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Shortest Feasible Paths with Charging Stops for Battery Electric Vehicles

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INSTITUTE OF THEORETICAL INFORMATICS · ALGORITHMICS GROUP

Route Planning for Electric Vehicles

Electric vehicles:

- Future means of transportation
- Run on regenerative energy sources

But:

- Restricted battery capacity
- Long recharging times

Therefore : Route planning applications have to consider:

- Energy consumption
- Charging stops

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Therefore : Route planning applications have to consider:

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. . . but we would still like to travel fast

Route Planning with Charging Stops

Task: Given some source s and target t in a road network

- Find the fastest route from s to t
- Such that the battery does not deplete

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(weakly) NP-hard

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1. Recuperation

- Vehicles recuperate energy (braking or going downhill)

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- Detour for reaching a charging station

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- Detour for reaching a charging station

4. Charging is not uniform
- Interrupt charging and take another station

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Observations

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Find the fastest route from s to t:

Reachable area

Charging station

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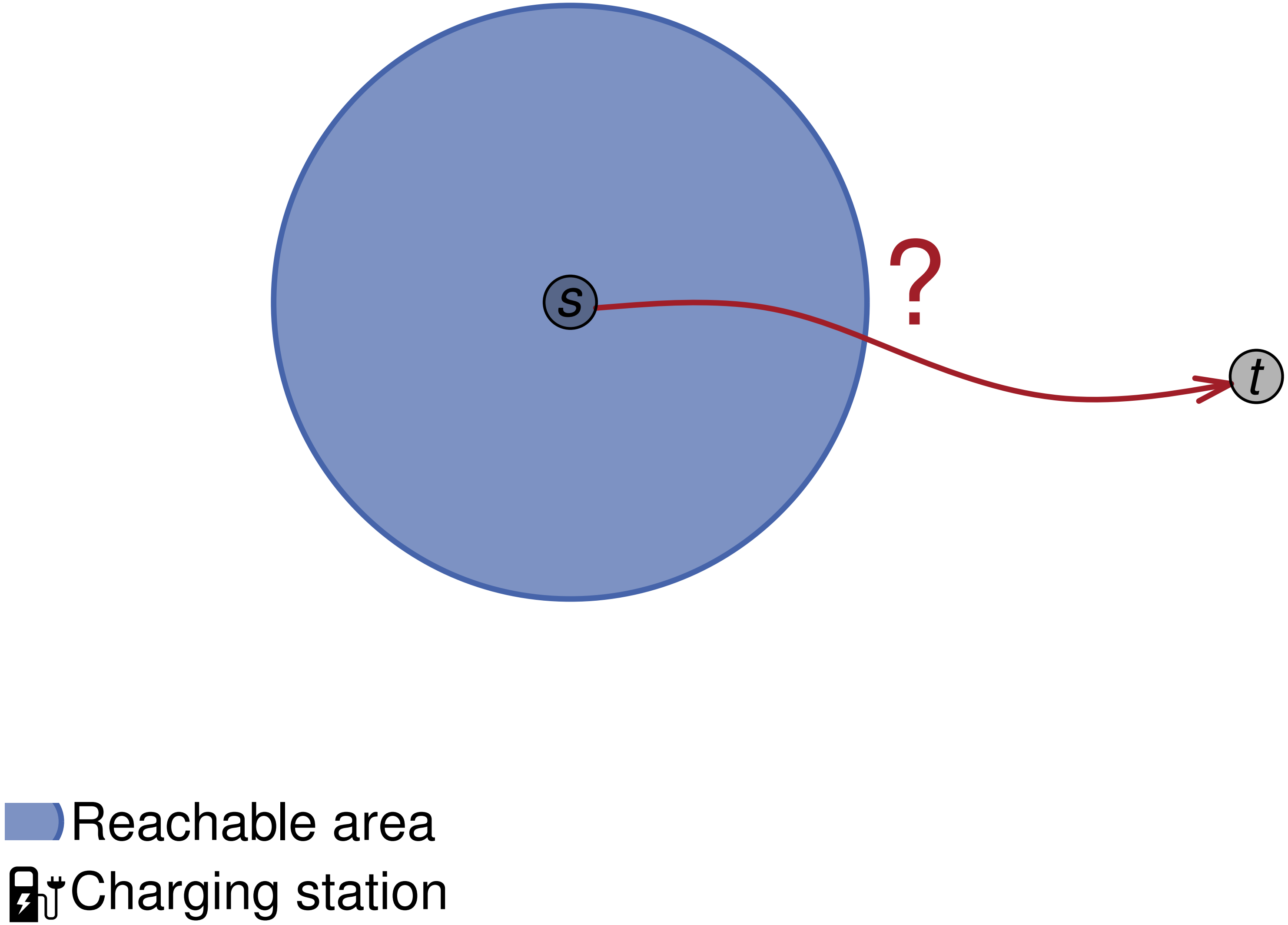

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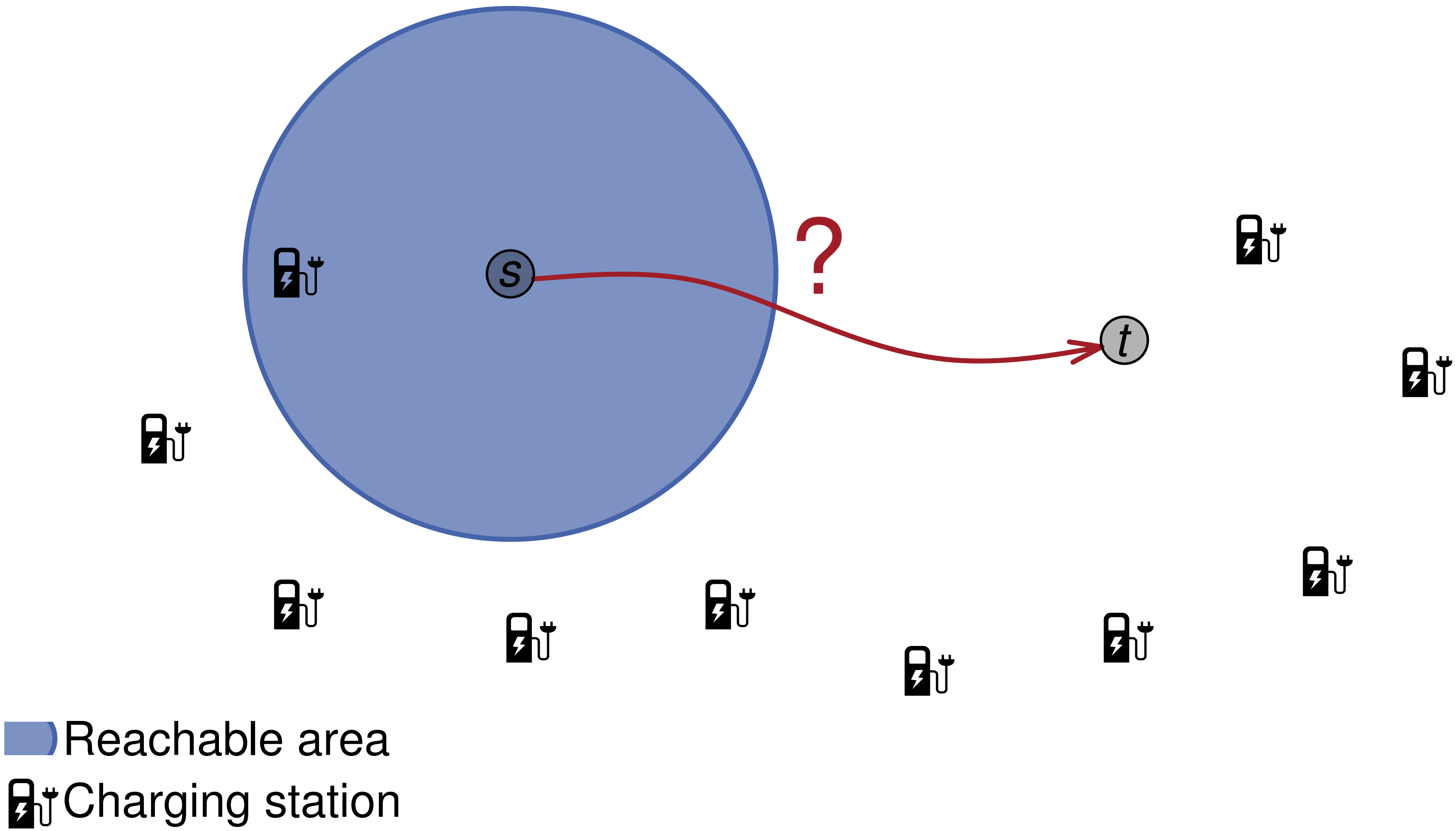

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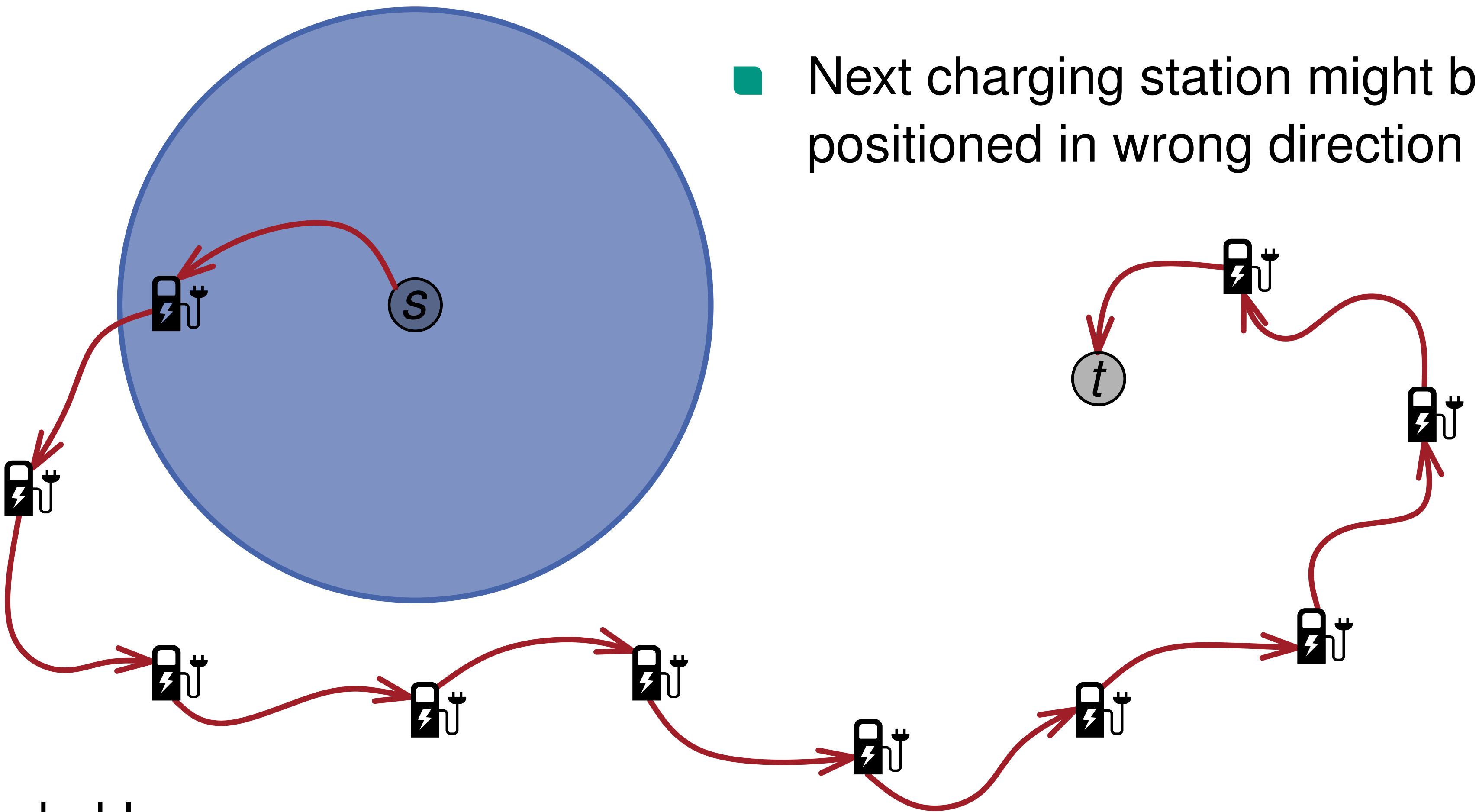

- Next charging station might be positioned in wrong direction

Reachable area
Charging station

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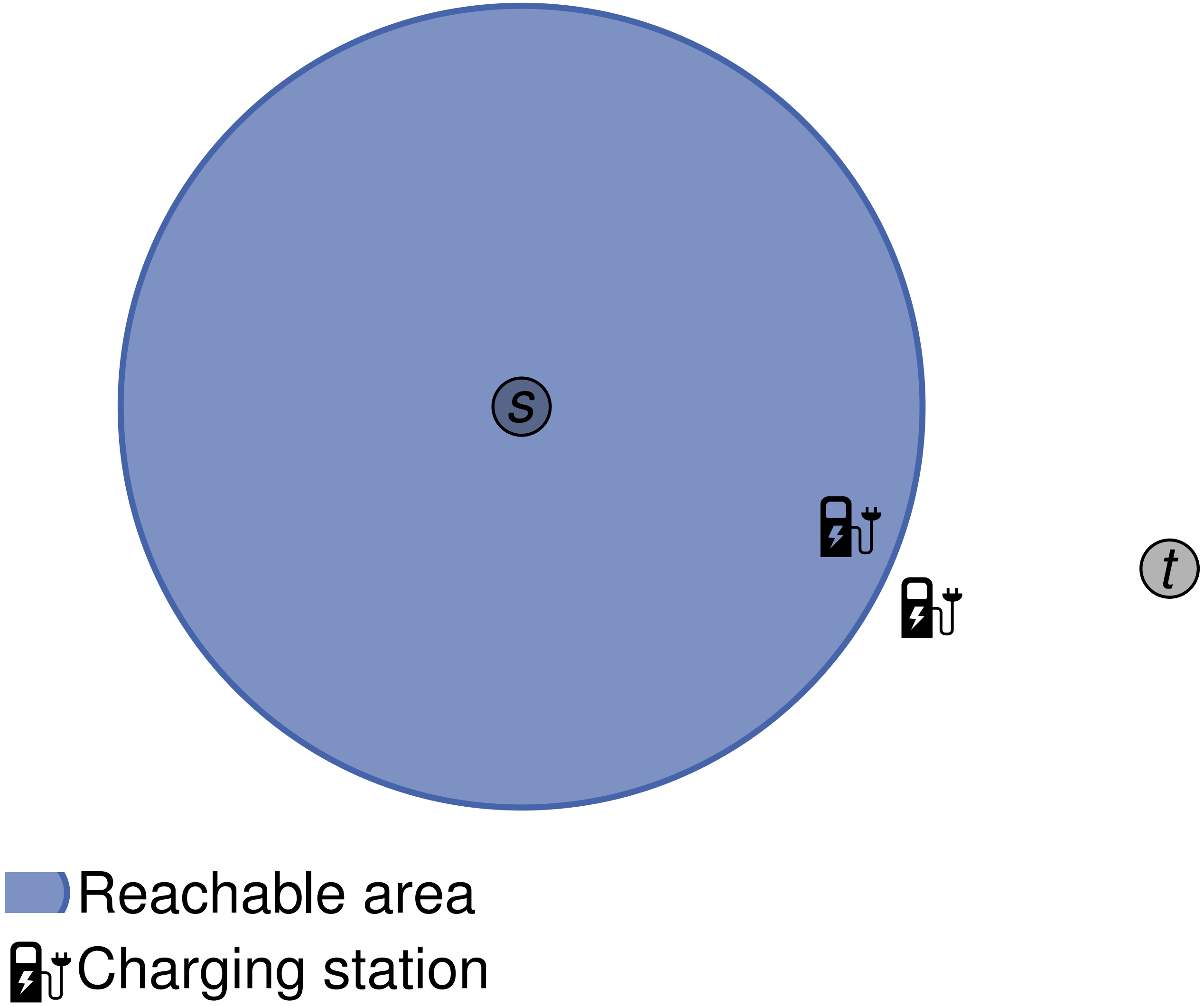

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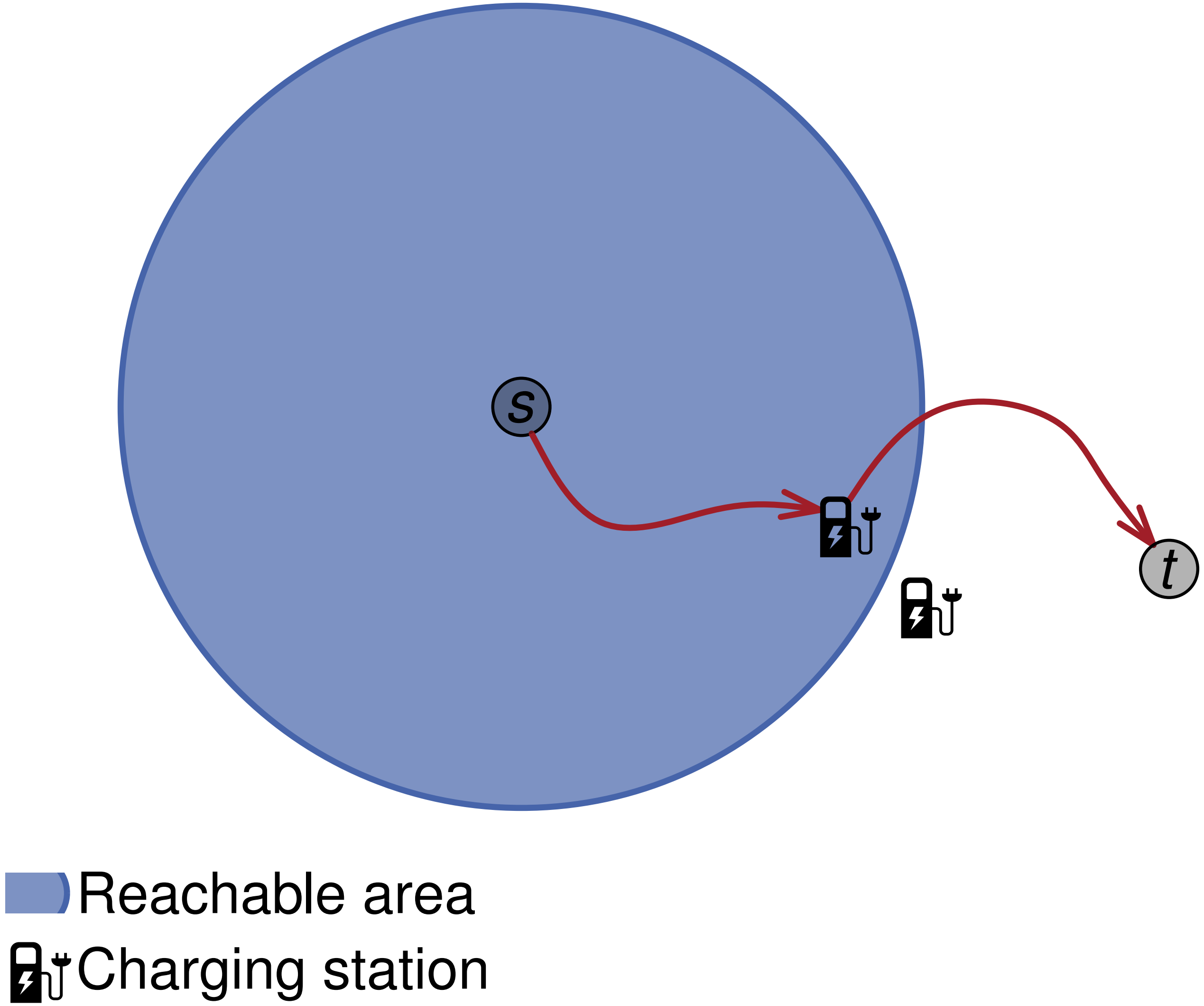

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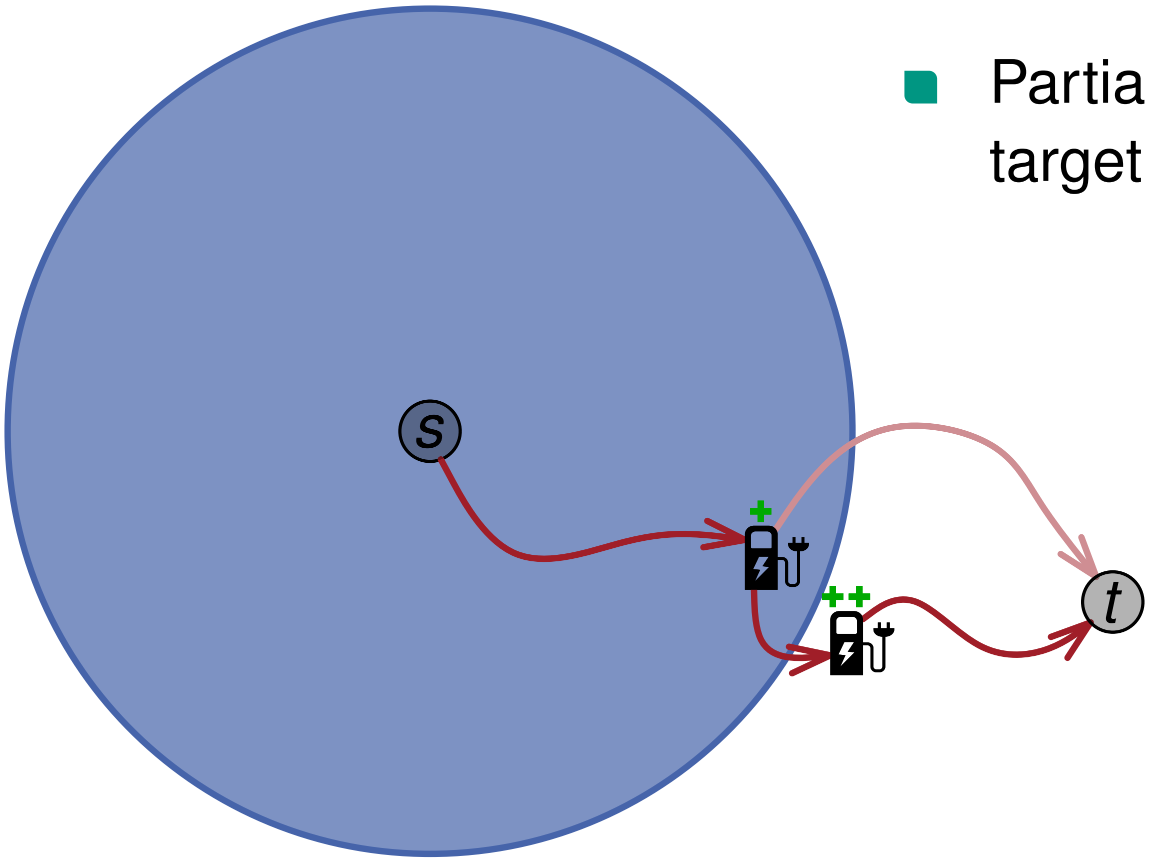

- Partial recharging, even if the target is already reachable

Reachable area

Charging station

Fast charging station / swapping station

Observations

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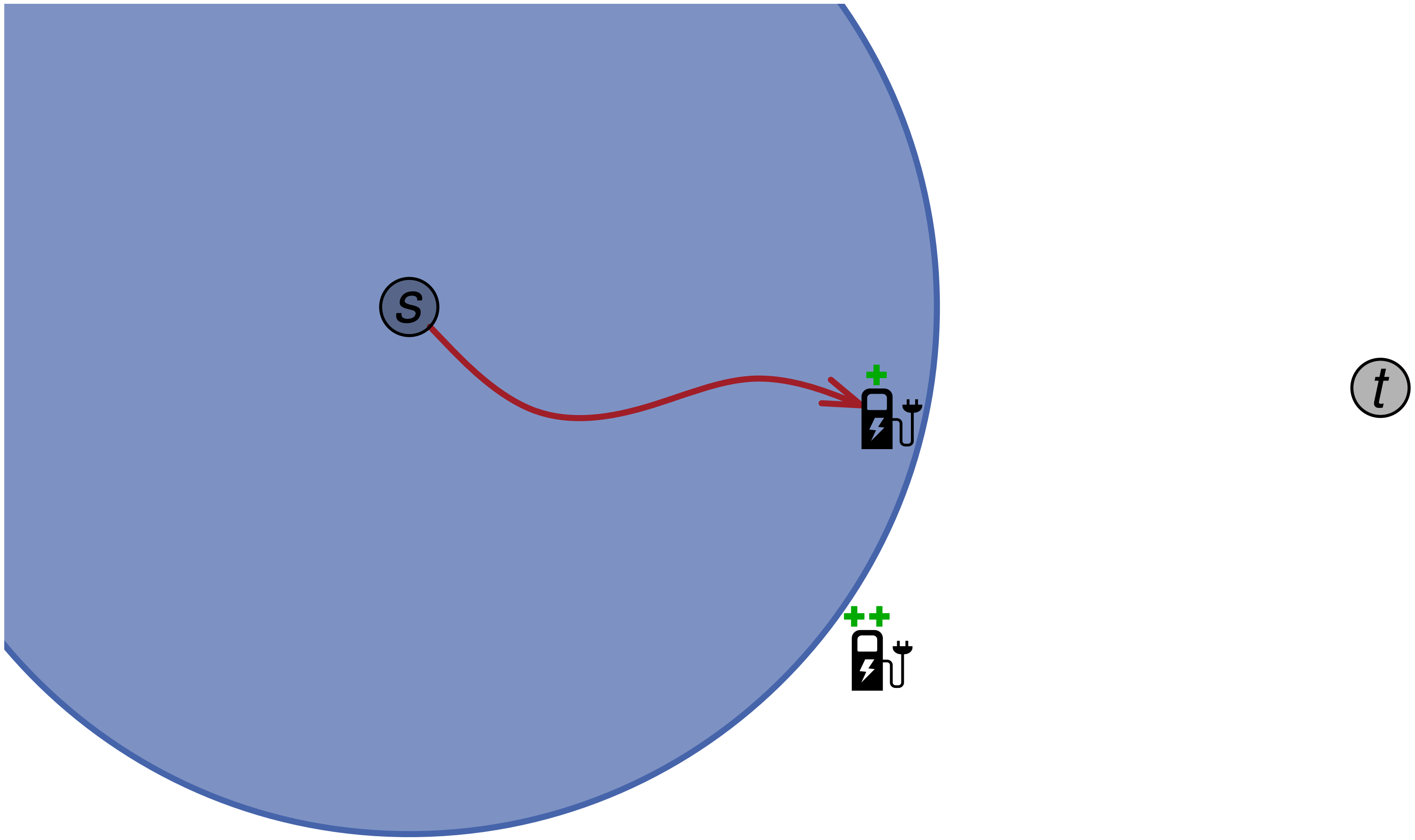

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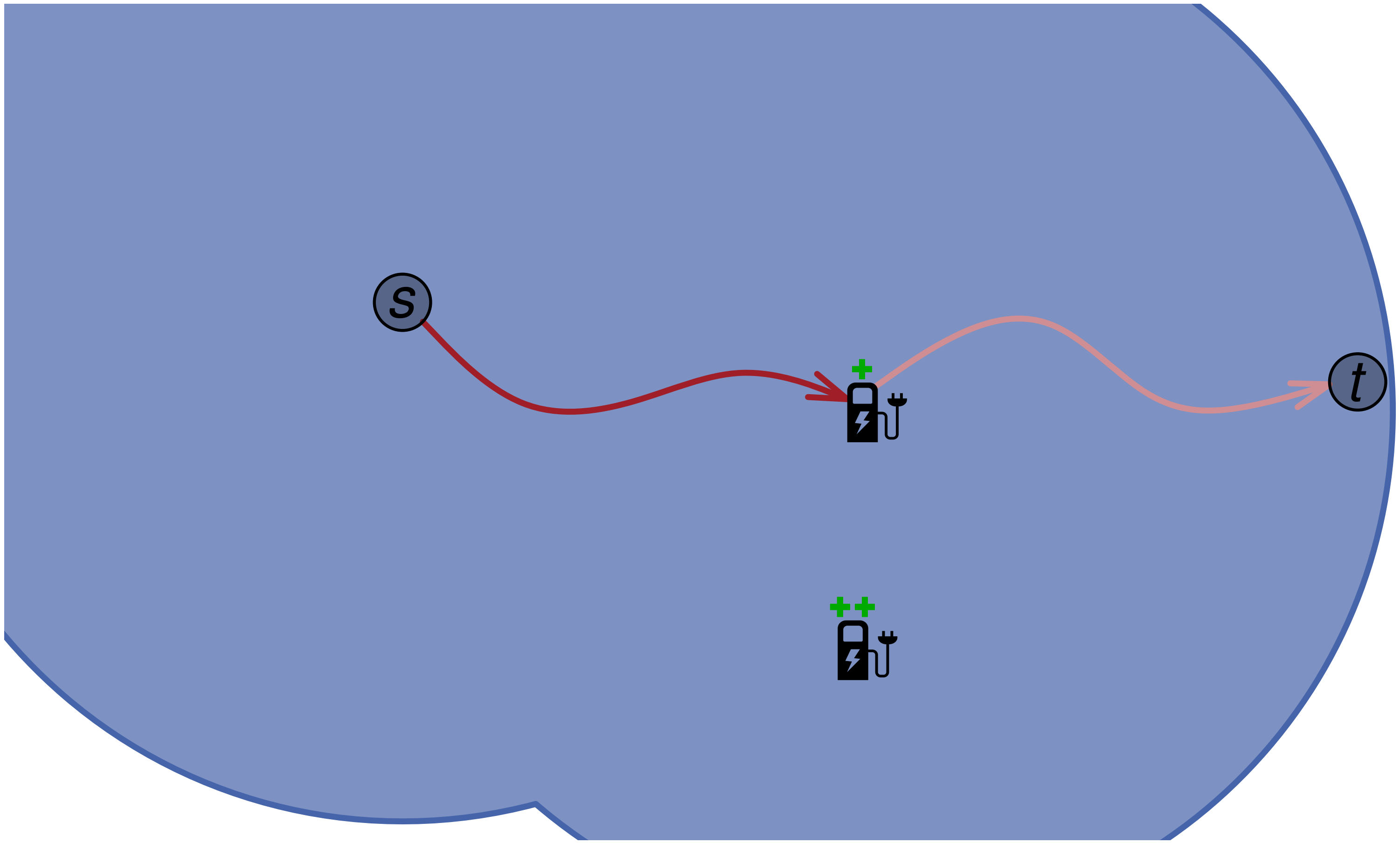

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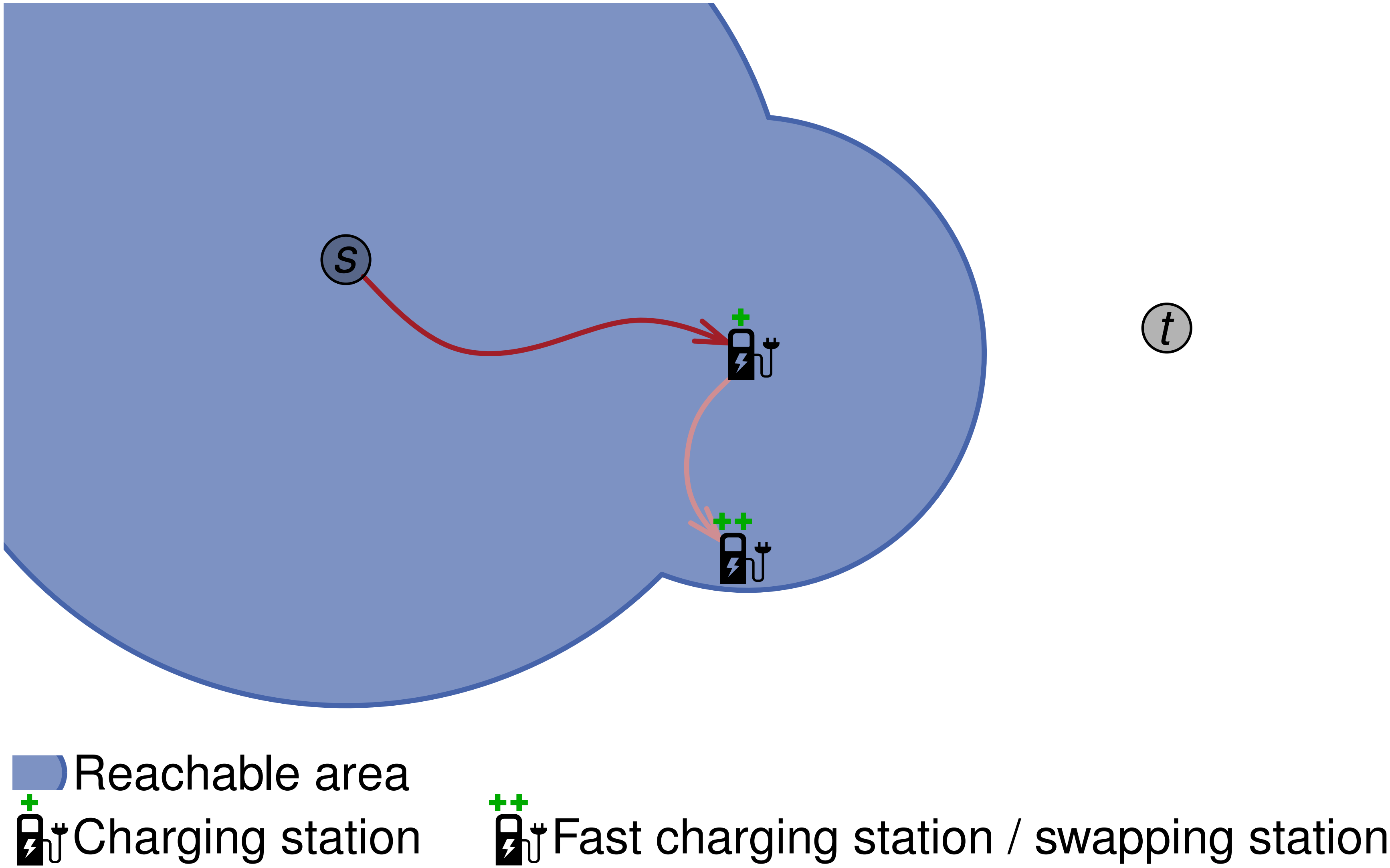

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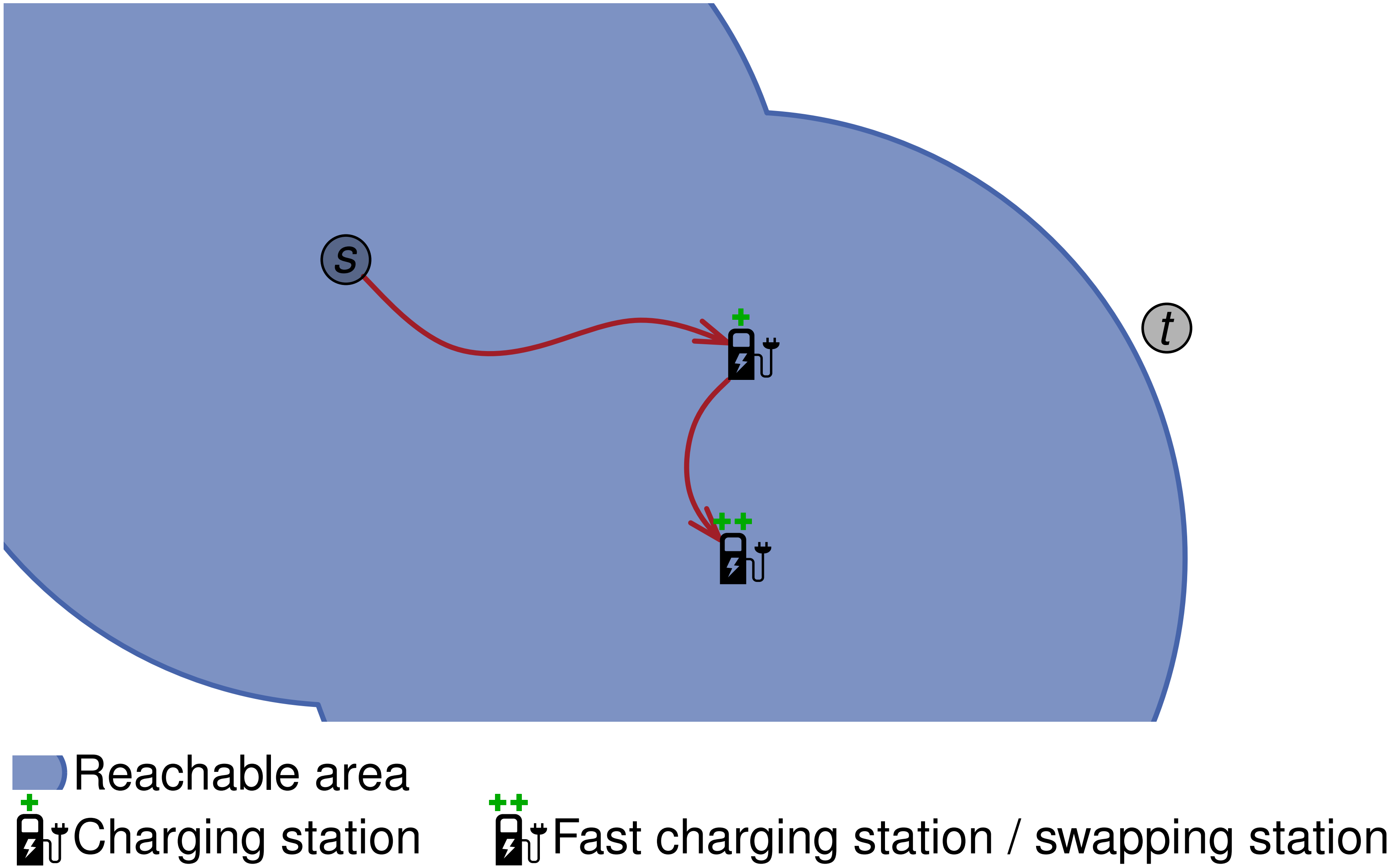

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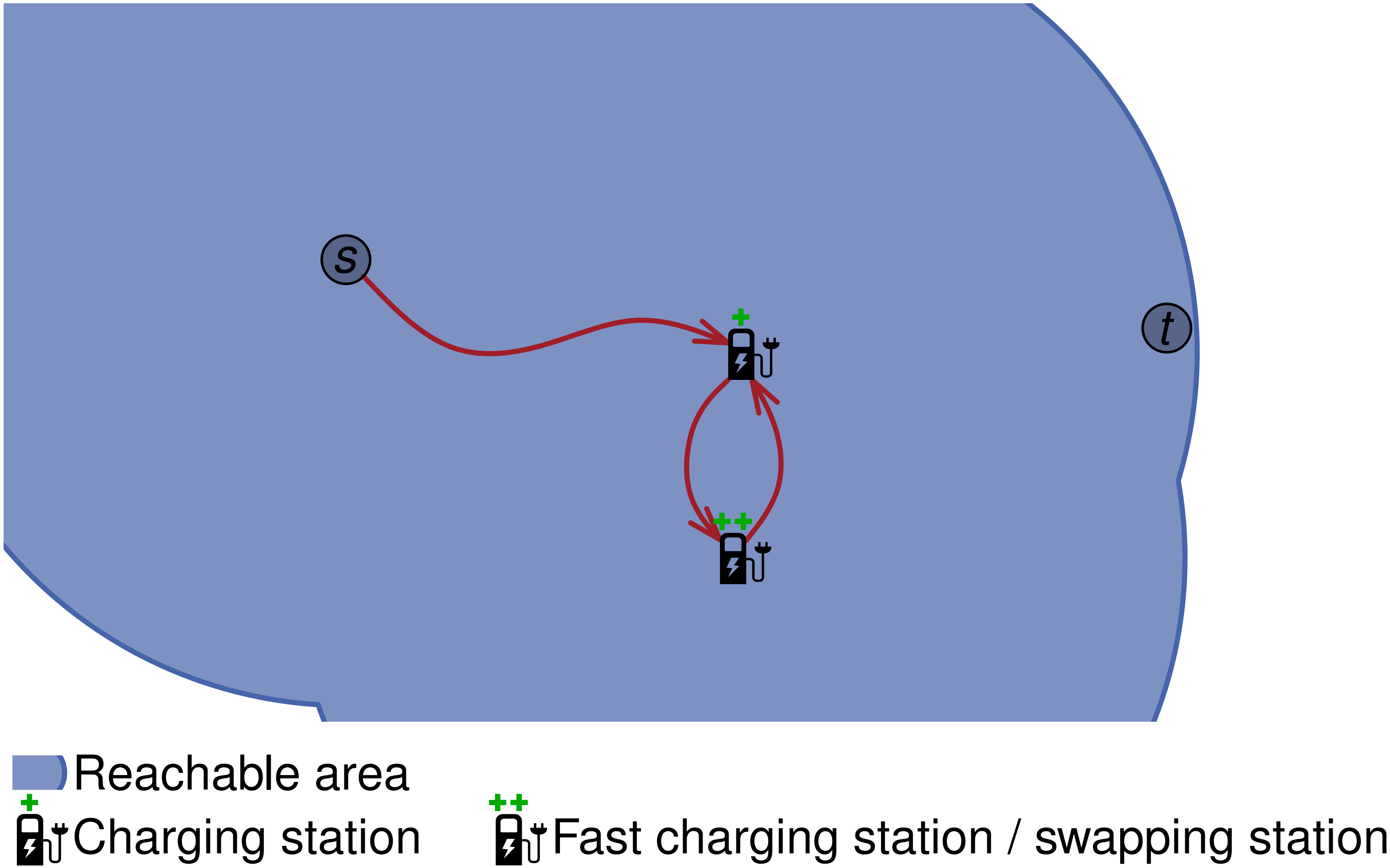

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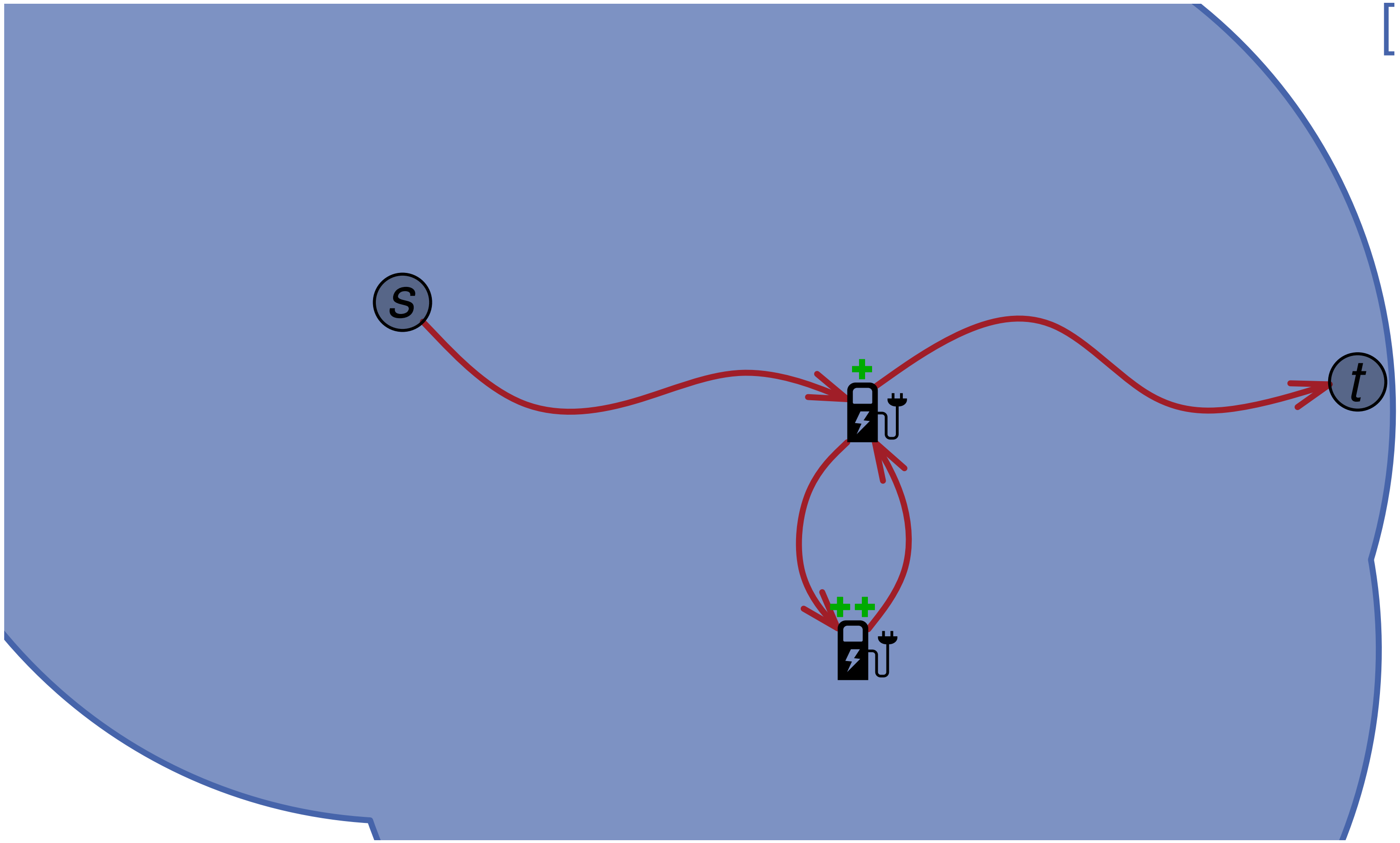
Observations

Find the fastest route from *s* to *t*:

- Fastest route may contain cycles [Merting et al. '15]



Reachable area
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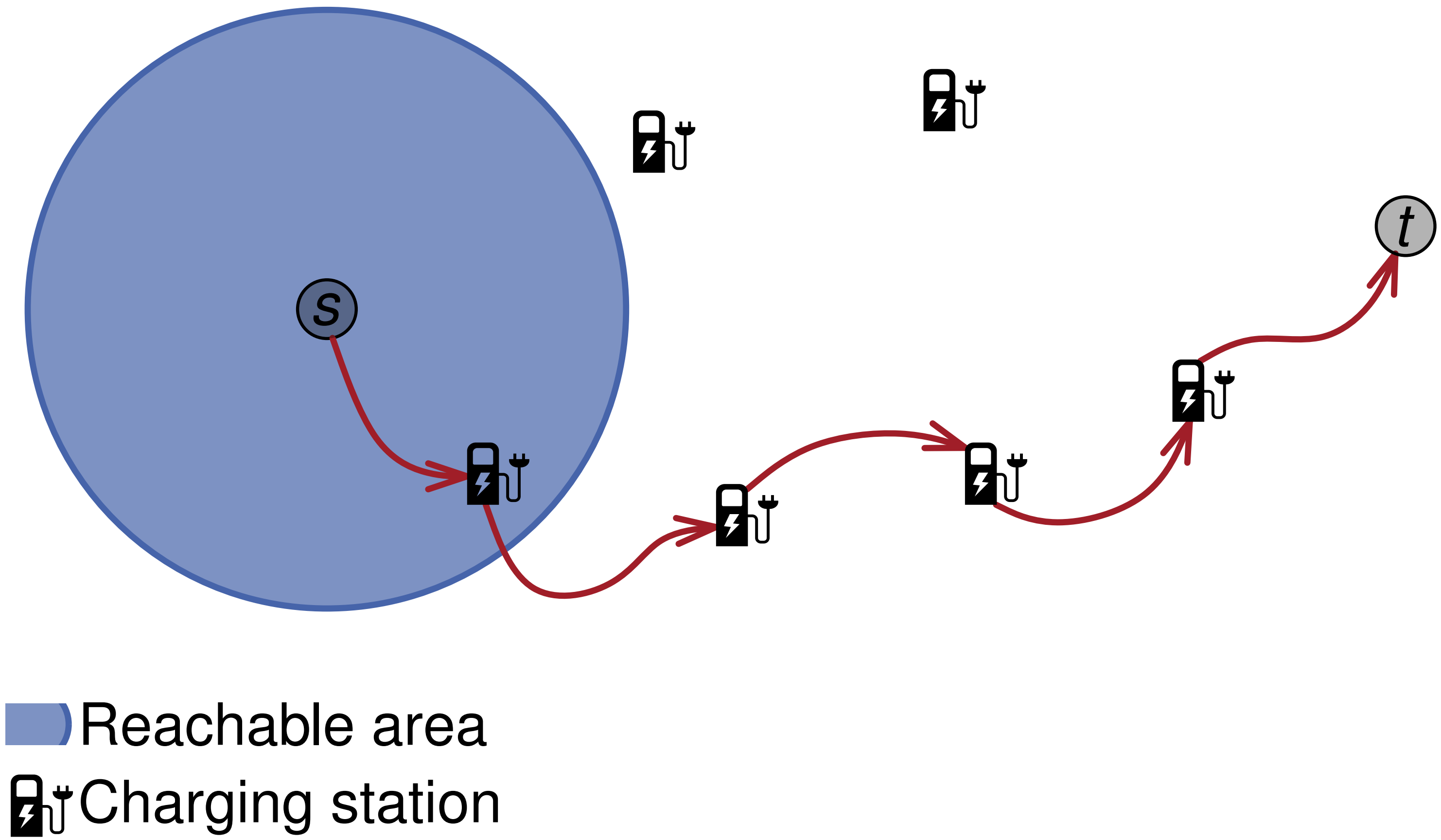

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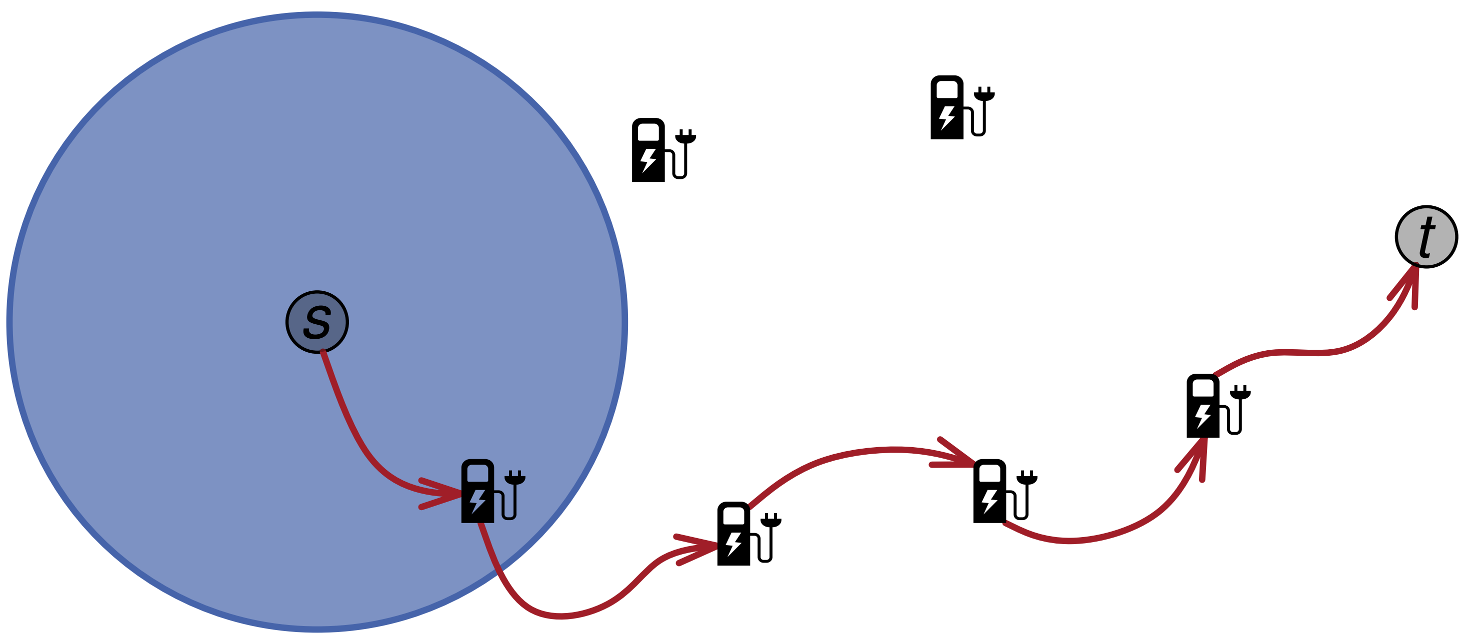
Find the fastest route from *s* to *t*:

- Larger battery ⇒ simpler problem ?



Reachable area

Charging station

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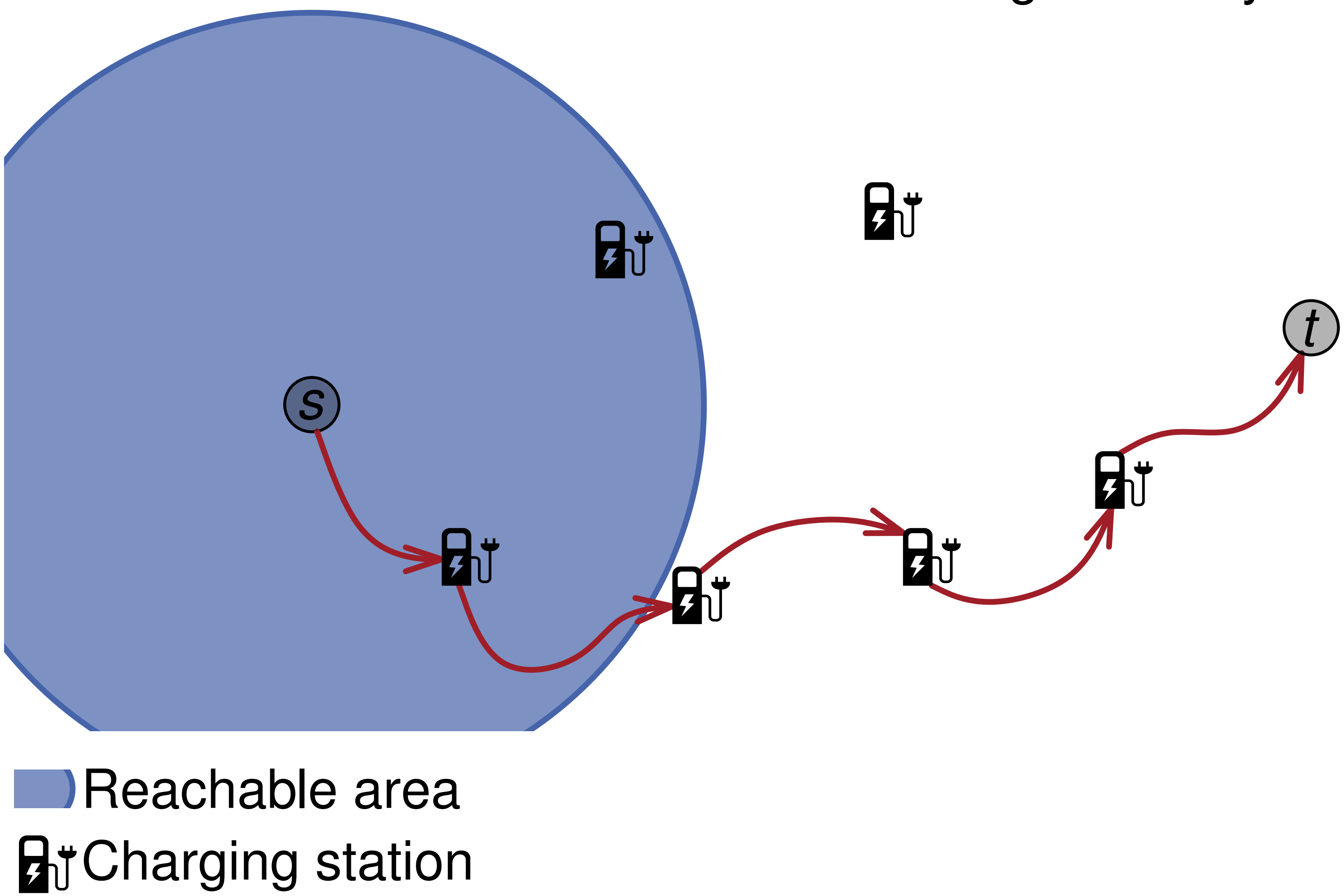
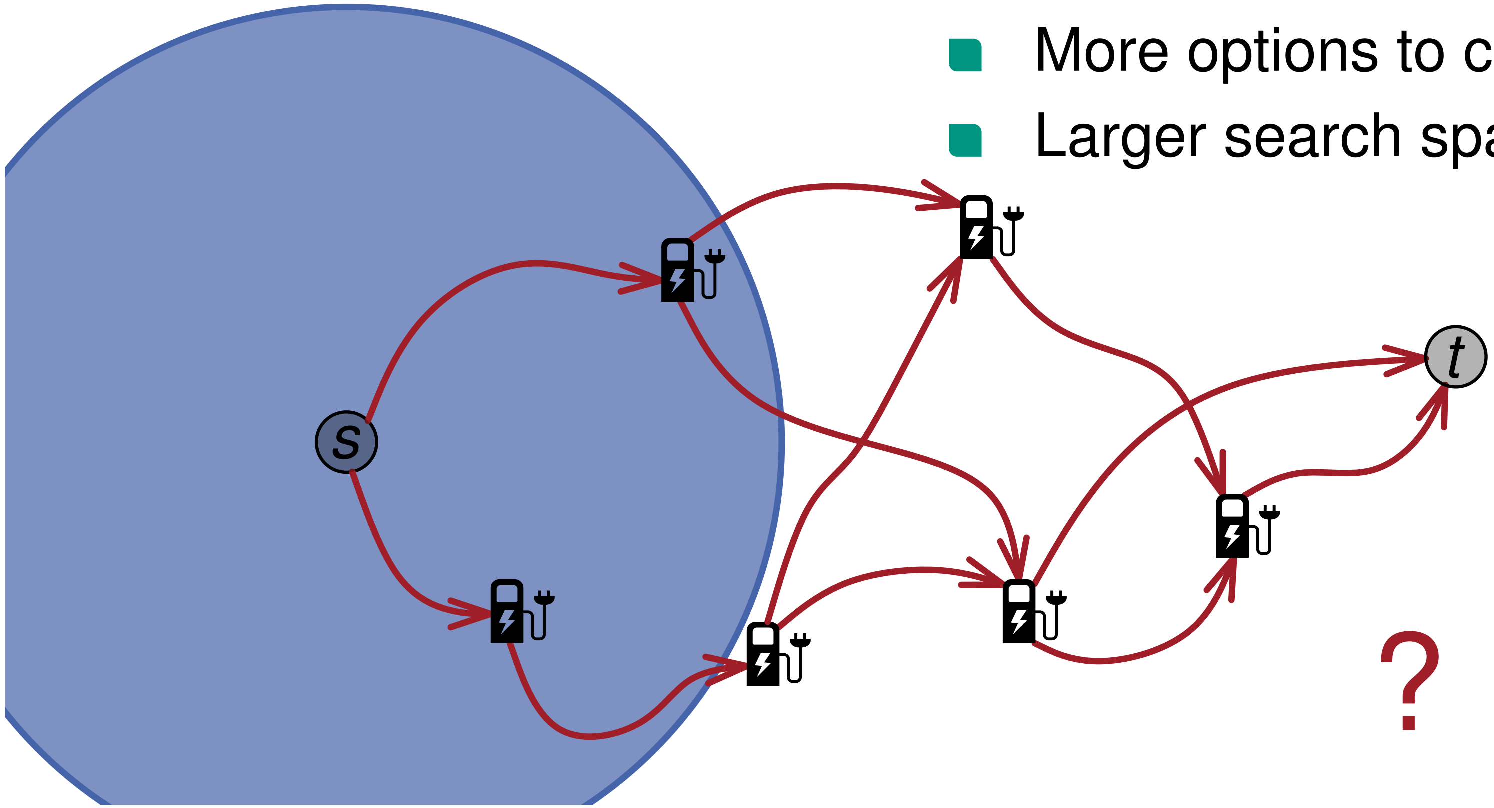


Observations

Find the fastest route from s to t:

- Larger battery $\Rightarrow$ simpler problem ?
- More options to consider
- Larger search space



Reachable area
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Related Work

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Quick and Energy-Efficient Routes: Computing Constrained Shortest Paths for Electric Vehicles [Storandt '12]

- Supports only battery swapping stations (BSS)
- Computes overlay graph of directly reachable BSS
- BSS fully recharges in constant time ⇒ simple scalar overlay graph

⇒ Not applicable / sub-optimal in our scenario

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Routing of Electric Vehicles: Constrained Shortest Path with Resource Recovering Nodes [Merting et al. '15]

- Theoretical analysis of the problem
- Show missing sub-path property
- Optimal solutions can visit a charging station several times

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Related Work – Consumption Profiles
[Eisner et al. '11], [Baum et al. '13]

- Incorporate battery constraints in one single function
  - Maps initial State of Charge (SoC) onto resulting SoC
  - Value $-\infty$ indicates an infeasible SoC

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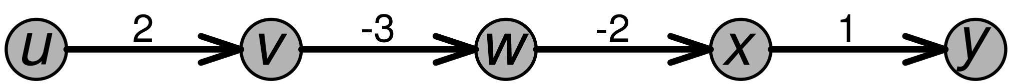

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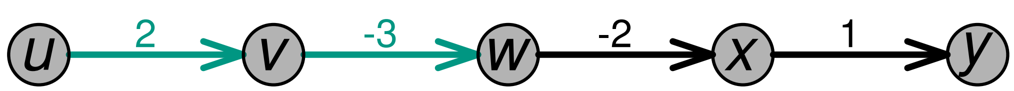

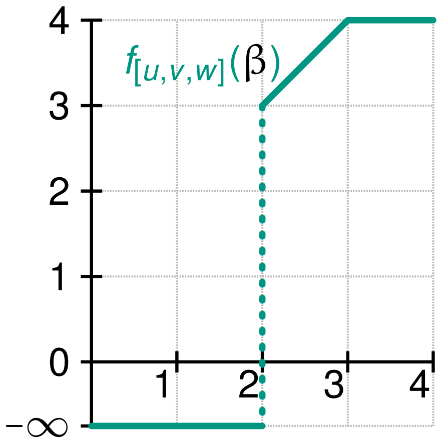

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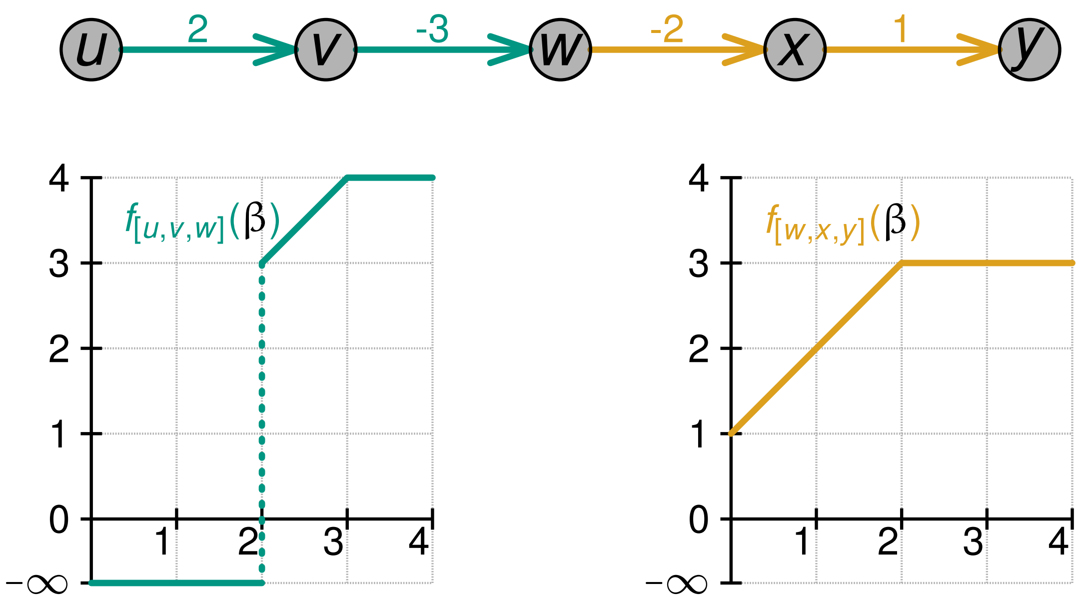

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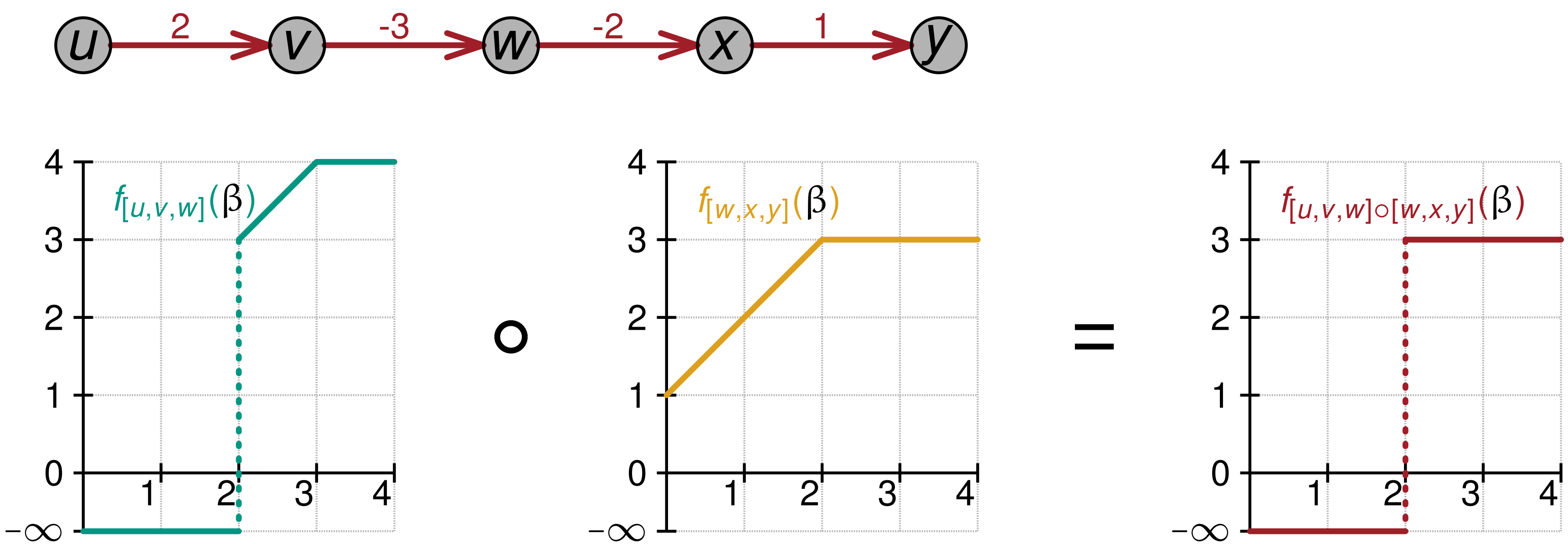

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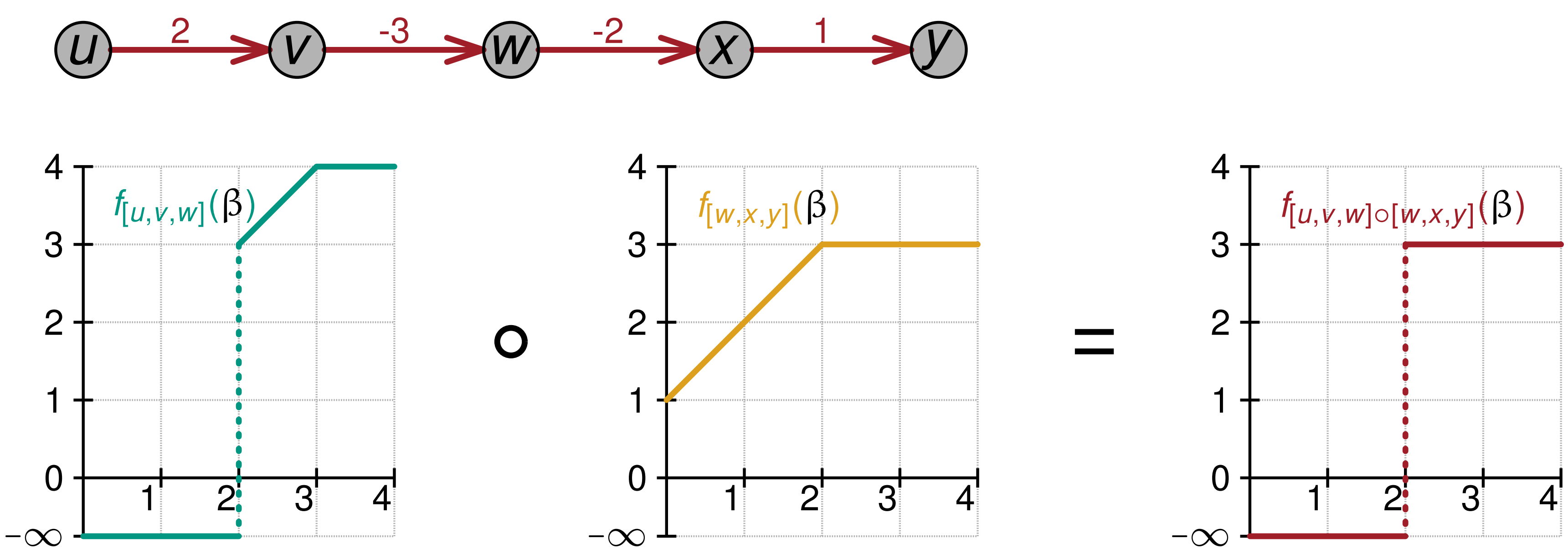

- For a single edge or path:
  - Representable using maximal 3 values

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Charging Functions

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Formally:

- A function $\text{cf}\colon [0, M] \times \mathbb{R}_{\geq 0} \to [0, M]$, which maps
  - Initial SoC β_s and
  - Desired charging time τ_c onto
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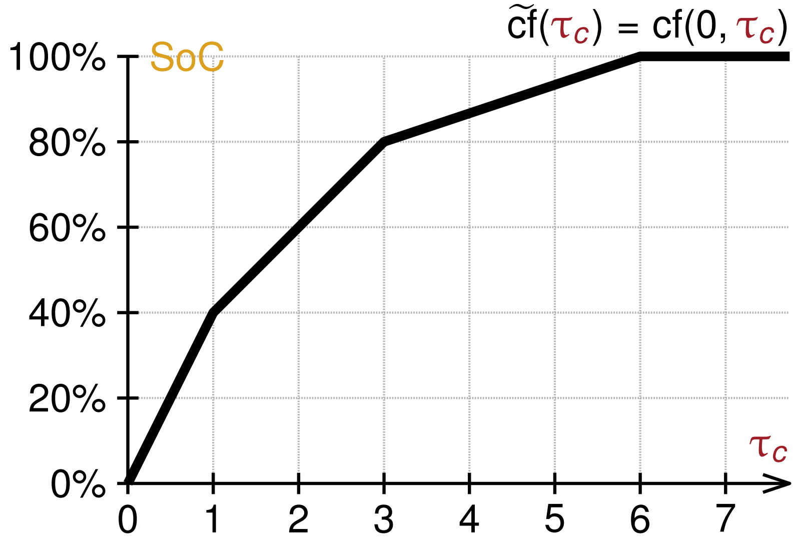
Observation:

- Realisitc charging functions are simpler
- Reducable to univariate function:

$$\widetilde{\mathrm{cf}}\colon \mathbb{R}_{\geq 0} \to [0, M]$$
$$\mathrm{cf}(\beta, \tau_c) := \widetilde{\mathrm{cf}}(\tau_c + \widetilde{\mathrm{cf}}^{-1}(\beta))$$



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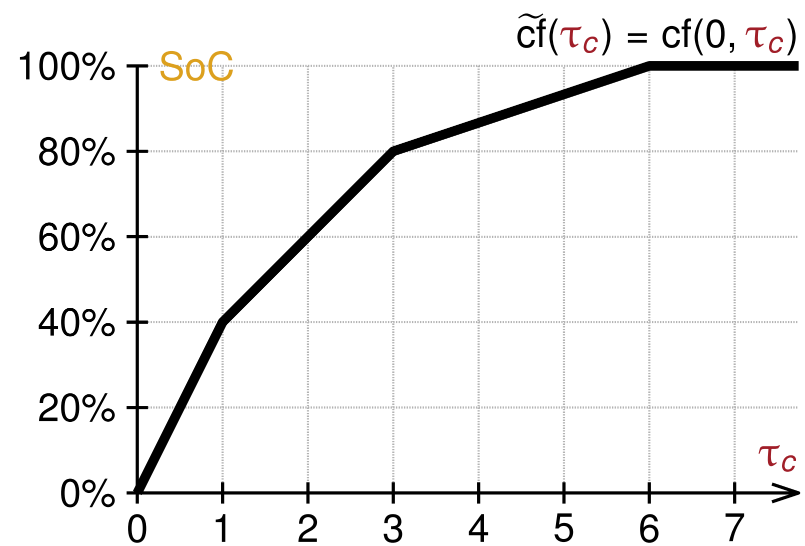

Example:

- Charging an 60% full battery for 1 time unit
  cf(60%, 1)

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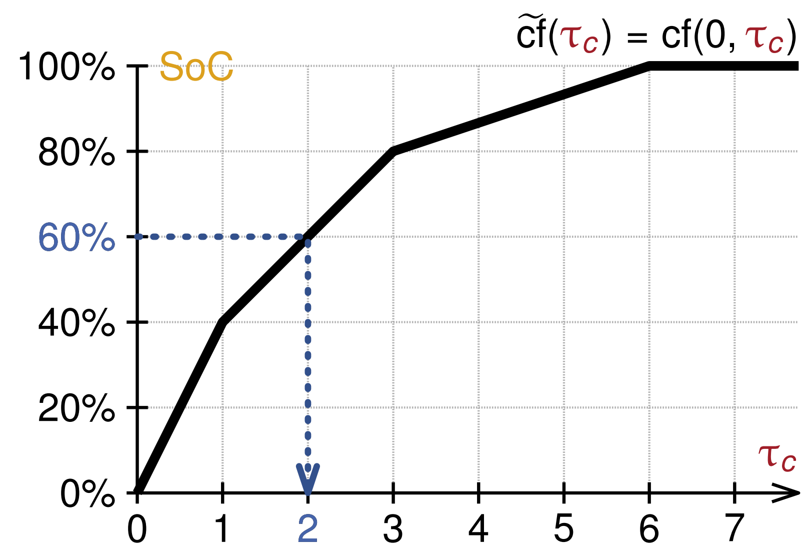

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  $\mathrm{cf}(60\%, 1) = \widetilde{\mathrm{cf}}(1 + 2)$

Charging Functions

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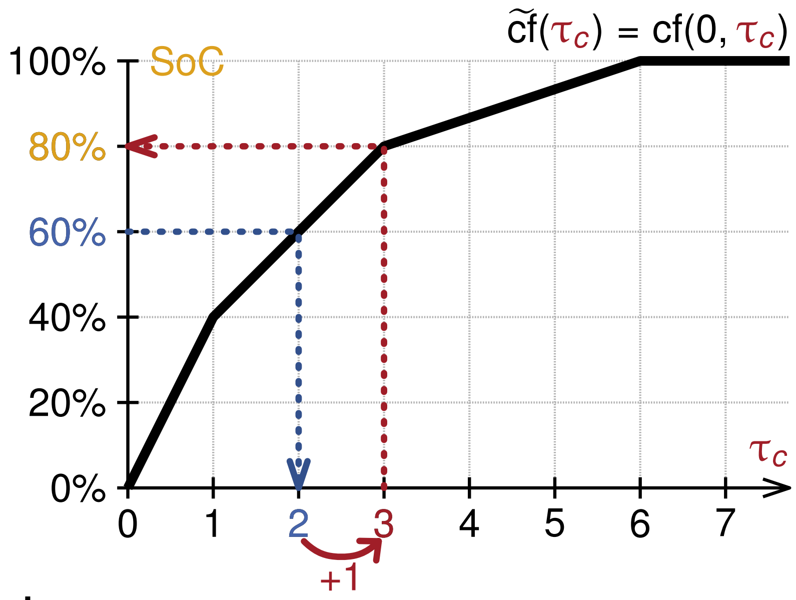

Example:

- Charging an 60% full battery for 1 time unit
  $\mathrm{cf}(60\%, 1) = \widetilde{\mathrm{cf}}(1 + 2) = 80\%$

Charging Functions

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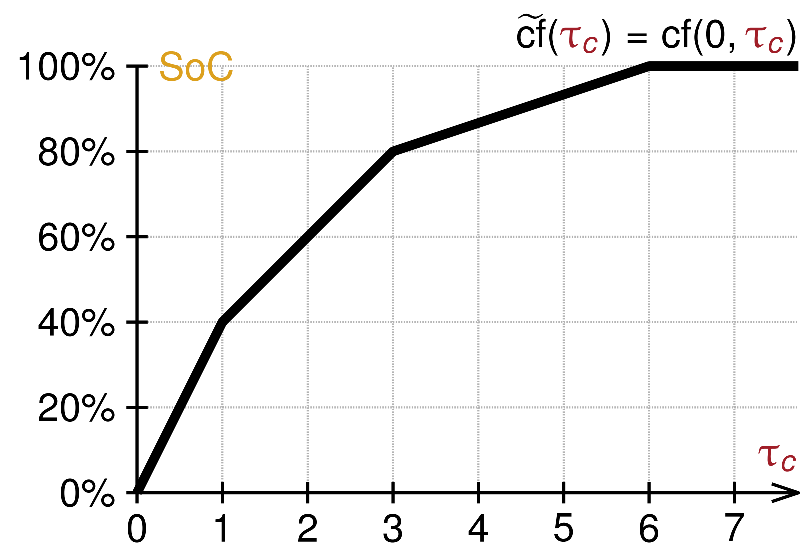

Properties:

- Monotonically increasing (Spending time will not decrease SoC)
- Concave (As SoC rises, the charging rate may only decline)

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Charging Function Propagation (CFP)

Algorithm:

- Based on multi-criteria Dijkstra
- If no charging station has been used: label = tuple (trip time, SoC)
- Per vertex: Maintain a set of Pareto-optimal labels

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Solution:

- Delay this decision!
- Keep track of the last passed charging station

Charging Function Propagation (CFP)

Label: A label ℓ at vertex v is a quadruple $(\tau_t, u, \beta_u, f_{[u,\dots,v]})$ with:

- Trip time τ_t from s to v (including charging times except at u)
- The last seen charging station u (initially $\perp$)
- SoC β_u by which the last charging station (u) was reached
- Consumption profile $f_{[u,\dots,v]}$ of the path from u to v (initially $\perp$)

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Interpretation: Label ℓ at $v = (\tau_t = 2, u, \beta_u = 1, f_{[u,\dots,v]})$

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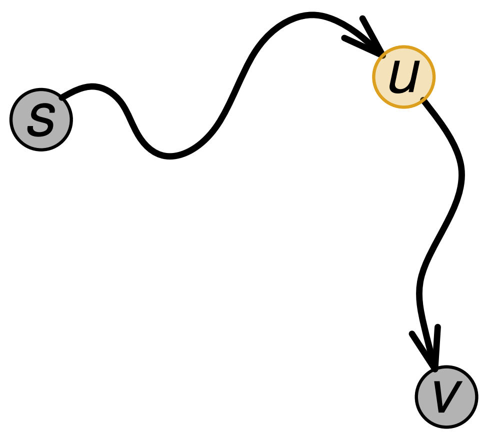

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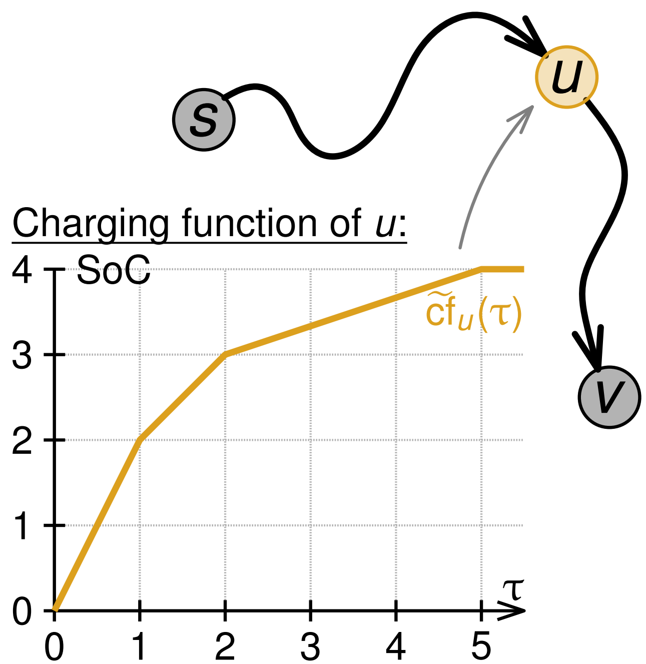

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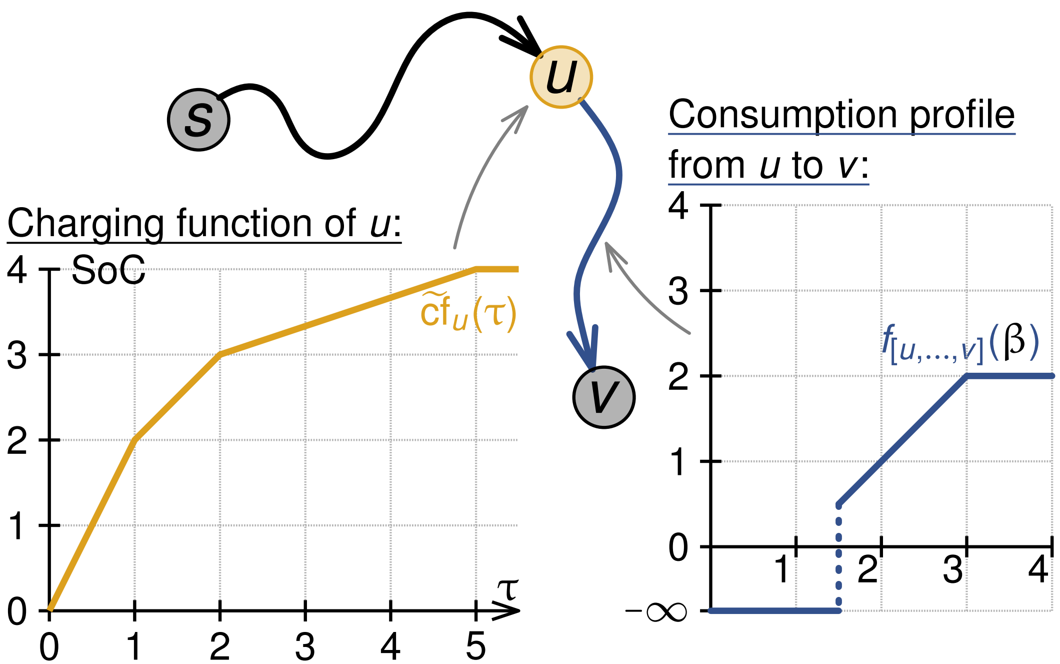

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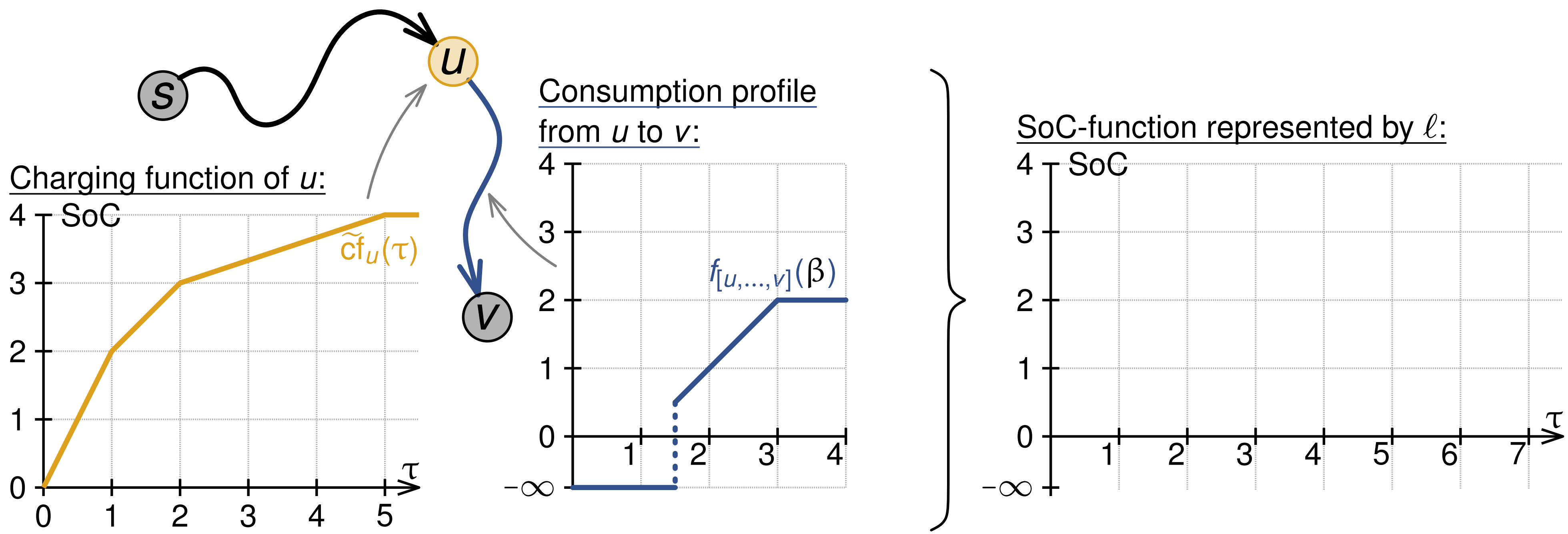

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Charging Function Propagation (CFP)

Label: A label ℓ at vertex v is a quadruple $(\tau_t, u, \beta_u, f_{[u,\ldots,v]})$ with:

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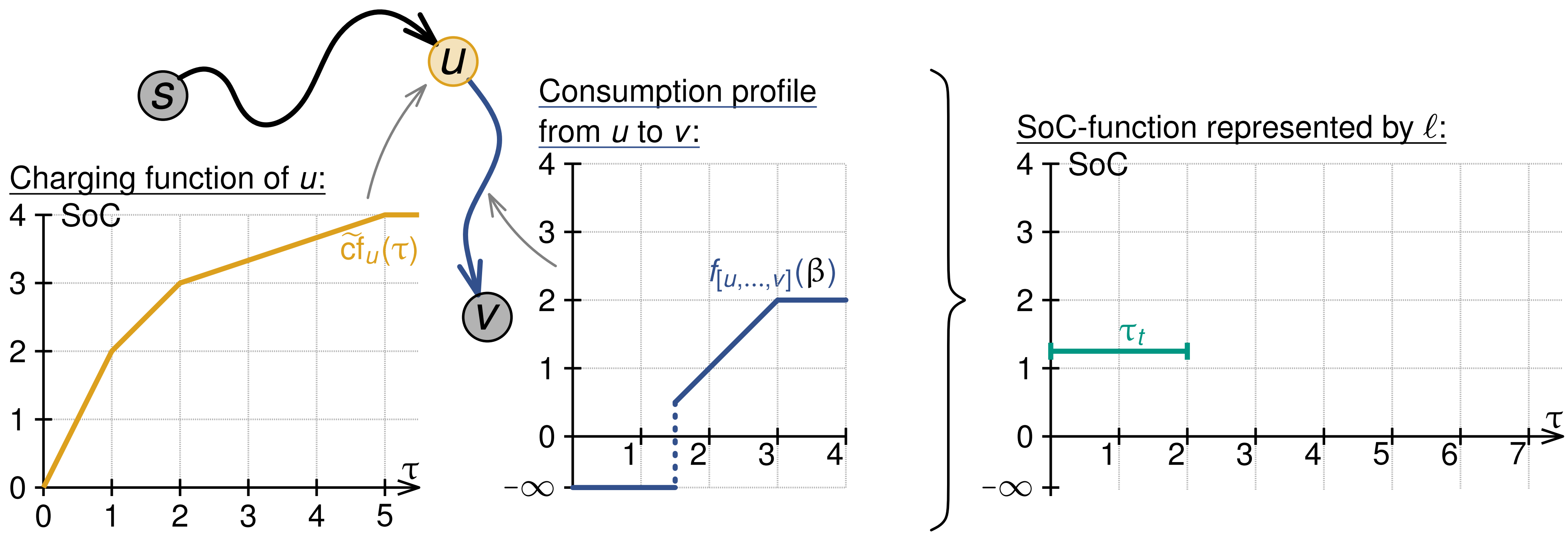

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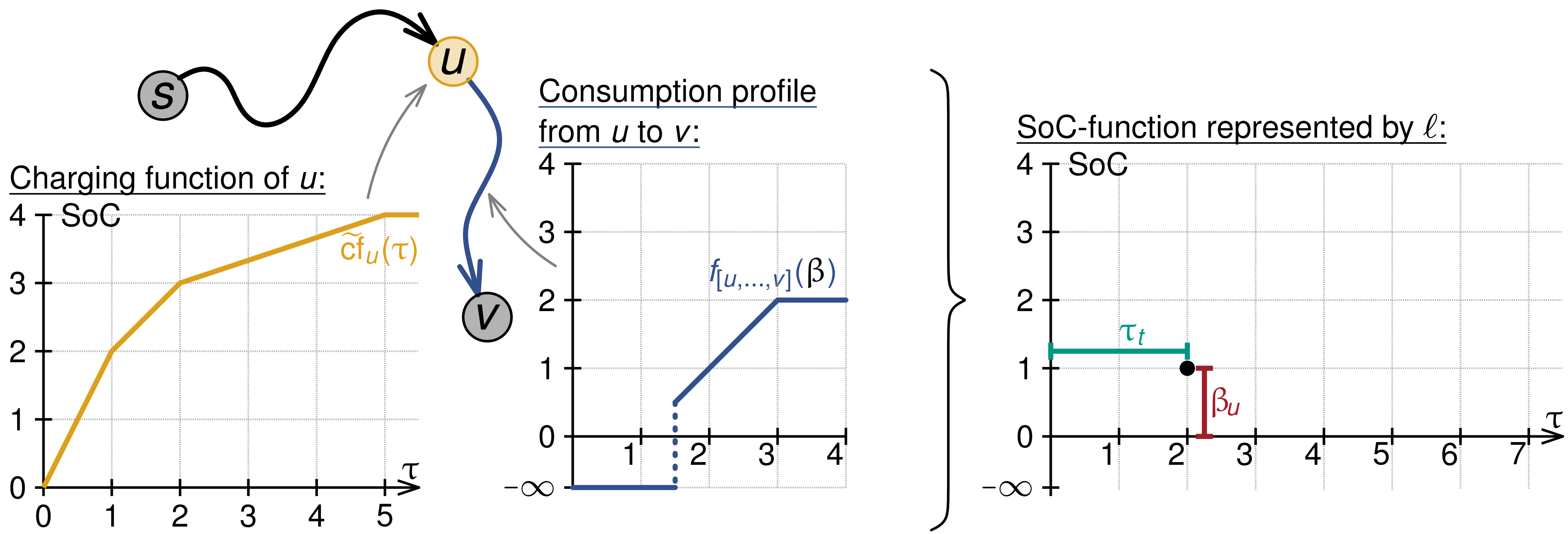

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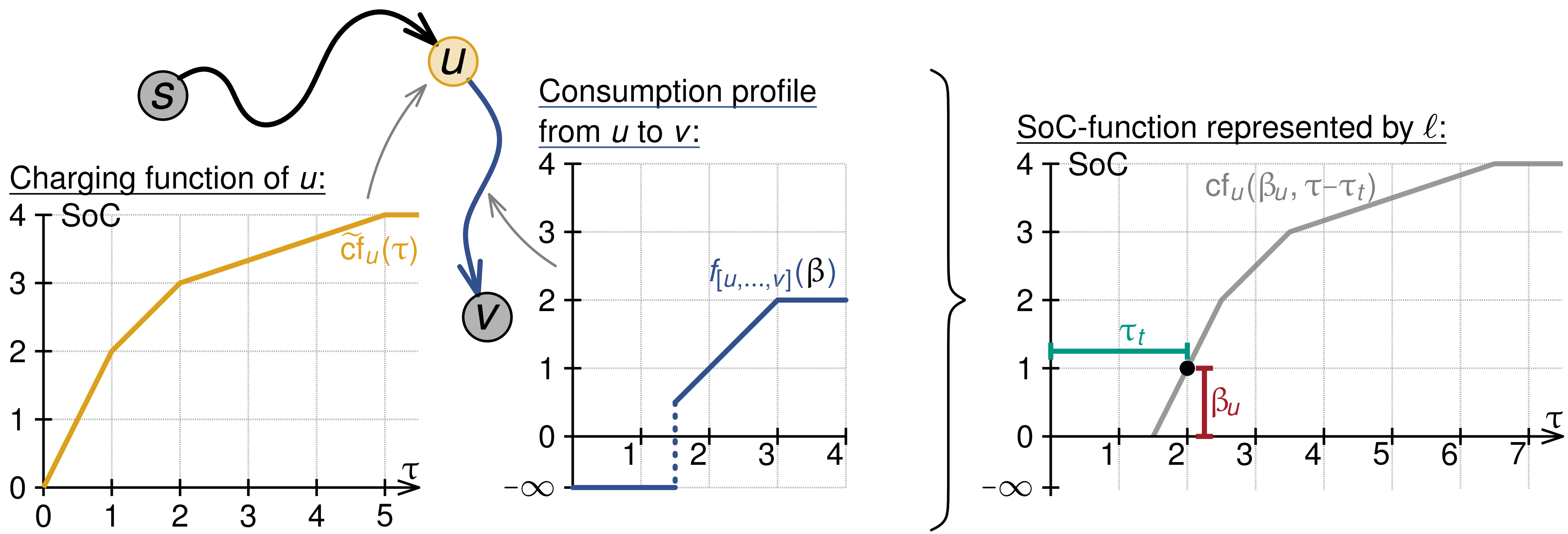

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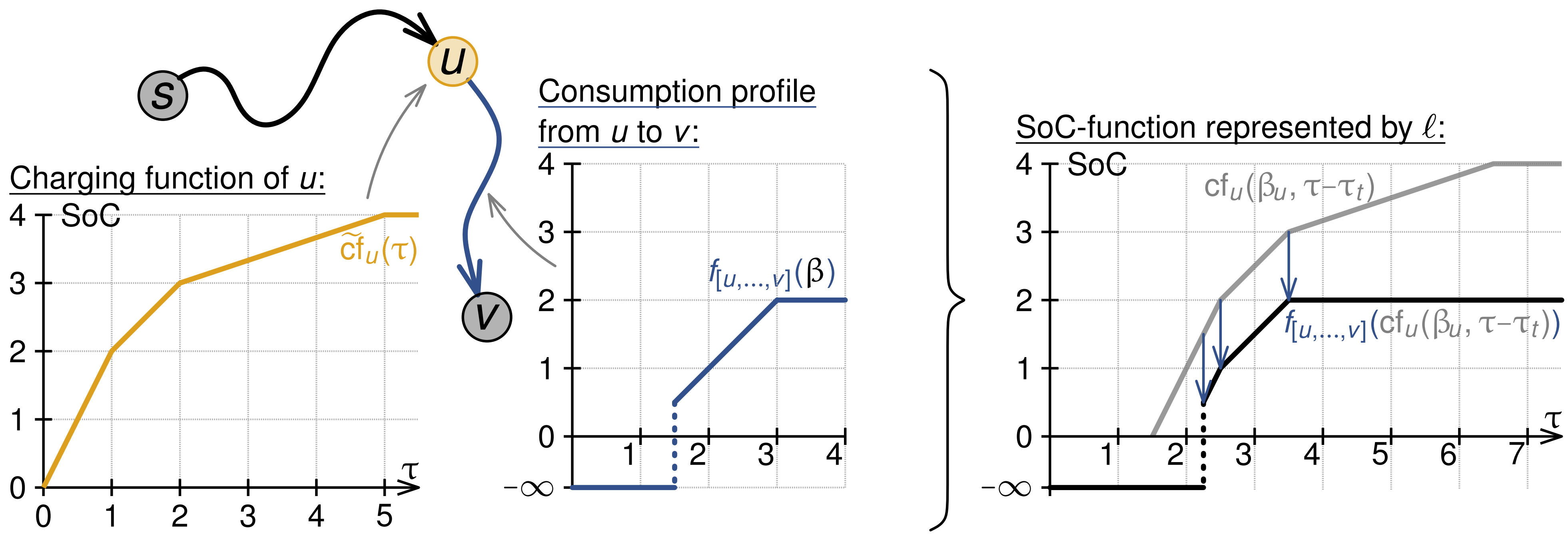

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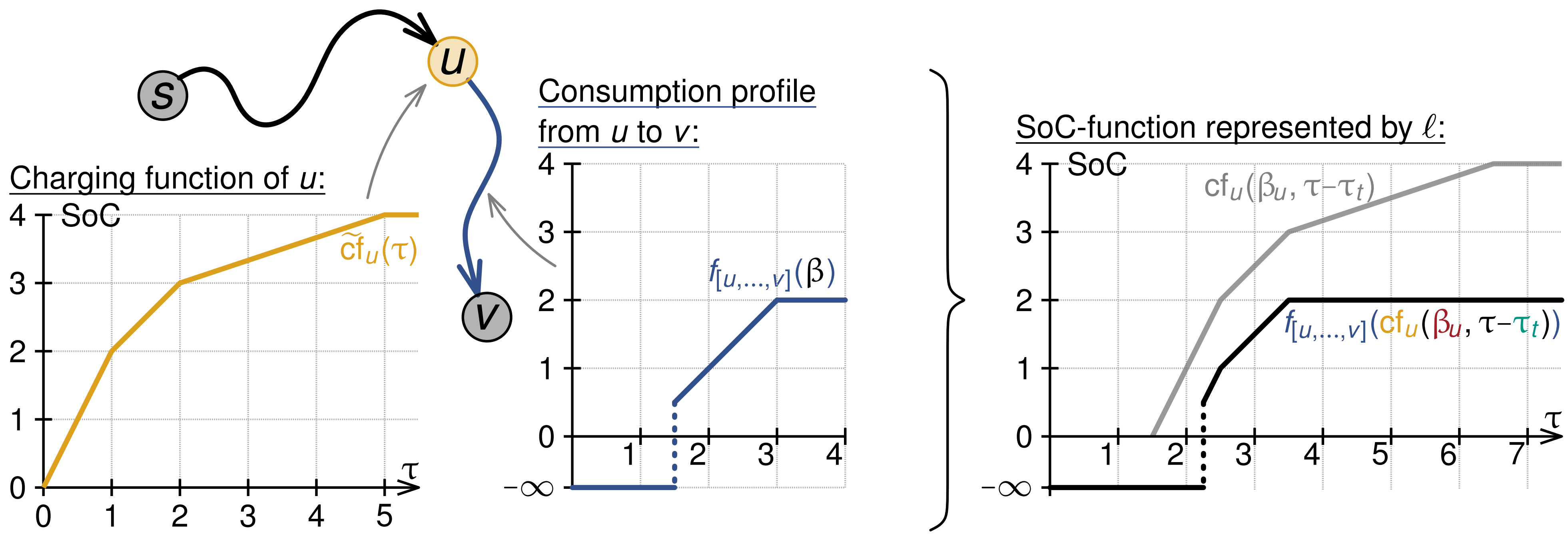

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Charging Function Propagation (CFP)

Karlsruhe Institute of Technology

Edge relaxation:

- Label propagation along an edge: Constant time operation
- Given a label $\ell_v = (\tau_t, u, \beta_u, f_{[u,\dots,v]})$ at v and an edge $e = (v, w)$:

$$\ell_w := (\tau_t + \tau_d(e), u, \beta_u, f_{[u,\dots,v]} \circ f_e)$$

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Label Pareto-domination:

- Linear in complexity of charging function
- **Our solution:** Check Pareto-domination rarely
  (Only for the next label to be settled)

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Label Pareto-domination:

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- **Our solution:** Check Pareto-domination rarely
  (Only for the next label to be settled)

Reaching another charging station:

- Our labels can store at most one charging station
- Have to specify the charging time for the second last station
- Theorem 1 in the paper proves that this is easy

Speed Up Techniques

CFP & Contraction Hierarchies:

- Shortcut-based technique
- Shortcuts have to maintain Pareto-sets
  (w.r.t. travel time & energy consumption)

  Problem: Shortcut size grows exponentially $\Rightarrow$ uncontracted core

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CFP & A*:

- Goal directed technique
- Potential function $\pi(v)$ estimates time from v to target t

  Our solution: Use bivariate potential $\pi(v, \beta)$ to account for SoC β

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CHArge = CH & A* & CFP:

- Stop contraction as mean core degree gets to big
- Combine CH-query with A*-search on core

Experiments

Karlsruhe Institute of Technology

- **Road Networks:**

Instance	# Vertices	# Arcs	# Arcs with $f_e < 0$	# CS
Ger (PTV)	4 692 091	10 805 429	1 119 710 (10.36%)	1 966
Eur (PTV)	22 198 628	51 088 095	6 060 648 (11.86%)	13 810
Osg (OSM)	5 588 146	11 711 088	1 142 391 (9.75%)	643

- **Elevation data:** SRTM, v4.1 (`srtm.csi.cgiar.org`)
- **Energy consumption:** [Hausberger et al. 09]
  Micro-scale emission model (PHEM), calibrated to Peugeot iOn
- **Charging stations:** ChargeMap (`chargemap.com`)
  random distributions
- **Station Types:**
  - Battery swapping stations (BSS)
  - Superchargers (50 % in 20 min, 80 % in 40 min)
  - Regular stations (44 kW; 22 kW; 11 kW)

Experiments

	Instance	# CS	M	Prepro. [mm:ss]	Query Feas.	Query [ms]	[Storandt '12] [ms]
Only BSS	Osg	1 000	100 km	11:37	100 %	122	539
	Osg	100	150 km	11:10	99 %	206	1 150
	Osg	643	100 km	11:21	98 %	326	—
	Osg	643	150 km	11:28	99 %	308	—
Only BSS	Ger	1 966	16 kWh	5:03	100 %	1 398	—
	Ger	1 966	85 kWh	4:59	100 %	1 013	—
	Eur	13 810	16 kWh	30:32	63 %	10 786	—
	Eur	13 810	85 kWh	30:16	100 %	47 921	—
Mixed CS	Ger	1 966	16 kWh	5:03	100 %	8 629	—
	Ger	1 966	85 kWh	4:59	100 %	2 614	—
	Eur	13 810	16 kWh	30:32	63 %	24 148	—
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Final Remarks & Conclusion

- Route planning for EVs raises new challenges
  - Considering energy consumption is essential
  - Charging stops should be planned in advance
  - Results in a (weakly) NP-hard problem

- Our approach **CHArge**:
  - Can handle arbitrary charging station types
  - Moderate preprocessing times
  - Fast queries on continental sized networks:
    Europe ∼1 min; Germany ∼1 sec
  - Even better results possible, using heuristics:
    Europe 0.1 – 1 sec; Germany 20 – 100 ms
    often optimal solutions, mean error ∼1%

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