OPERATIONS RESEARCH CENTER

Electric Vehicle Routing: Subpath-Based Decomposition

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Motivation, problem setting

Biden administration plan seeks elimination of transportation emissions

calls for a transition to electric vehicles and more walkable neighborhoods by 2050

A 40-ton Mercedes-Benz e-truck just drove 1,000 km with only one stop to charge

Michelle Lewis | Oct 5 2023 - 10:48 am PT | 66 Comments

LOGISTICS REPORT

California's Electric-Truck Drive Draws Startups Building Charging Networks

aggressive emissions-slashing mandate means thousands of
arging sites are needed in the coming years

Paul Berger Follow

y 29, 2023 7:00 am ET

Biden administration plan calls for $5 billion network of electric-vehicle chargers along interstates

Grants included in the infrastructure law will help states build a charging network designed to reach highways in almost every corner of the country

By Ian Duncan

Updated February 10, 2022 at 1:46 p.m. EST | Published February 10, 2022 at 5:00 a.m. EST

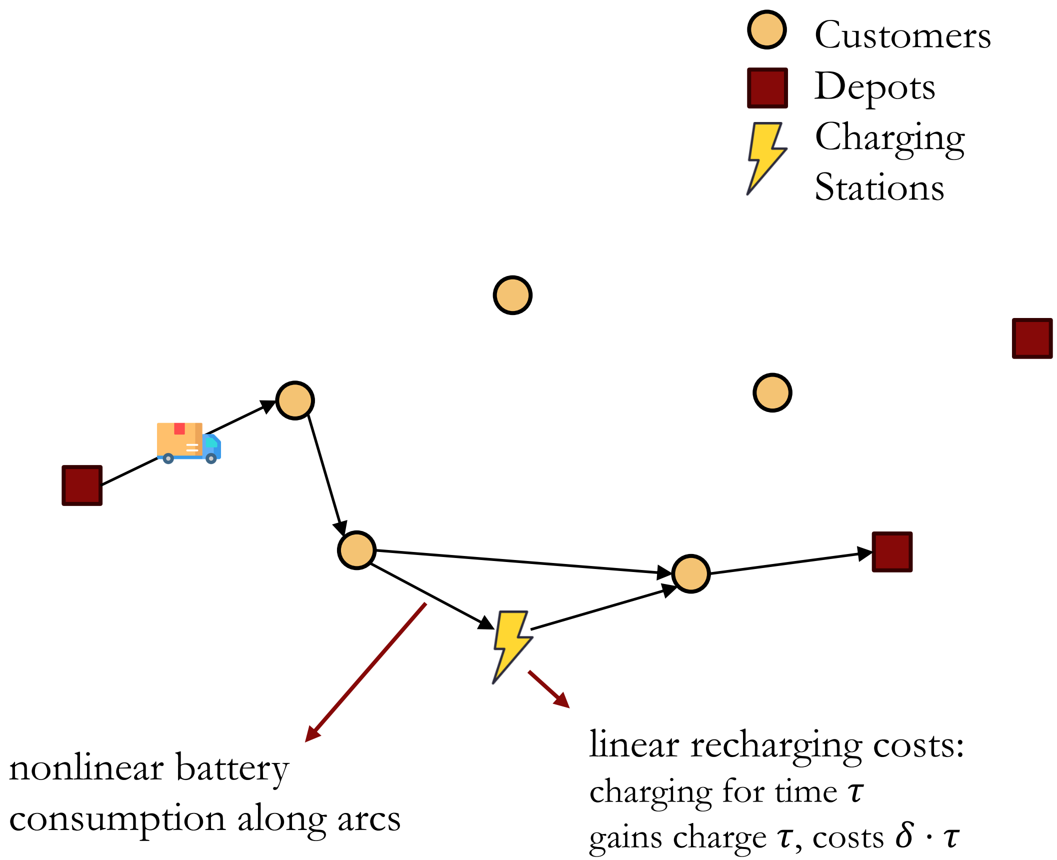
New routing algorithms for electrified logistics

Contributions

Electric vehicle routing: subpath-based decomposition algorithm

Modeling	Electric vehicle routing: semi-infinite set-partitioning formulation with continuous time and continuous charge
Optimization	• Subpath-based decomposition algorithm for column generation subproblem • Iteratively growing *ng*-route neighborhoods to yield linear relaxation solution with elementary paths • Cutting planes to strengthen linear relaxation
Computational results	Significantly outperforms path-based benchmark, and scales to realistic problem instances
Practical impact	Benefits over "business-as-usual" routing operations

The Electric VRP



Semi-infinite set-partitioning model

$$
\begin{array}{llll}
\min & \displaystyle\sum_{p\in\mathcal{P}} c^p z^p & & \text{(minimize total cost of paths)} \\
\text{s.t.} & \displaystyle\sum_{p\in\mathcal{P}} \mathbb{1}\left(n^p_{\text{start}} = j\right) z^p = v_j^{\text{start}} & \forall \text{ depots } j & \text{(each depot } j \text{ starts with } v_j^{\text{start}} \text{ vehicles)} \\
& \displaystyle\sum_{p\in\mathcal{P}} \mathbb{1}\left(n^p_{\text{end}} = j\right) z^p \geq v_j^{\text{end}} & \forall \text{ depots } j & \text{(each depot } j \text{ ends with at least } v_j^{\text{end}} \text{ vehicles)} \\
& \displaystyle\sum_{p\in\mathcal{P}} \gamma_i^p z^p = 1 & \forall \text{ customers } j & \text{(each customer served once)} \\
& z^p \in \mathbb{Z}_+ & \forall\, p \in \mathcal{P} &
\end{array}
$$

- Set-partitioning formulation with path-based variables z^p
- Infinitely many variables
  - **Discrete** routing and timing decisions (as in traditional VRP)
  - **Continuous** charging decisions (new to E-VRP)

Column generation

Restricted Master Problem

$$
\begin{aligned}
\min \quad & \sum_{p \in \mathcal{P}'} c^p z^p \\
\text{s.t.} \quad & \sum_{p \in \mathcal{P}'} \mathbb{1}\left(n^p_{\text{start}} = j\right) z^p = v^{\text{start}}_j && \forall \text{ depots } j && [\boldsymbol{\kappa}] \\
& \sum_{p \in \mathcal{P}'} \mathbb{1}\left(n^p_{\text{end}} = j\right) z^p \geq v^{\text{end}}_j && \forall \text{ depots } j && [\boldsymbol{\mu}] \\
& \sum_{p \in \mathcal{P}'} \gamma^p_i z^p = 1 && \forall \text{ customers } j && [\boldsymbol{\nu}] \\
& z^p \in \mathbb{Z}_+ && \forall\, p \in \mathcal{P}'
\end{aligned}
$$

dual values $\boldsymbol{\kappa}, \boldsymbol{\mu}, \boldsymbol{\nu}$

Pricing Problem

$$
\min_{p \in \mathcal{P}} \left\{ \bar{c}^p := c^p - \kappa_{\text{start}(p)} - \mu_{\text{end}(p)} - \sum_{i \in \mathcal{V}_C} \gamma^p_i \nu_i \right\}
$$

paths not in $\mathcal{P}'$

Challenges:

1. How to solve the pricing problem?
2. How to ensure finite convergence?

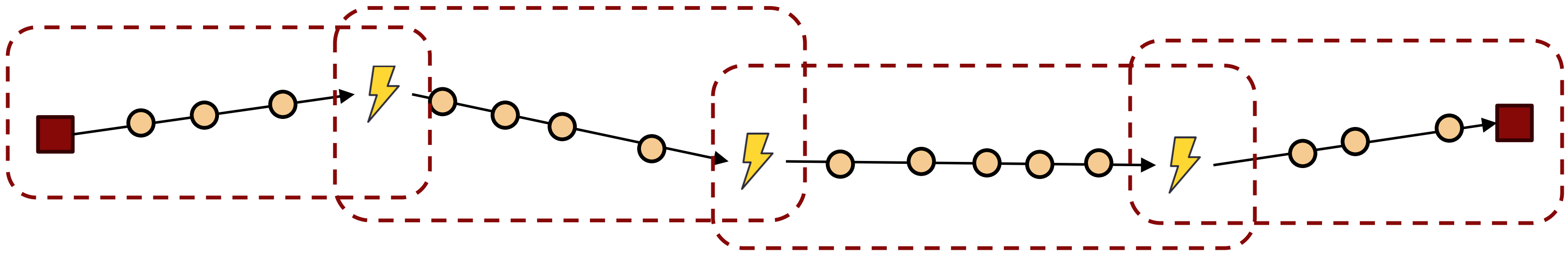
Challenges

1. **The pricing problem in CG**
2. **Finite termination of CG**
3. **Path elementarity**
4. **Eliminating fractional solutions**

Required for correctness of CG in solving LP relaxation of EVRP

Acceleration strategies and relaxation tightening

Pricing problem in CG



- Finding paths of negative reduced cost via DP
  - Resource-Constrained Shortest Path Problem (RCSPP)[1]

Extend partial paths along edges

Prune "dominated" paths using domination criteria

$$D(p) = \Big(\bar{c}(p),\ t(p),\ -b(p)\Big)$$

reduced cost | time | (negative of) charge

Challenges:

1. Grows exponentially with no. of customers
2. How to determine charging time? → Extra labels[2]

[1] Irnich, S., & Desaulniers, G. (2005). Shortest Path Problems with Resource Constraints. In G. Desaulniers, J. Desrosiers, & M. M. Solomon (Eds.), *Column Generation* (pp. 33–65). Springer US. https://doi.org/10.1007/0-387-25486-2_2

[2] Desaulniers, G., Errico, F., Irnich, S., & Schneider, M. (2016). Exact Algorithms for Electric Vehicle-Routing Problems with Time Windows. Operations Research, 64(6), 1388–1405. https://doi.org/10.1287/opre.2016.1535

Key idea: two-level label-setting

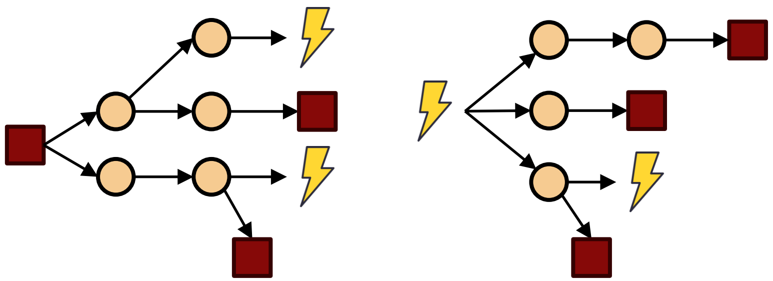
Level 1: Generate **subpaths** s

- Label-setting, with domination criteria:

$$D(s) = \left(\bar{c}(s),\ t(s),\ b(s)\right)$$

Level 2: Extend **paths** p along subpaths s

- A subpath valid at time 0 is still valid at time t with the same reduced cost
- Charging action between subpaths is the minimum possible
- Reduced cost of path = r.c. of subpaths + r.c. of charging actions



A closer look at domination

Our work:

Def: $s_1 \succcurlyeq_L s_2$ if: $L(s_1) \leq L(s_2)$

$$D(s) = \Big(\underbrace{\bar{c}(s)}_{\text{reduced cost}},\ \underbrace{t(s)}_{\text{time taken}},\ \underbrace{b(s)}_{\text{charge taken}}\Big)$$

Traditionally[1]:

Def: $p_1 \succcurlyeq_L p_2$ if: $L(p_1) \leq L(p_2)$

$$D(p) = \Big(\underbrace{\bar{c}(p)}_{\text{reduced cost}},\ \underbrace{t(p)}_{\text{time}},\ \underbrace{-b(p)}_{\text{(negative of) charge}}\Big)$$

$s_1 \succcurlyeq_L s_2$

2 — $s_1 \oplus e \succcurlyeq_L s_2 \oplus e$ for any edge e

3 — $p \oplus s_1 \succcurlyeq_L p \oplus s_2$ for any path p

$p_1 \succcurlyeq_L p_2$

1 — $p_1 \oplus s \succcurlyeq_L p_2 \oplus s$ for any subpath s

[1] Irnich, S., & Desaulniers, G. (2005). Shortest Path Problems with Resource Constraints. In G. Desaulniers, J. Desrosiers, & M. M. Solomon (Eds.), *Column Generation* (pp. 33–65). Springer US. https://doi.org/10.1007/0-387-25486-2_2

Key results

Theorem 1: Two-level label-setting finds negative reduced-cost paths, or certifies that none exists

Proof (sketch):

- Use properties 1 2 3 arising from domination criteria

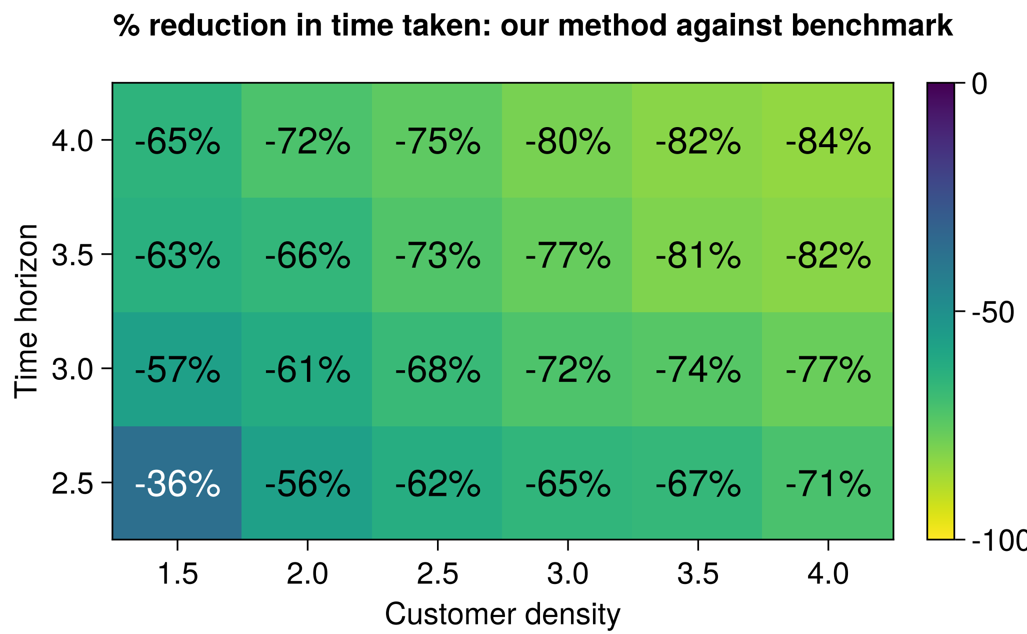
Theorem 2: With two-level label-setting, CG converges **finitely** to LP optimum of EVRP

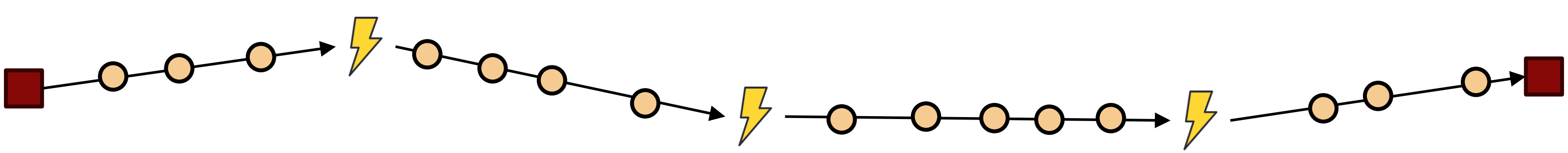
Proof (sketch):

- infinitely many paths, but finitely many subpath sequences
- once a path is added to RMP, no other path w/ same subpath sequence will be added in future iterations

Comparison to benchmark

- Significant speedups against path-based benchmark
- Stronger improvement with:
  - Higher customer density ≈ **longer subpaths**
  - Longer time horizon ≈ **more subpaths per path**





Challenges

1. The pricing problem in CG
2. Finite termination of CG
3. **Path elementarity**
4. Eliminating fractional solutions

The elementarity constraint

- Ideally, each path serves each customer at most once! (elementarity)
- Affects the structure of the label-setting in the pricing problem:

Option 1:
Ignore elementarity

Option 2:
Enforce elementarity

Q: can we get the best of both worlds?

One binary resource per customer[1]:

$$D(p) = \Big(\bar{c}(p),\ t(p),\ -b(p),\ \overbrace{\gamma_1^p, \ldots, \gamma_n^p}\Big)$$

Option 1:

- \+ Computationally cheap!
- − Good LP solutions, but bad IP solutions

Option 2:

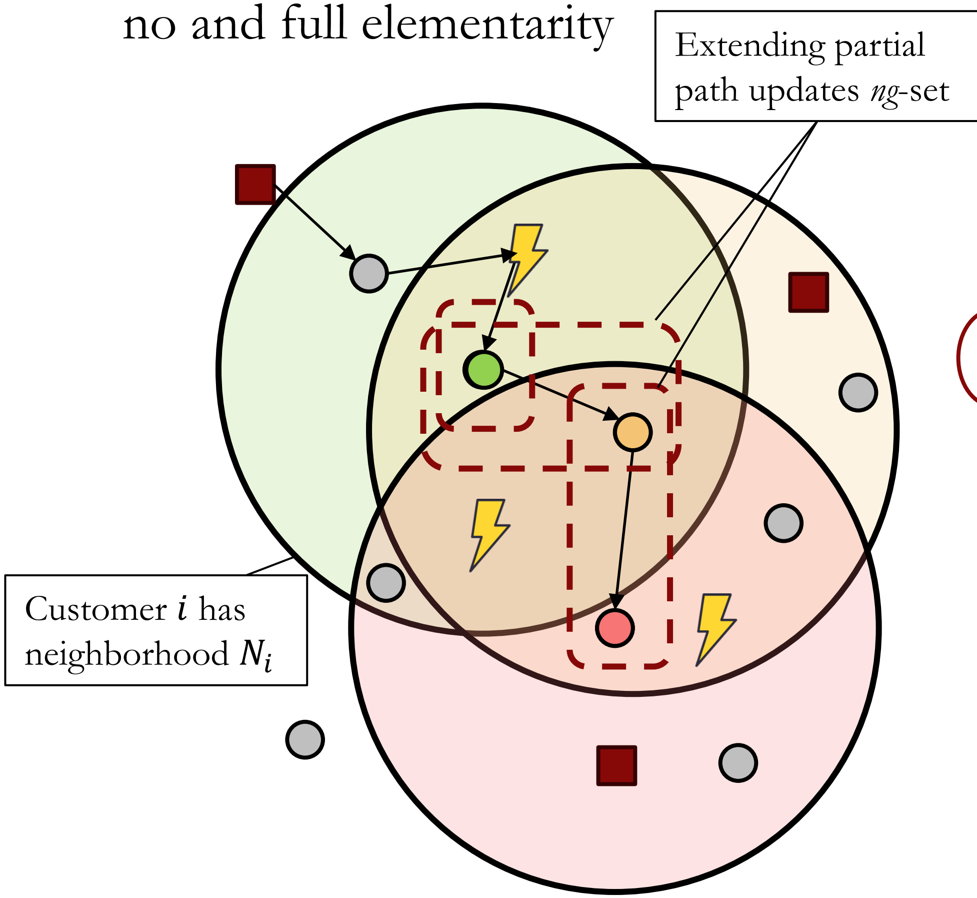
- − Expensive: NP-hard[2]
- \+ Better IP solutions

[1] Beasley, J. E., & Christofides, N. (1989). An algorithm for the resource constrained shortest path problem. *Networks*, *19*(4), 379–394. https://doi.org/10.1002/net.3230190402
[2] Dror, M. (1994). Note on the Complexity of the Shortest Path Models for Column Generation in VRPTW. *Operations Research*, *42*(5), 977–978. https://doi.org/10.1287/opre.42.5.977

Adaptive[2] *ng*-relaxations[1]

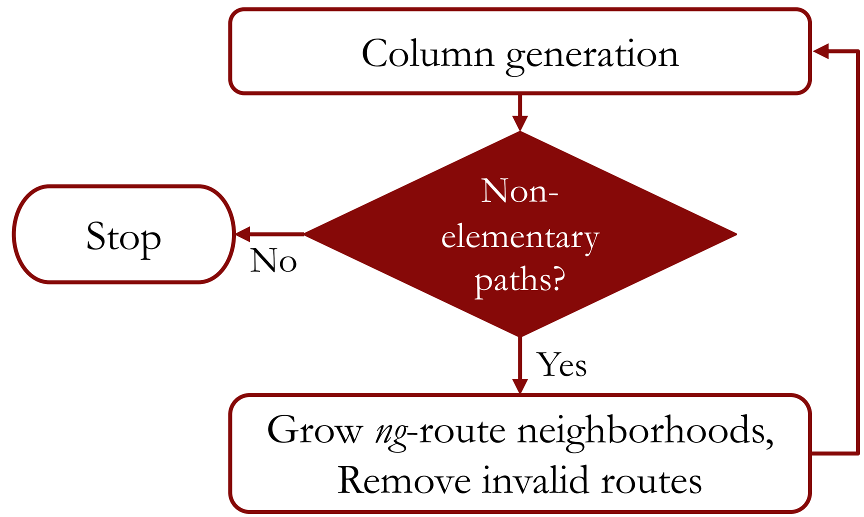
_ng_-route relaxation[1]:

Interpolates between
no and full elementarity



Nested _ng_-route relaxations

Start with a loose *ng*-relaxation,
tighten when necessary[2]!



Prop: This yields the solution to the LP relaxation of EVRP with elementary routes

[1] Baldacci, R., Mingozzi, A., & Roberti, R. (2011). New Route Relaxation and Pricing Strategies for the Vehicle Routing Problem. *Operations Research*, *59*(5), 1269–1283.

[2] Martinelli, R., Pecin, D., & Poggi, M. (2014). Efficient elementary and restricted non-elementary route pricing. *European Journal of Operational Research*, *239*(1), 102–111. https://doi.org/10.1016/j.ejor.2014.05.005

ng-routes in two-level label-setting

Traditionally:

- Forward labelling keeps track of **forward** *ng*-sets [1]

$$\Pi(P) = \left\{ i_r \colon i_r \in \bigcap_{s=r+1}^{k} N_{i_s},\ r = 1, \ldots, k-1 \right\} \bigcup \{i_k\}.$$

- Backward labelling (bidirectional label setting) tracks **backward** *ng*-sets [1]

$$\Pi^{-1}(\bar{P}) = \{i_k\} \cup \left\{ i_r \colon i_r \in \bigcap_{s=k}^{r-1} N_{i_s},\ r = k+1, \ldots, h \right\}.$$

Our work:

- Path domination criteria include forward *ng*-set inclusions:

$$L(p) = \Big(\bar{c}(p),\ t(p),\ -b(p),\ \{\mathbb{1}\,(i \in \Pi(p))\}_i \Big)$$

- Subpath domination criteria include **both** forward and backward *ng*-sets:

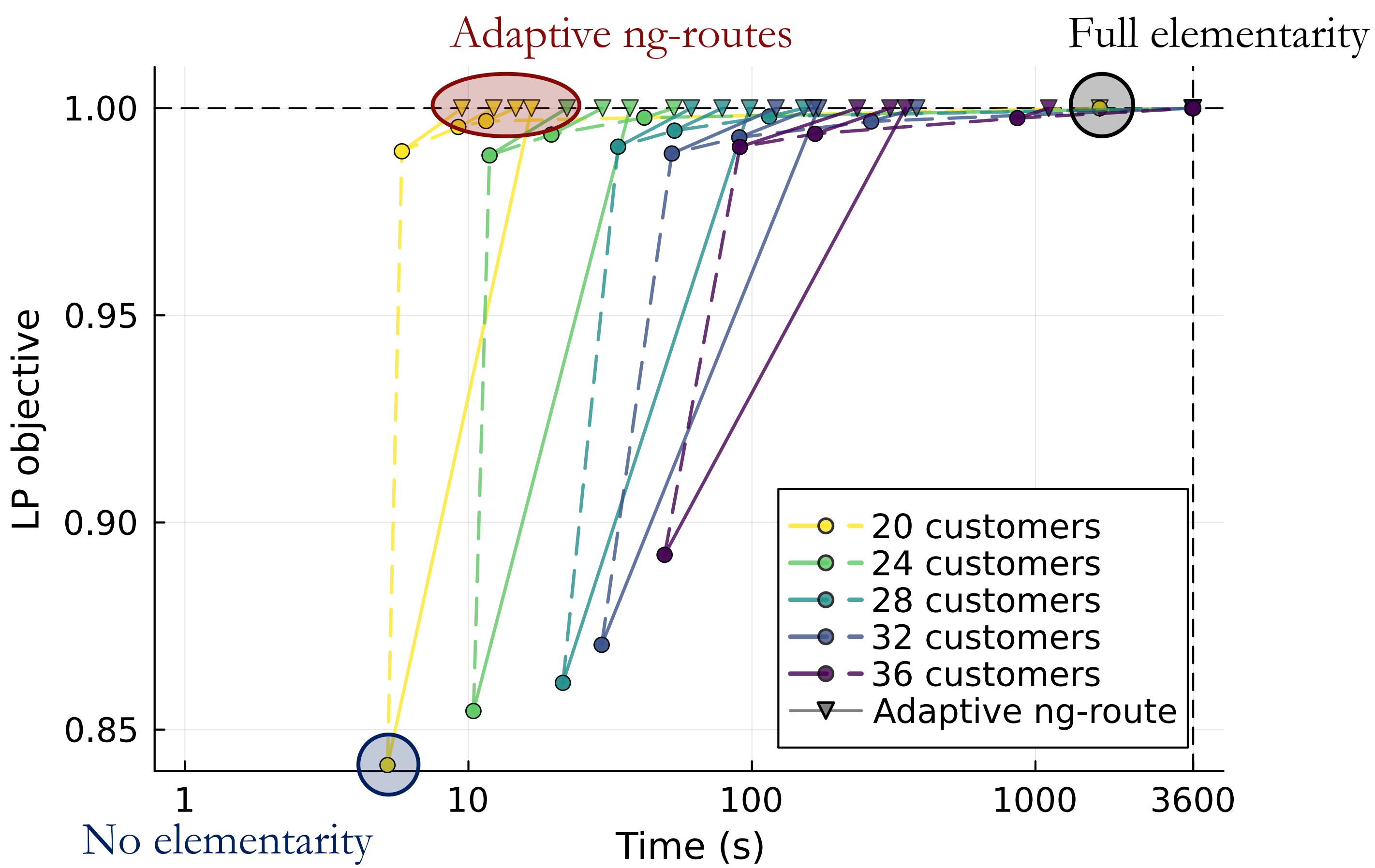
$$L(s) = \Big(\bar{c}(s),\ t(s),\ b(s),\ \{\mathbb{1}\,(i \in \Pi(p))\}_i, \{\mathbb{1}\,(i \in \Pi^{-1}(p))\}_i \Big)$$

Reason: need $L(s)$ to satisfy:

$\boxed{s_1 \succcurlyeq_L s_2}$ $\rightarrow$ **3** $\boxed{p \oplus s_1 \succcurlyeq_L p \oplus s_2 \text{ for any path } p}$

[1] Baldacci, R., Mingozzi, A., & Roberti, R. (2011). New Route Relaxation and Pricing Strategies for the Vehicle Routing Problem. *Operations Research*, *59*(5), 1269–1283.

Benefits of adaptive *ng*-relaxations



Challenges

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Subset-row cuts

- Consider a cut defined by a subset S of customers:
  - At most $\lfloor n/k \rfloor$ routes visiting at least k out of n customers[1] (Chvatal-Gomory cut of rank 1)

$$\sum_{p \in \mathcal{P}} \sum_{i \in S} \gamma_i^p z^p = |S| \Longrightarrow \sum_{p \in \mathcal{P}} \left\lfloor \frac{1}{k} \sum_{i \in S} \gamma_i^p \right\rfloor z^p \leq \left\lfloor \frac{|S|}{k} \right\rfloor$$

- *Non-robust* cuts which change subproblem structure (new duals)
  - Track resource $\sum_{i \in S} \gamma_i^p \pmod{k}$ for each subset S
  - When resource hits 0, subtract dual from reduced cost
  - Track $\sum_{i \in S} \gamma_i^s \pmod{k}$ and $\sum_{i \in S} \gamma_i^p \pmod{k}$ for subpaths and paths respectively:

$$D(s) = \left(\ldots,\ \{\textstyle\sum_{i \in S} \gamma_i^s\}_S\right)$$

$$D(p) = \left(\ldots,\ \{\textstyle\sum_{i \in S} \gamma_i^p\}_S\right)$$

[1] Jepsen, M., Petersen, B., Spoorendonk, S., & Pisinger, D. (2008). Subset-Row Inequalities Applied to the Vehicle-Routing Problem with Time Windows. Operations Research, 56(2), 497–511. https://doi.org/10.1287/opre.1070.0449

Limited-memory subset-row cuts

- Limited-memory subset-row cuts[1] include a *memory neighborhood* for each cut
  - Smaller state space
  - Weaker cuts
- Requires tracking forward and backward criteria

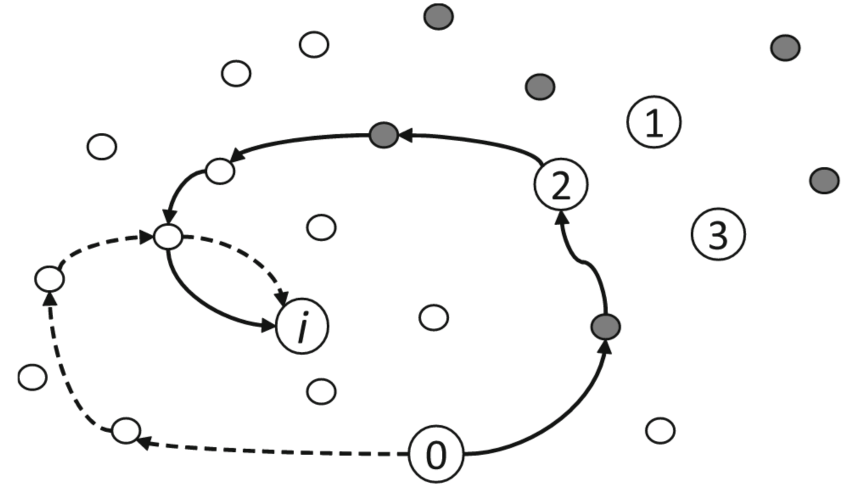
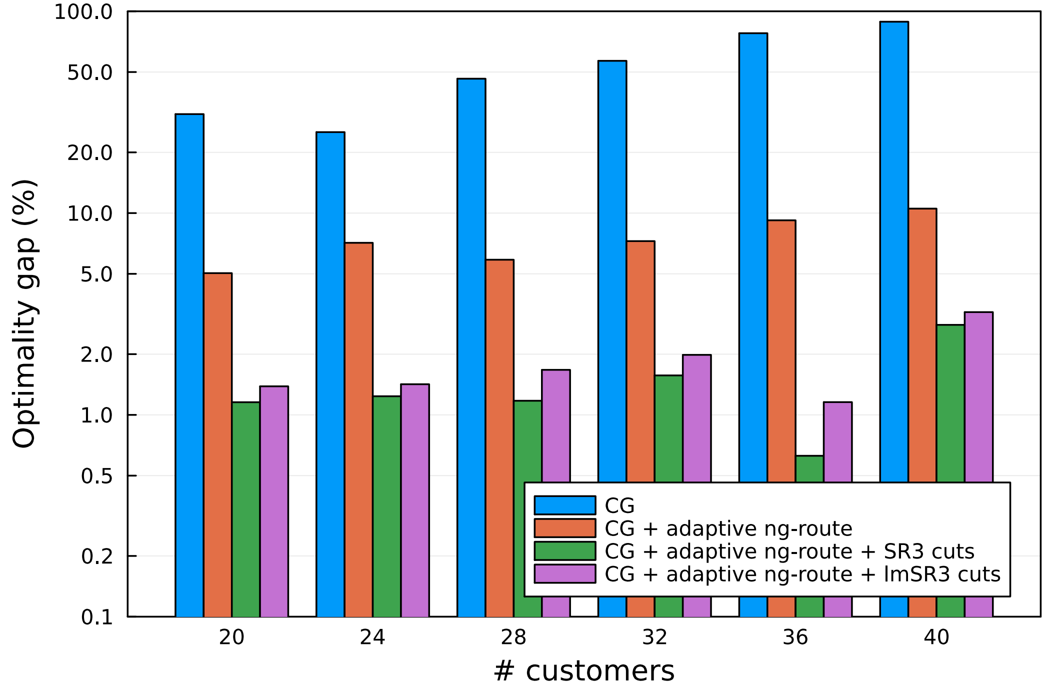


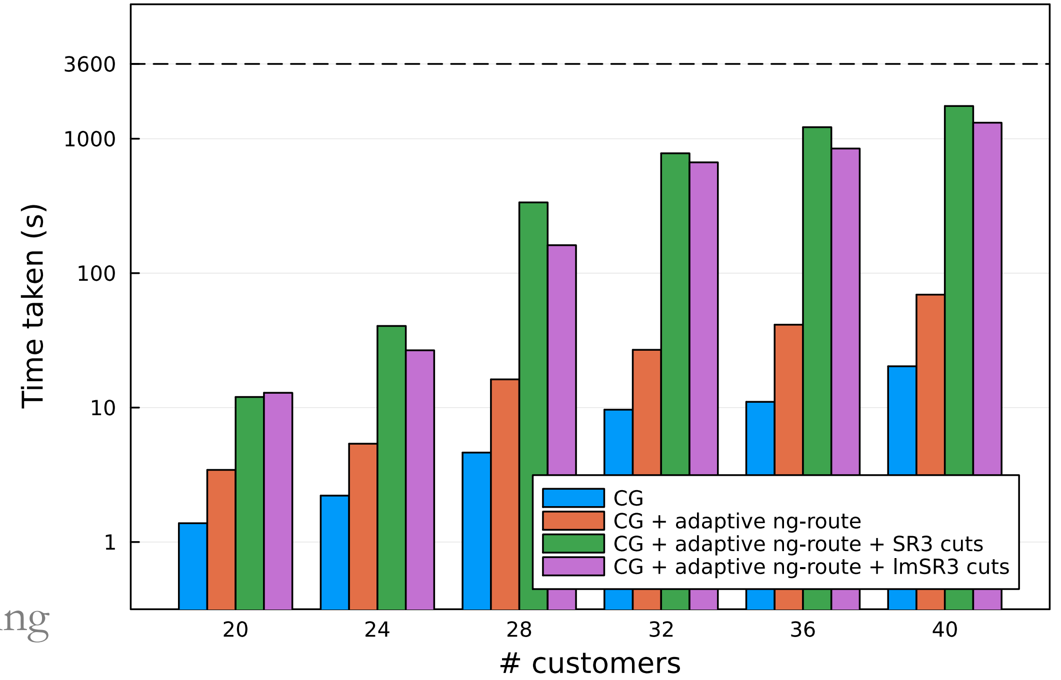
Fig. 2 Example illustrating the performance gain in the pricing when using lm-SRCs

[1] Pecin, D., Pessoa, A., Poggi, M., & Uchoa, E. (2017). Improved branch-cut-and-price for capacitated vehicle routing. *Mathematical Programming Computation*, *9*(1), 61–100. https://doi.org/10.1007/s12532-016-0108-8

Computational results

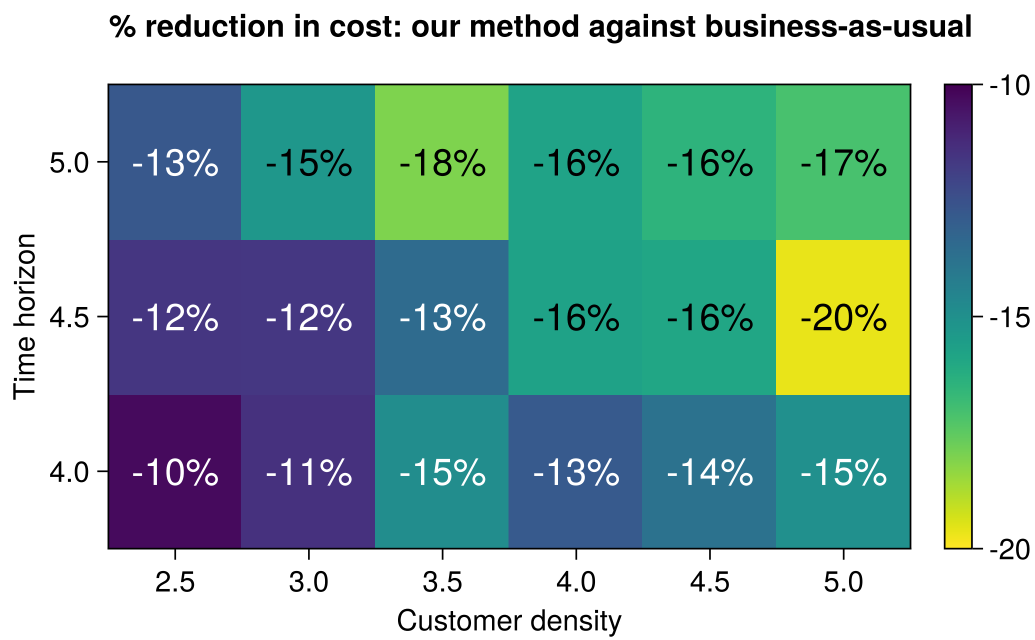
- Cuts further close the optimality gap at the cost of more time
- IP solution obtained typically optimal
- *lm*-SR3 cuts provides an intermediate approach





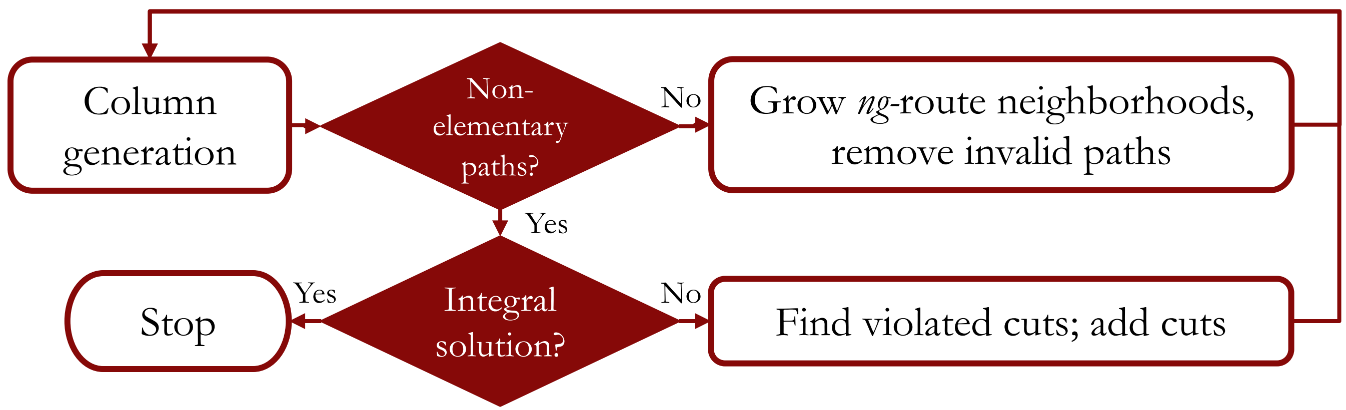
The benefits of optimization

- Improvement compared to business-as-usual solution:
  - Solve a VRP w/o charge
  - Then optimize charging stations with fixed routes
- Benefit of **jointly** optimizing charging and routing decisions



Summary

Electric vehicle routing: subpath-based decomposition algorithm

Modeling	**Electric vehicle routing: semi-infinite set-partitioning formulation with continuous time and continuous charge**
Optimization	
Computational results	**Significantly outperforms path-based benchmark, and scales to realistic problem instances**
Practical impact	**Benefits over “business-as-usual” routing operations**

Additional slides

Comparison with literature

Setting

[1]:

- Continuous time and charge
- Single / multiple recharges, partial / full recharging
- Time windows
- No charging costs

Our work:

- Continuous time and charge
- Multiple recharges, partial recharging
- **No** time windows
- Linear constant / heterogenous charging costs (charging τ at i costs $\delta_i \cdot \tau$)

[1] Desaulniers, G., Errico, F., Irnich, S., & Schneider, M. (2016). Exact Algorithms for Electric Vehicle-Routing Problems with Time Windows. Operations Research, 64(6), 1388–1405. https://doi.org/10.1287/opre.2016.1535

Comparison with literature

	[1]:	Our work:
Methods	• Bidirectional label-setting, with bidirectional criteria	• Unidirectional, two-level label-setting, with bidirectional criteria
	• *ng*-route relaxation	• Adaptive tightening of *ng*-route relaxations
	• 2-path cuts and subset-row cuts	• SRC and lm-SRC
	• Branching	• No branching

[1] Desaulniers, G., Errico, F., Irnich, S., & Schneider, M. (2016). Exact Algorithms for Electric Vehicle-Routing Problems with Time Windows. Operations Research, 64(6), 1388–1405. https://doi.org/10.1287/opre.2016.1535