

Branch-and-price algorithms for a VRP with time windows and variable departure times

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- 2 Computational experiments
- 3 Conclusions and future work

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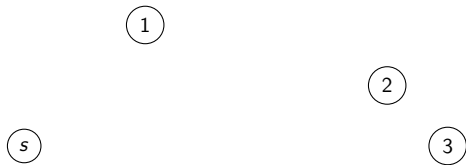
- 1 Branch-and-Price Algorithms
- 2 Computational experiments
- 3 Conclusions and future work

The problem

- Variant of the VRP with time windows
 - Objective is the total route duration.
 - Route start time is a decision variable.
 - Maximum duration defined for each route.
- Solution method: Branch-and-Price (BP)
 - The pricing problem is the Elementary Shortest Path Problem with Resource Constraints (ESPPRC).
- Basic algorithm for the ESPPRC: Feillet's label extension procedure.
- We aim to rigorously compare several advanced algorithms for the ESPPRC within a BP framework.

Standard labeling algorithm

- Each label L_i represents a partial path ending at node i .
- L_i keeps track of the consumption of resources along the partial path.



$$L_s = (C_s = 0, \mathbf{R}_s = \mathbf{0}, \mathbf{E}_s = \mathbf{0})$$

Standard labeling algorithm

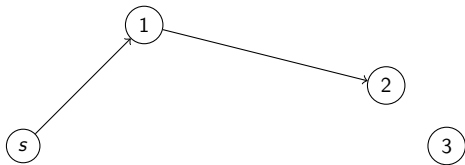
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$$L_1 = (C_1, \mathbf{R}_1, \mathbf{E}_1)$$

Standard labeling algorithm

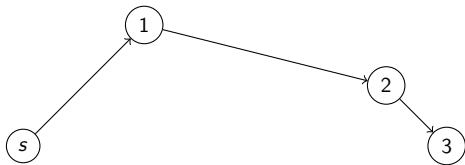
- Each label L_i represents a partial path ending at node i .
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$$L_2 = (C_2, \mathbf{R}_2, \mathbf{E}_2)$$

Standard labeling algorithm

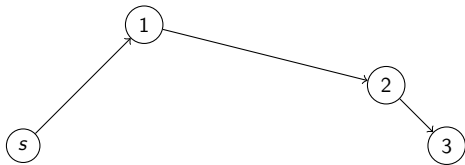
- Each label L_i represents a partial path ending at node i .
- L_i keeps track of the consumption of resources along the partial path.



$$L_3 = (C_3, \mathbf{R}_3, \mathbf{E}_3)$$

Standard labeling algorithm

- Each label L_i represents a partial path ending at node i .
- L_i keeps track of the consumption of resources along the partial path.

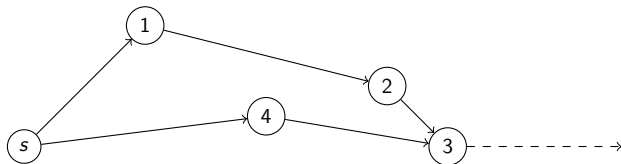


$$L_3 = (C_3, \mathbf{R}_3, e_3^1, e_3^2, \dots, e_3^n)$$

- Keeping binary resources for every node ensures elementarity.
- This makes label domination more difficult.

Standard labeling algorithm

- Each label L_i represents a partial path ending at node i .
- L_i keeps track of the consumption of resources along the partial path.



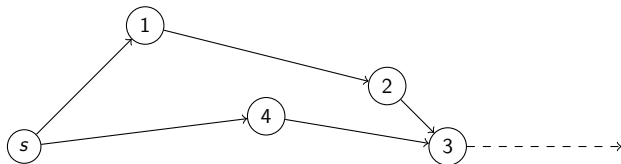
$$L_3 = (C_3, \mathbf{R}_3, e_3^1, e_3^2, \dots, e_3^n)$$

$$L'_3 = (C'_3, \mathbf{R}'_3, e_3'^1, e_3'^2, \dots, e_3'^n)$$

- Keeping binary resources for every node ensures elementarity.
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Standard labeling algorithm

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$$L'_3 = (C'_3, \mathbf{R}'_3, e_3'^1, e_3'^2, \dots, e_3'^n)$$

- Keeping binary resources for every node ensures elementarity.
- This makes label domination more difficult.
- The following algorithms relax the state space with regard to the elementarity resources.

Decremental State Space Relaxation (DSSR)¹

- Maintain a set Θ of *critical* nodes on which elementarity is enforced.

Algorithm 1 DSSR

```
1: Initialize  $\Theta$ 
2: repeat
3:    $P = \text{LabelExtension}(\Theta)$ 
4:    $\Phi = \text{MultipleVisits}(P)$ 
5:    $\Theta = \Theta \cup \Phi$ 
6: until  $P$  is elementary
```

- We manipulate the state space in a *global* way.

¹Righini and Salani 2008.

Parameters — DSSR

- Critical set initialization:
 - `dssr_init_s`: *none, tca, hca, wtca, whca, mixed*
 - `dssr_init_n`:]0, 1[
- Critical set update rules:
 - `dssr_ins_path_s`: *all-paths, one-path, in-between*
 - `dssr_ins_path_n`:]0, 1[
 - `dssr_ins_node_s`: *all-nodes, one-node, in-between*
 - `dssr_ins_node_n`:]0, 1[

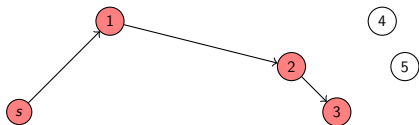
ng-route Relaxation²

- Define neighbourhoods
 $N_i, \forall i.$

²Baldacci et al. 2010.

ng-route Relaxation²

- Define neighbourhoods $N_i, \forall i$.
- E_i = set of unreachable nodes for path ending at i .

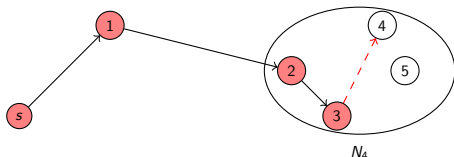


- $E_3 = \{s, 1, 2, 3\}$

²Baldacci et al. 2010.

ng-route Relaxation²

- Define neighbourhoods $N_i, \forall i$.
- $E_i =$ set of unreachable nodes for path ending at i .
- When extending to j :
 $\forall k \in E_i$, insert k in E_j only if $k \in N_j$.

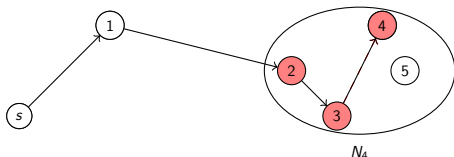


- $E_3 = \{s, 1, 2, 3\}$
- $j = 4, N_4 = \{2, 3, 4, 5\}$

²Baldacci et al. 2010.

ng-route Relaxation²

- Define neighbourhoods $N_i, \forall i$.
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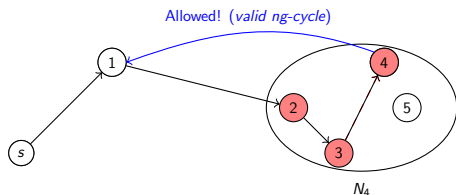


- $E_3 = \{s, 1, 2, 3\}$
- $j = 4, N_4 = \{2, 3, 4, 5\}$
- $E_4 = (E_3 \cap N_4) \cup \{4\} = \{2, 3, 4\}$

²Baldacci et al. 2010.

ng-route Relaxation²

- Define neighbourhoods $N_i, \forall i$.
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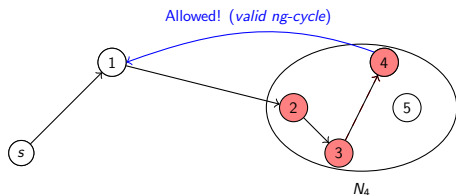


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ng-route Relaxation²

- Define neighbourhoods $N_i, \forall i$.
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 $\forall k \in E_i$, insert k in E_j only if $k \in N_j$.
- Resulting path may **not** be elementary.

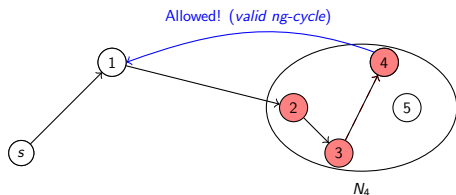


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ng-route Relaxation²

- Define neighbourhoods $N_i, \forall i$.
- $E_i =$ set of unreachable nodes for path ending at i .
- When extending to j :
 $\forall k \in E_i$, insert k in E_j only if $k \in N_j$.
- Resulting path may **not** be elementary.
- We manipulate the state space in a *local* way.



- $E_3 = \{s, 1, 2, 3\}$
- $j = 4, N_4 = \{2, 3, 4, 5\}$
- $E_4 = (E_3 \cap N_4) \cup \{4\} = \{2, 3, 4\}$

²Baldacci et al. 2010.

Parameters — *ng-route*

- Neighborhood size `ng_size`: $]0, 1[$
- Node metric `ng_type`: *travel-time*, *cycle-risk*, *mixed*
- Coefficient for the mixed metric `ng_mix`: $]0, 1[$

ng-route Relaxation and DSSR

- We can combine both algorithms in several ways.
- The straightforward combination uses both neighbourhoods and the set of critical nodes.

Algorithm 2 ng-DSSR-global

- 1: Initialize Θ , $N_i \forall i$
 - 2: **repeat**
 - 3: $P = \text{LabelExtension}(\Theta, N_i)$
 - 4: $\Phi = \text{MultipleVisits}(P, \{N_i\}_i)$ {Only takes nodes in invalid ng-cycles}
 - 5: $\Theta = \Theta \cup \Phi$
 - 6: **until** P is ng-route
-

ng-route Relaxation and DSSR

- Let us define *applied* neighbourhoods $\hat{N}_i \subseteq N_i \forall i$ to use throughout label extension³.
- When best path has invalid cycle C , update applied neighbourhoods of nodes in C .

Algorithm 3 ng-DSSR-local

- 1: Initialize $N_i, \hat{N}_i, \forall i$
 - 2: **repeat**
 - 3: $P = \text{LabelExtension}(\{\hat{N}_i\}_i)$
 - 4: $C = \text{InvalidCycle}(P, \{N_i\}_i)$
 - 5: Update $(\{\hat{N}_i\}_i, C)$
 - 6: **until** P is ng-route
-

³Dayarian et al. 2015.

ng-route Relaxation and DSSR

- We can derive a different version of DSSR using this local approach⁴.
- Let us define local critical sets $\hat{\Theta}_i, \forall i$.
- When best path has cycle C , update critical sets of nodes in C .

Algorithm 4 DSSR-local

- 1: Initialize $\hat{\Theta}_i, \forall i$
 - 2: **repeat**
 - 3: $P = \text{LabelExtension}(\{\hat{\Theta}_i\}_i)$
 - 4: $C = \text{Cycle}(P)$
 - 5: Update $(\{\hat{\Theta}_i\}_i, C)$
 - 6: **until** P is elementary
-

⁴Martinelli, Pecin, and Poggi 2014.

ng-route Relaxation and DSSR

- ng-DSSR-local (global) outputs ng-routes.
- We can follow-up with DSSR-local (global) to obtain elementary routes.

Algorithm 5 ng-DSSR-local, corrected

- 1: $P = \text{ng-DSSR-local}()$
 - 2: **if** P is not elementary **then**
 - 3: $P = \text{DSSR-local}(P)$
 - 4: **end if**
-

Branch-and-Price framework

- After solving the linear relaxation at the root node, solve the integer program with the available columns to obtain an upper bound.
- Branch on the most fractional arc.
- Parameters:
 - Maximum number of generated paths `concat_stop`: $]0, 10000]$
 - Maximum number of paths inserted in the master problem `num_col`: $]0, 1[$
 - Tree navigation strategy `tree_nav`:
 - Depth-first search
 - Breadth-first search
 - Best-first search

Overview

- *ng*-route relax.
 - *ng*-DSSR-global
 - *ng*-DSSR-local
- } *ng*-routes
-
- DSSR
 - Local DSSR
 - *ng*-DSSR-global, corrected
 - *ng*-DSSR-local, corrected
- } Elementary routes

Parameters

Parameter	DSSR	<i>ng-r.</i>	G. <i>ng-D.</i>	L. <i>ng-D.</i>	L. DSSR	G. <i>ng-D., corr.</i>	L. <i>ng-D., corr.</i>	Range
<i>tree_trav</i>	×	×	×	×	×	×	×	{breadth, depth, best}
<i>n_conc</i>	×	×	×	×	×	×	×]0, 10000]
<i>n_col</i>	×	×	×	×	×	×	×]0, 1]
<i>dssr_init_s</i>	×		×		×	×		{hca, tca, whca, wtca, mix}
<i>dssr_init_n</i>	×		×		×	×]0, 1[
<i>dssr_path_s</i>	×		×	×	×	×	×	{1_path, in_btw, all_paths}
<i>dssr_path_n</i>	×		×	×	×	×	×]0, 1[
<i>dssr_node_s</i>	×		×			×		{1_node, in_btw, all_nodes}
<i>dssr_node_n</i>	×		×			×]0, 1[
<i>ng_type</i>		×	×	×		×	×	{tt, ccr, mix}
<i>ng_size</i>		×	×	×		×	×]0, 1[
<i>ng_mix</i>		×	×	×		×	×]0, 1[

Table: Parameters choices

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Methodology

- Tune the parameters with the `irace` package⁵
- The tuning set is derived from the Gehring & Homberger instances for the VRPTW.
- Set of 6 instances, one per type (clustered, random, random-clustered) and per size (25 and 50 customers).
- Tuning budget of 5000 experiments for each algorithm, time limit $TL = 3$ hours per experiment.
- Measure of performance:

$$\left\{ \begin{array}{ll} t & \text{if } t < TL \text{ seconds (3 hours)} \\ TL + \text{best UB} & \text{if best UB has been obtained} \\ \text{big M} & \text{otherwise} \end{array} \right.$$

- Run the best configuration of each algorithm on the Solomon instances.
- Perform Friedman test + post-hoc Wilcoxon signed rank test on the results.

⁵López-Ibáñez et al. 2016.

Statistical tests on Solomon instances

- The Friedman test reports a p-value $< 2.2e-16$, denoting statistically significant difference among the data
- Post-hoc test reports that Local DSSR outperforms DSSR, ng-route relaxation, global ng-DSSR, and global corrected ng-DSSR with a p-value $< 1e-7$
- Local DSSR, local ng-DSSR and its corrected version are statistically equivalent

Solved instances

	DSSR	DSSR-L	NG	NG-DSSR-G	NG-DSSR-L	NG-DSSR-G-C	NG-DSSR-L-C
C1-25	(5, 1, 3)	(6, 3, 0)	(5, 4, 0)	(5, 2, 2)	(5, 4, 0)	(5, 1, 3)	(5, 3, 1)
R1-25	(12, 0, 0)	(12, 0, 0)	(12, 0, 0)	(12, 0, 0)	(12, 0, 0)	(12, 0, 0)	(12, 0, 0)
RC1-25	(8, 0, 0)	(8, 0, 0)	(8, 0, 0)	(8, 0, 0)	(8, 0, 0)	(8, 0, 0)	(8, 0, 0)
C1-50	(4, 0, 5)	(6, 0, 3)	(6, 0, 3)	(4, 0, 5)	(5, 1, 3)	(5, 0, 4)	(6, 1, 2)
R1-50	(5, 6, 1)	(9, 3, 0)	(7, 5, 0)	(6, 6, 0)	(9, 3, 0)	(5, 7, 0)	(10, 2, 0)
RC1-50	(0, 6, 2)	(1, 7, 0)	(1, 7, 0)	(1, 7, 0)	(1, 7, 0)	(1, 7, 0)	(1, 7, 0)

Table: Solved Solomon instances, 3 hour time limit

$$(n_s, n_p, n_u)$$

- $n_s = \#$ of solved instances
- $n_p = \#$ of partially solved instances (at least the root node)
- $n_u = \#$ of unsolved instances

Additional tests

- We run the best four algorithms on the Solomon instances for 6 hours, on 25, 50, 75 and 100 customers
- The Friedman test reports a p-value = $5.093e-5$
- Post-hoc reports that ng is rejected with p-value <0.01 by the other algorithms

Solved instances — 2

	DSSR-L	NG-DSSR-L-C	NG	NG-DSSR-L
C1-25	(7, 2, 0)	(6, 3, 0)	(6, 3, 0)	(7, 2, 0)
R1-25	(12, 0, 0)	(12, 0, 0)	(12, 0, 0)	(12, 0, 0)
RC1-25	(8, 0, 0)	(8, 0, 0)	(8, 0, 0)	(8, 0, 0)
C1-50	(6, 1, 2)	(6, 1, 2)	(6, 0, 3)	(6, 1, 2)
R1-50	(9, 3, 0)	(10, 2, 0)	(8, 4, 0)	(9, 3, 0)
RC1-50	(2, 6, 0)	(1, 7, 0)	(1, 7, 0)	(1, 7, 0)
C1-75	(5, 1, 3)	(5, 1, 3)	(5, 0, 4)	(5, 0, 4)
R1-75	(3, 9, 0)	(4, 8, 0)	(4, 8, 0)	(4, 8, 0)
RC1-75	(0, 8, 0)	(0, 8, 0)	(0, 8, 0)	(1, 7, 0)
C1-100	(5, 0, 4)	(5, 0, 4)	(4, 0, 5)	(5, 0, 4)
R1-100	(2, 2, 8)	(3, 1, 8)	(2, 2, 8)	(3, 1, 8)
RC1-100	(0, 2, 6)	(0, 2, 6)	(0, 3, 5)	(0, 5, 3)

Table: Solved Solomon instances, 6 hour time limit

Solved instances — 2

	DSSR-L				NG-DSSR-L-C			
	gap	root gap	time	nodes	gap	root gap	time	nodes
C1-25	0.17%	0.17%	7547.5	51.0	0.13%	0.13%	9236.3	54.8
C1-50	0.01%	0.01%	8333.8	2.1	0.01%	0.01%	7604.8	2.0
C1-75	0.07%	0.07%	11974.3	1.6	0.10%	0.10%	10592.8	1.2
C1-100	0.0%	0.0%	10653.5	0.6	0.00%	0.00%	10130.8	0.6
R1-25	0.42%	0.56%	12.1	7.8	0.42%	0.56%	23.1	14.5
R1-50	0.84%	0.94%	6546.3	167.8	0.76%	1.03%	6600.6	539.2
R1-75	1.02%	1.03%	16213.6	77.2	0.92%	1.05%	16041.1	257.2
R1-100	0.42%	0.50%	19520.2	93.4	0.39%	0.48%	18881.6	93.8
RC1-25	1.15%	1.15%	11.2	25.5	1.15%	1.15%	24.3	13.5
RC1-50	5.67%	5.70%	18819.6	8677.4	5.60%	5.71%	19051.6	8616.4
RC1-75	3.12%	3.14%	21600	1587.3	3.03%	3.10%	21600	2717.1
RC1-100	1.27%	1.78%	21600	261.6	1.72%	1.72%	21600	366.1

Table: Performance on Solomon instances, 6 hour time limit — 1

Solved instances — 2

	NG				NG-DSSR-L			
	gap	root gap	time	nodes	gap	root gap	time	nodes
C1-25	0.17%	0.17%	9125.1	189.3	0.43%	0.47%	8845.6	112.8
C1-50	0.01%	0.01%	7820.6	1.6	0.01%	0.01%	7817.9	1.9
C1-75	0.08%	0.08%	11607.5	1.4	0.08%	0.09%	11262.3	1.4
C1-100	0.00%	0.00%	12608.4	0.4	0.00%	0.00%	10545.3	0.8
R1-25	0.60%	0.78%	33.3	33.0	0.48%	0.69%	13.1	9.2
R1-50	1.00%	1.21%	8317.2	978.5	0.84%	1.04%	6823.3	333.6
R1-75	0.98%	1.08%	15062.0	196.5	1.01%	1.03%	15375.1	176.8
R1-100	0.38%	0.44%	19211.7	59.6	0.39%	0.56%	17823.0	120.5
RC1-25	1.97%	3.77%	1968.1	786.5	1.19%	1.19%	96.8	17.5
RC1-50	6.33%	6.72%	19907.2	10364.8	5.87%	6.14%	18992.2	10211.4
RC1-75	3.50%	3.65%	21600	3591.0	3.26%	3.27%	21101.7	3030.5
RC1-100	1.97%	1.97%	21600	470.8	2.05%	2.38%	21600	302.9

Table: Performance on Solomon instances, 6 hour time limit — 2

Parameter configurations

	n_col_root	conc_stop_root	n_col	conc_stop	tree_nav
DSSR-L					
Best	82%	2820	31%	9247	best-first
Avg	42%	3998	35%	8902	best-first (5)
Range	[10%,81%]	[2764,8481]	[22%,63%]	[7308,9867]	
NG-DSSR-L-C					
Best	27%	7910	42%	9845	depth-first
Avg	45%	5949	37%	8688	depth-first (6)
Range	[26%,98%]	[1003,8320]	[36%,42%]	[5234,9923]	
NG-DSSR-L					
Best	4%	8752	14%	3079	depth-first
Avg	10%	6900	24%	3540	depth-first (6)
Range	[1%,35%]	[5476,8752]	[11%,63%]	[1100,4519]	

Table: BP parameters

Parameter configurations

	init_str_root	init_n_root	ins_path_str_root	ins_path_n_root
DSSR-L				
Best	none	n/a	in-between	25%
Avg	none (6)		in-between (6)	38%
Range				[24%,47%]
NG-DSSR-L-C				
Best	n/a	n/a	one-path	n/a
Avg			one-path (6)	
Range				
NG-DSSR-L				
Best	n/a	n/a	all-paths	n/a
Avg			all-paths (5)	
Range				

Table: DSSR parameters, root

Parameter configurations

	init_str	init_n	ins_path_str	ins_path_n
DSSR-L				
Best	none	n/a	in-between	39%
Avg	none (6)		in-between (6)	57%
Range				[38%,80%]
NG-DSSR-L-CORR				
Best	n/a	n/a	in-between	98%
Avg			in-between (6)	81%
Range				[72%,97%]
NG-DSSR-L				
Best	n/a	n/a	in-between	35%
Avg			in-between (6)	31%
Range				[26%,34%]

Table: DSSR parameters

Parameter configurations

	ng_type_root	ng_size_root	ng_type	ng_size
NG-DSSR-L CORR				
Best	travel-time	6%	travel-time	23%
Avg	travel-time (5)	9%	travel-time (6)	24%
Range		[4%,21%]		[16%,45%]
NG-DSSR-L				
Best	travel-time	17%	travel-time	88%
Avg	travel-time (6)	17%	travel-time (5)	81%
Range		[14%,24%]		[50%,97%]

Table: NG parameters

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Conclusions

- It is a good idea to use a strong methodology for comparing algorithm performance.
- “Local” approach for treating elementarity resources works.
- It makes sense to parametrize differently the algorithm in the root node.
- Best parameter values might be different than the ones suggested in the literature.

Current work

- Perform an instance size—dependant tuning of the best algorithms and compare it with the current ones.
- Perform the same experiments on the classic VRPTW.
- Adapt the algorithms to the multitrip VRPTW.

Thanks for your attention.