Dynamic EV Routing with Uncertain Availability: Heuristics and Lower Bounds

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Odysseus 2018

e-VRO
Electric Vehicle Routing Optimization

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Outline

- Motivation
- Problem description
- Literature review
- Dynamic routing model
- Solution methods & Results (parts I & II)
- Lower bound for the dynamic routing model
- Improving bounds: Information penalties
- Summary

Motivation

Motivation

Electric vehicles (EVs)

- Reducing petroleum dependency in shift to sustainable transport
- Increased the use of EVs in their operations: La Poste, EDF, Coca Cola, UPS, ...



Motivation

Why do EVs lead to new VRPs?

- New technological constraints
  - Limited battery capacity & range → More frequent charging
  - Longer charging times
  - Fewer charging stations

→ +

Greater impact of queueing

Motivation

Why do EVs lead to new VRPs?

More frequent charging

+

Greater impact of queueing

1. Charge only at depot
   - Additional travel time
   - Less queueing time

2. Mid-route recharging
   - Less travel time
   - Additional queueing time

Motivation

Villegas et al. (2018) — ENEDIS & Mid-route recharging

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- Results
  - Mid-route recharging offered cost savings

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  - ENEDIS chose not to employ mid-route recharging
    - Uncertainty in access to CS

Motivation

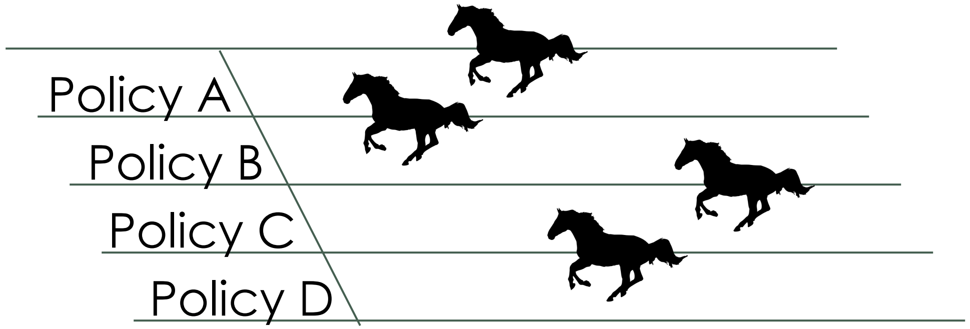
Villegas et al. (2018) — ENEDIS & Mid-route recharging

- Results
  - Mid-route recharging offered cost savings
  - ENEDIS chose not to employ mid-route recharging
    - Uncertainty in access to CS
- Solution should consider
  - Mid-route recharging | CS uncertainty | **Dynamic routing**

Motivation

A few words on dynamic routing

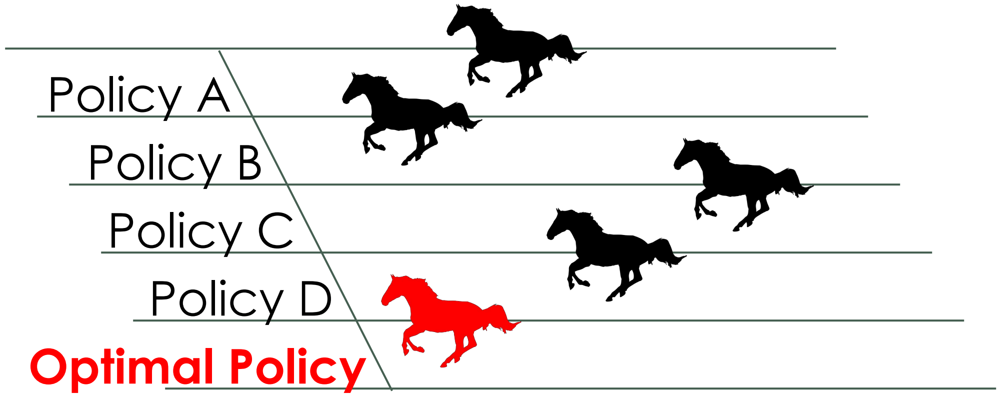
- Common criticism
  - "Horse race" method of comparing solutions
  - Curse of dimensionality, lack of optimality
  - Benchmarks, but how much better can we do?



Motivation

A few words on dynamic routing

- Common criticism:
  - “Horse race” method of comparing solutions
  - Curse of dimensionality, lack of optimality
  - Benchmarks, but how much better can we do?
- In this work:
  - Lower bounds via information relaxation & information penalties
  - Evidence for goodness of policies



Problem description:
E-VRP-UA

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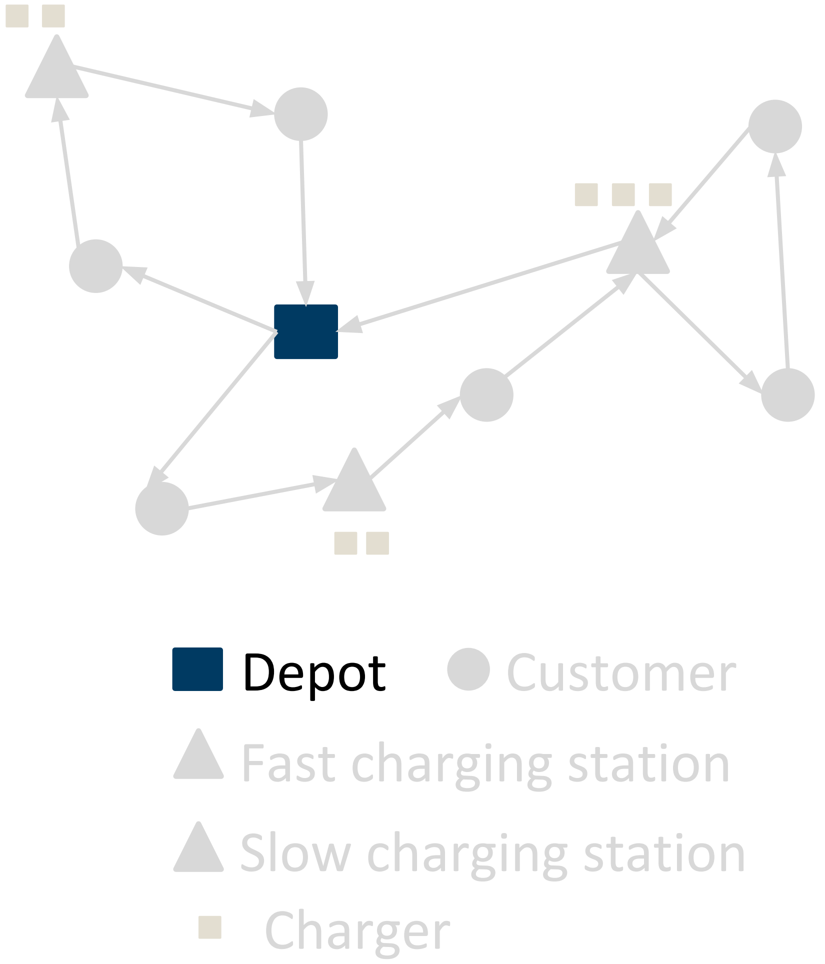
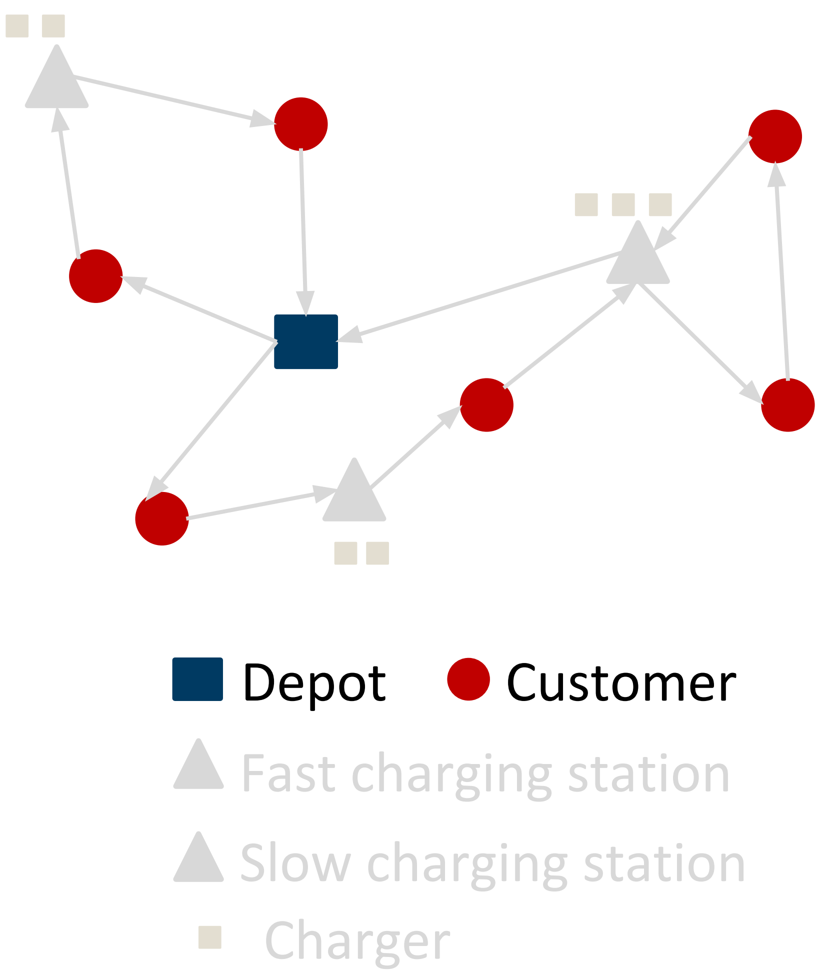
- One depot



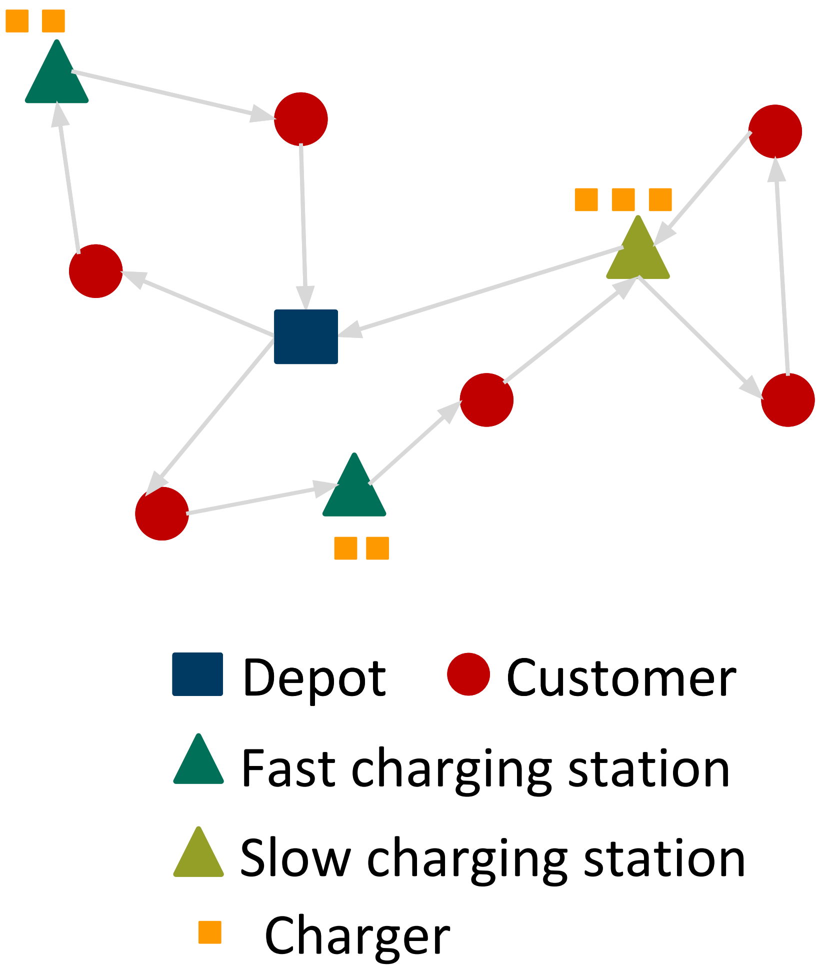
Problem description: E-VRP-UA

- One depot
- *N* customers



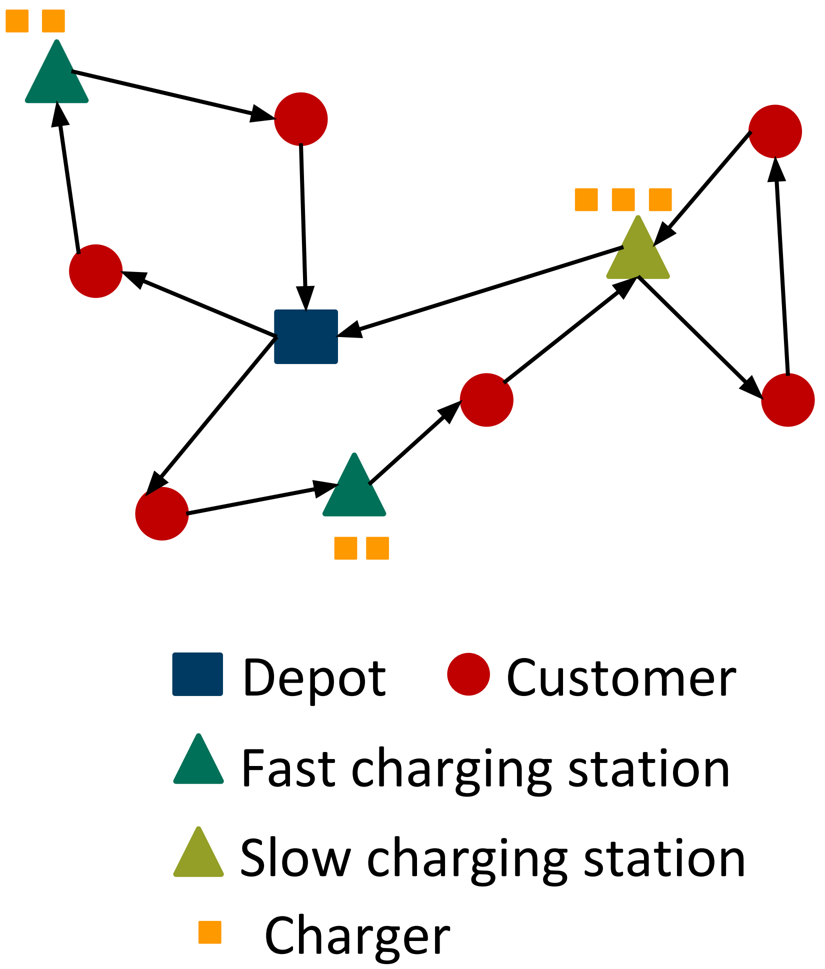
Problem description: E-VRP-UA

- One depot
- *N* customers
- *C* charging stations
  - Fast, medium, slow
  - l_c chargers at CS c
  - Queues unknown prior to arrival
  - $M/M/l_c$



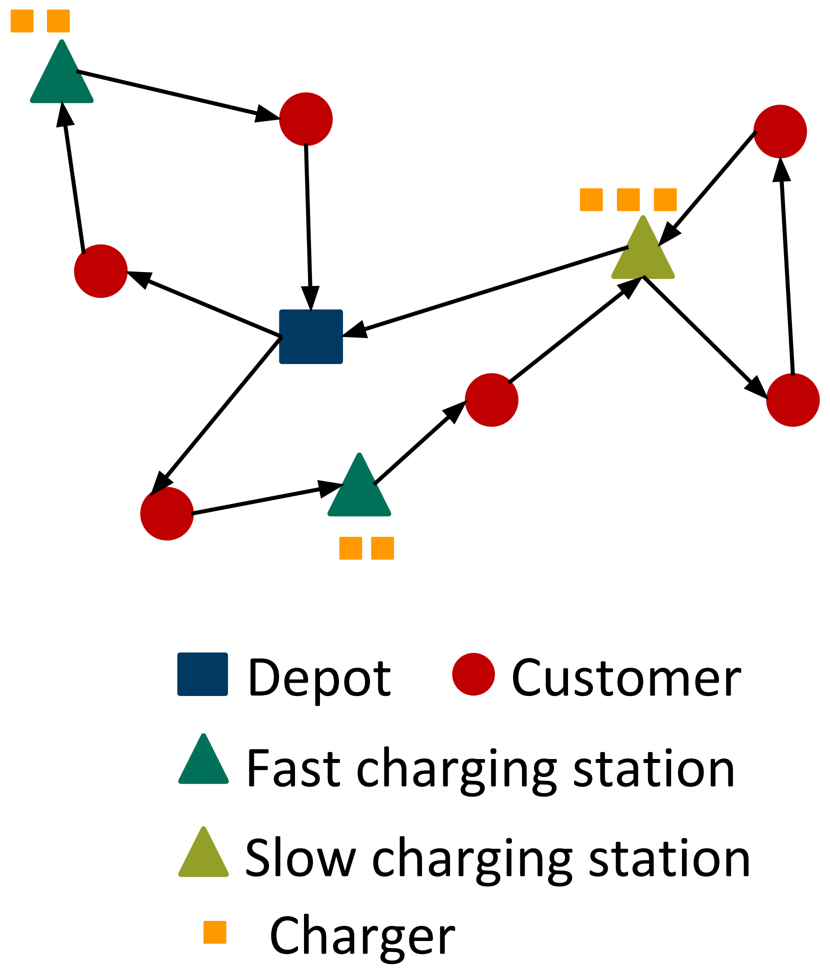
Problem description: E-VRP-UA

- One depot
- *N* customers
- *C* charging stations
- Arcs *(i,j)*:
  - e_{ij} energy consumption
  - t_{ij} time



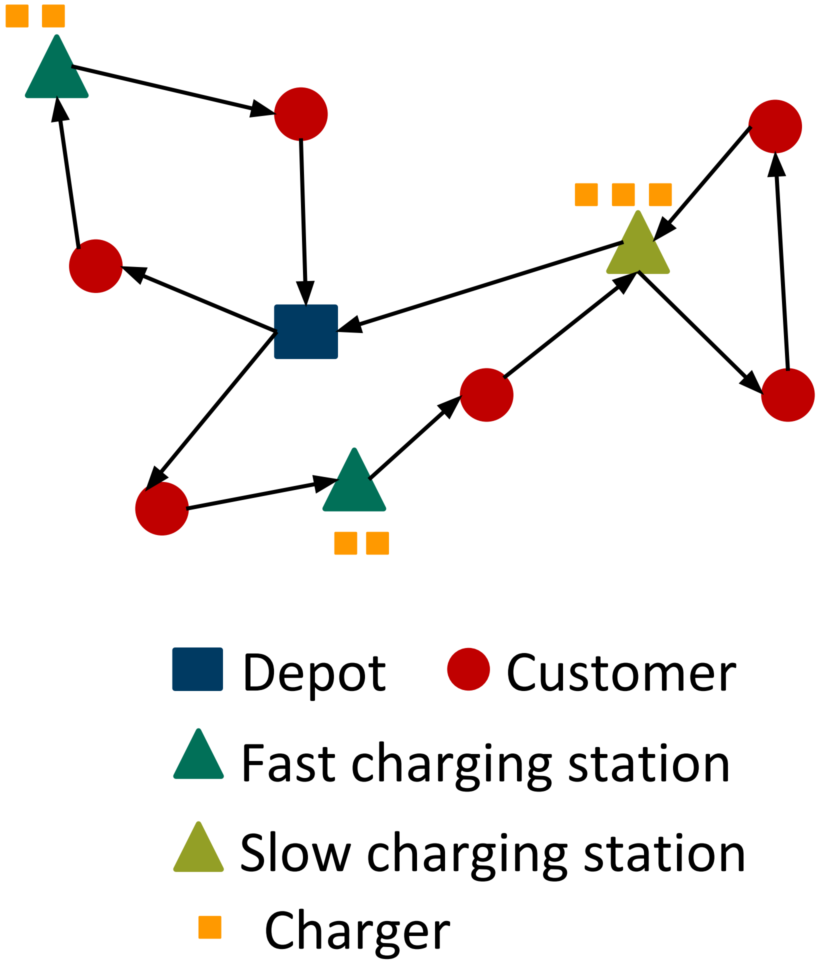
Problem description: E-VRP-UA

- One depot
- *N* customers
- C charging stations
- Arcs *(i,j)*
- Single vehicle
    - Battery capacity Q
    - Non-linear charging function
    - Discrete charging decisions



Problem description: E-VRP-UA

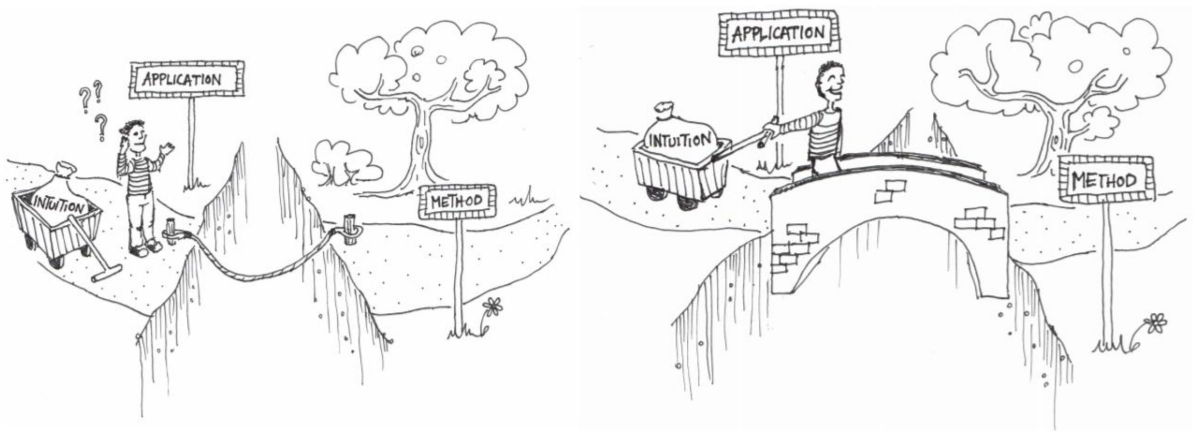
- One depot
- *N* customers
- C charging stations
- Arcs *(i,j)*
- Single vehicle
- Objective: Minimize time to serve all customers and return to depot



Literature

Literature

- **Dynamic vehicle routing**
  - Pillac et al. (2013)
  - Ulmer et al. (2018)

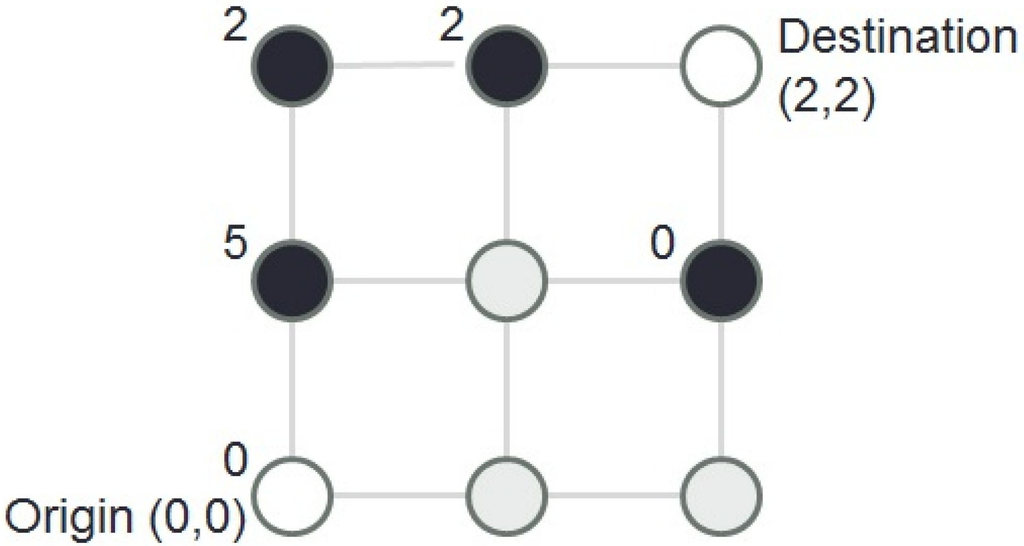


(a) Conventional MDP

(b) Route-Based MDP

Literature

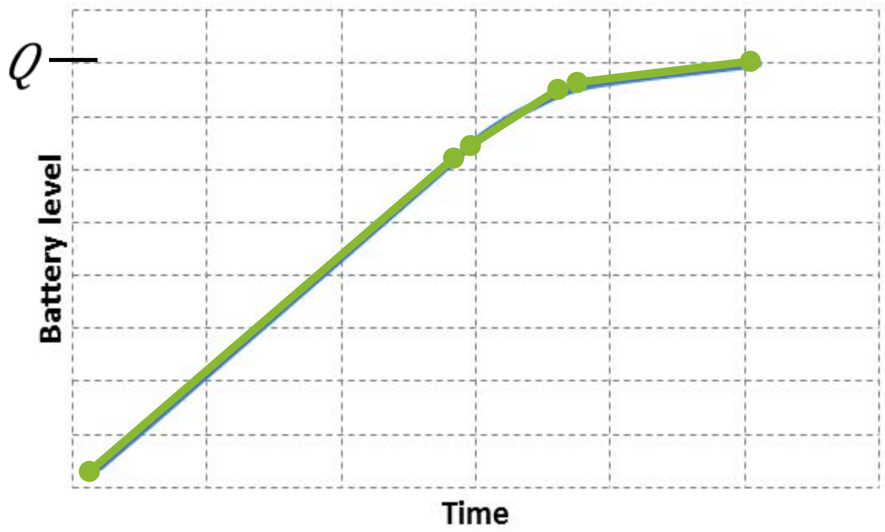
- Dynamic vehicle routing
- **Dynamic EV routing**
  - Adler, Mirchandani (2014)
  - Sweda, Dolinskaya, Klabjan (2017)



Literature

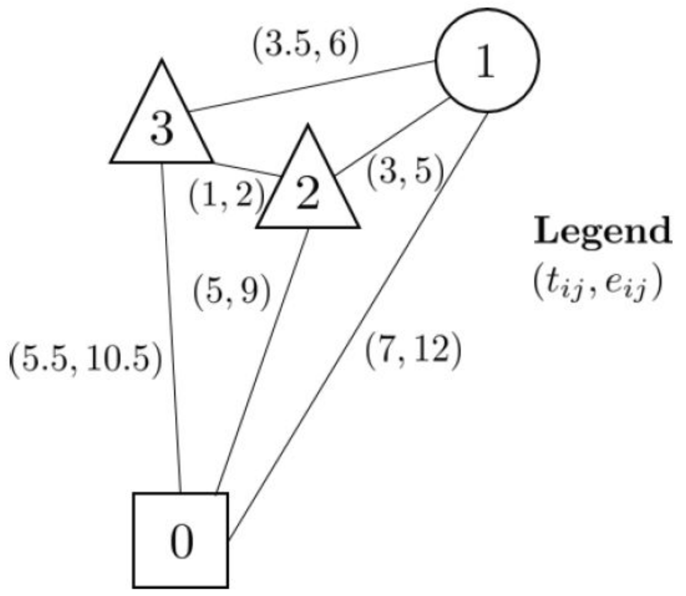
Machinery

- **Partial charging & non-linear charging function**
  - Montoya et al. (2017)
  - Pelletier, Jabali, Laporte (2017)



Literature
Machinery

- Partial charging & non-linear charging function
- **Labeling algo for fixed-route vehicle charging problem (FRVCP)**
  - Froger et al. (2018)



Literature

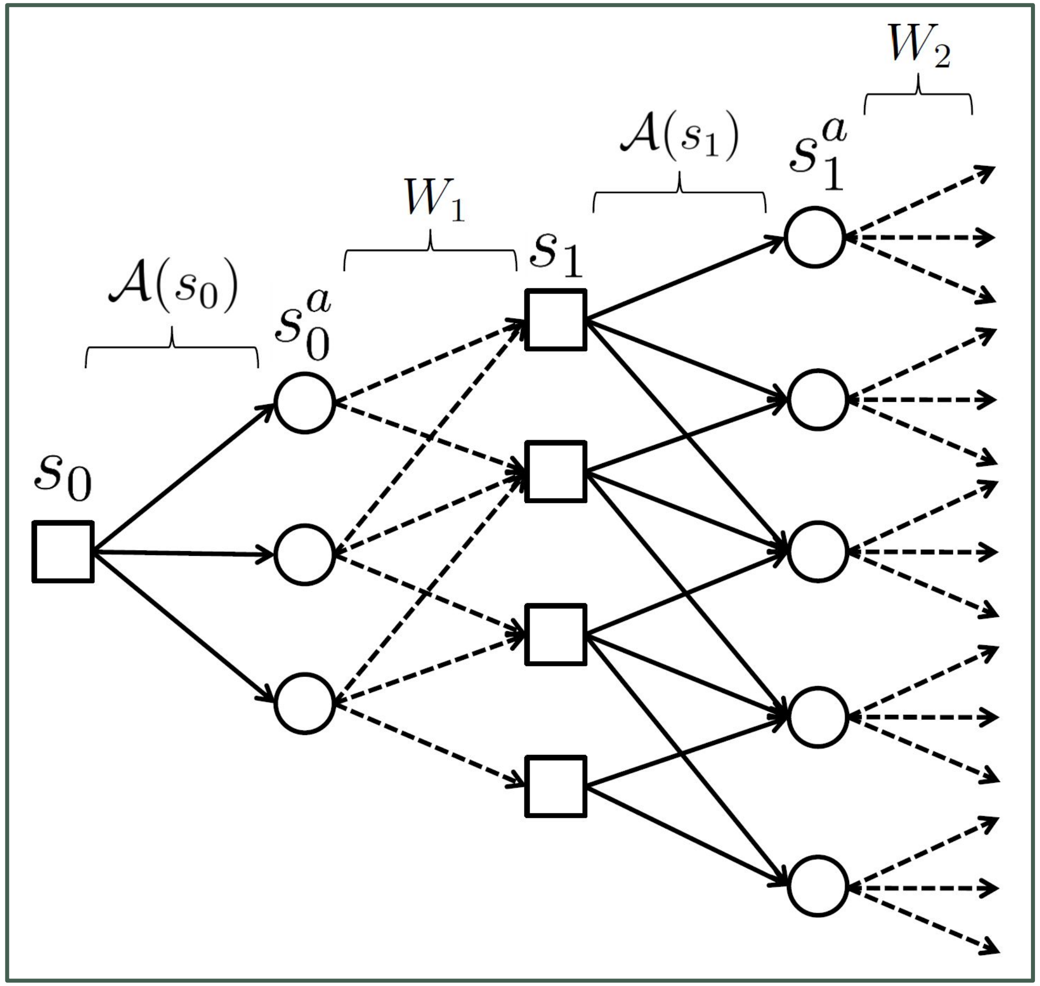
Machinery

- Partial charging & non-linear charging function
- Labeling algo for fixed-route vehicle charging problem (FRVCP)
- **Information penalties**
    - Brown, Smith, Sun (2010)

$$\boxed{z_t(a) = \mathbb{E}[w_t(a) \mid \mathcal{G}_t] - \mathbb{E}[w_t(a) \mid \mathcal{F}_t]}$$

Dynamic Routing Model

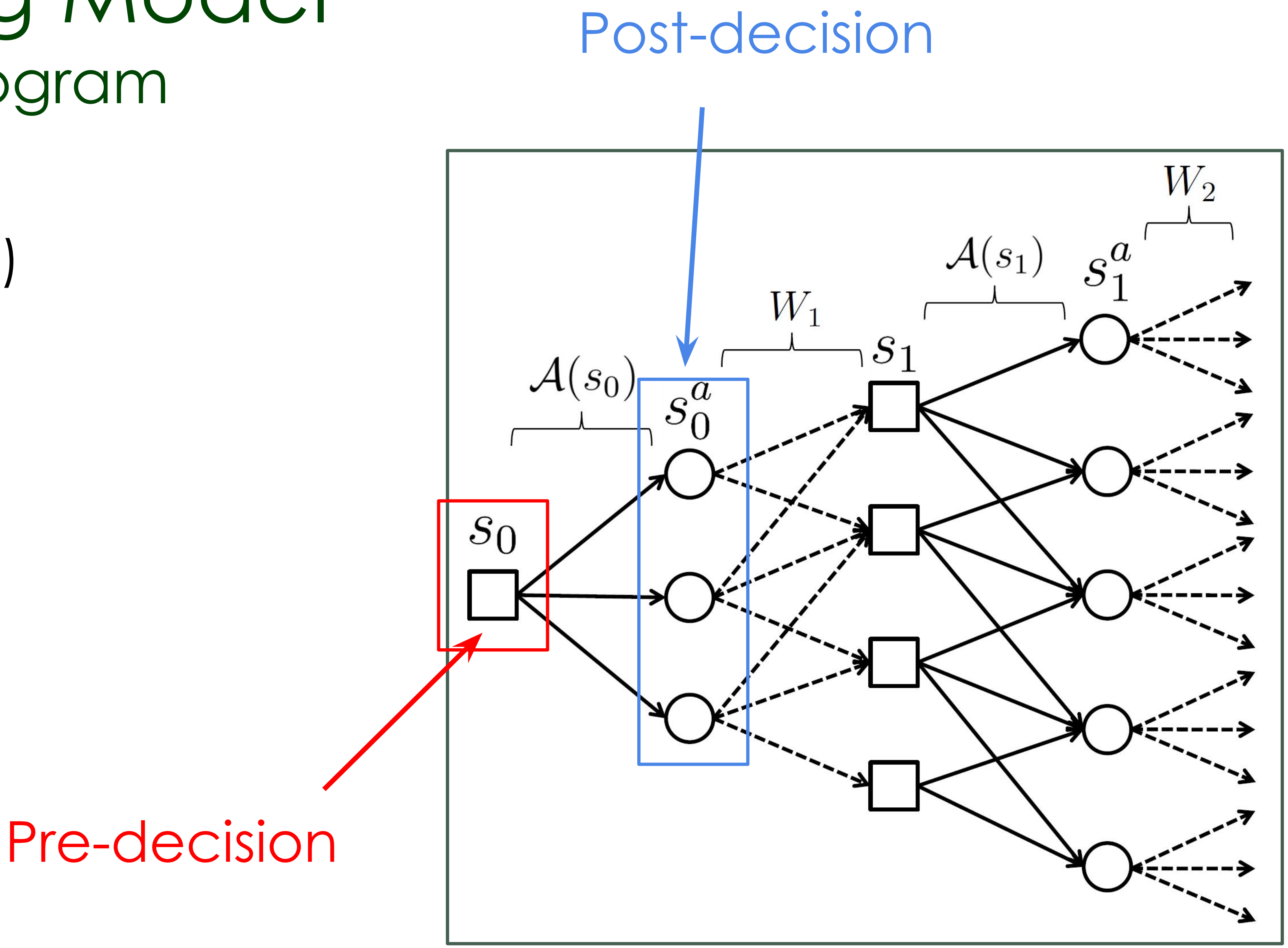
Dynamic Routing Model
Stochastic dynamic program



Dynamic Routing Model

Stochastic dynamic program

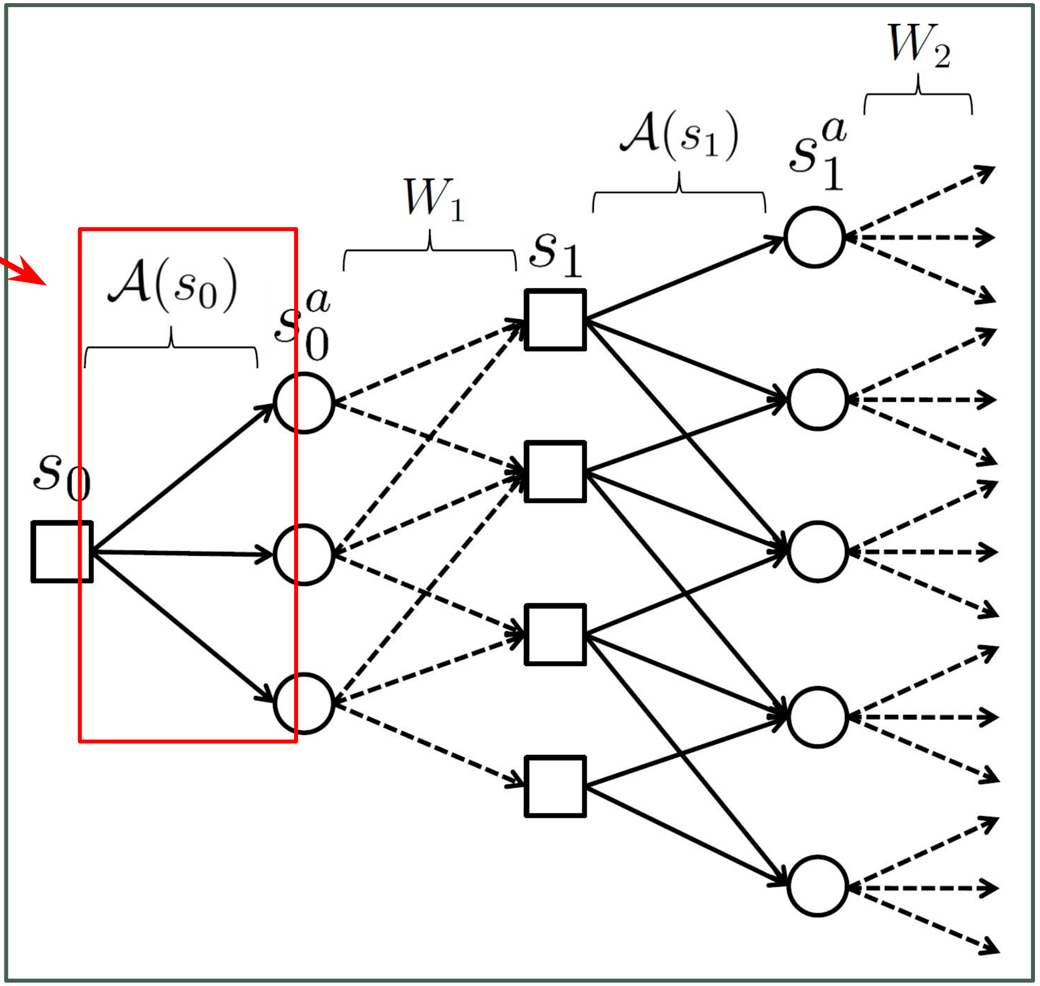
- States
  - State of charge (SoC)
  - Previous SoC
  - Time
  - Location
  - Unvisited customers
  - Queue length



Dynamic Routing Model

Stochastic dynamic program

- States
- Action space
  - Move
  - Join queue & wait
  - Charge



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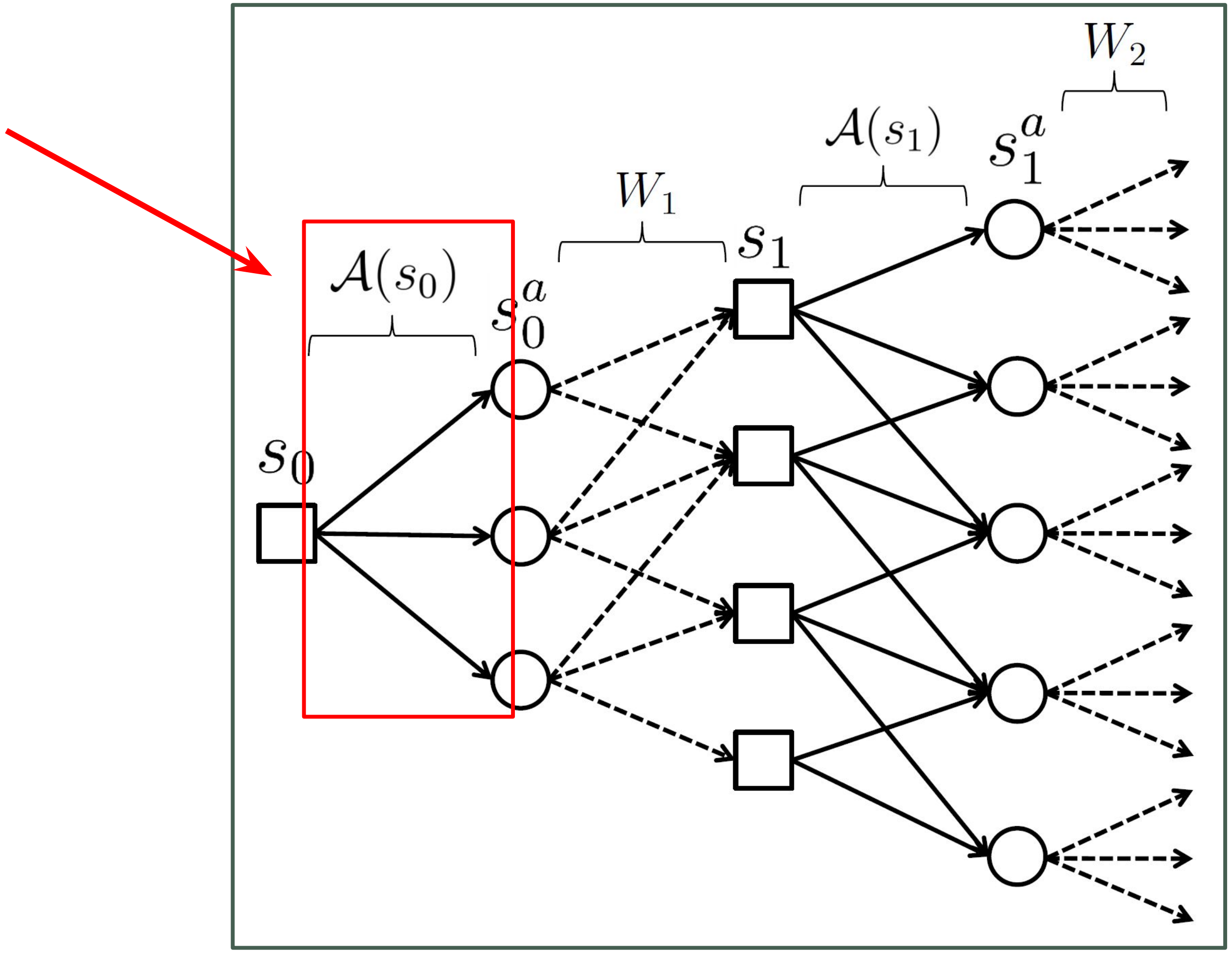
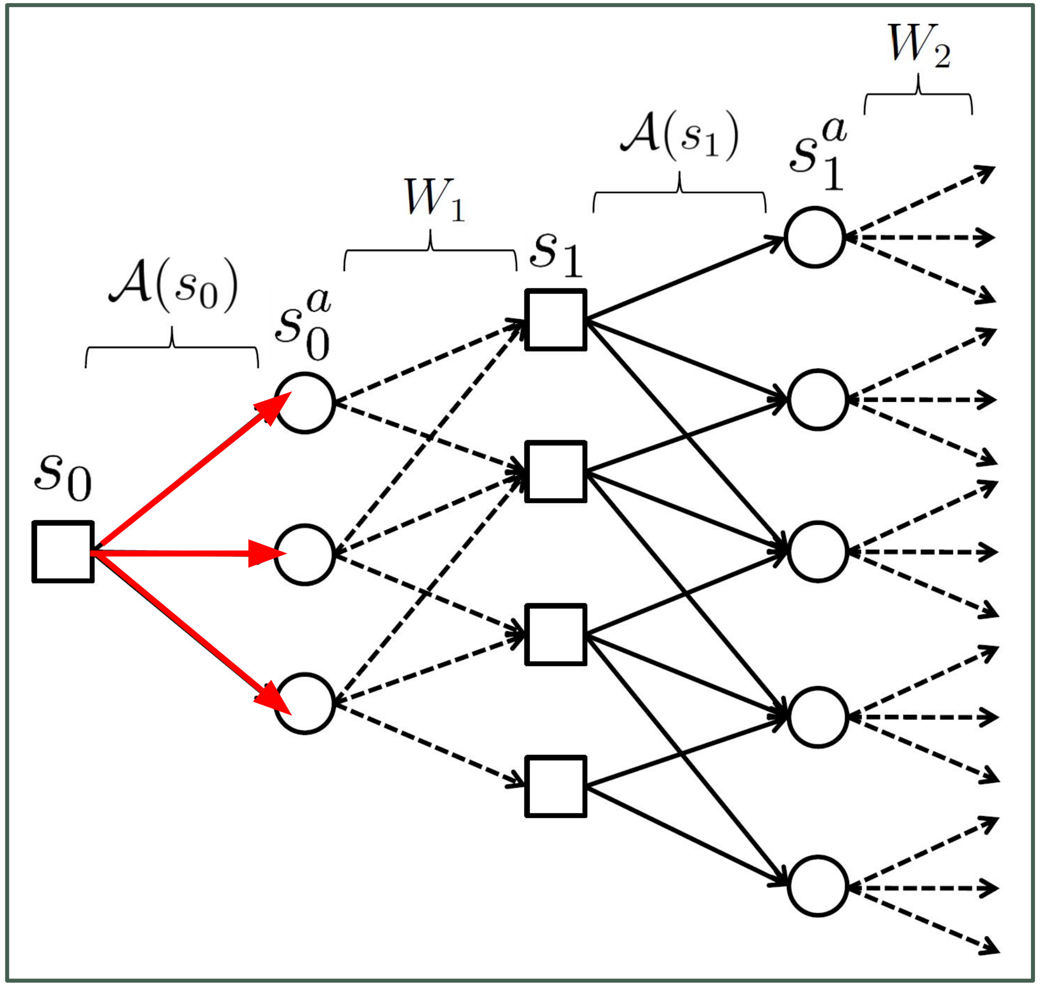


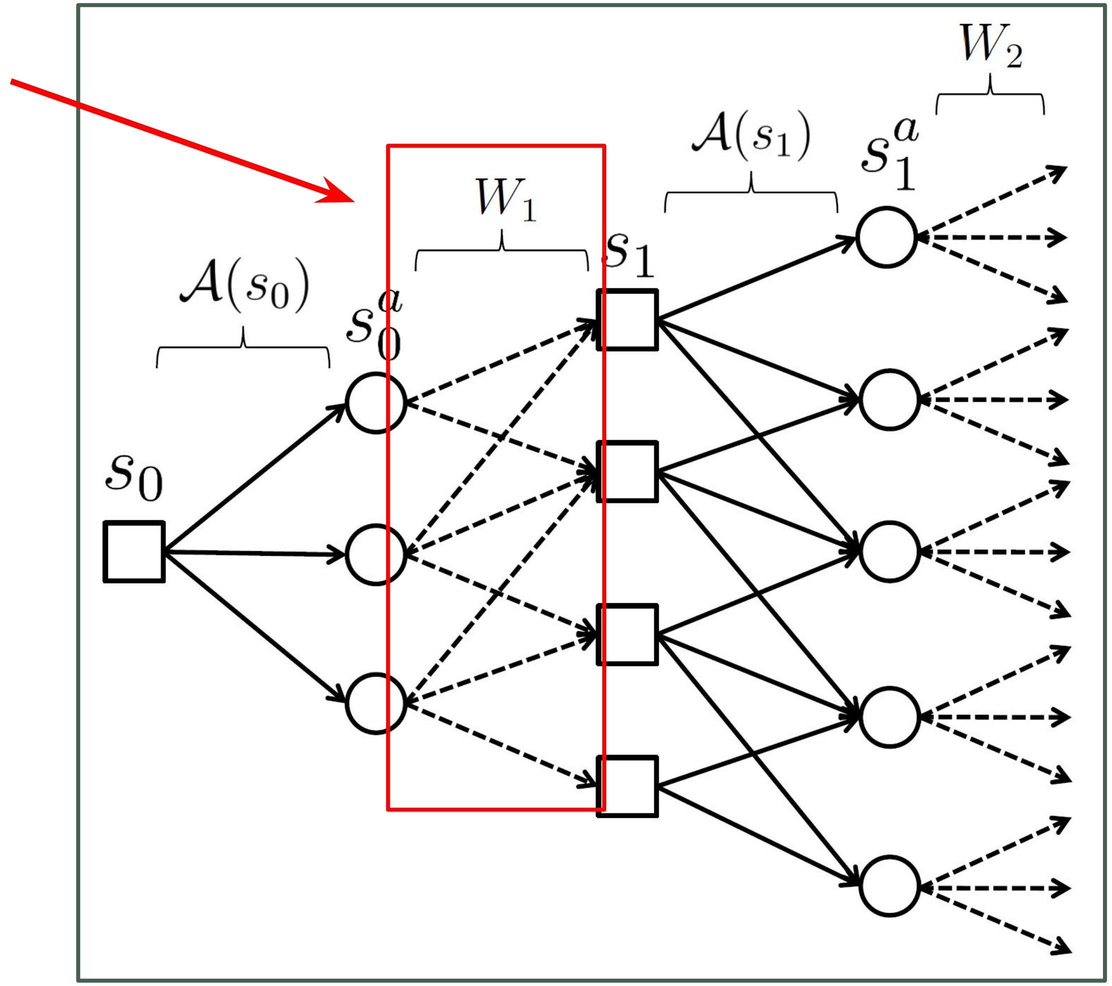
Dynamic Routing Model
Stochastic dynamic program

- States
- Action space
- Actions
  - Destination
  - SoC



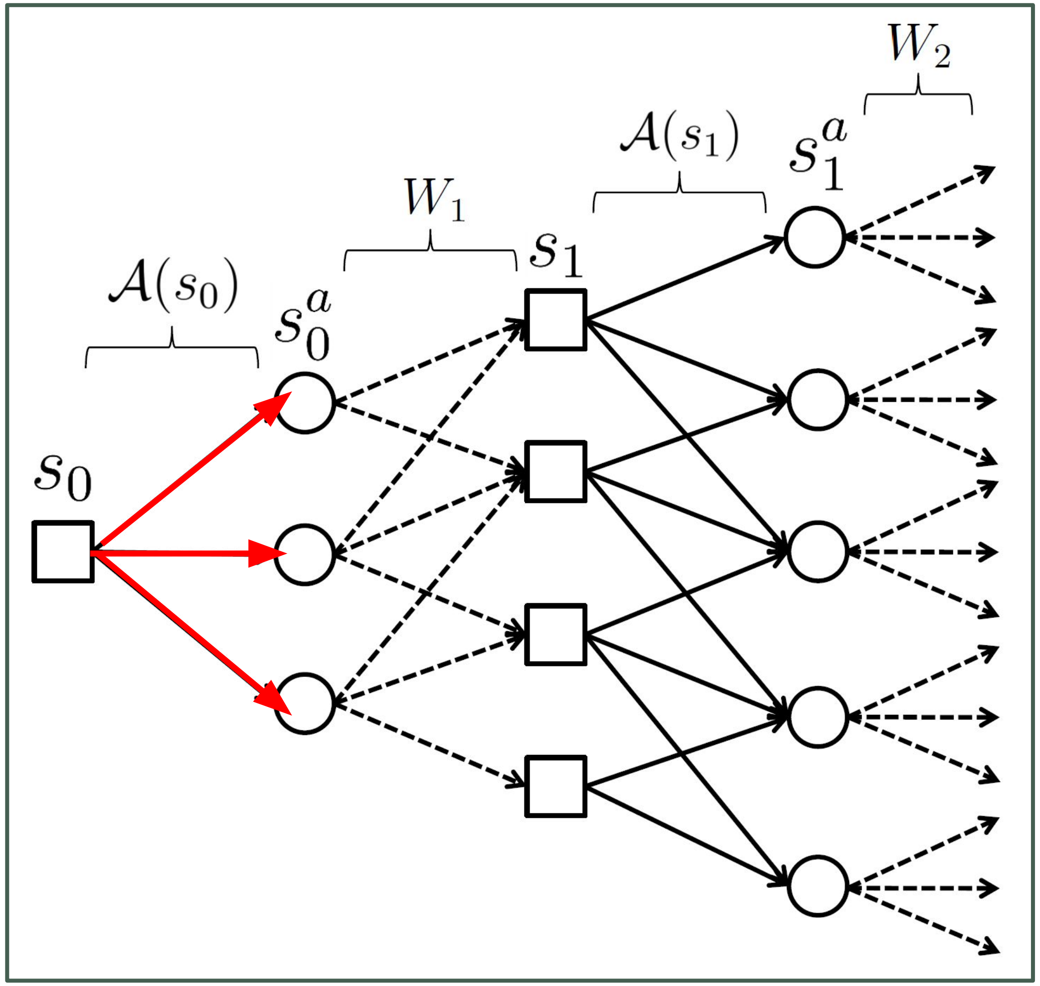
Dynamic Routing Model
Stochastic dynamic program

- States
- Action space
- Actions
- Exogenous information
  - Queue lengths (upon arrival to CS)
  - Time until we enter service (after joining queue)



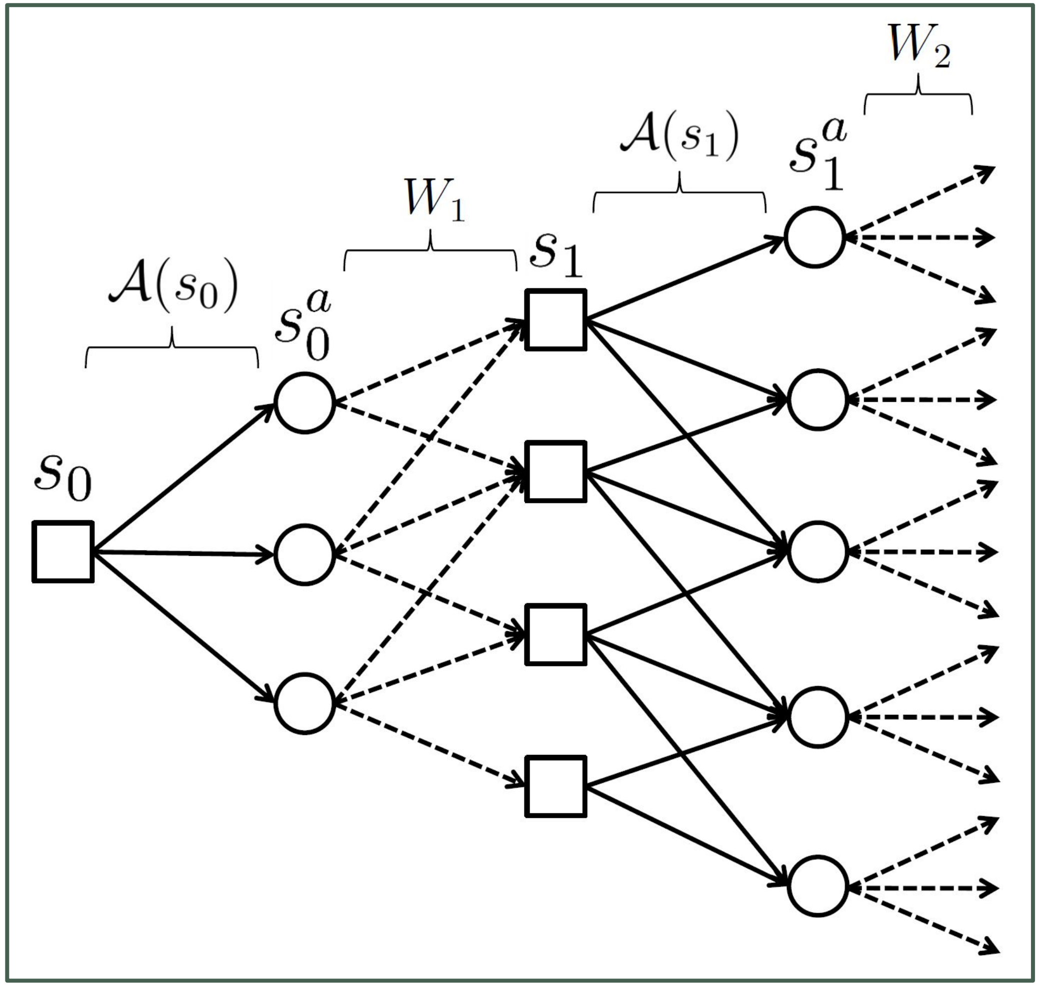
Dynamic Routing Model
Stochastic dynamic program

- States
- Action space
- Actions
- Exogenous information
- Contributions (costs)
  - Function of state and action
  - Expected time until next epoch



Dynamic Routing Model
Stochastic dynamic program

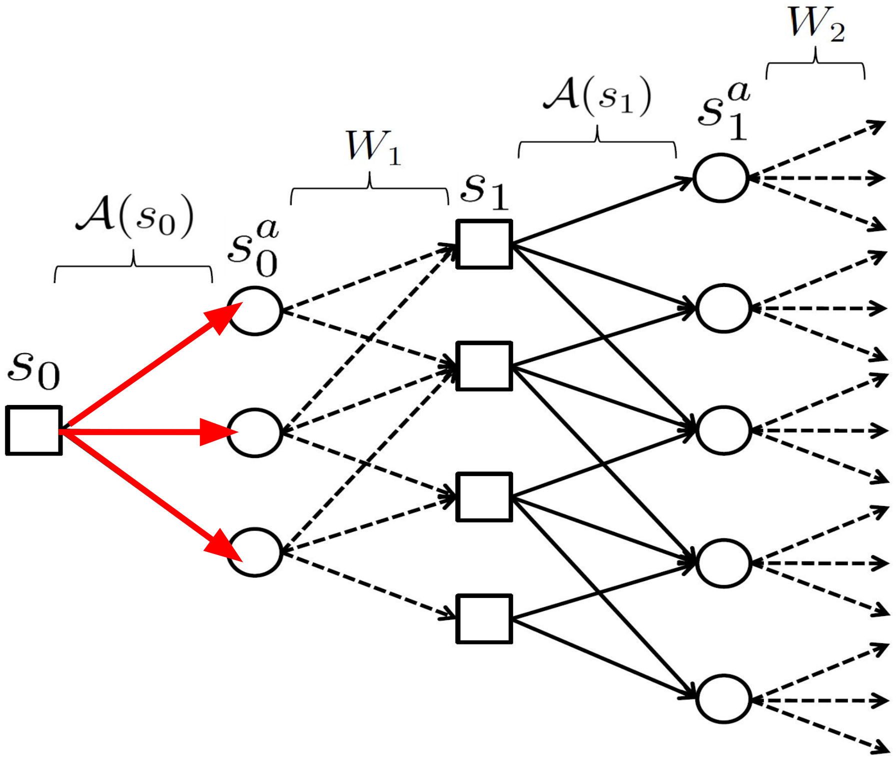
- States
- Action space
- Actions
- Exogenous information
- Contributions (costs)
- Objective function
    - Minimize expected time to reach terminal state



Solution Methods & Results: Part 1
larger instances

Solution methods

Policies - what is a policy?



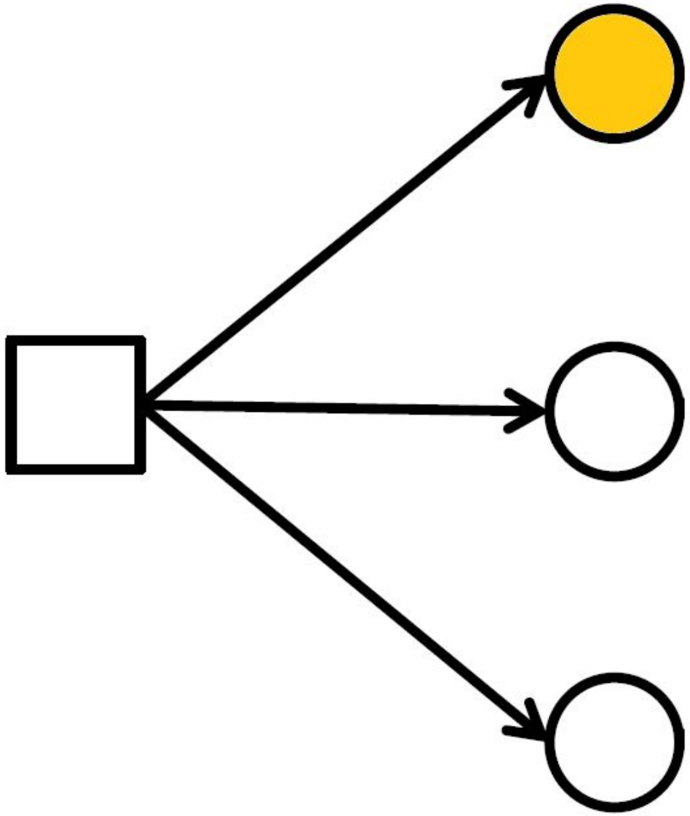
$$s_k \mapsto \mathcal{A}(s_k)$$

Solution methods

Policies	Type
1. Myopic	Dynamic
2. Myopic + Rollout	Dynamic
3. Heuristic static (fixed route)	Static
4. Heuristic static + Rollout	Dynamic

Solution methods

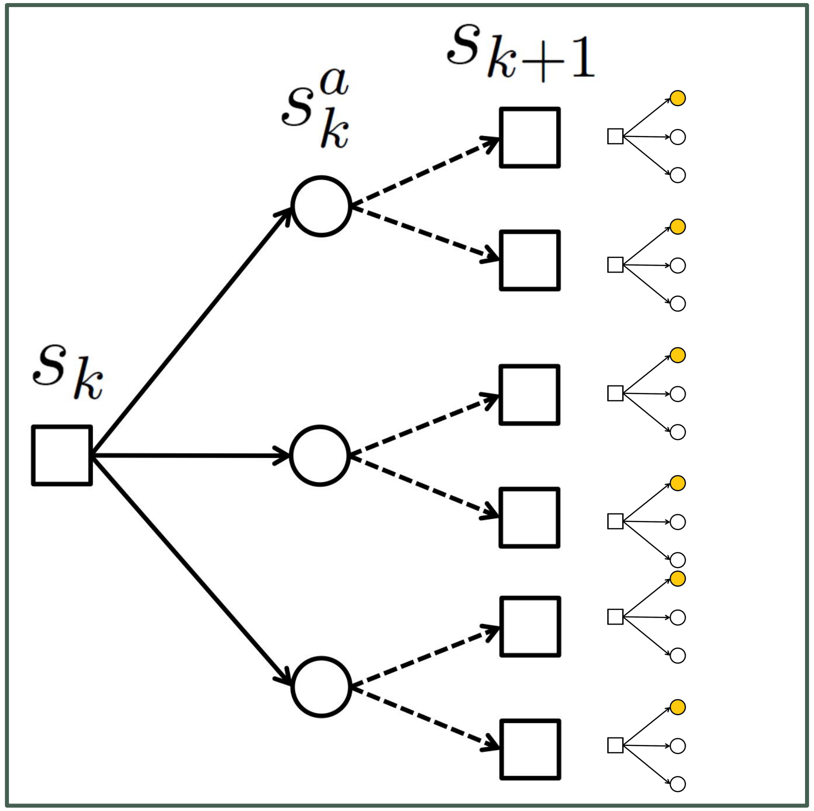
1) Myopic policy (dynamic)



$$\text{argmin}_a\{C(s_k, a)\}$$

Solution methods

2) Myopic + Rollout (dynamic)



$$\operatorname{argmin}_a \left\{ C_k(s_k, a) + \mathbb{E}\left[\sum_{i=k+1}^{K} C_i\left(s_i, \delta_i^{\pi_{\mathcal{H}(s_{k+1})}}\right) \middle| s_k \right] \right\}$$

Solution methods

3) Heuristic Static (fixed route) Policy

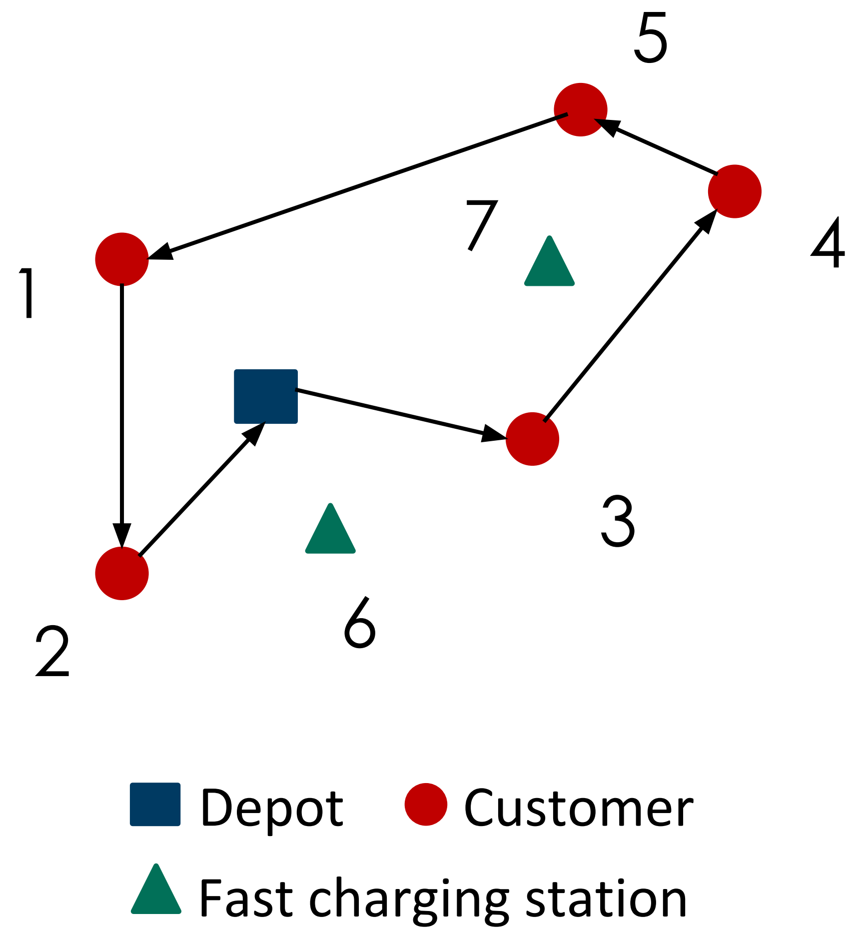
- Static (non-dynamic) policy
- Fix sequence of customers and charging stations
- Policy:
  - Follow fixed route, charge, wait as required

Solution methods

3) Heuristic Static (fixed route) Policy

Optimally solve customer-only TSP:

Customer sequence	0-3-4-5-1-2-0



Solution methods

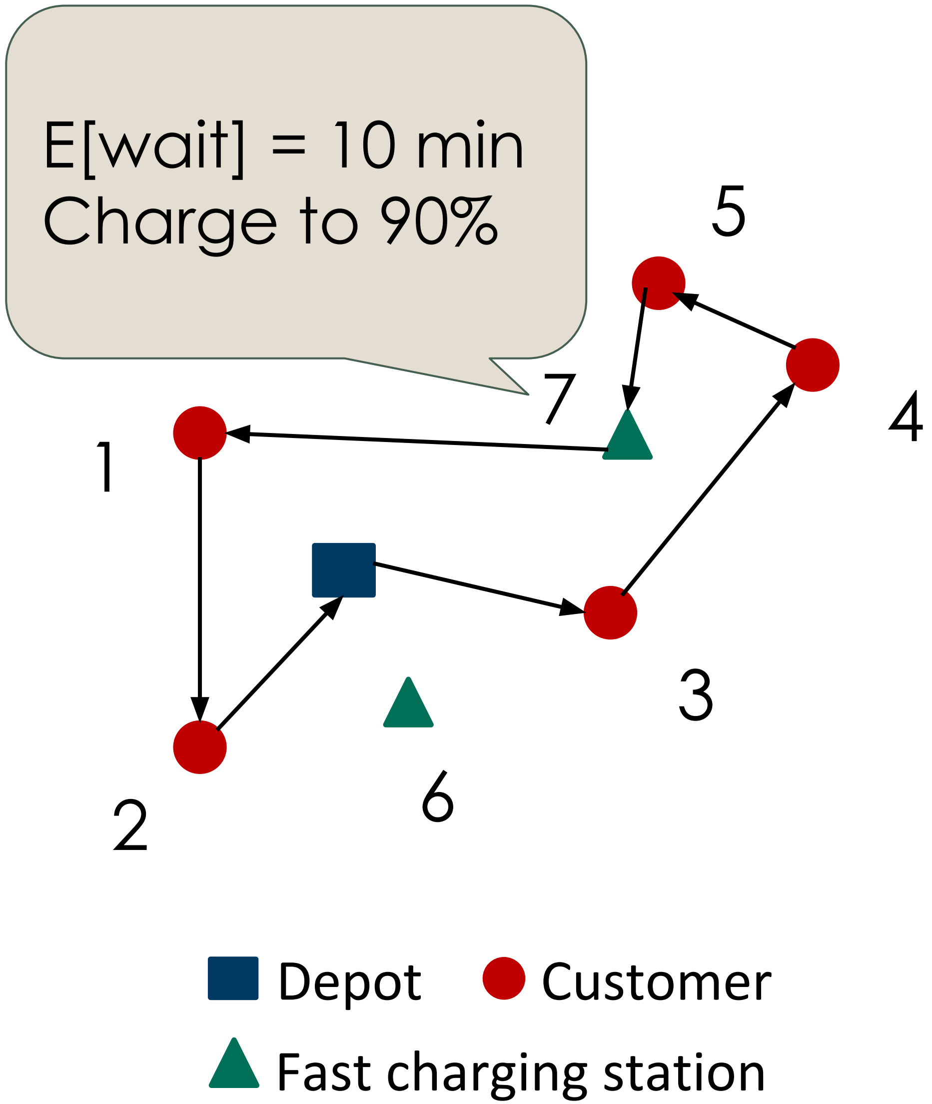
3) Heuristic Static (fixed route) Policy

Optimally solve customer-only TSP:

Customer sequence 0-3-4-5-1-2-0

Solve fixed-route vehicle charging problem (Froger et al. (2018)):

Energy feasible 0-3-4-5-**7-**1-2-0



Solution methods

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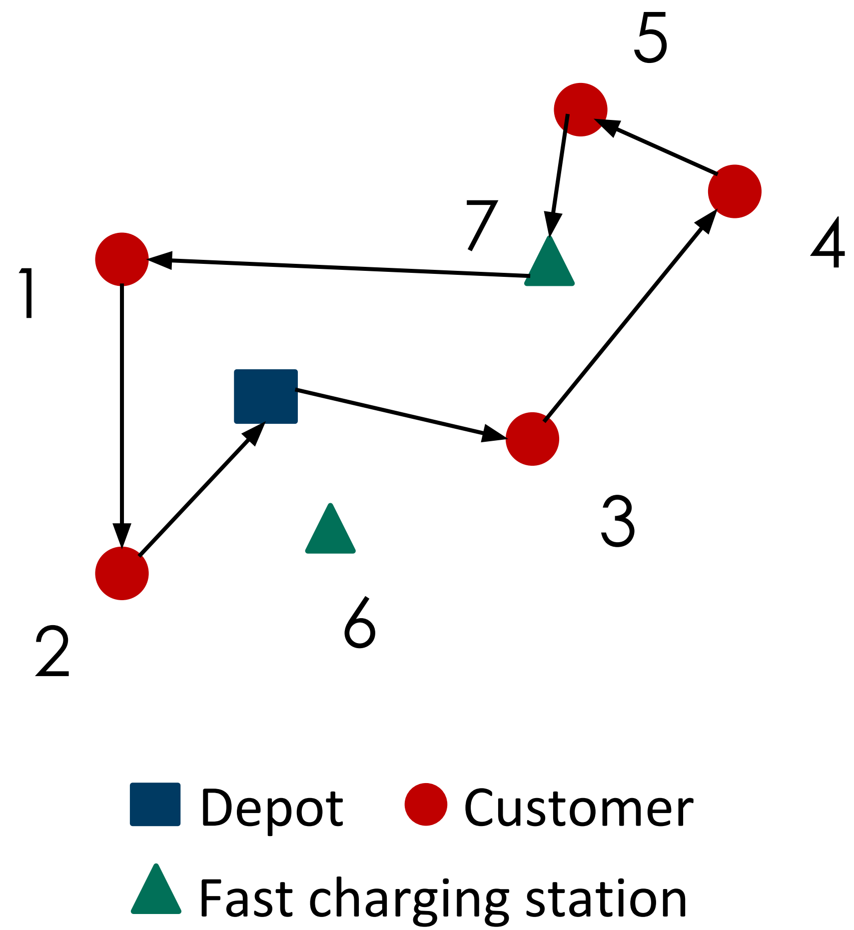


Policy:

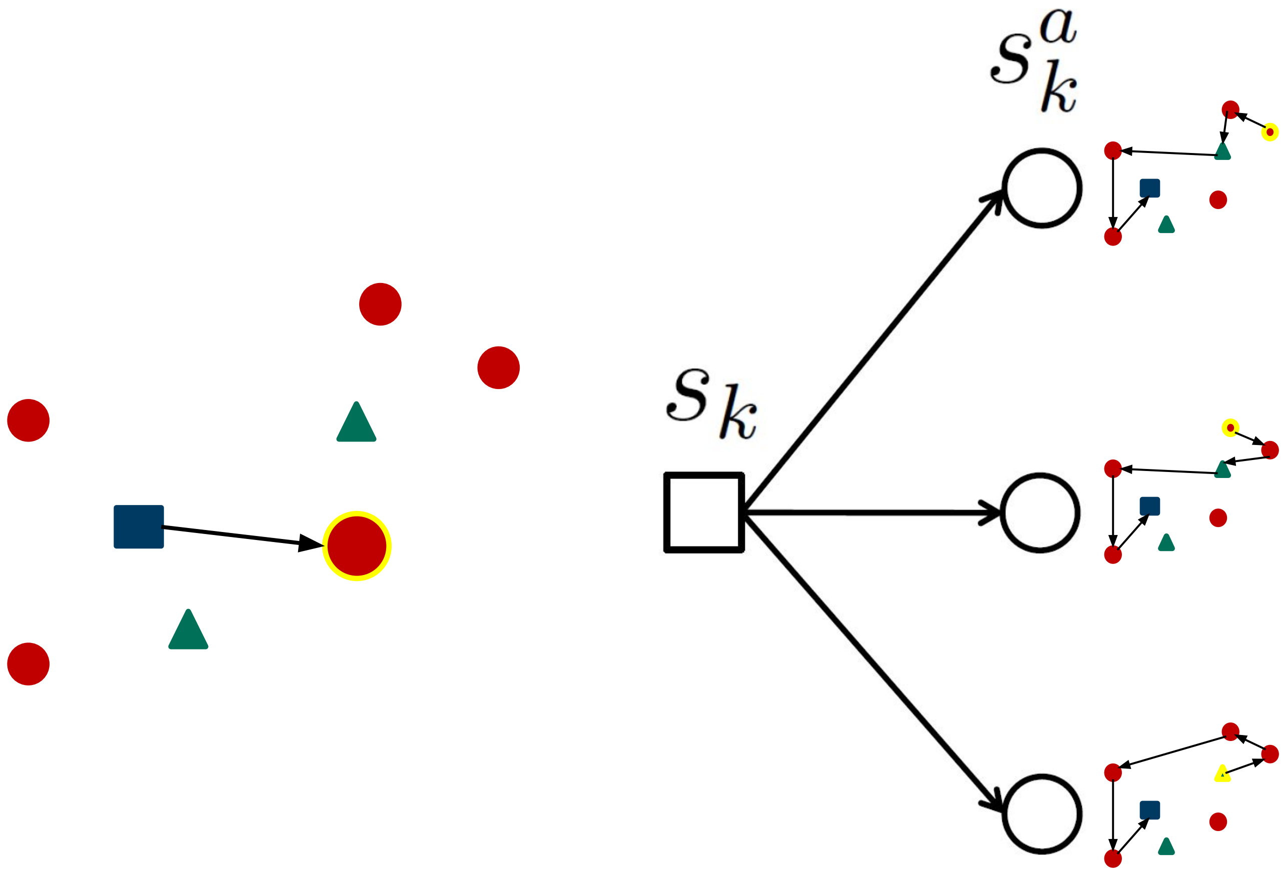
- Follow fixed-route, charge, wait as required

Solution methods

4) Heuristic static + Rollout (dynamic)

Solution methods

4) Heuristic static + Rollout (dynamic)



Results: 20+ customer instances

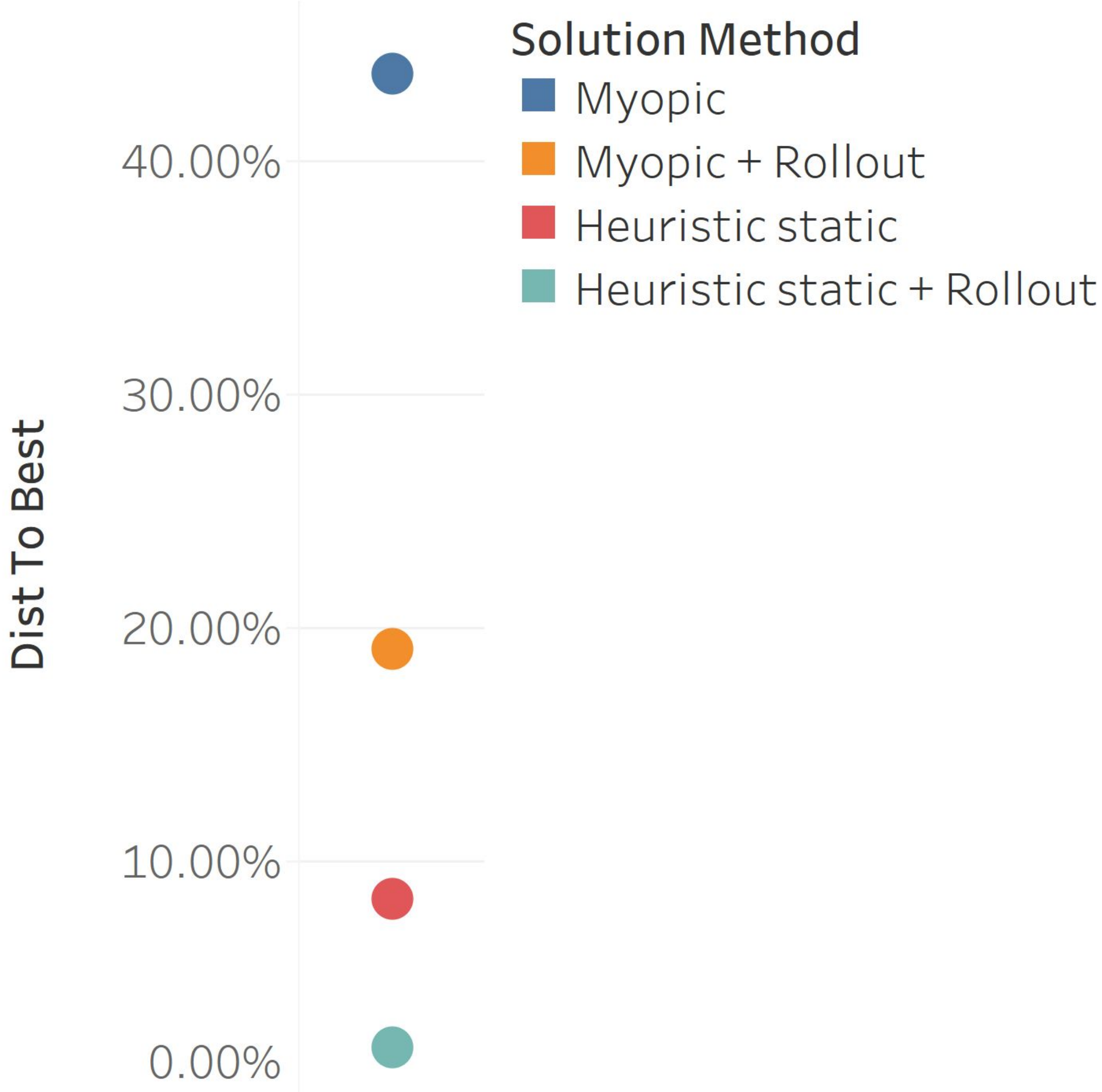
Instances:

20 cust/3 CS
30 cust/4 CS
40 cust/5 CS

- Randomly distributed
- 5 geographies
- 3 chargers/CS
- CS speeds {fast, medium, slow}
  - chosen at random
- Utilizations {45%, 60%, 75%, 90%}
  - chosen at random
  - 5 demand scenarios

Results: 20+ customer instances

20+ customers:
Distance to best



Instances:

- 20 cust/3 CS
- 30 cust/4 CS
- 40 cust/5 CS
  - Randomly distributed
  - 5 geographies
  - 3 chargers/CS
  - CS speeds {fast, medium, slow}
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  - Utilizations {45%, 60%, 75%, 90%}
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    - 5 demand scenarios

Solution Methods & Results: Part 2 smaller instances

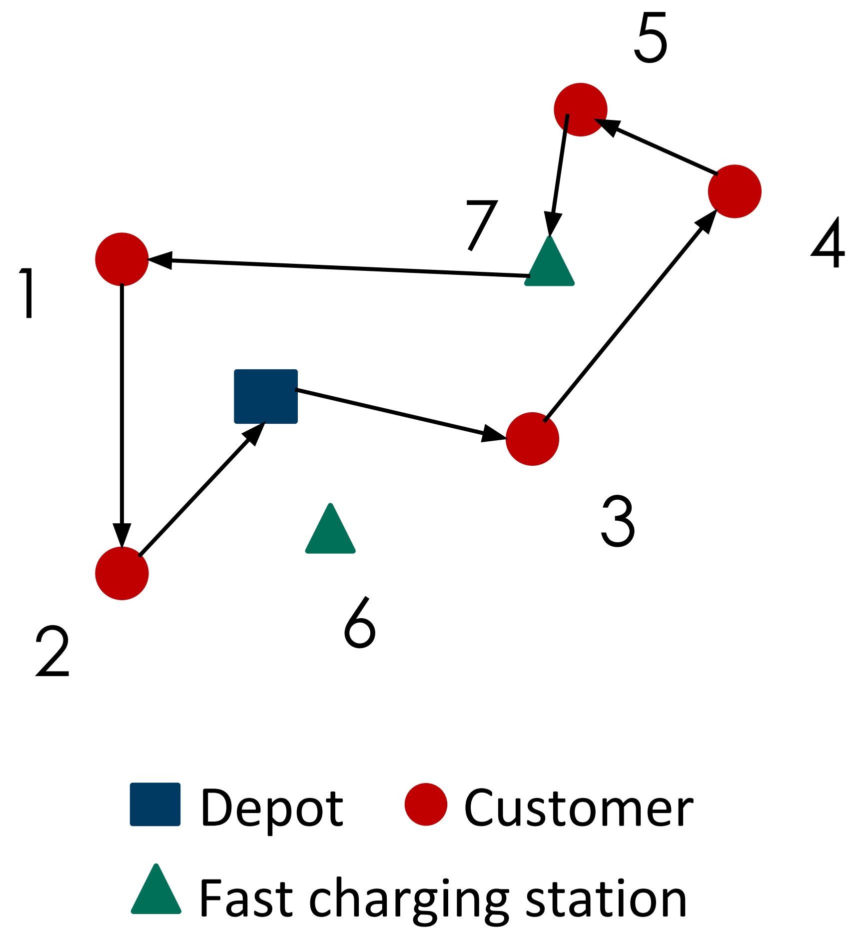
Solution methods

Policies	Type
5. Optimal Static	Static
6. Optimal Static + Rollout	Dynamic

Solution methods

5) Optimal Static (static)

Solve static problem to optimality



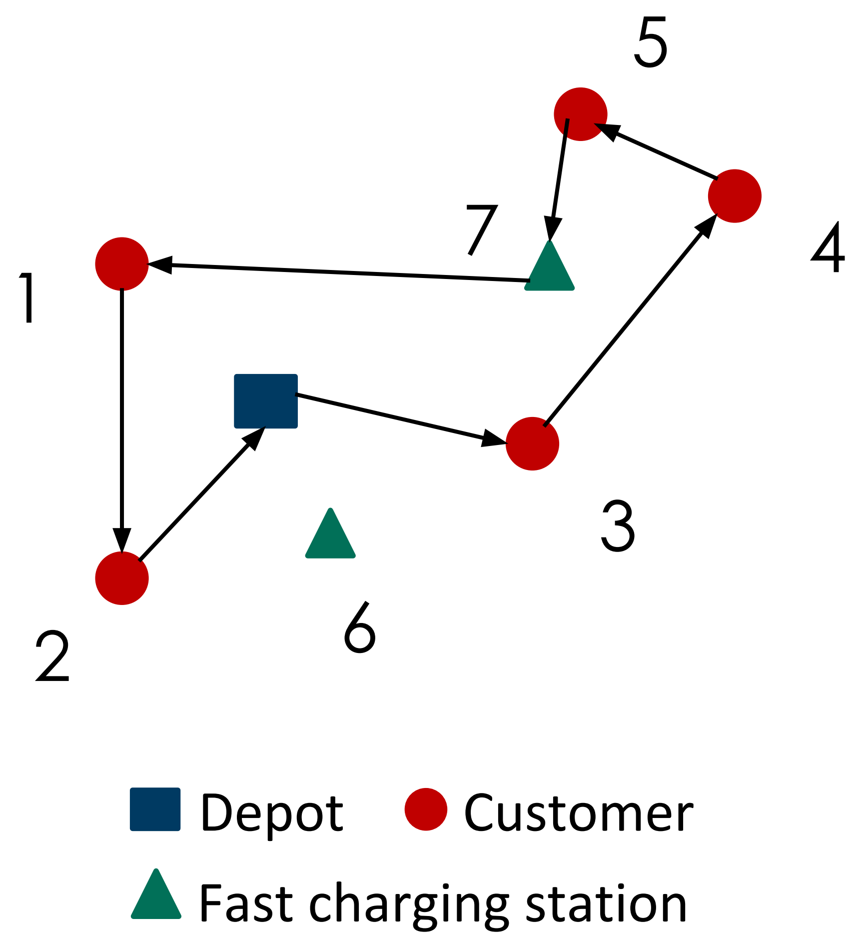
Solution methods

5) Optimal Static (static)

Solve static problem to optimality

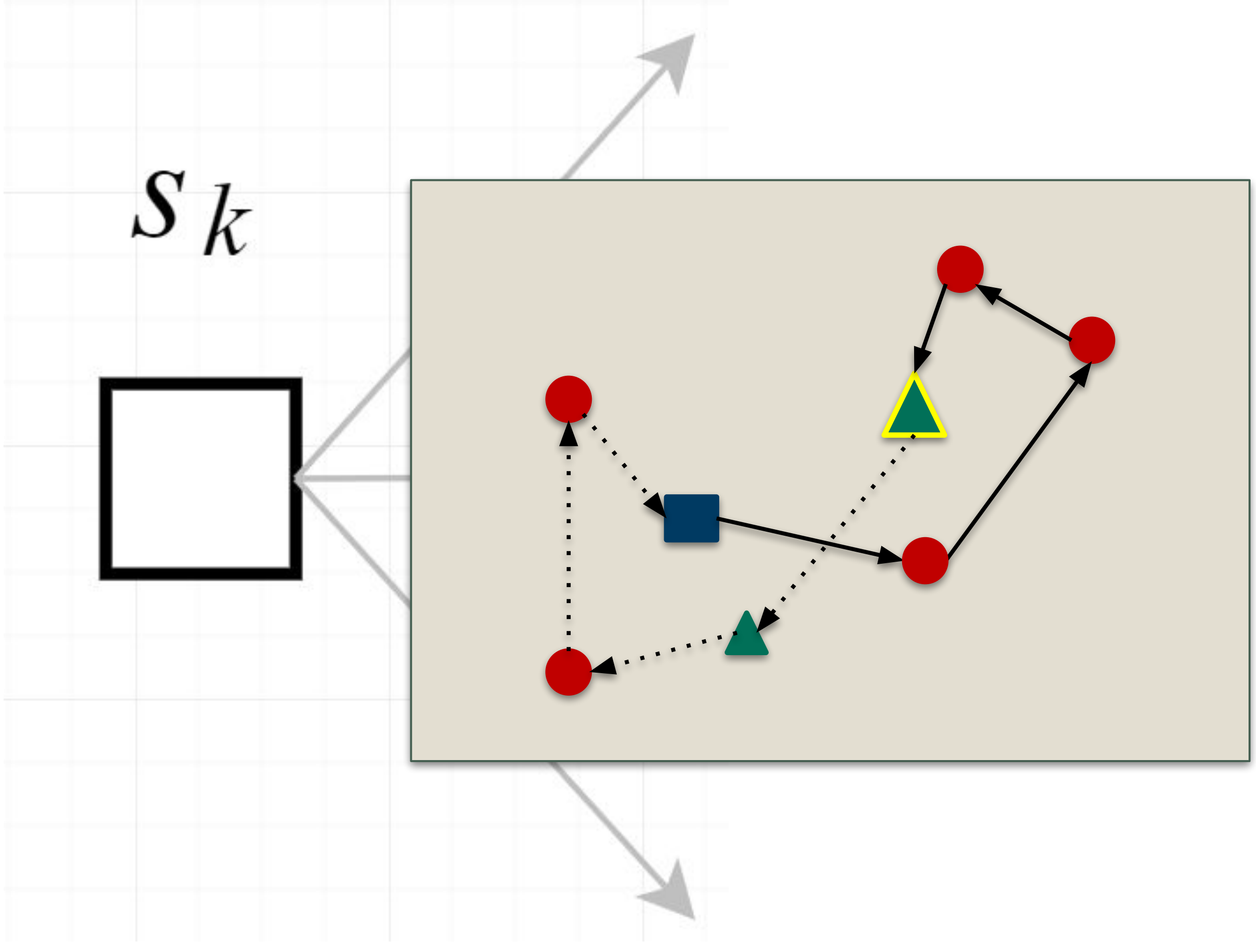
Benders decomposition:

- Master problem: customer sequences
- Subproblem: charging decisions
  - Expected waiting times



Solution methods

6) Optimal static + Rollout (dynamic)



From each pre-decision state, solve static problem to optimality

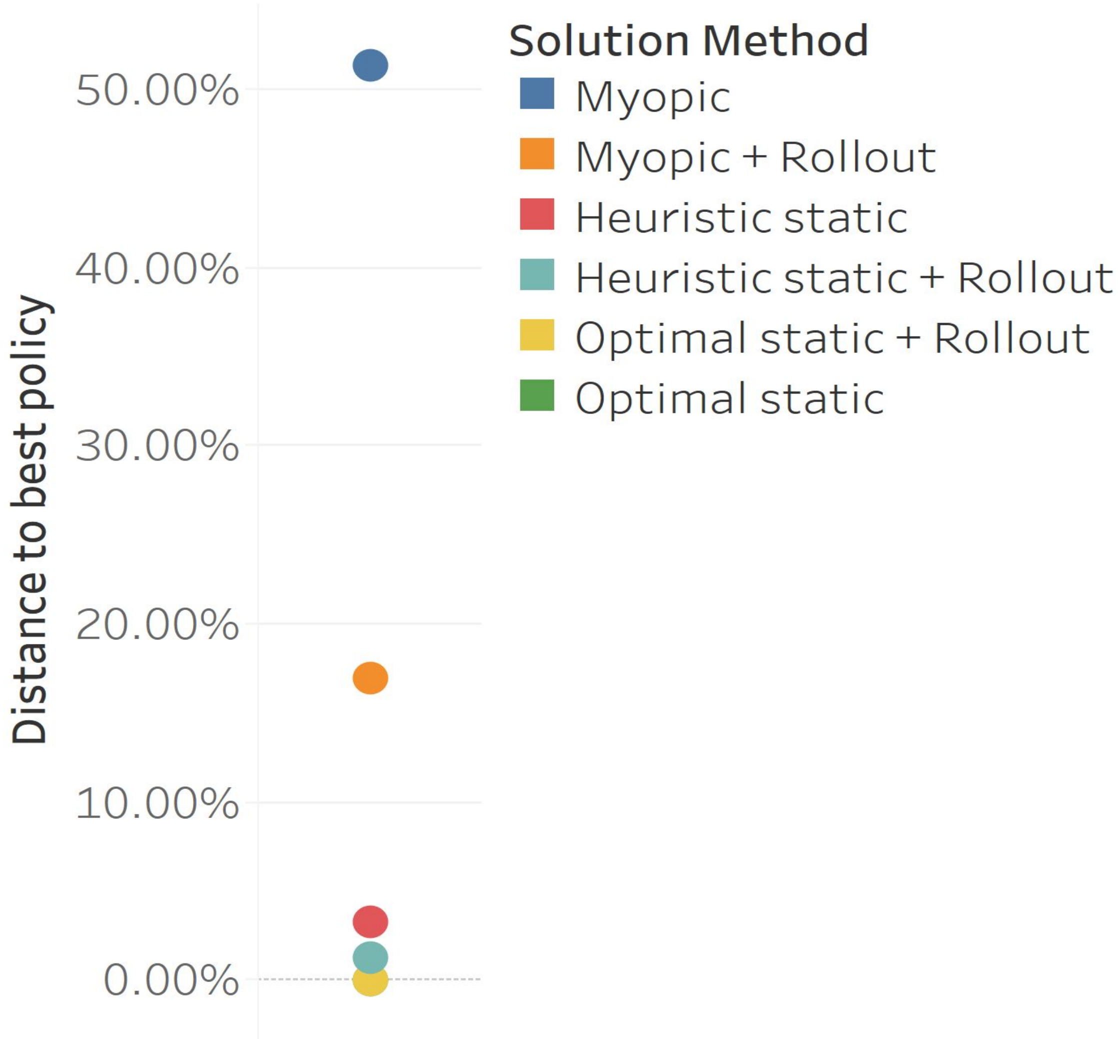
Results: 10 customer instances

Instances:

- 10 cust/2 CS
- 10 cust/4 CS
  - Randomly distributed
  - 10 geographies
  - 3 chargers/CS
  - CS speeds {fast, medium, slow}
    - chosen at random
  - Utilizations {45%, 60%, 75%, 90%}
    - chosen at random
    - 5 demand scenarios

Results: 10 customer instances

10 Customers: Distance to best policy



Instances:

- 10 cust/2 CS
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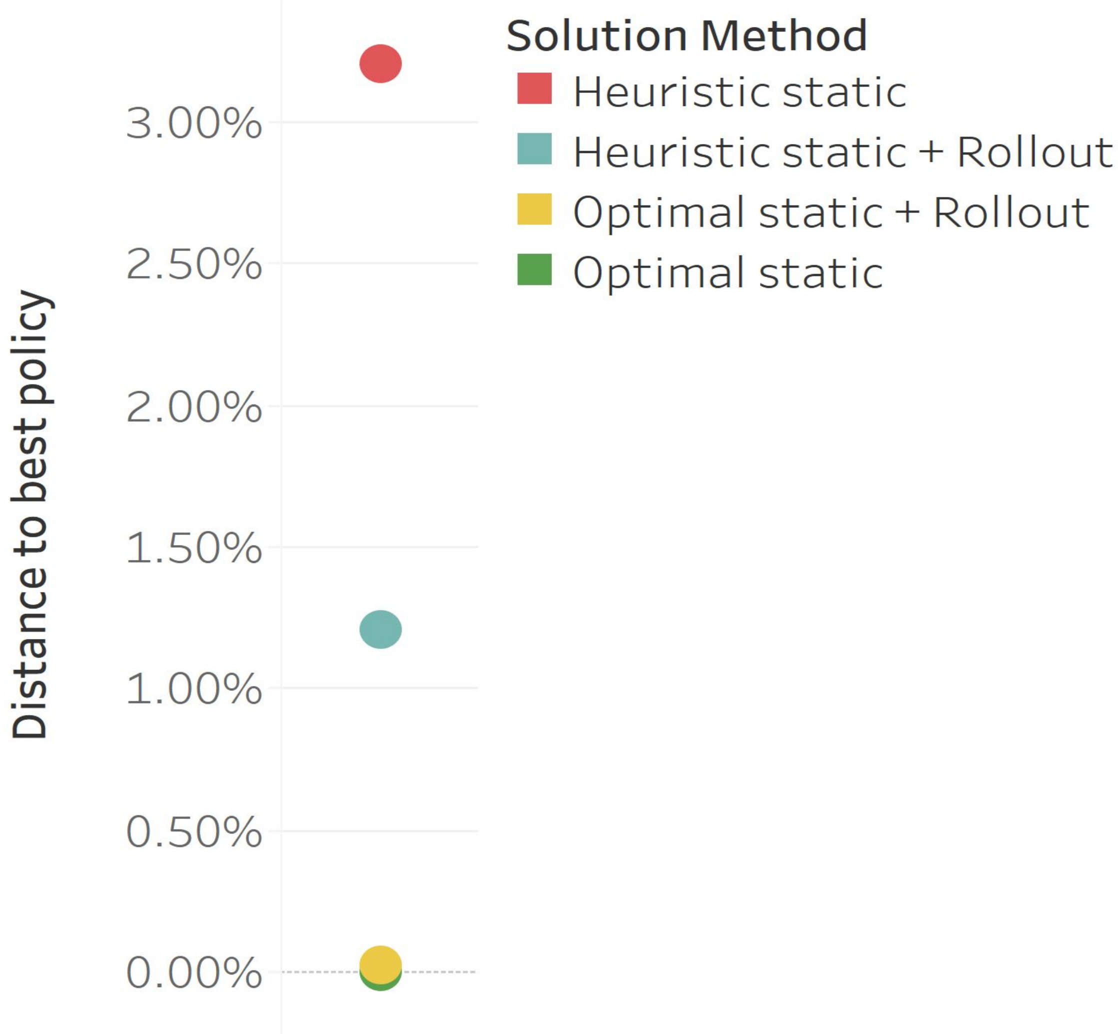
  - 3 chargers/CS
  - CS speeds {fast, medium, slow}
    - chosen at random
  - Utilizations {45%, 60%, 75%, 90%}
    - chosen at random
    - 5 demand scenarios

Results: 10 customer instances

Without myopic-based policies

10 Customers:
Distance to best policy (no myopic)



Instances:

- 10 cust/2 CS
- 10 cust/4 CS
  - Randomly distributed
  - 10 geographies
  - 3 chargers/CS
  - CS speeds {fast, medium, slow}
    - chosen at random
  - Utilizations {45%, 60%, 75%, 90%}
    - chosen at random
    - 5 demand scenarios

Results: 10 customer instances

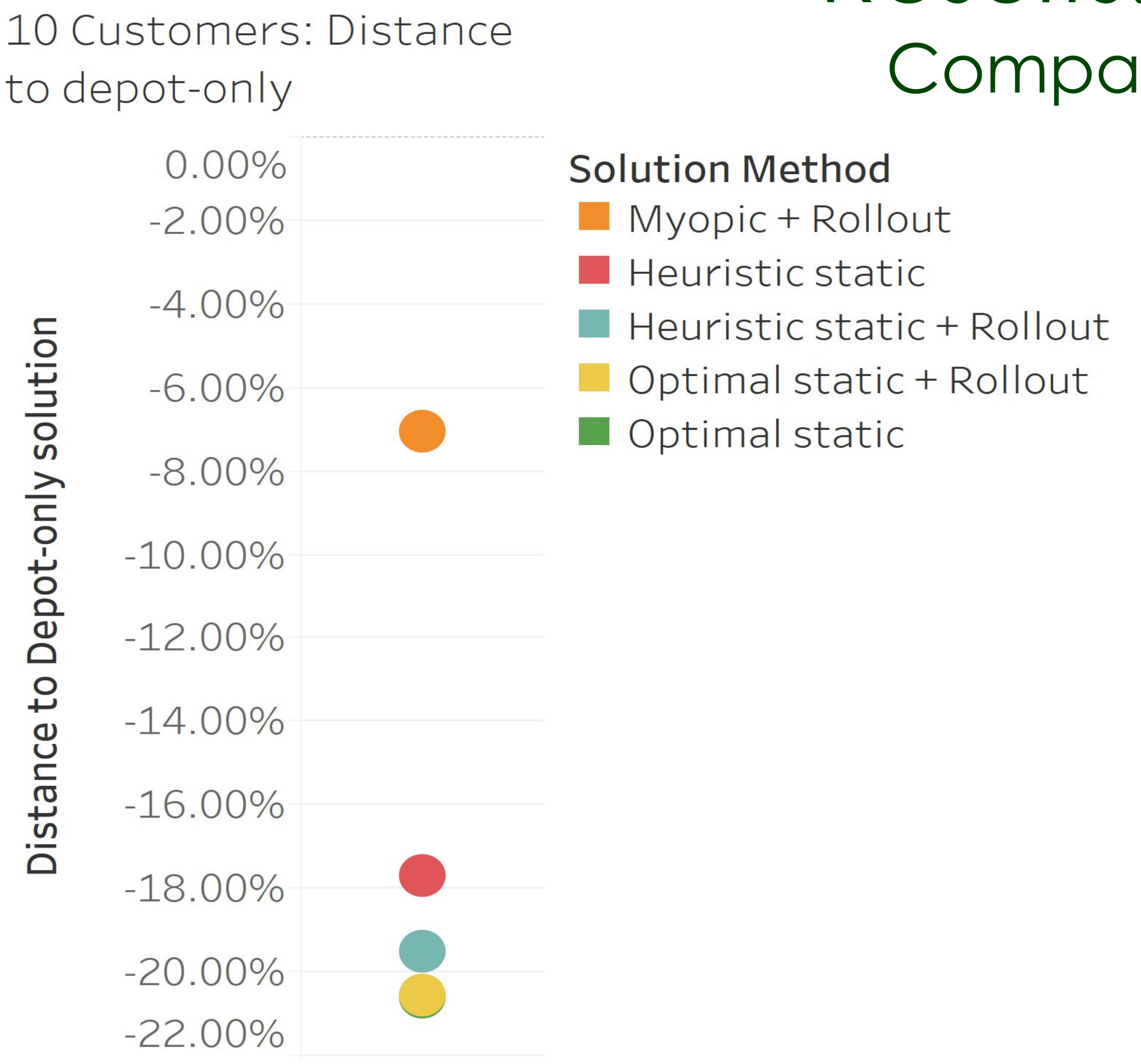
Comparison with depot-only performance

Comparison with depot-only

- Same set of instances
- Remove all non-depot CSs
- Optimally solve non-depot problem
- Compare optimal depot-only solution with average policy performance

Results: 10 customer instances

Comparison with depot-only performance

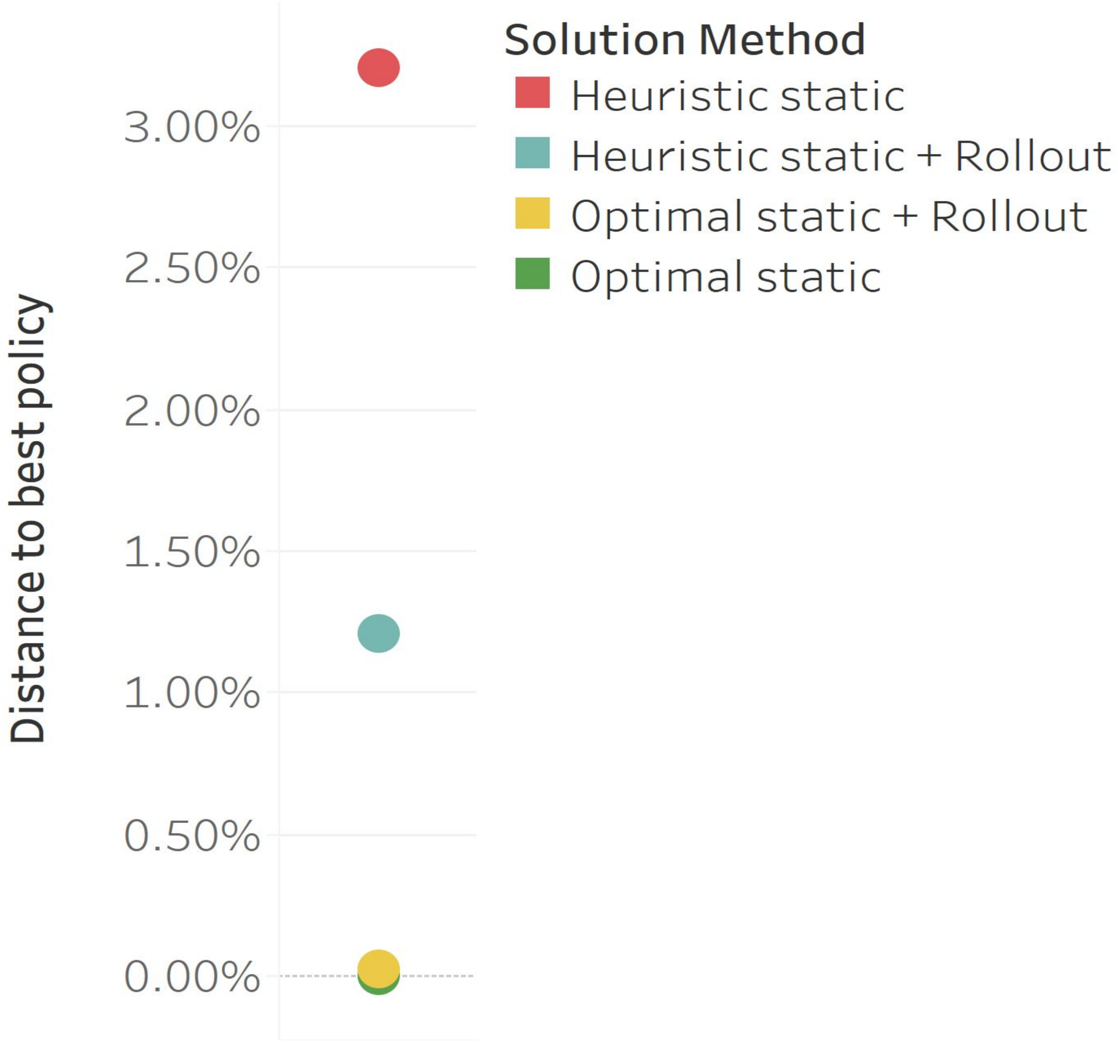


Comparison with depot-only

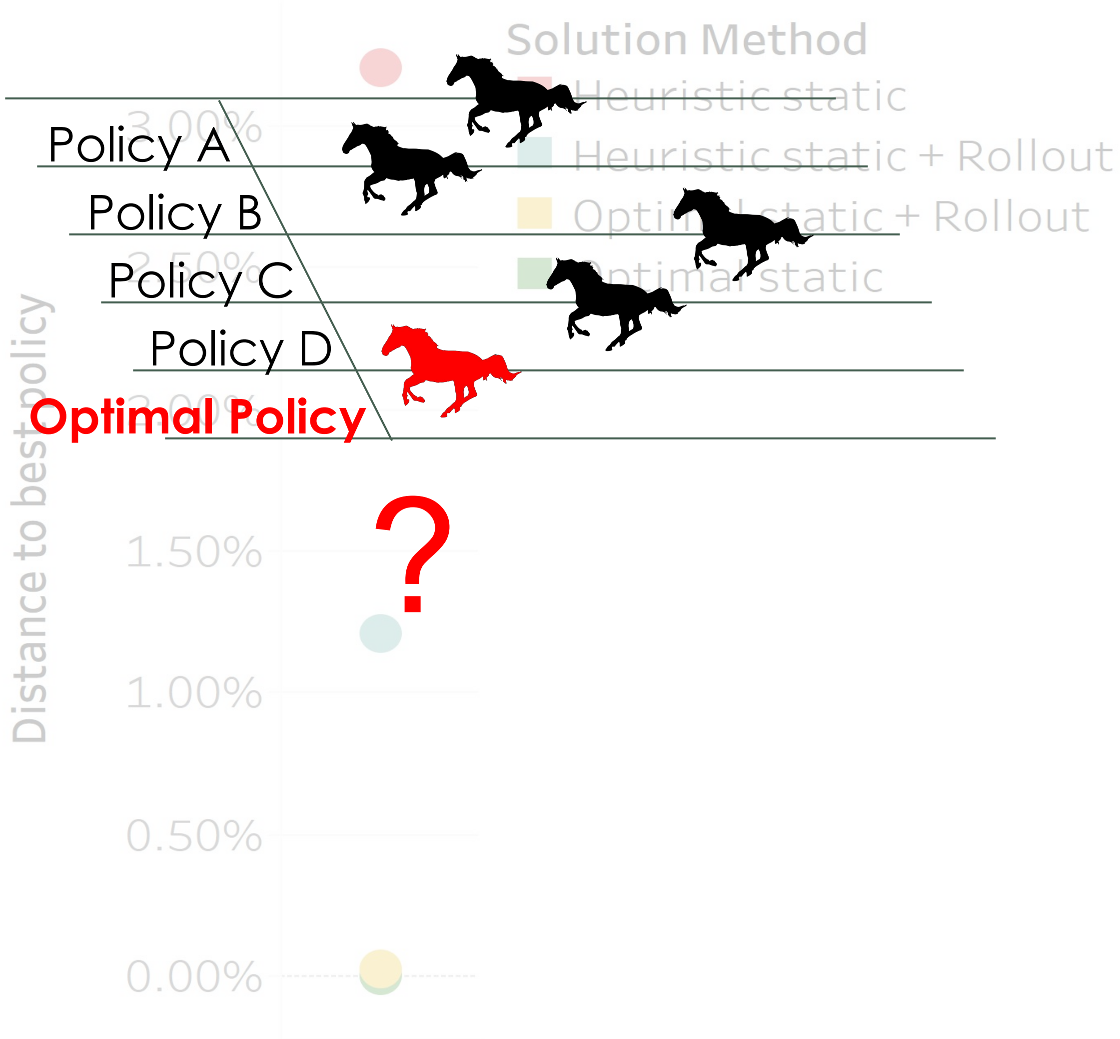
- Same set of instances
- Remove all non-depot CSs
- Optimally solve non-depot problem
- Compare optimal depot-only solution with average policy performance

Deriving lower bounds: Information relaxation

10 Customers:
Distance to best policy (no myopic)

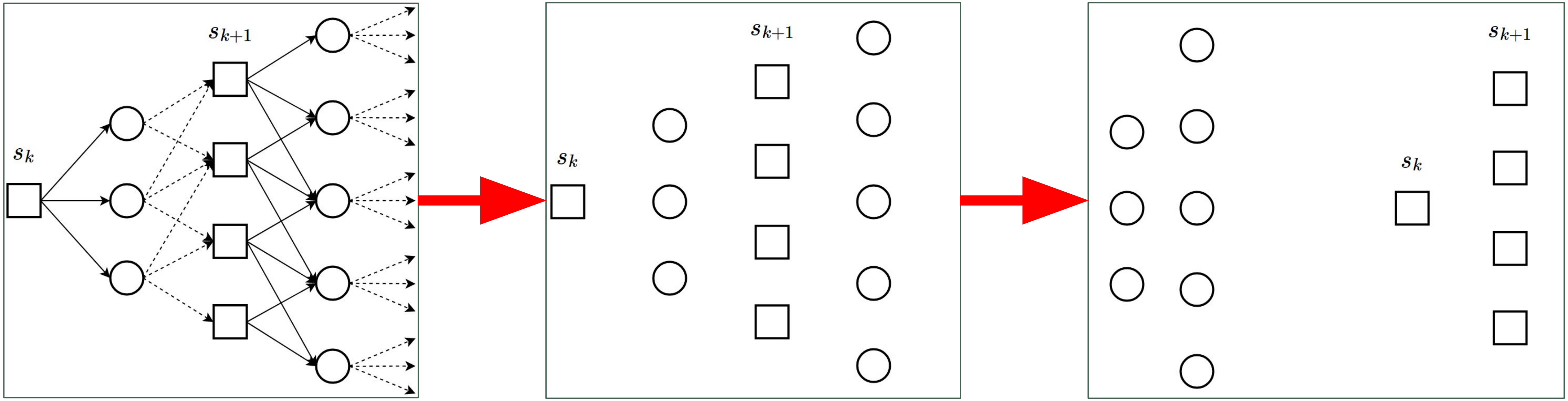


10 Customers: Distance to best policy (no myopic)



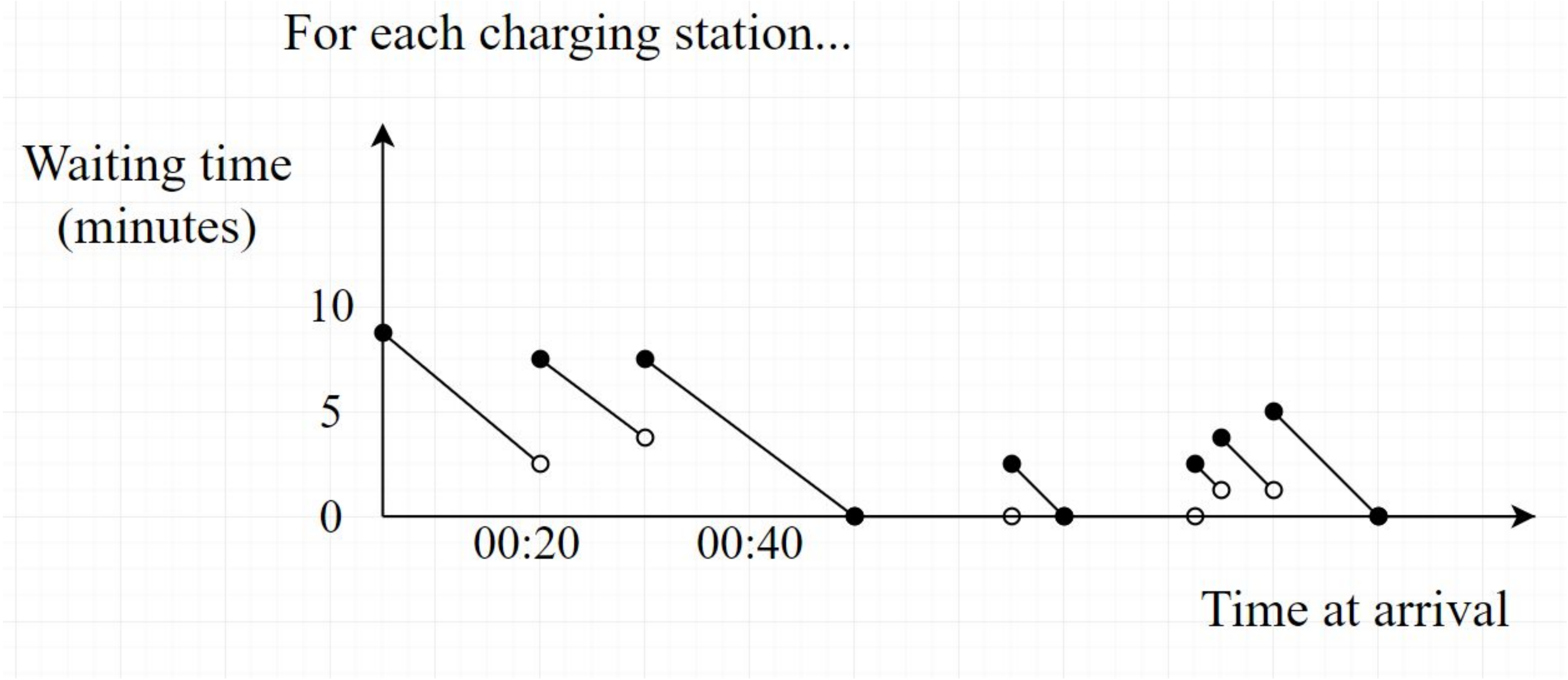
Information relaxation

Perfect information



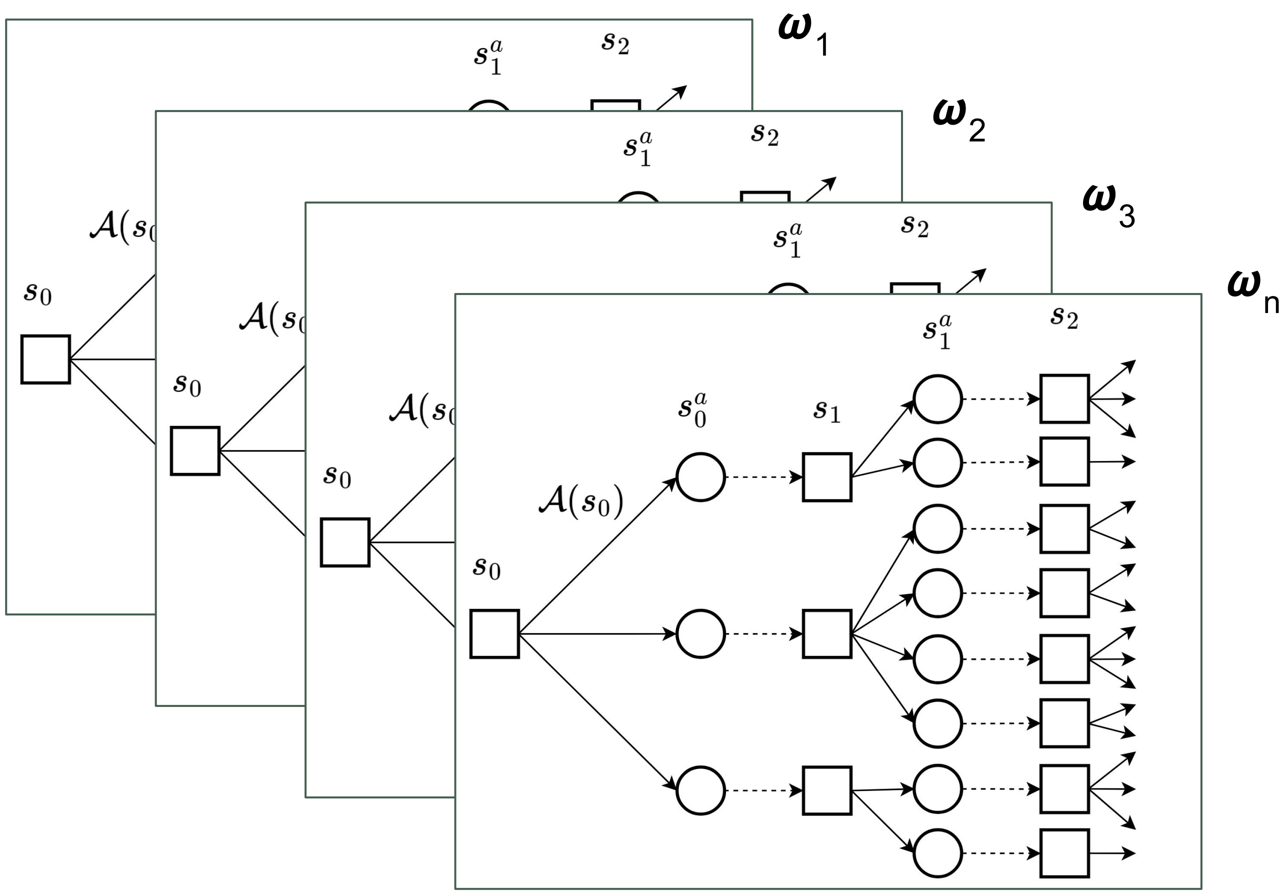
Information relaxation

What does perfect information look like?



Information relaxation

Solving for optimal solution with perfect information



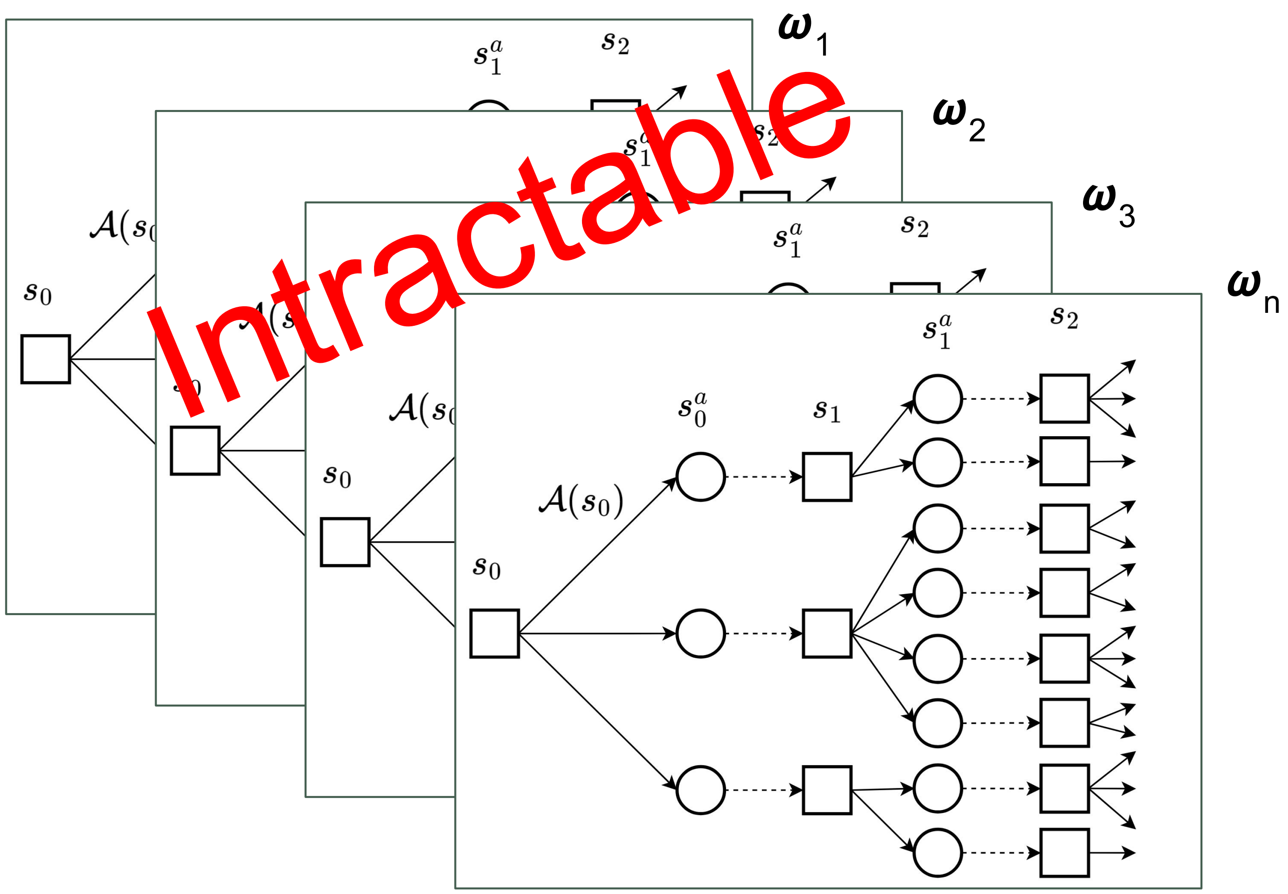
For *n* realizations:

- Build tree, solve recursively

Average results to get unbiased estimator of objective with perfect information

Information relaxation

Solving for optimal solution with perfect information



For *n* realizations:

- Build tree, solve recursively

Average results to get unbiased estimator of objective with perfect information

Information relaxation

Solving for optimal solution with perfect information

Similar to solving optimal static problem

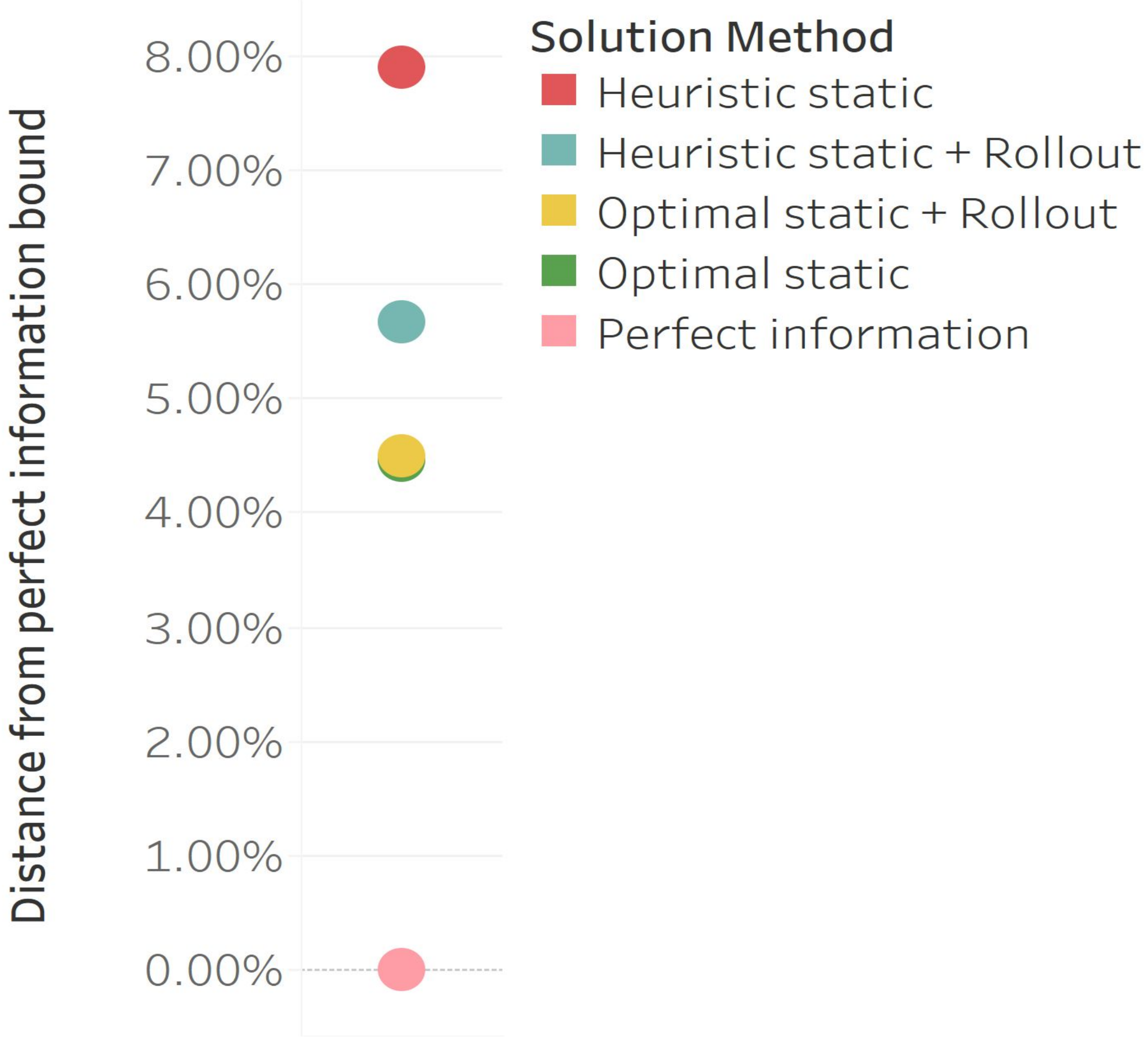
Benders decomposition:

- Master problem: customer sequences
- Subproblem: charging decisions
    - Actual waiting times

Results: 10 customer instances

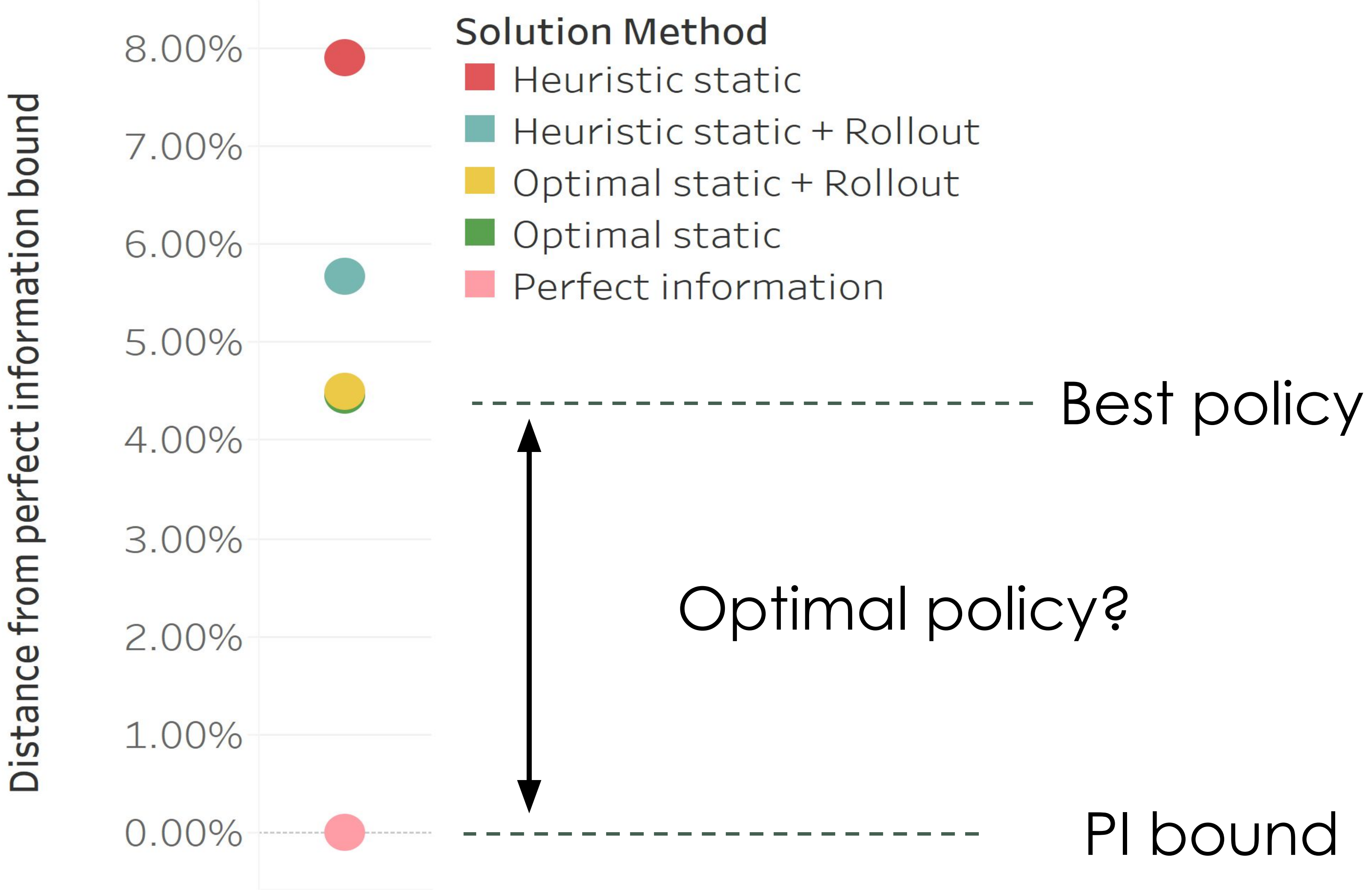
With perfect information bound

10 Customers: Policies vs lower bound



Improve lower bound: Information penalties

10 Customers: Policies vs lower bound



Information penalties

Perfect information

(waiting time at each CS at all times)

Naturally available to DM

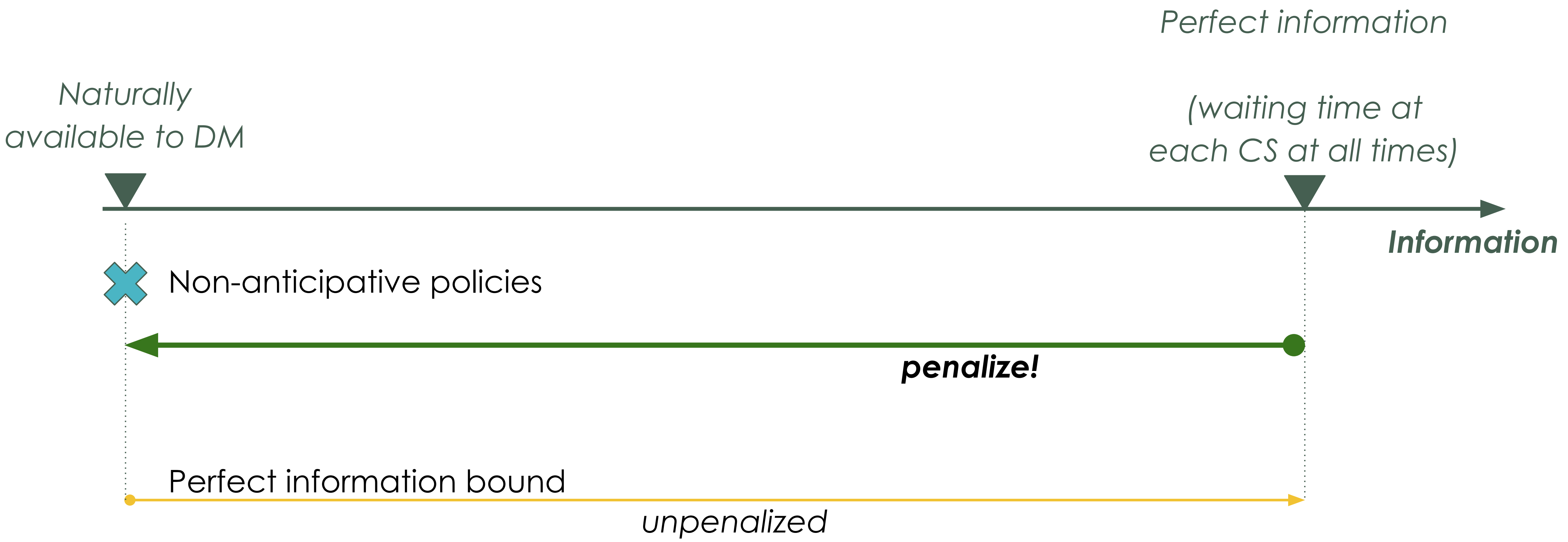
Information

Non-anticipative policies

Perfect information bound

unpenalized

Information penalties



Information penalties

Results

Instances:

- Intended to produce large gap (having access to additional information is very valuable)

- 4 cust/2 CS
- More influence of waiting and uncertainty on objective value

Information penalties
Results

Penalty Results

Solution Method	
Perfect Information	0.00%
Heuristic static + Rollout	17.22%
Optimal static + Rollout	22.62%
Optimal static	52.73%

(best policy)

Instances:
- Intended to produce large gap (having access to additional information is very valuable)

- 4 cust/2 CS
- More influence of waiting and uncertainty on objective value

Information penalties

Results

Penalty Results

Solution Method	
Perfect Information	0.00%
Perfect Info w/ Penalty	10.59%
Heuristic static + Rollout	17.22%
Optimal static + Rollout	22.62%
Optimal static	52.73%

(best policy)

Instances:

- Intended to produce large gap (having access to additional information is very valuable)

- 4 cust/2 CS
- More influence of waiting and uncertainty on objective value

Summary

Summary

- Introduced and solved new E-VRP variant
- Derived optimal static policy, competitive dynamic policies
- Derived lower bounds for dynamic routing policies
- Imposed information penalties to tighten lower bounds

Thank you

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e-VRO
Electric Vehicle Routing Optimization

POLYTECH TOURS

Équipe OC
ERL-CNRS 6305

Laboratoire d'Informatique
EA 6300

SAINT LOUIS UNIVERSITY

Appendices

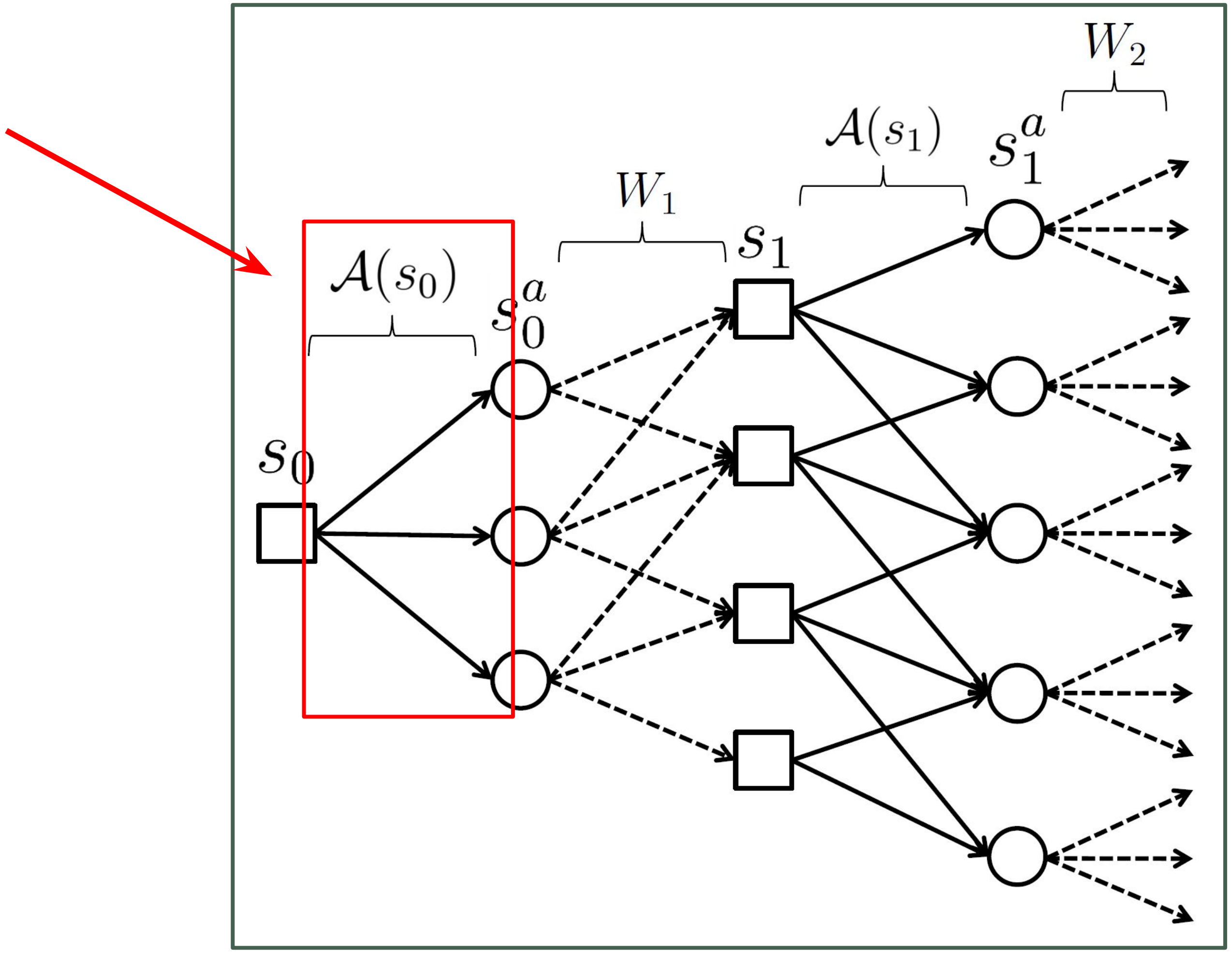
Dynamic Routing Model

Stochastic dynamic program - Action space restrictions

- Action space
  - Move
  - Join queue & wait
  - Charge

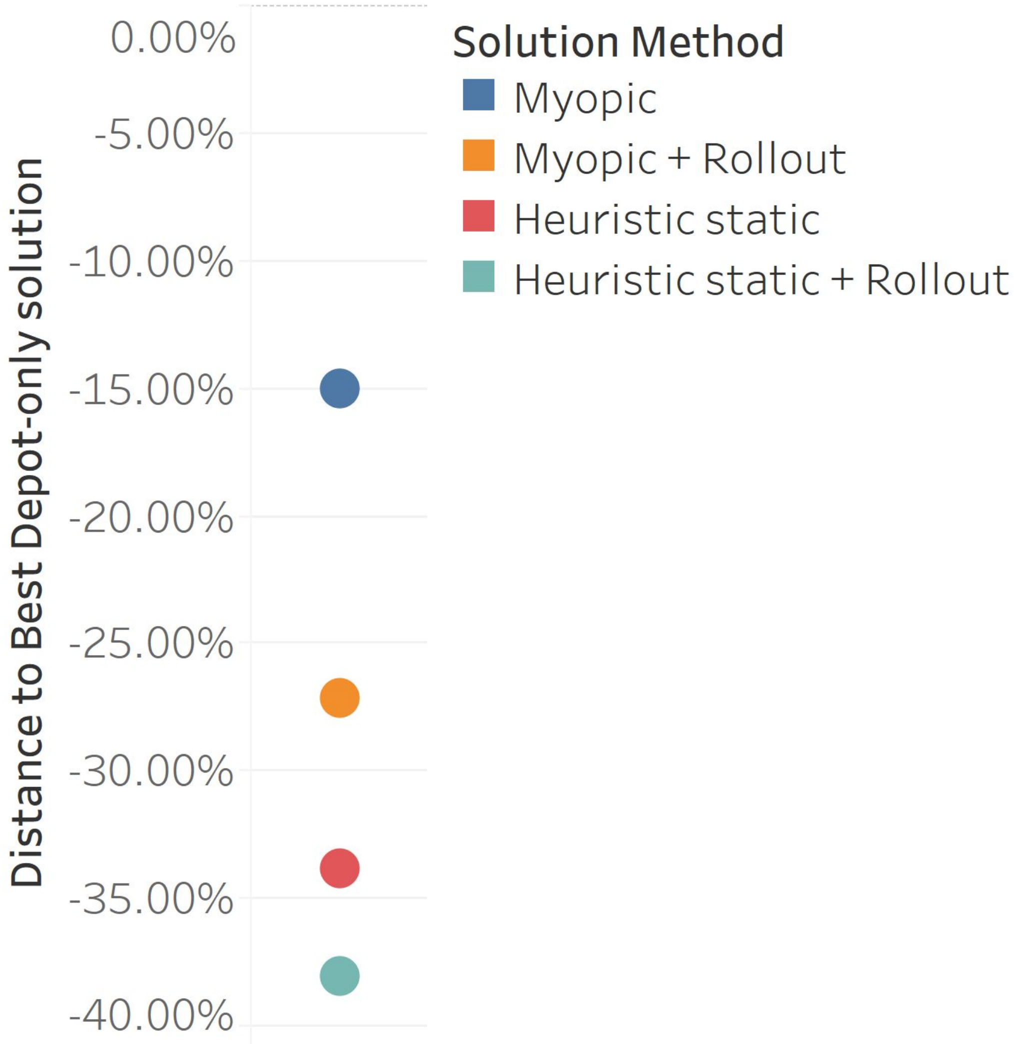
Restrictions:

- Can only move to energy-feasible locations
- Can only wait if there's a queue
- Can't charge twice consecutively
- No queue balking



Results: 20+ customer instances
Comparison with depot-only performance

20+ customers: Distance to Best Depot-Only



Comparison with depot-only
- Same set of instances
- Remove all non-depot CSs
- Use same policies to solve depot-only instance*
- Keep the best
- Compare best depot-only solution with average policy performance

* *loose bound on optimal solution*