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p -step formulations for vehicle routing problems: a generalized class of models based on column generation

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- ▶ Conclusions and future work.

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$$\lambda_r = \begin{cases} 1, & \text{if route } r \text{ is used in the solution;} \\ 0, & \text{o.w.} \end{cases}$$

Two-index vehicle flow formulation (CVRP)

$$\begin{aligned} \min \quad & \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} c_{ij} x_{ij} \\ \text{s.t.} \quad & \sum_{\substack{j=1 \\ j \neq i}}^{n+1} x_{ij} = 1, & i = 1, \dots, n, \\ & \sum_{\substack{i=0 \\ i \neq h}}^n x_{ih} - \sum_{\substack{j=1 \\ j \neq h}}^{n+1} x_{hj} = 0, & h = 1, \dots, n, \\ & \sum_{j=1}^n x_{0j} \leq K, \\ & y_j \geq y_i + q_j x_{ij} - Q(1 - x_{ij}), & i, j = 0, \dots, n+1, \\ & d_i \leq y_i \leq Q, & i = 0, \dots, n+1, \\ & x_{ij} \in \{0, 1\}, & i, j = 0, \dots, n+1. \end{aligned}$$

Set partitioning formulation (CVRP)

$$\begin{aligned} \min \quad & \sum_{r \in \mathcal{R}} c_r \lambda_r \\ \text{s.t.} \quad & \sum_{r \in \mathcal{R}} a_{ri} \lambda_r = 1, \quad i = 1, \dots, n, \\ & \sum_{r \in \mathcal{R}} \lambda_r \leq K, \\ & \lambda_r \in \{0, 1\}, \quad r \in \mathcal{R}. \end{aligned}$$

- ▶ \mathcal{R} : set of feasible (complete) routes;
- ▶ Routes generated by solving Resource Constrained Elementary Shortest Path Problems (or relaxations).

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- ▶ They are particular cases of a generalized formulation.

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 - ▶ all k -step paths ($1 \leq k < p$) that starts on 0 (depot).
- ▶ For each $s \in \mathcal{S}$ we have the decision variable:

$$\lambda_s = \begin{cases} 1, & \text{if partial path } s \text{ is used in the solution;} \\ 0, & \text{o.w.} \end{cases}$$

p -step formulation (CVRP)

$$\begin{array}{ll}
\min & \sum_{s \in \mathcal{S}} c_s \lambda_s \\
\text{s.t.} & \sum_{s \in \mathcal{S}} e_i^s \lambda_s = 1, & i = 1, \dots, n, \\
& \sum_{s \in \mathcal{S}} a_i^s \lambda_s = 0, & i = 1, \dots, n, \\
& \sum_{s \in \mathcal{S}} a_0^s \lambda_s \leq K, \\
\varphi_j \geq \varphi_i + q_j & \sum_{s \in \mathcal{S}_{ij}} \lambda_s - Q(1 - \sum_{s \in \mathcal{S}_{ij}} \lambda_s), & i = 0, \dots, n, j = 1, \dots, n+1, \\
& q_i \leq \varphi_i \leq Q, & i = 1, \dots, n, \\
& \lambda_s \in \{0, 1\}, & s \in \mathcal{S}.
\end{array}$$

p -step formulation (CVRP)

- ▶ c_s is the total cost of traversing arcs in path s ;
- ▶ e^s and a^s are $n + 1$ -vectors defined as

$$e_i^s = \begin{cases} +1, & \text{if } i \text{ is visited by path } s, \text{ but it is not the last node of } s, \\ 0, & \text{otherwise,} \end{cases}$$

$$a_i^s = \begin{cases} +1, & \text{if } i \text{ is the first node visited by path } s, \\ -1, & \text{if } i \text{ is the last node visited by path } s, \\ 0, & \text{otherwise,} \end{cases}$$

for all $i = 0, 1, \dots, n$ and $s \in \mathcal{S}$.

- ▶ $\mathcal{S}_{ij} \subset \mathcal{S}$ contains only the paths that traverse arc (i, j) for a pair $i, j \in \mathcal{N}$.

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p -step formulation (VRPTW)

$$\begin{aligned}
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 \text{s.t.} \quad & \sum_{s \in \mathcal{S}} e_i^s \lambda_s = 1, & i = 1, \dots, n, \\
 & \sum_{s \in \mathcal{S}} a_i^s \lambda_s = 0, & i = 1, \dots, n, \\
 & \sum_{s \in \mathcal{S}} a_0^s \lambda_s \leq K, \\
 & \varphi_j \geq \varphi_i + q_j \sum_{s \in \mathcal{S}_{ij}} \lambda_s - Q(1 - \sum_{s \in \mathcal{S}_{ij}} \lambda_s), & i = 0, \dots, n, j = 1, \dots, n+1, \\
 & \omega_j \geq \omega_i + (s_i + t_{ij}) \sum_{s \in \mathcal{S}_{ij}} \lambda_s - M(1 - \sum_{s \in \mathcal{S}_{ij}} \lambda_s), & i = 0, \dots, n, j = 1, \dots, n+1, \\
 & q_i \leq \varphi_i \leq Q, & i = 1, \dots, n, \\
 & w_i^a \leq \omega_i \leq w_i^b, & i = 0, \dots, n+1, \\
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- ▶ The good point is that the number of partial paths is small (quadratic), so path generation is easy and quick;
- ▶ In the $(n + 1)$ -step formulation all arcs are already attached, so the model has less freedom when assigning value to them (and the feasible set of the linear relaxation becomes more restricted);
- ▶ The number of paths is huge (exponential) and requires column generation, label-setting and branch-and-price.

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Proposition 2. Let \tilde{z}_p be the optimal value of the linear relaxation of the p -step formulation, for $p = 1, \dots, n + 1$. For any $p \in \{1, \dots, n\}$, we have that $\tilde{z}_{p+1} \geq \tilde{z}_p$.

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Proof. (cont.) Hence, both formulations have all k -step paths starting on 0, for $k = 1, \dots, p$. The difference between them lies in the partial paths starting on $v_0 > 0$ and in the $(p+1)$ paths starting on 0.

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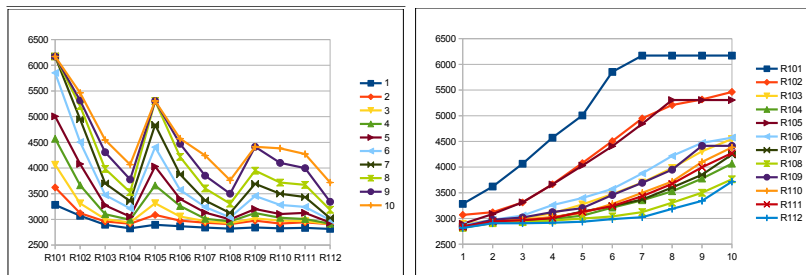


Figure 1. Objective values of the linear relaxations for class R1.

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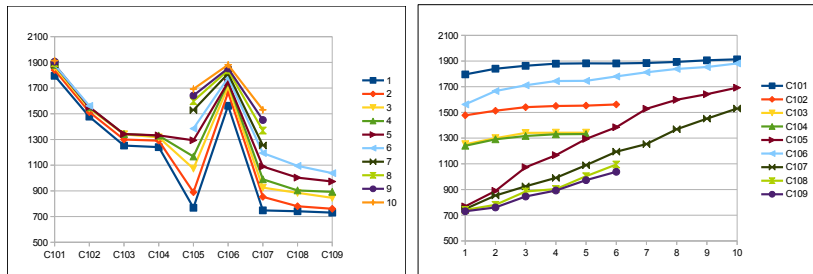


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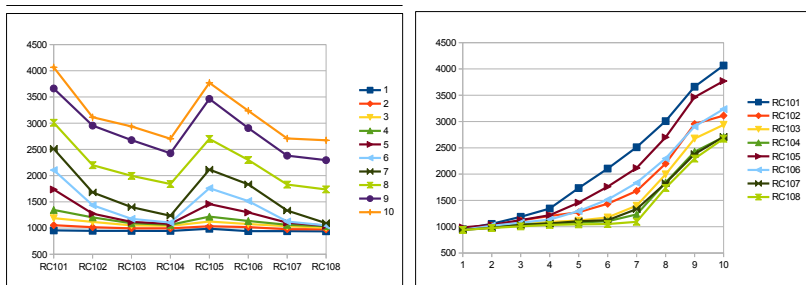


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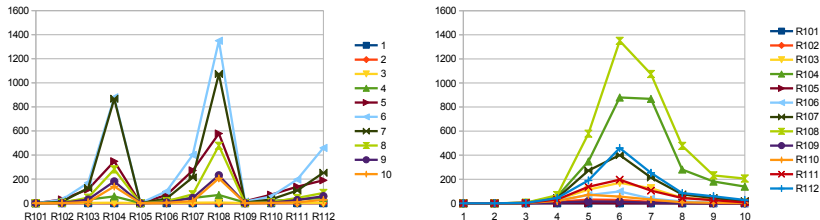


Figure 4. Computational times to solve the linear relaxations for class R1.

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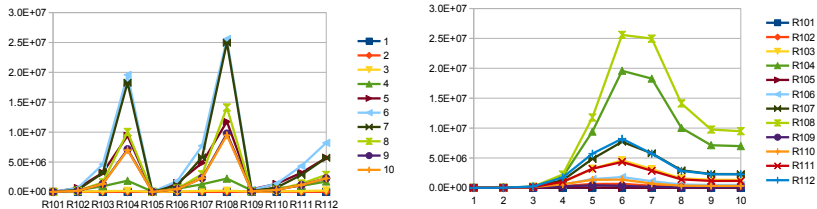


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Restricted master problem, with $\bar{\mathcal{S}} \subset \mathcal{S}$:

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- ▶ This allows for any type of partitioning in the label-extension, instead of two partitions only (e.g. several partitions of time).

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- ▶ Future developments: branch-price-and-cut for p -step formulations; extending the idea of p -step formulations to other types of optimization problems.

Thank you!

Acknowledgments



My webpage

<http://www.dep.ufscar.br/docentes/munari>

PDCGM webpage

<http://www.maths.ed.ac.uk/~gondzio/software/pdcm.html>