

Electric Vehicle Routing: Subpath-Based Decomposition

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Background and motivation

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

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

Paul Berger [Follow](#)

July 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

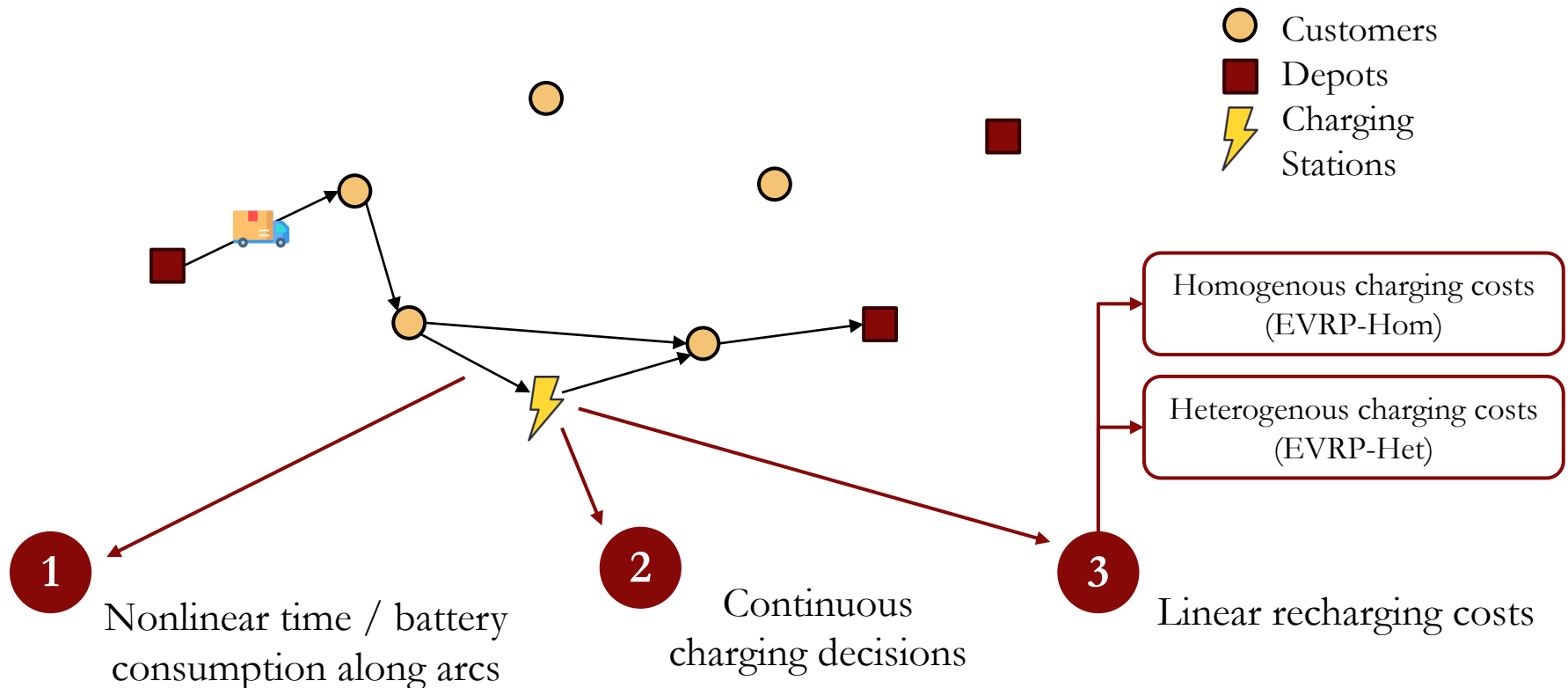


By Ian Duncan

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

Electric Vehicle Routing Problem



Overview of literature

VRP: models and variants

- VRP with Time Windows, Capacitated VRP

routing (discrete) \Rightarrow time, load (continuous)

- Electric VRP

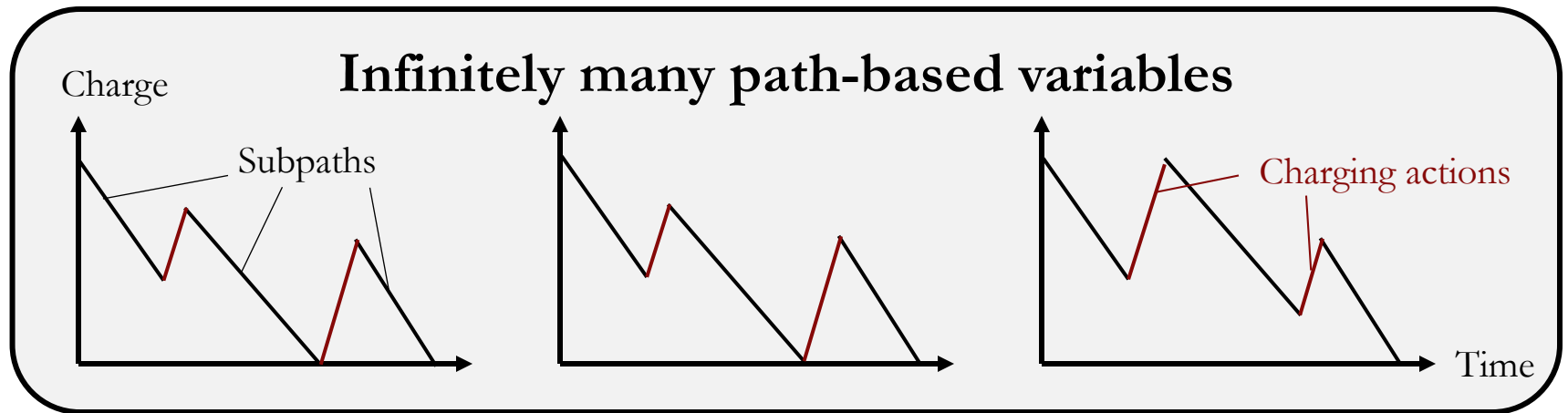
routing (discrete) \vdots charge (continuous)

- EVRP-Het: **new**

VRP: approaches

- Metaheuristics
 - Large-scale neighborhood search
 - Genetic algorithms
- Exact methods
 - Column generation
 - Path-based label-setting
 - Branch-and-price-and-cut

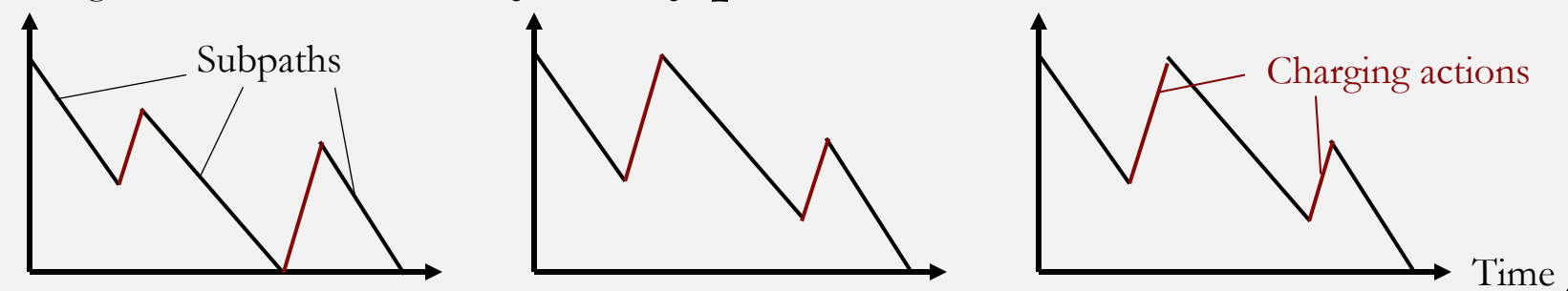
Challenges



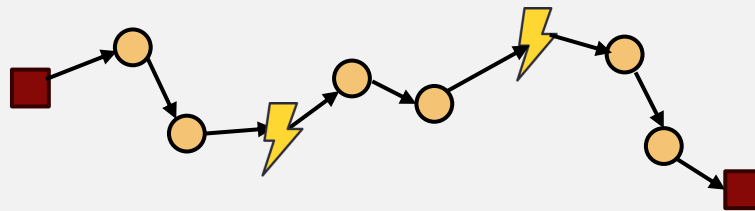
Challenges

Infinitely many path-based variables

Charge

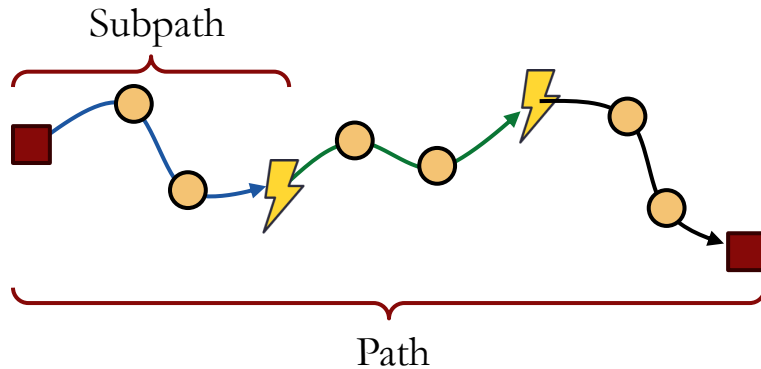


Long paths \longrightarrow Large DP in pricing problem

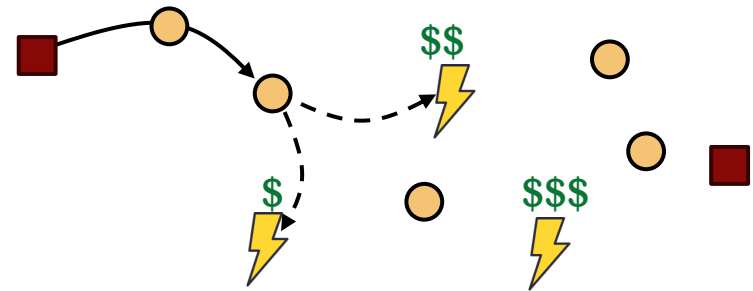


Contributions

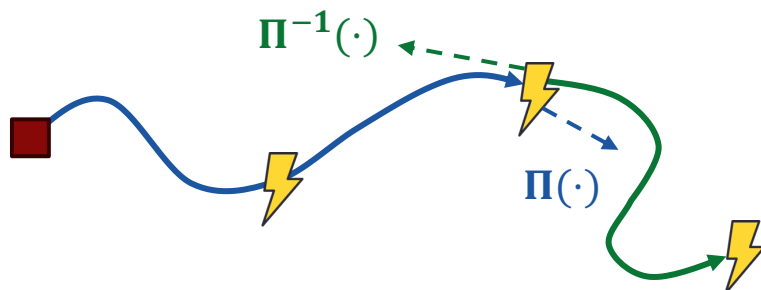
Two-level label-setting (2LLS)



Heterogenous charging costs



Accelerations



Forward and backward resources

Results + Impact

- 2-10x speedup
- 8% cost improvement over heuristics
- 5-20% charging cost saved (heterogenous charging costs)

Semi-infinite set-partitioning model

$$\begin{aligned} \min \quad & \sum_{p \in \mathcal{P}} c^p z^p \\ \text{s.t.} \quad & \sum_{p \in \mathcal{P}} \mathbb{1}(n_{\text{start}}^p = j) z^p = v_j^{\text{start}} \quad \forall \text{ depots } j \\ & \sum_{p \in \mathcal{P}} \mathbb{1}(n_{\text{start}}^p = j) z^p \geq v_j^{\text{end}} \quad \forall \text{ depots } j \\ & \sum_{p \in \mathcal{P}} \gamma_i^p z^p = 1 \quad \forall \text{ customers } i \\ & z^p \in \mathbb{Z}_{\geq 0} \quad \forall p \in \mathcal{P} \end{aligned}$$

- Set-partitioning formulation with path-based variables z^p
- Infinitely many variables
 - **Discrete** routing and timing decisions
 - **Continuous** charging decisions

Column generation

Restricted Master Problem

$$\begin{aligned} \min \quad & \sum_{p \in \mathcal{P}'} c^p z^p \\ \text{s.t.} \quad & \sum_{p \in \mathcal{P}'} \mathbb{1}(n_{\text{start}}^p = j) z^p = v_j^{\text{start}} \quad \forall \text{ depots } j \quad [\kappa] \\ & \sum_{p \in \mathcal{P}'} \mathbb{1}(n_{\text{start}}^p = j) z^p \geq v_j^{\text{end}} \quad \forall \text{ depots } j \quad [\mu] \\ & \sum_{p \in \mathcal{P}'} \gamma_i^p z^p = 1 \quad \forall \text{ customers } i \quad [\nu] \\ & z^p \in \mathbb{R}_{\geq 0} \quad \forall p \in \mathcal{P}' \end{aligned}$$

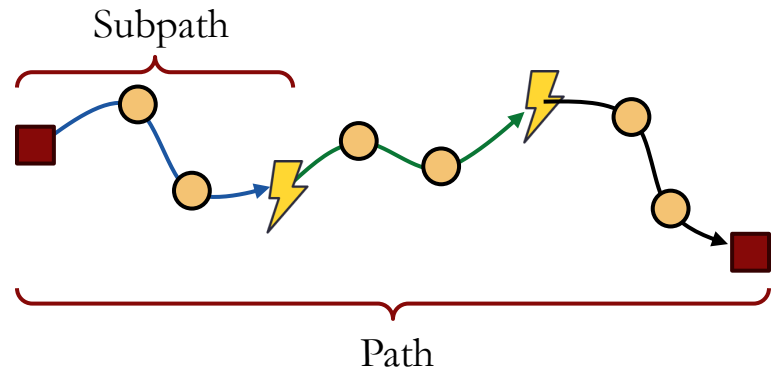
dual values κ, μ, ν

paths not in \mathcal{P}'

Pricing Problem

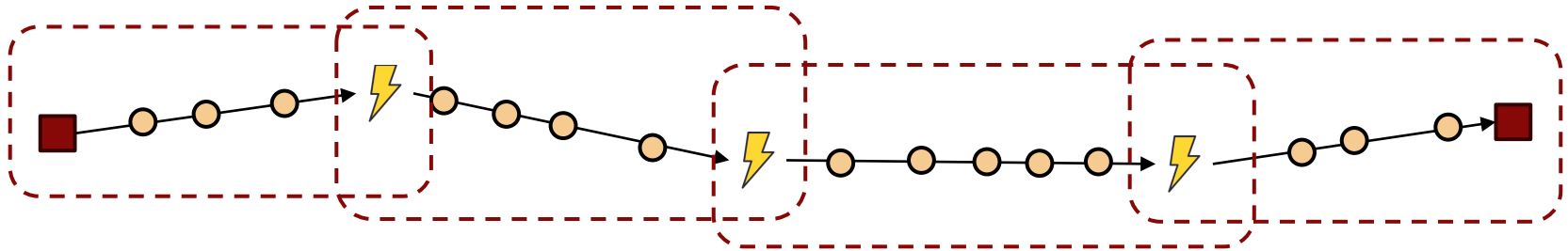
$$\min_{p \in \mathcal{P}} \left\{ \bar{c}^p := c^p - \kappa_{\text{start}(p)} - \mu_{\text{end}(p)} - \sum_{i \in \mathcal{V}_C} \gamma_i^p \nu_i \right\}$$

Two-level label-setting (2LLS)



Two-level label-setting
in the pricing problem

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

p_1 dominates p_2 if $D(p_1) \leq D(p_2)$ ^[2];

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

reduced cost time (negative of charge)

[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>

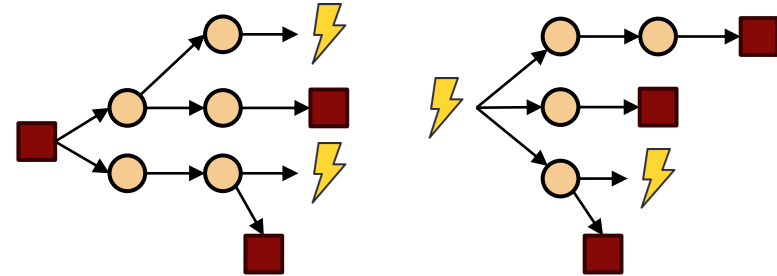
Key idea: two-level label-setting

Level 1: Generate subpaths s

- Label-setting, with domination criteria:

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

charge
taken

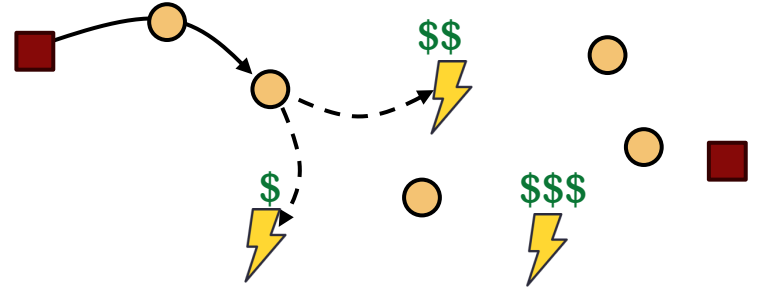


Level 2: Extend paths p along subpaths s

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

- WLOG, the charging decision between subpaths is the minimum possible
- Reduced cost of path =
r.c. of subpaths + cost of charging

Heterogenous charging costs

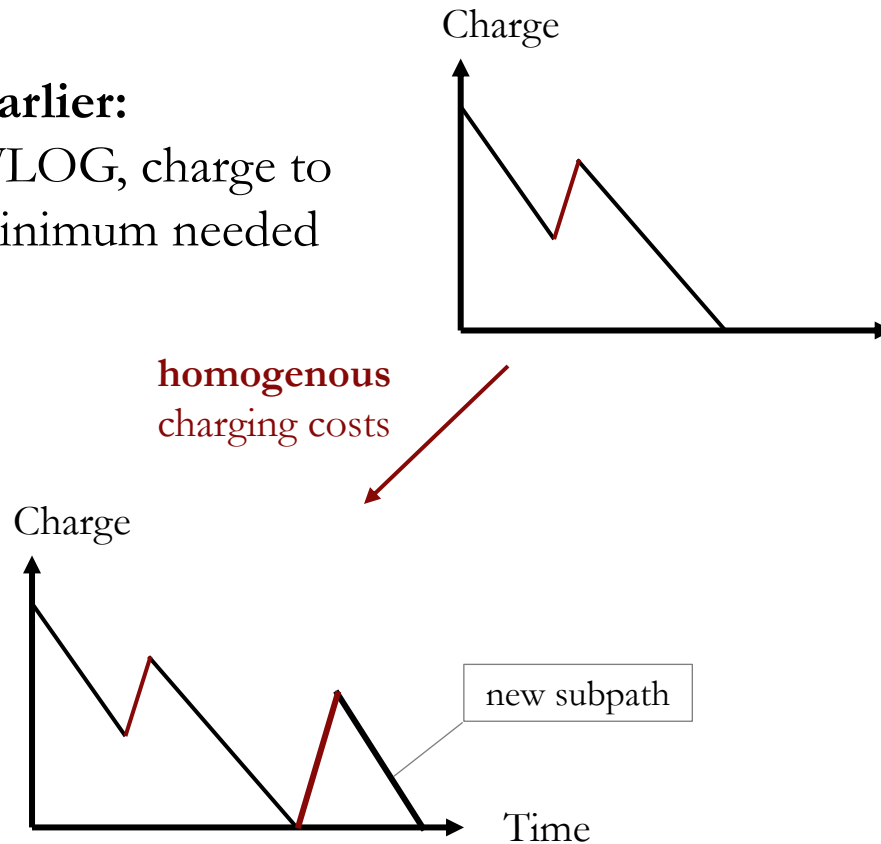


Heterogenous charging costs

Two-level label-setting: determining charging times

Earlier:

WLOG, charge to
minimum needed

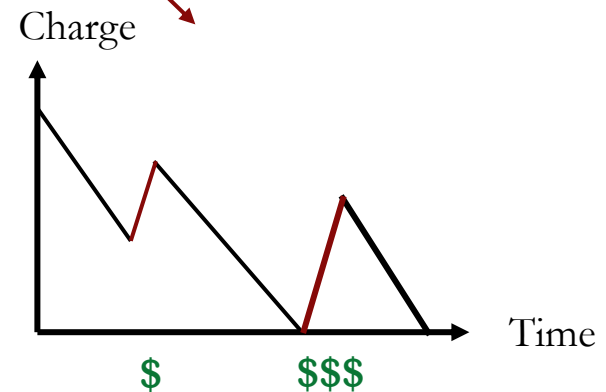


Now:

Need to rebalance
charging actions
dynamically!

Time

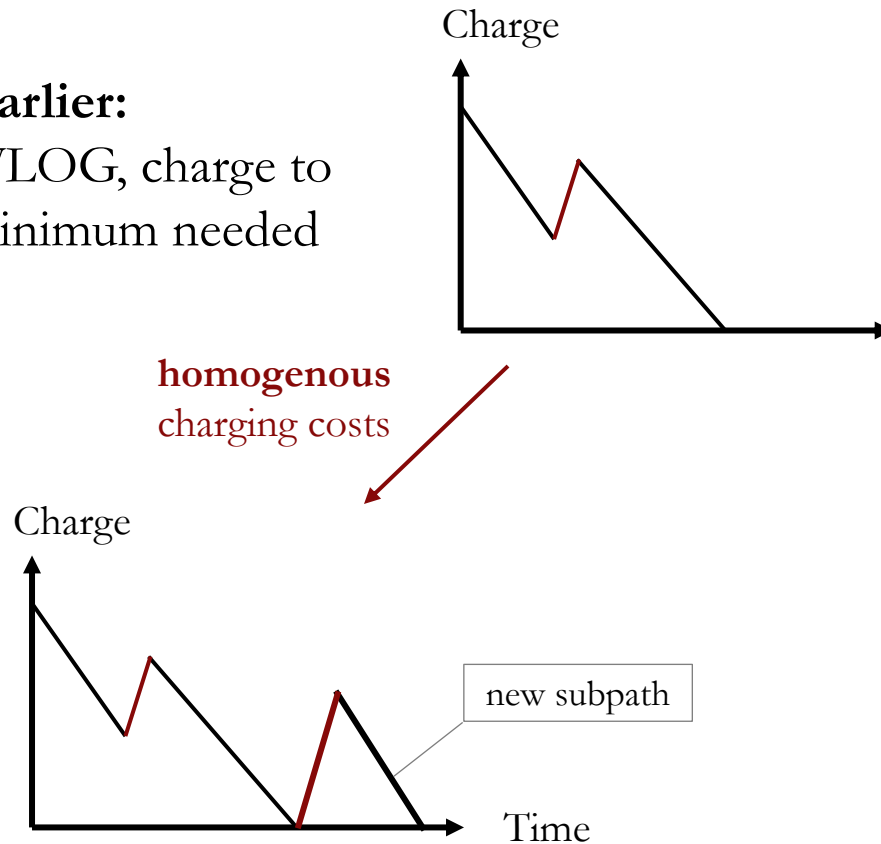
heterogenous
charging costs



Two-level label-setting: determining charging times

Earlier:

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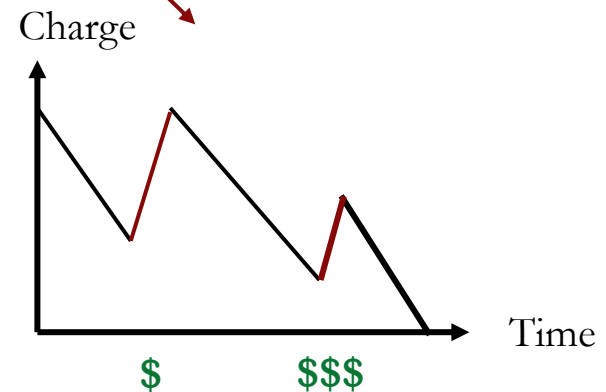


Now:

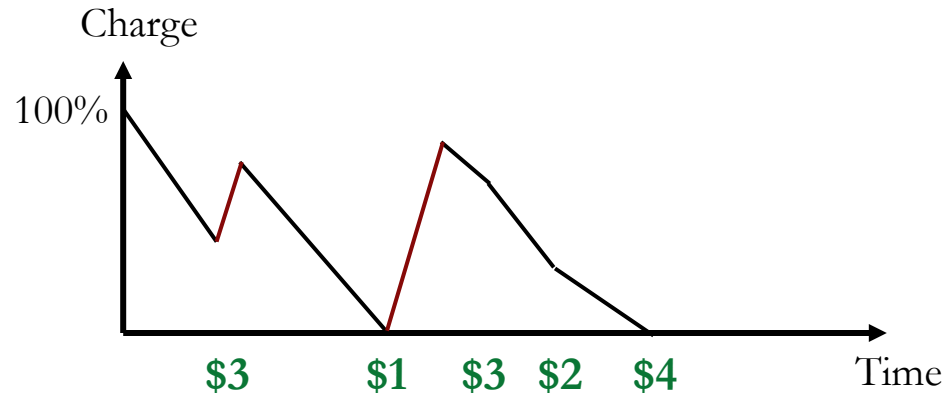
Need to rebalance
charging actions
dynamically!

Time

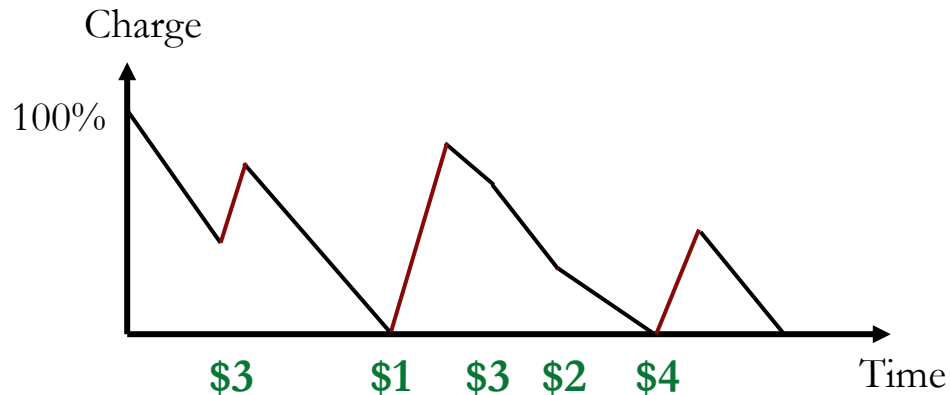
heterogenous
charging costs



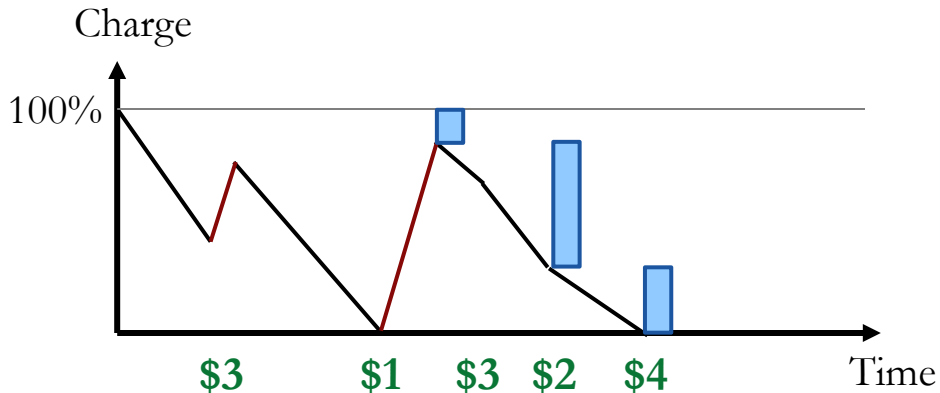
2L-LS: extra resources



- 2L-LS decouples charging and routing decisions
- In stitching subpaths to paths, rebalance charging actions dynamically (DP)

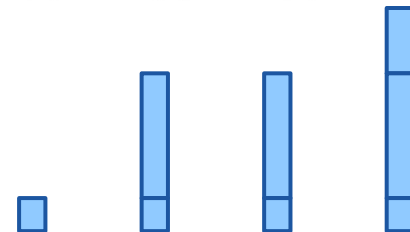


2L-LS: extra resources



- 2L-LS decouples charging and routing decisions
- In stitching subpaths to paths, rebalance charging actions dynamically (DP)
- Extra resources in 2nd level representing “rebalancing opportunities”:

$$D(p) = \left(\bar{c}(p), t(p), -b(p), \right. \\ \left. -Z_1(p), -Z_2(p), -Z_3(p), -Z_4(p), \dots \right)$$



Theory:

domination for paths and subpaths

A closer look at domination^[1]

1st level (subpaths)

Def: $s_1 \succcurlyeq s_2$ if: $D(s_1) \leq D(s_2)$

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

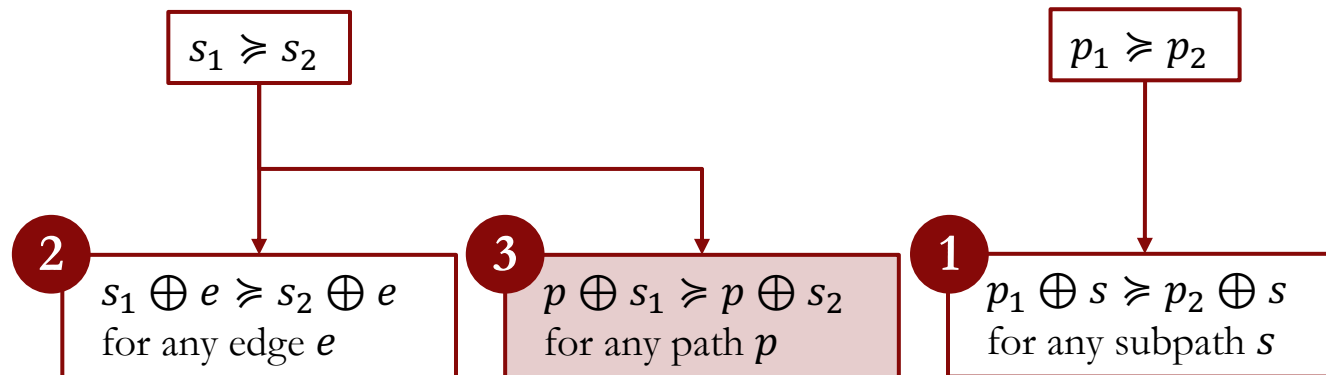
reduced time charge
cost taken taken

2nd level (paths)

Def: $p_1 \succcurlyeq p_2$ if: $D(p_1) \leq D(p_2)$

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

reduced time (negative of)
cost charge



Rigorous and generalizable framework for domination criteria

Key results

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

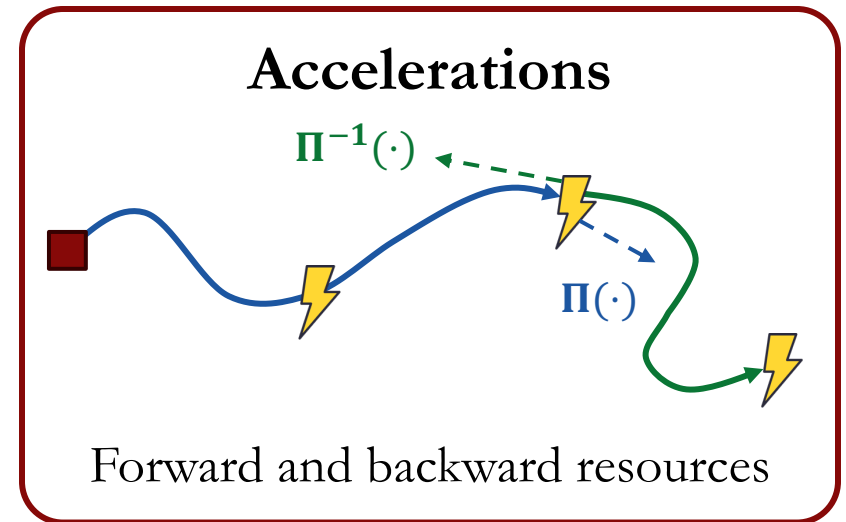
Proof idea:

- 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 idea:

- Infinitely many paths, but **finitely** many subpath sequences (sequences of subpaths, w/ routing but w/o charging decisions)



Accelerations:

Incorporating *ng*-relaxations and
subset-row cuts

The *ng*-route relaxation^[1]

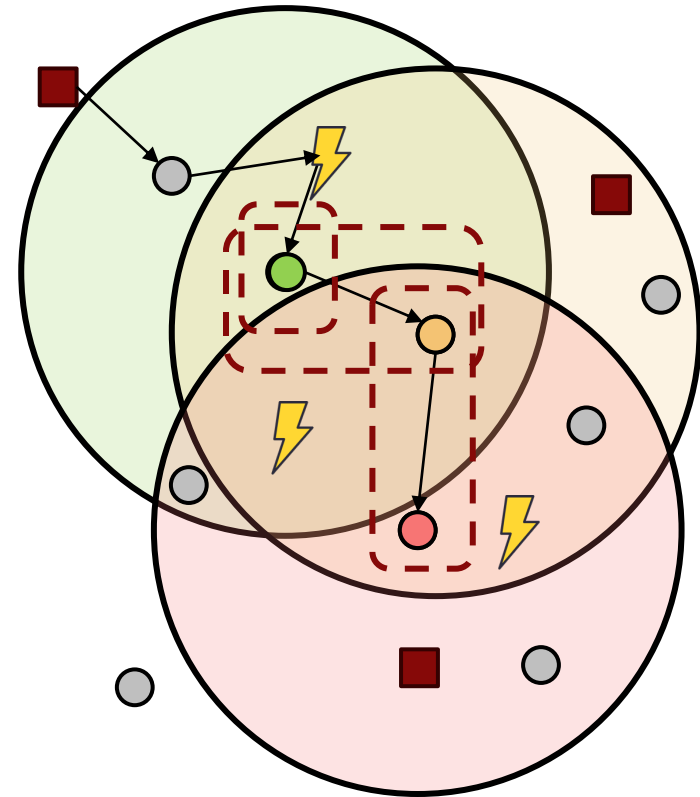
ng-route relaxation: intermediate between no and full elementarity

- Each customer i has a neighborhood N_i ($i \in N_i$)
- Each partial path has forward *ng*-set $\Pi(p)$:
“nodes p cannot visit next”

$$\Pi(p) = \left\{ n_r \mid n_r \in \bigcap_{\rho=r+1}^m N_{n_\rho}, r \in \{0, \dots, m-1\} \right\} \cup \{n_m\}$$

- Domination criteria uses *ng*-sets:

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

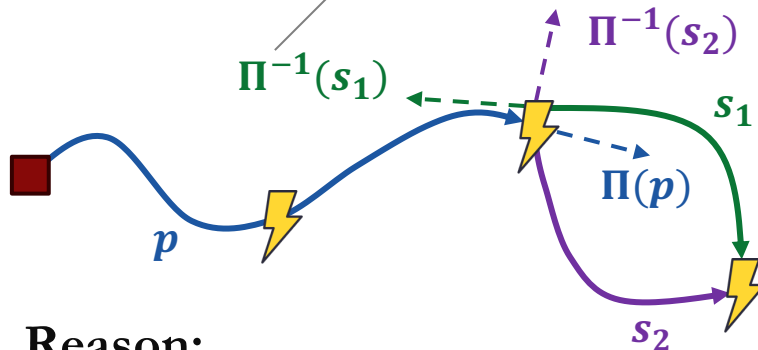


ng -routes in two-level label-setting

- 1st level (subpaths):

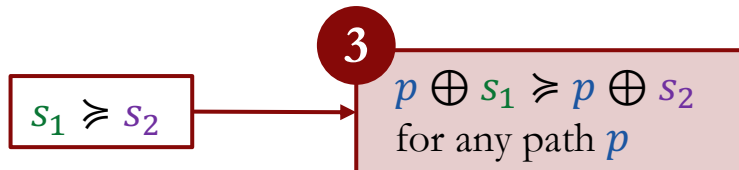
Also include backward ng -set^[1]:

“nodes which appear in all previous ng -neighborhoods”



Reason:

- Require this property:



- $p \oplus s$ feasible $\Leftrightarrow \Pi(p) \cap \Pi^{-1}(s) = \{\text{lightning bolt}\}$

- 2nd level (paths):

Only uses forward ng -set

Domination **properties**
for subpaths and paths

Design of domination
criteria for variants

Subset-row cuts in 2L-LS

- Subset-row cuts^[1]:

- At most $\lfloor n/k \rfloor$ routes visiting at least k out of n customers^[1]

(Chvatal-Gomory cut of rank 1):

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

- Track resource $\sum_{i \in S} \gamma_i^p \pmod{k}$ for each subset S in label-setting
- *Limited-memory* subset-row cuts (*lm*-SRCs)^[2]
 - Only track $\sum_{i \in S} \gamma_i^p \pmod{k}$ inside a memory set M (zero it out when p steps outside M)
 - Not symmetric – requires forward/backward trackers $\vec{\alpha}(p), \tilde{\alpha}(p)$

Domination **properties** for
subpaths and paths

Design of domination
criteria for variants

[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>

[2] 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>

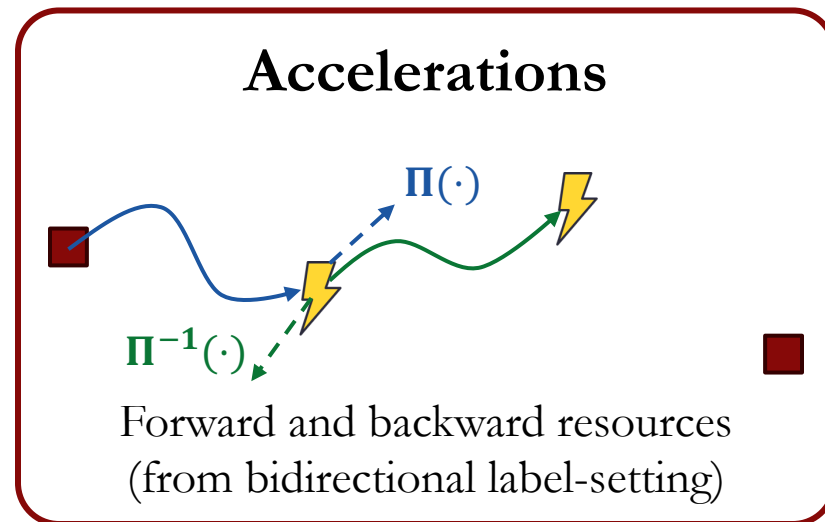
Accelerations:

incorporating *ng*-relaxations...

- Additional resources from bidirectional LS
- Higher-dimensional domination

...and subset-row cuts

- Forward and backward cut quantities $\overrightarrow{\alpha}_q, \overleftarrow{\alpha}_q$ for cut q
- Weaker domination comparison for reduced costs



Results + Impact

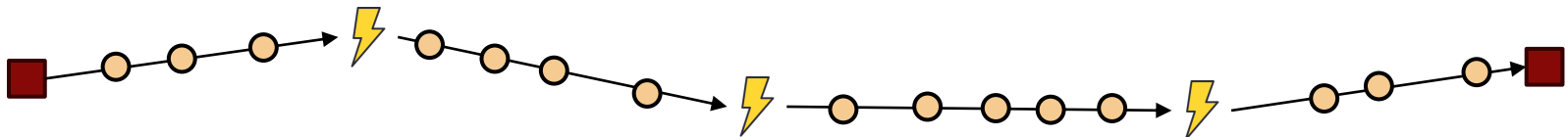
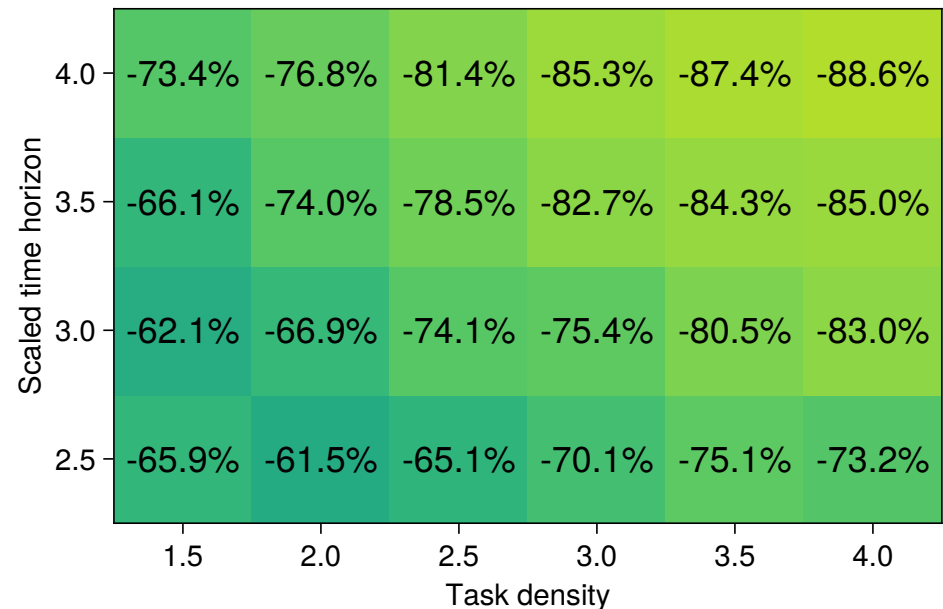
- 2-10x speedup
- 8% cost improvement over heuristics
- 5-20% charging cost saved (heterogenous charging costs)

Results, practical impact

Result 1: 2L-LS is faster than LS

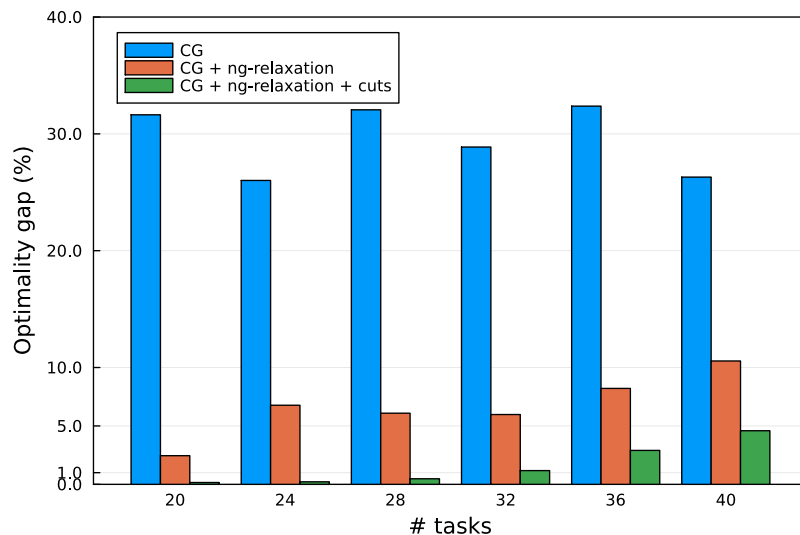
- Significant speedups against path-based benchmark
- Stronger improvement with:
 - Higher customer density
≈ **longer subpaths**
 - Longer time horizon
≈ **more subpaths per path**

% time reduction vs.
path-based benchmark

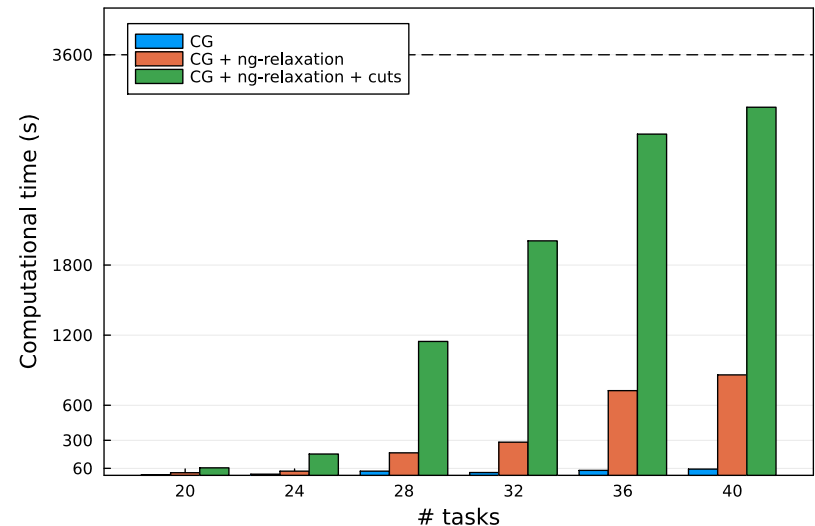


Result 2: Scalability

Optimality gap (%)



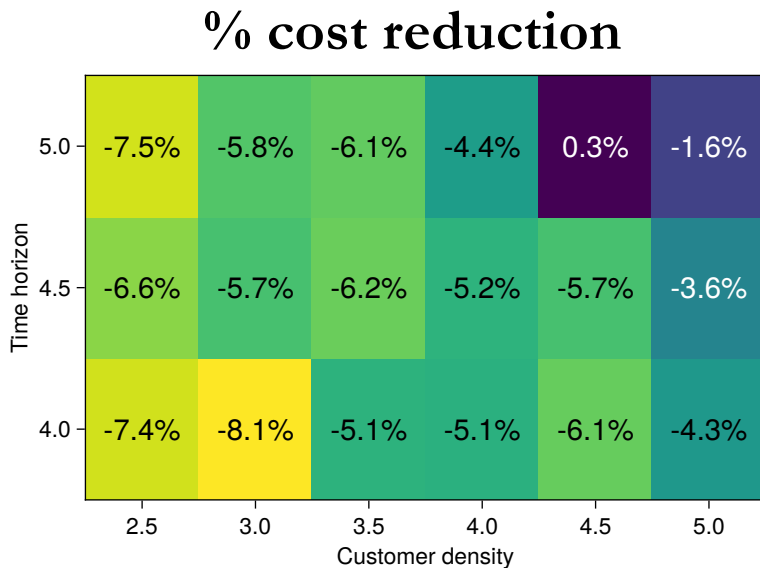
Computational time



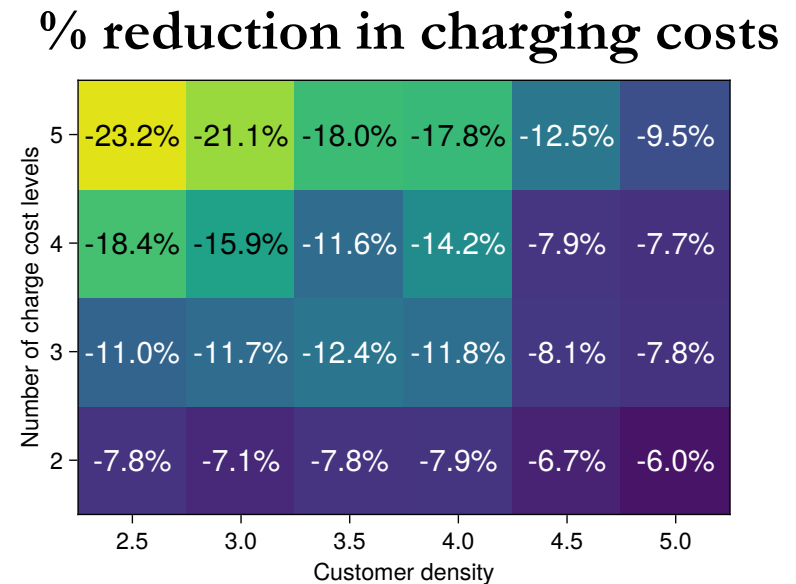
- Baseline column generation algorithm is fast and weak
- Iteratively tightening *ng*-relaxations gives the LP relaxation w/ elementary paths (and good solution quality)
- Cuts further narrow the gap, but take a long time

Result 3: Practical benefits

a Jointly optimizing charging and routing decisions, v.s. route-then-charge heuristic



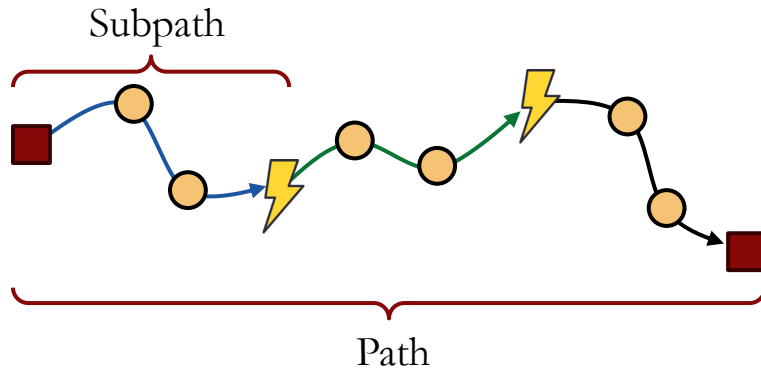
b Using EVRP-Het algorithm instead of EVRP-Hom, with heterogenous charging costs



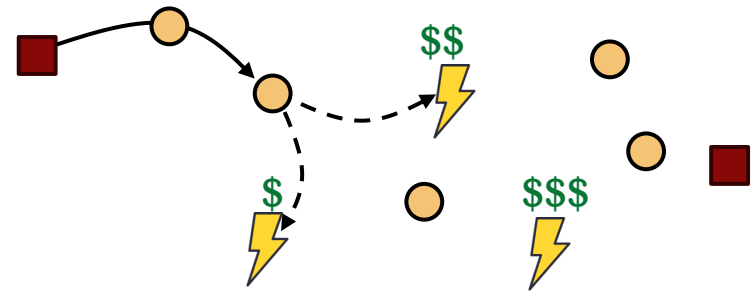
Benefits from large-scale optimization algorithms to support emerging vehicle technologies and operating models toward sustainable logistics

Contributions

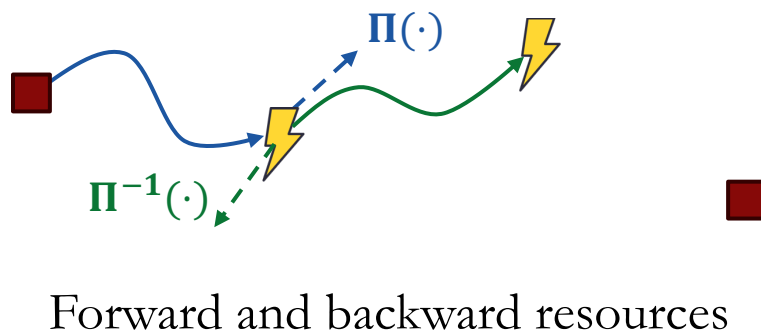
Two-level label-setting (2LLS)



Heterogenous charging costs



Accelerations



Results + Impact

- 2-10x speedup
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Additional slides