7	3625.6	2874.1	1310.6	2833.5	22465.8	3209.4
Distance (km)	229.0	120.0	227.8	200.9	141.5	184.4	157.9	1261.4	180.2
Attended bins	138	77	151	134	105	95	94	794	113
Ratio (kg/km)	22.5	22.0	17.6	18.1	20.3	7.1	17.9	17.8	17.8
Gap	**8.0%**	**11.0%**	**7.0%**	**15.3%**	**16.2%**	**58.6%**	**20.3%**	**-**	**-**
Comp. Time (s)	**14400**	**14400**	**14400**	**14400**	**14400**	**14400**	**14400**	**100800**	**14400**
Vehicles used	2	2	2	2	2	2	2	14	2

[2](Ramos *et al.*, 2018)

Problem: Low computational performance

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Objectives

To propose two heuristic approaches to solve the SWCRP, improving the solution performance of the VRPP mathematical model.

1) Optimization-based heuristic

2) Hybrid simulated-annealing/local-search metaheuristic

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Optimization-based Heuristic

Optimization-based Heuristic

Decomposes the problem by reducing the set of waste bins to be inserted as input to the VRPP mathematical model

Cluster First - Route Second:

selects a dynamic subset of waste bins to be considered, and then uses this dynamic set to feed the VRPP model that decides which waste bins are worth to be collected, considering their fill-levels and locations.

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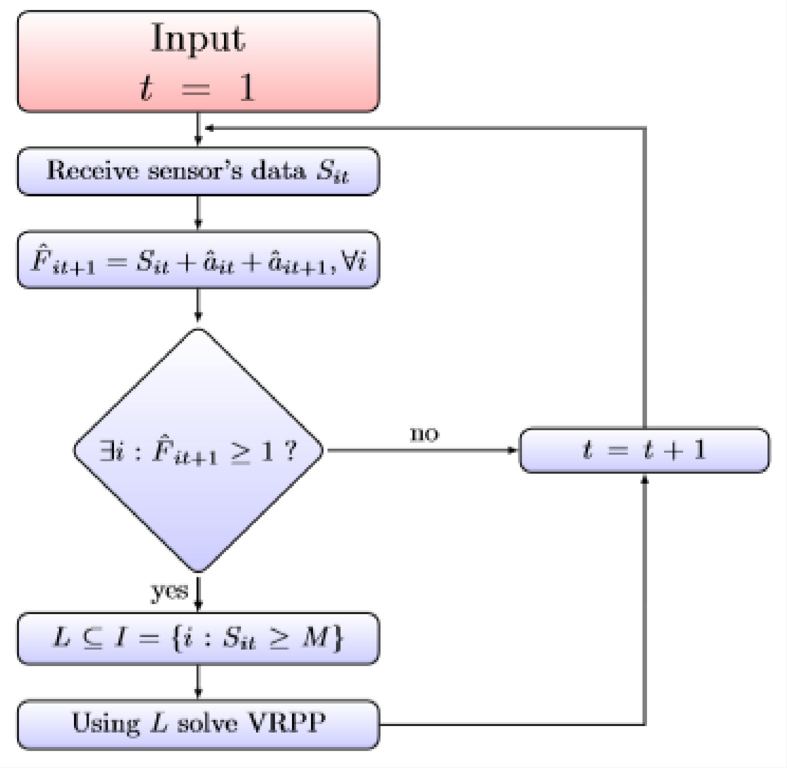
Optimization-based Heuristic



VRPP model is combined with two heuristics:

1) Waste bins are visited as late as possible

Heuristic procedure that defines when (in which day) the model should be run to maximize the profit within a time horizon;

2) Cluster First - Route Second

Heuristic rule that selects as a dynamic set of waste bins to be considered as an input for the VRPP model only those bins that have fill-levels higher than a defined threshold M.

Sensitive analysis

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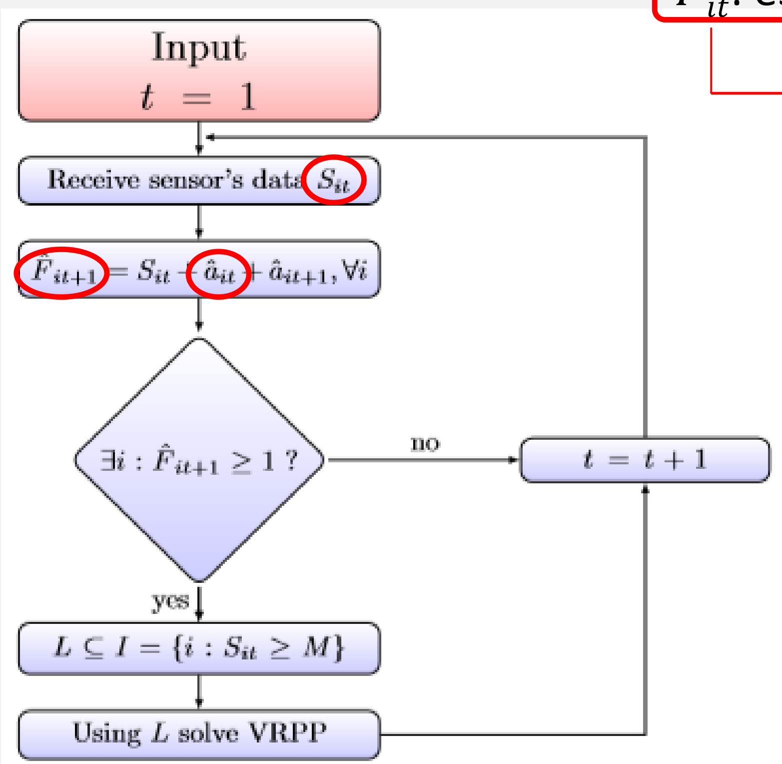
Optimization-based Heuristic

S_{it}: waste bins' fill-level → Sensors' information

$\hat{a}_{it}$: expected daily accumulation rate

$\hat{F}_{it}$: estimate of the waste bins' fill-level at the end of day t

→ $\hat{F}_{it+1}$: estimate of the waste bins' fill-level at the end of day t+1



At day t, if there are waste bins about to overflow at t+1, then the waste bins for which the fill level S_{it} is higher than M are selected and, for those bins the model is solved and the routes are defined; if not, the next iteration is set to be carried out on the next day ($t = t$+1).

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Hybrid Simulated-annealing / Local-search Metaheuristic

Initial solution generation ←
- Nearest neighbor
- Random

↓

Uncross arcs

↓

Simulated Annealing ←
- Move
- Swap
- Add
- Remove

←
- Random: all with the same probability
- With different probabilities

↓

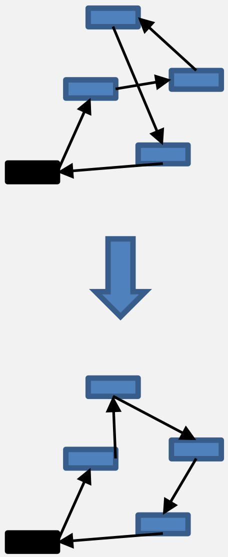
Uncross arcs

↓

Local search ←
- Insert
- Remove

↓

Uncross arcs



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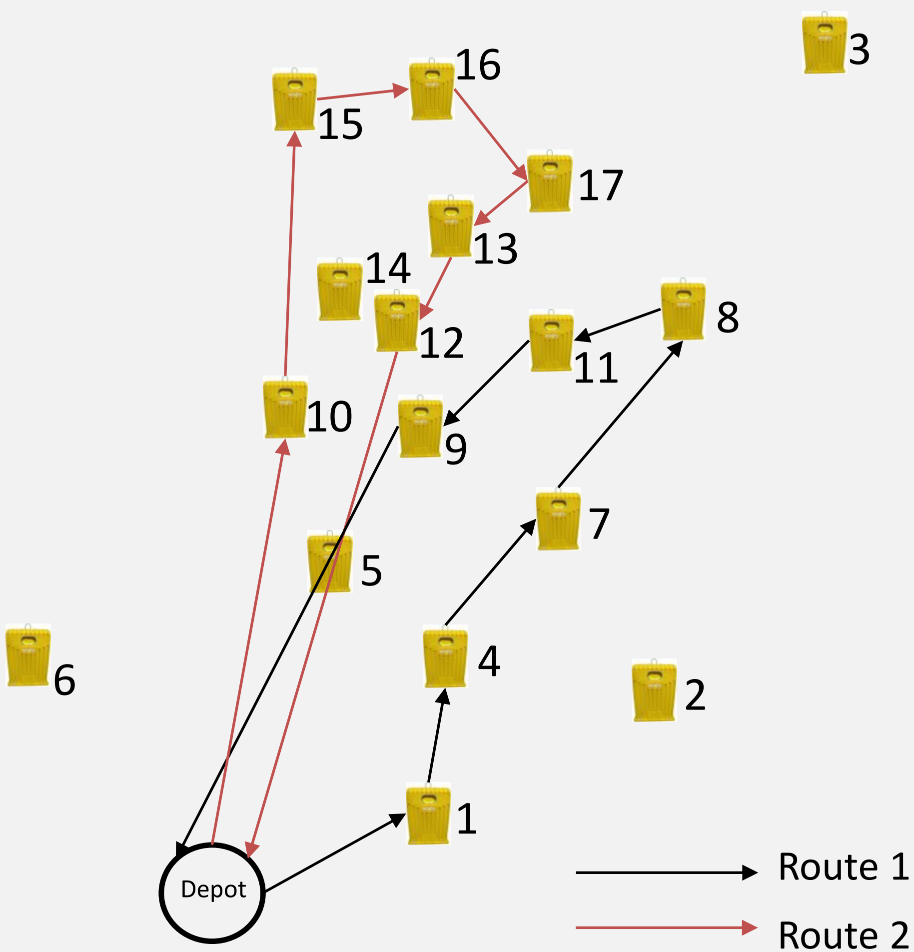
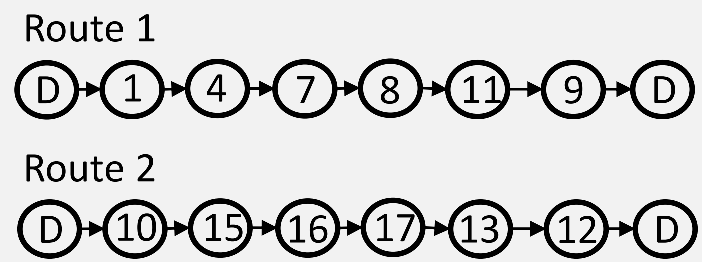
Hybrid Simulated-annealing / Local-search Metaheuristic

Example





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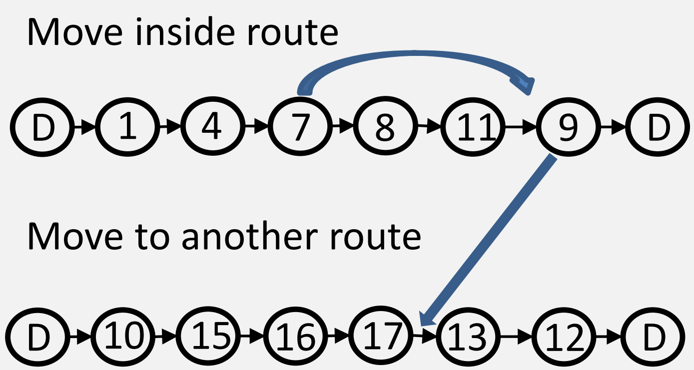
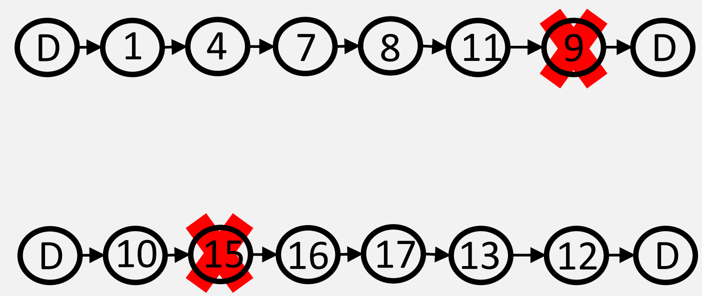
Hybrid Simulated-annealing / Local-search Metaheuristic

Simulated Annealing bin moving strategies

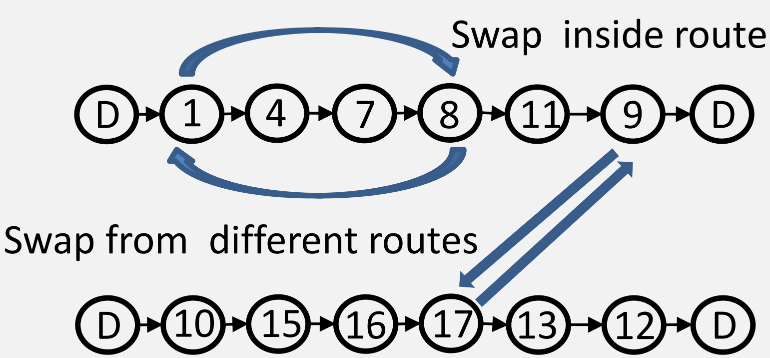
Moving



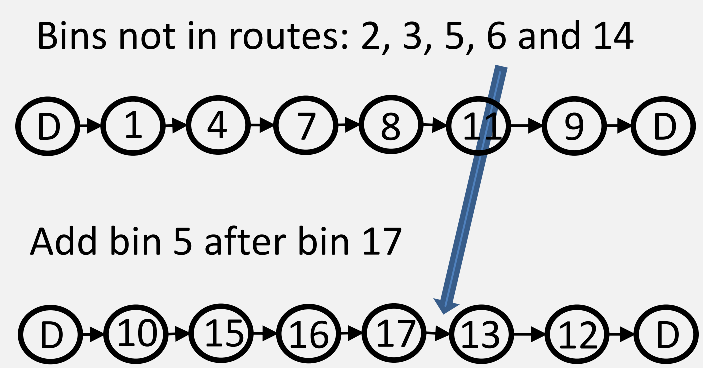
Removing



Swapping



Adding



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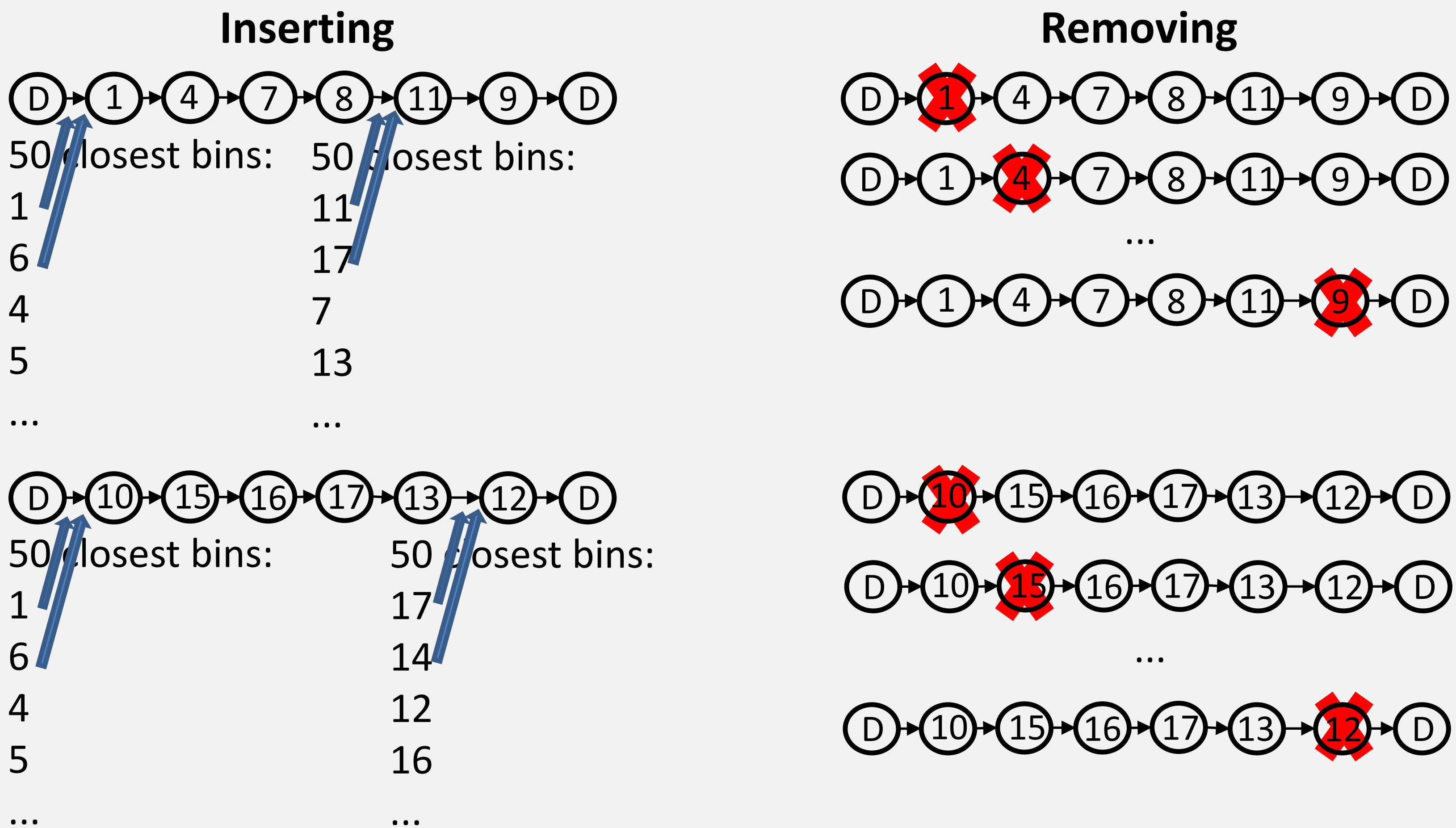
Hybrid Simulated-annealing / Local-search Metaheuristic

Local search bin moving strategies



After each change OF is evaluated and new solution is only accepted if OF is improved

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Results for real-case instance

Case-study from a portuguese company responsible for the recyclable waste collection at 14 municipalities in Portugal;

Recyclable materials: glass, paper/cardboard and plastic/metal;

Paper/cardboard: 26 different static routes performed periodically.

Routes number 6, 11 and 13
226 bins

3rd January 2013 - 2nd February 2013
(T = 30 days)

Route 6 (68 bins): performed 2 times
Route 11 (74 bins): performed 3 times
Route 13 (84 bins): performed 5 times

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Results for real-case instance

Case-study from a portuguese company responsible for the recyclable waste collection at 14 municipalities in Portugal;

Recyclable materials: glass, paper/cardboard and plastic/metal;

Paper/cardboard: 26 different static routes performed periodically.

Date	03/01	09/01	10/01	10/01	17/01	21/01	24/01	24/01	01/02	01/02		
Route	Route 13	Route 11	Route 6	Route 13	Route 13	Route 11	Route 6	Route 13	Route 11	Route 13		
KPI	Day 1	Day 7	Day 8	Day 8.	Day 15	Day 19	Day 22	Day 22.	Day 30	Day 30.	Total	Average
Profit (€)	117.5	94.0	-73.2	112.1	125.5	74.9	-77.1	81.7	73.5	107.6	636.3	63.6
Weight (kg)	2471.8	2342.7	1420.4	2564.1	2693.2	2250.5	1512.6	2195.1	2213.6	2490.3	22154.3	2215.4
Distance (km)	117.3	128.6	208.2	131.5	130.4	138.9	220.8	126.9	136.8	129.0	1468.4	146.8
Attended bins	84	74	68	84	84	74	68	84	74	84	778	78
Empty visited bins	6	17	26	7	7	2	1	7	2	6	81	8
Ratio (kg/km)	21.1	18.2	6.8	19.5	20.7	16.2	6.9	17.3	16.2	19.3	15.1	15.1
Vehicles used	1	1	1	1	1	1	1	1	1	1	10	1
Vehicles usage rate (%)	61.8	58.6	35.5	64.1	67.3	56.3	37.8	54.9	55.3	62.3	-	55.4

66% of the collected waste bins had a fill-level equal or lower than 50%

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Results for real-case instance

Optimization-based heuristic

M=0% conceptually corresponds to the solution obtained in Ramos *et al.* (2018), where all bins are considered within the route definition - 226 bins

M = 0%								
KPI	Day 1	Day 6	Day 13	Day 20	Day 25	Day 30	Total	Average
Profit (€)	253.1	186.9	224.4	223.9	147.9	106.7	1142.8	190.5
Weight (kg)	3999.6	3990.5	3953.6	3998.6	3781.5	2865.3	22589.2	3764.9
Distance (km)	126.8	192.2	151.2	155.9	211.3	165.5	1002.8	167.1
Attended bins	98	118	121	119	136	97	689	115
|L|	226	226	226	226	226	226	1356	226
Ratio (kg/km)	31.5	20.8	26.2	25.6	17.9	17.3	22.5	22.5
Gap (%)	2.8	7.3	6.3	9.4	13.4	10.6	-	-
Computational time (s)	16201.2	16203.7	16200.4	16201.1	16204.4	16203.2	97213.9	16202.3
Vehicles used	1	1	1	1	1	1	6	1
Vehicle Usage Rate (%)	99.99%	99.76%	98.84%	99.97%	94.54%	71.63%	-	94.12%

M = 10%								
KPI	Day 1	Day 6	Day 13	Day 19	Day 26	Day 29	Total	Average
Profit (€)	253.9	187.4	219.2	181.6	195.4	38.8	1076.3	179.4
Weight (kg)	3991.7	3968.0	3994.6	3994.6	3818.2	2490.9	22258.0	3709.7
Distance (km)	125.3	189.5	160.3	197.8	167.2	197.8	1037.9	173.0
Attended bins	88	112	119	140	111	113	683	114
|L|	124	121	154	165	158	131	853	142
Ratio (kg/km)	31.9	20.9	24.9	20.2	22.8	12.6	21.4	21.4
Gap (%)	0.0	2.6	5.8	7.8	5.9	27.9	-	-
Computational time (s)	3275.0	16205.3	16201.2	16203.1	16202.2	16202.6	84289.3	14048.2
Vehicles used	1	1	1	1	1	1	6	1
Vehicle usage rate (%)	99.79%	99.20%	99.86%	99.86%	95.46%	62.27%	-	92.74%

M = 20%								
KPI	Day 1	Day 6	Day 13	Day 20	Day 25	Day 29	Total	Average
Profit (€)	253.9	166.1	193.8	220.6	137.8	80.3	1052.5	175.4
Weight (kg)	3991.7	3657.5	3616.4	3995.9	3409.1	2754.1	21424.8	3570.8
Distance (km)	125.3	181.3	149.7	159.0	186.0	181.2	982.5	163.8
Attended bins	82	90	114	104	110	100	600	100
|L|	114	98	137	132	135	114	730	122
Ratio (kg/km)	31.9	20.2	24.2	25.1	18.3	15.2	21.8	21.8
Gap (%)	0.0	3.6	4.8	4.6	5.4	13.3	-	-
Computational time (s)	883.7	16208.9	16204.7	16203.0	16202.9	16200.1	81903.3	13650.5
Vehicles used	1	1	1	1	1	1	6	1
Vehicle usage rate (%)	99.79%	91.44%	90.41%	99.90%	85.23%	68.85%	-	89.27%

M = 30%								
KPI	Day 1	Day 7	Day 13	Day 19	Day 25	Day 29	Total	Average
Profit (€)	238.8	178.2	196.3	199.8	172.6	3.0	988.8	164.8
Weight (kg)	3976.8	3488.2	3421.9	3998.4	3512.2	1677.0	20074.5	3345.7
Distance (km)	139.0	153.1	128.8	180.0	161.0	156.2	918.0	153.0
Attended bins	75	70	82	95	87	43	452	75
|L|	96	78	96	129	98	53	550	92
Ratio (kg/km)	28.6	22.8	26.6	22.2	21.8	10.7	21.9	21.9
Gap (%)	0.0	5.5	0.0	4.2	0.0	75.0	-	-
Computational time (s)	6717.8	16210.0	1547.8	16203.9	1846.7	16200.0	58726.3	9787.7
Vehicles used	1	1	1	1	1	1	6	1
Vehicle usage rate (%)	99.42%	87.20%	85.55%	99.96%	87.80%	41.93%	-	83.64%

M = 40%								
KPI	Day 1	Day 7	Day 13	Day 19	Day 25	Day 29	Total	Average
Profit (€)	230.5	142.8	213.2	196.5	167.2	10.1	960.3	160.0
Weight (kg)	3858.9	3092.0	3534.0	3929.3	3315.9	1965.6	19695.7	3282.6
Distance (km)	136.1	150.9	122.5	176.7	147.7	176.6	910.5	151.7
Attended bins	71	62	70	83	69	45	400	67
|L|	88	56	77	89	83	49	442	74
Ratio (kg/km)	28.4	20.5	28.8	22.2	22.4	11.1	21.6	21.6
Gap (%)	0.0	6.4	0.0	2.1	1.4	0.0	-	-
Computational time (s)	4415.6	16213.2	3847.6	16212.2	16203.6	96.4	56988.6	9498.1
Vehicles used	1	1	1	1	1	1	6	1
Vehicle usage rate (%)	96.47%	77.30%	88.35%	98.23%	82.90%	49.14%	-	82.07%

M = 50%													
KPI	Day 1	Day 6	Day 8	Day 13	Day 15	Day 17	Day 19	Day 21	Day 22	Day 25	Day 30	Total	Average
Profit (€)	206.1	69.2	29.2	152.1	3.8	44.6	3.2	41.4	-48.5	34.9	197.0	732.9	66.6
Weight (kg)	3882.3	1398.6	1504.3	3065.0	520.3	1959.0	559.2	1537.4	689.8	1822.8	3383.4	20321.9	1847.4
Distance (km)	162.7	63.7	113.7	139.0	45.6	141.5	49.9	104.6	114.0	138.2	124.3	1197.1	108.8
Attended bins	68	24	29	55	10	38	32	10	14	36	60	376	34
|L|	72	34	38	61	25	43	22	41	17	44	70	467	42
Ratio (kg/km)	23.9	22.0	13.2	22.1	11.4	13.8	11.2	14.7	6.0	13.2	27.2	17.0	17.0
Gap (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	4.0	0.0	0.0
Computational time (s)	197.2	3.7	123.3	1275.6	3.5	28.8	0.7	45.3	2.3	16228.3	16200.0	34108.8	3100.8
Vehicles used	1	1	1	1	1	1	1	1	1	1	1	11	1
Vehicle usage rate (%)	97.06%	34.96%	37.61%	76.62%	13.01%	48.97%	13.98%	38.43%	17.24%	45.57%	84.58%	-	46.19%

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Results for real-case instance

Hybrid simulated-annealing/local-search metaheuristic

KPI	Day 1	Day 5	Day 6	Day 12	Day 15	Day 20	Day 24	Day 28	Day 30	Total	Average
Profit (€)	250.4	57.4	80.4	162.6	81.9	171.9	53.3	98.3	-22.8	933.4	103.7
Weight (kg)	3951.1	1112.0	2315.5	3063.4	2156.1	3901.4	1794.1	2819.6	218.0	21331.2	2370.1
Distance (km)	125.2	48.2	139.5	128.4	122.8	198.6	121.3	169.4	43.4	1097.7	121.9
Attended bins	105	30	83	93	92	126	79	102	9	719	80
Ratio (kg/km)	31.6	23.1	16.6	23.9	17.6	19.6	14.8	16.6	5.0	18.8	18.8
Comp. time (s)	2000	1400	1500	1700	1700	1900	1700	1800	1400	15000	1700
Vehicles used	1	1	1	1	1	1	1	1	1	9	1
Vehicles usage rate (%)	98.8	27.8	57.9	76.6	53.9	97.5	44.9	70.5	5.5	-	59.3

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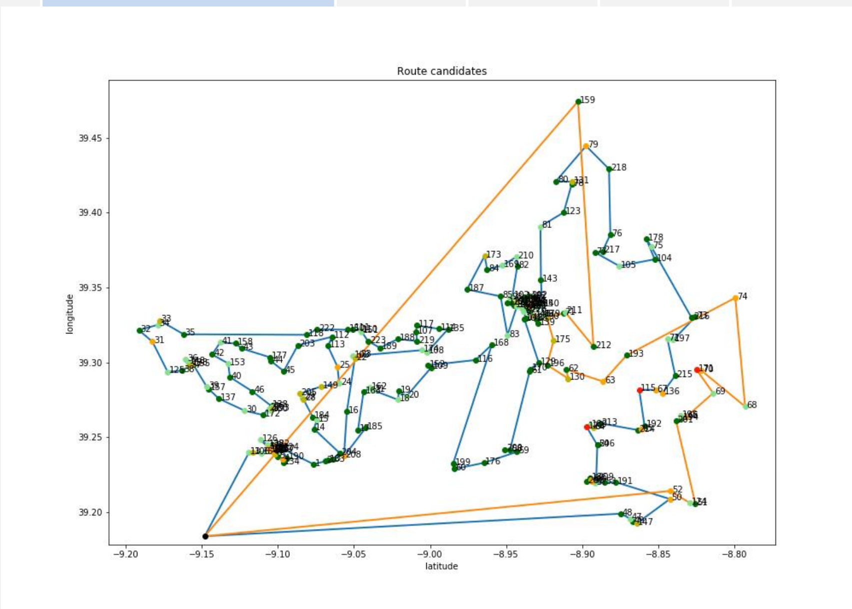
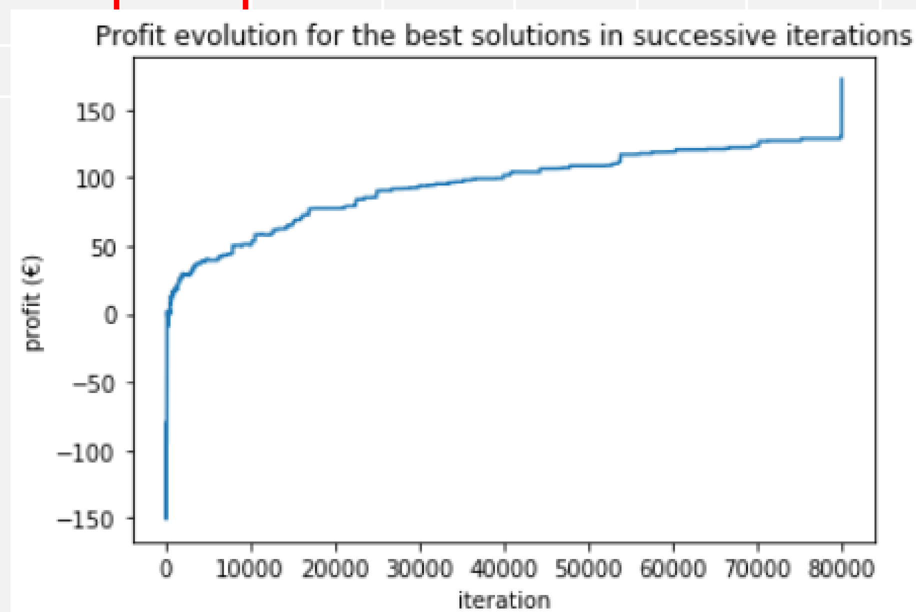
Results for real-case instance

Hybrid simulated-annealing/local-search metaheuristic

KPI	Day 1	Day 5	Day 6	Day 12	Day 15	Day 20	Day 24	Day 28	Day 30	Total	Average
Profit (€)	250.4	57.4	80.4	162.6	81.9	171.9	53.3	98.3	-22.8	933.4	103.7
Weight (kg)	3951.1	1112.0	2315.5	3063.4	2156.1	3901.4	1794.1	2819.6	218.0	21331.2	2370.1
Distance (km)	125.2	48.2	139.5	128.4	122.8	198.6	121.3	169.4	43.4	1097.7	121.9
Attended bins	105	30	83	93	92	126	79	102	9	719	80
Ratio (kg/km)	31.6	23.1	16.6	23.9	17.6	19.6	14.8	16.6	5.0	18.8	18.8
Comp. time (s)	2000	1400	1500	1700	1700	1900	1700	1800	1400	15000	1700





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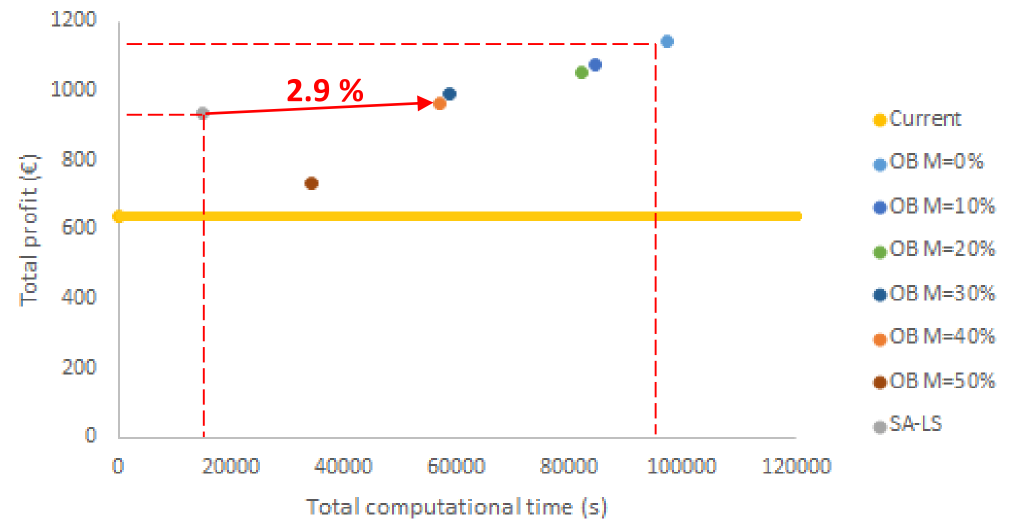
Results for real-case instance

Total

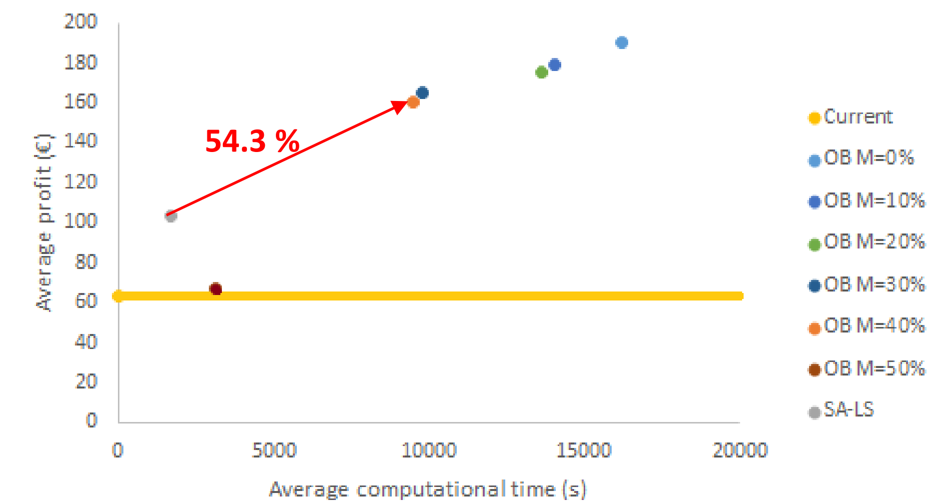
Comparation: Profit *versus* Computational time



KPI	Current situation - Total	OB - *M*=0% - Total	OB - *M*=40% - Total	SA-LS - Total
Profit (€)	636.3	1142.8	960.3 2.9 %	933.4
Attended bins	778	689	400	719
Number of routes	10	6	6	9
Ratio (kg/km)	15.1	22.5	21.6	18.8
Comp. time (s)	-	97213.3	56988.6 3.8 x	15000
Vehicles used	10	6	6	9
Vehicles usage rate (%)	-	-	-	-

Average

KPI	Current situation - Average	OB - *M*=0% - Average	OB - *M*=40% - Average	SA-LS - Average
Profit (€)	63.6	190.5	160.0 54.3 %	103.7
Attended bins	78	115	67	80
Number of routes	1	1	1	1
Ratio (kg/km)	15.1	22.5	21.6	18.8
Comp. time (s)	-	16202.3	9498.1 5.6 x	1700
Vehicles used	1	1	1	1
Vehicles usage rate (%)	55.4	94.1	82.1	59.3



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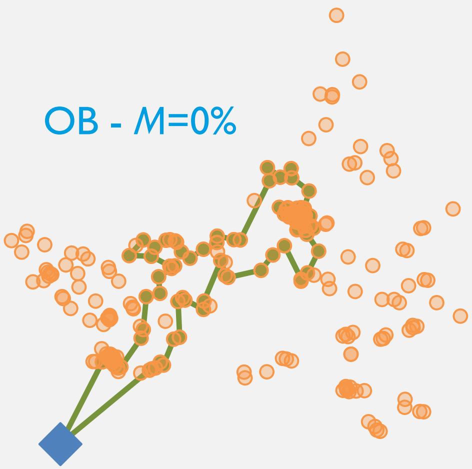
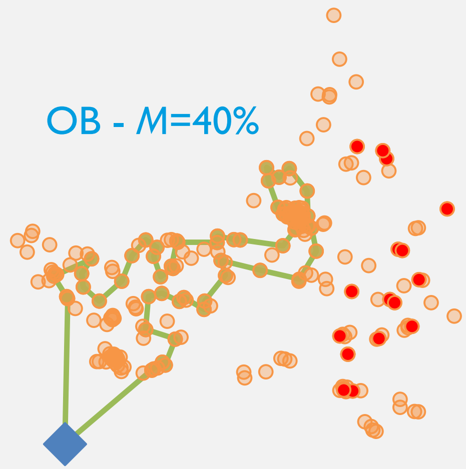
Results for real-case instance

Comparation: Day 1

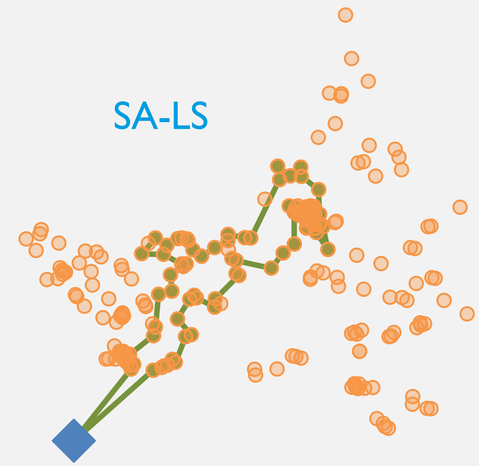
OB - *M*=0%



OB - *M*=40%



SA-LS



KPI	OB - *M*=0%	OB - *M*=40%	SA-LS
Profit (€)	253.1	230.5	250.4
Weight (kg)	3999.6	3858.9	3951.1
Distance (km)	126.8	136.1	125.2
Attended bins	98	71	105
|L|	226	88	226
Ratio (kg/km)	31.5	28.4	31.6
Gap (%)	2.8	0	-
Comp. time (s)	16201.2	4415.6	2000
Vehicles used	1	1	1
Vehicles usage rate (%)	99.9	96.5	98.8

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Conclusions

To solve the SWCRP, two new solution approaches were proposed: an optimization-based heuristic and a hybrid simulated-annealing/local-search metaheuristic;

- both approaches define more profitable routing plans comparing with the current situation: improvements from 47% to 80%;
- considering the optimization-based heuristic, the sensitive analysis on the threshold *M* shows that: as *M* increases, less computational time is required, but lower profits are obtained;
- the hybrid simulated-annealing/local-search metaheuristic proved to be faster than the optimization-based heuristic: 5 times faster;
- the optimization-based heuristic proved to find more profitable routes for the 30-day planning period than the hybrid simulated-annealing/local-search metaheuristic: 54% more profitable.

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Future Work

- Improving the optimization-based heuristic to consider not only the fill-levels, but also the locations;
- improving the hybrid simulated-annealing/local-search metaheuristic by changing parameters;
- exploring the balance between routes, limiting shift time;
- exploring Inventory Routing Problem models that allow a weekly profit maximization instead of daily.

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THANK YOU FOR YOUR ATTENTION!

WSMARTROUTE

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