Scalable Attention-based Reinforcement Learning Method for Multi-asset Control

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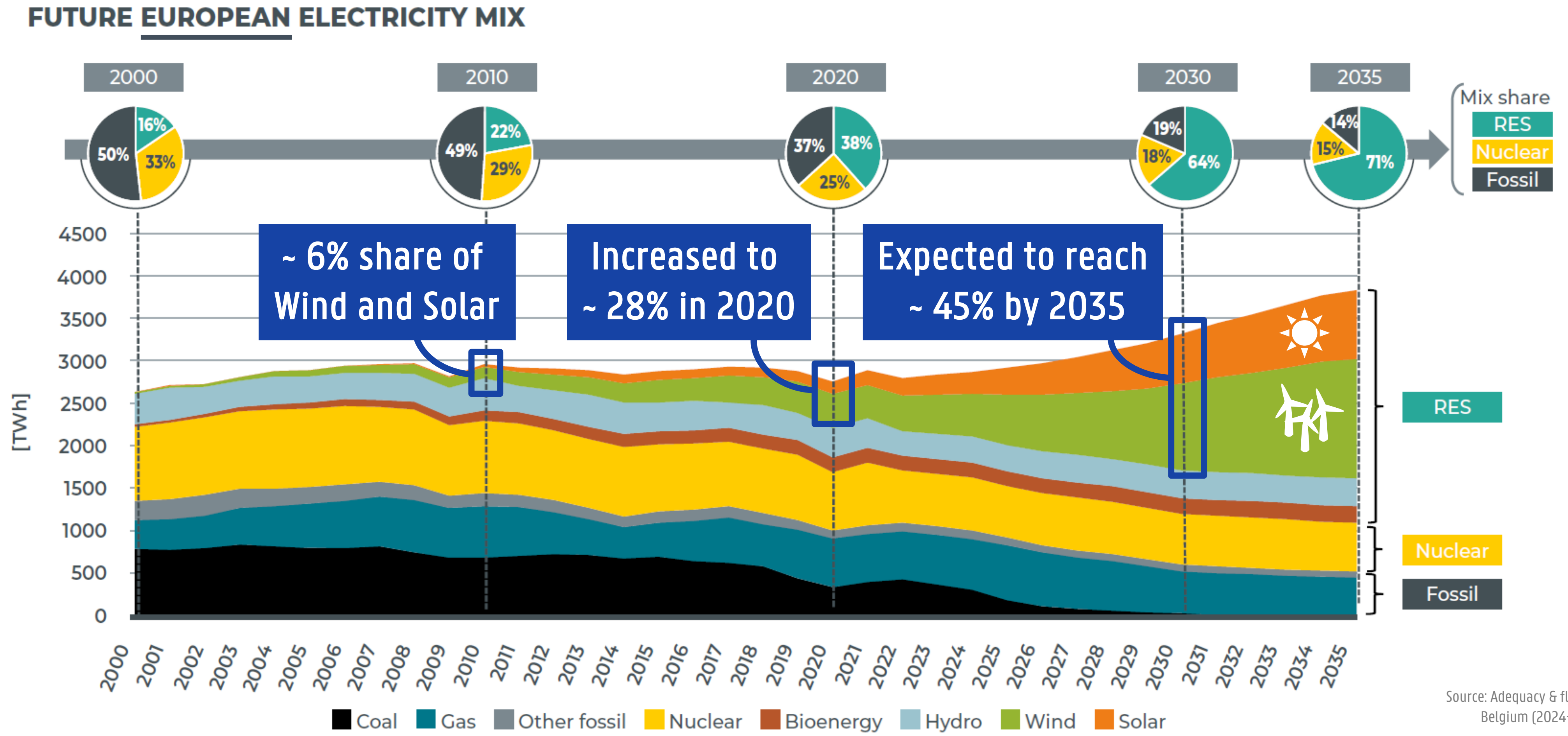
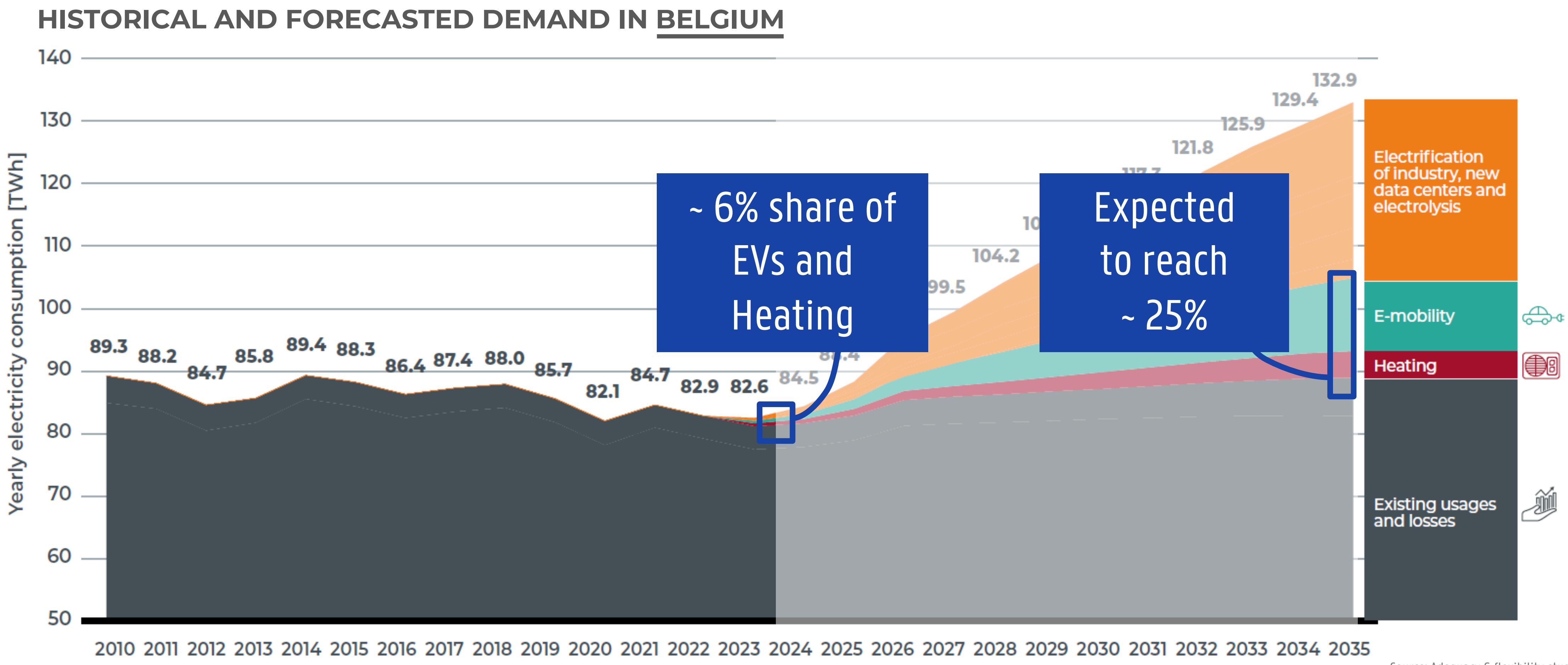
Energy Transition – Supply



Source: Adequacy & flexibility study for Belgium (2024-2034), ELIA

Energy Transition – (Residential) Demand



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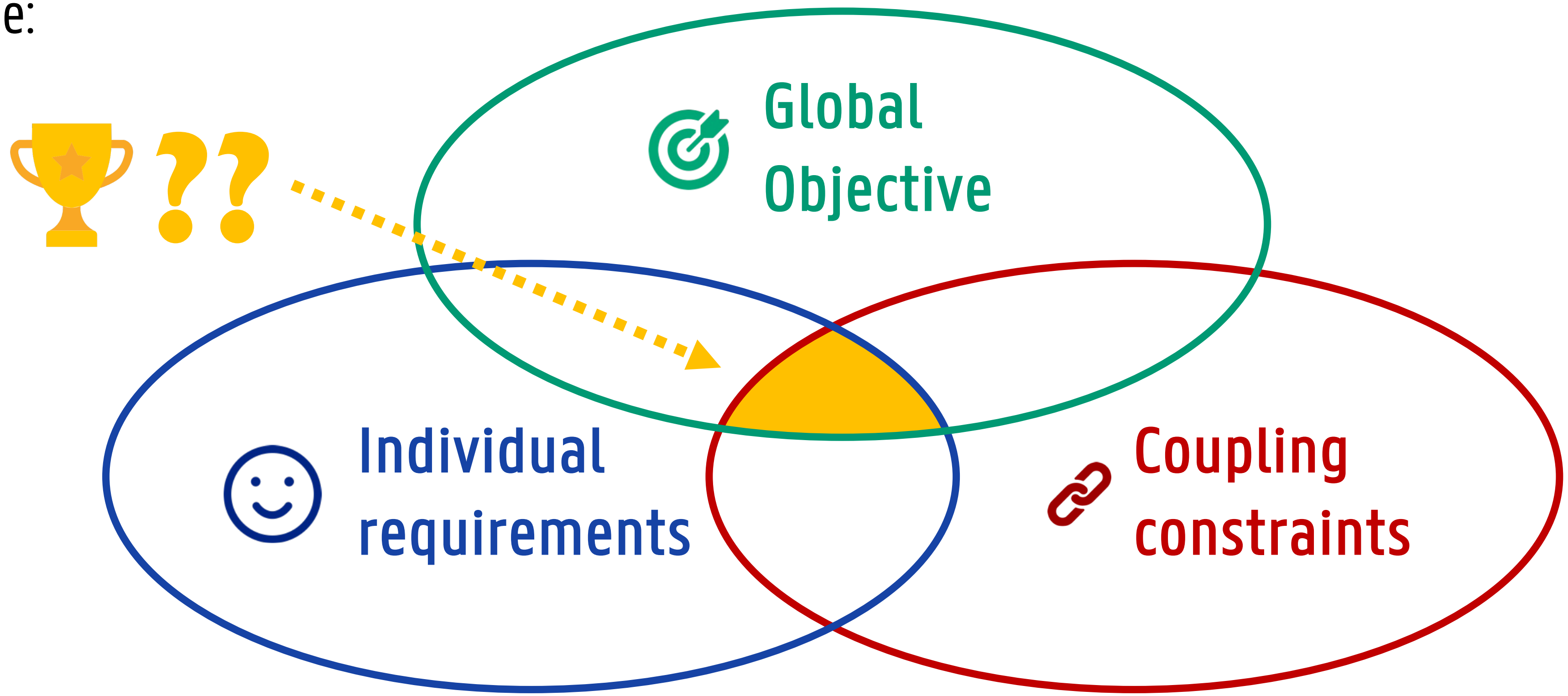
Opportunity: Exploit flexibility of (aggregated!) residential assets

- We need algorithms for multi-asset control
- Challenge:



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- We need algorithms for multi-asset control
- Challenge: Achieve global objective + Joint constraints + Individual constraints
- Candidate algorithms:

Requirements	Optimization-based	Centralized RL	Distributed RL
View	Global ✓	Global ✓	Local ✗
Scalable to large pools	No ✗	No ✗	Yes ✓
System model required	Yes ✗	No ✓	No ✓
Forecaster required	Yes ✗	No ✓	No ✓
Inference time	High ✗	Low ✓	Low ✓

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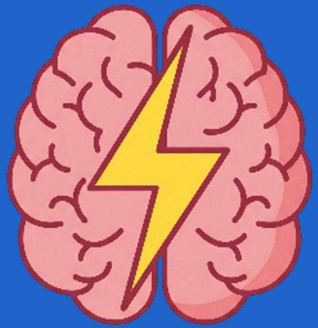
Syste				No √
Fore				No √
Infer				No √

Our contributions:

1. Attention-based RL = scalable control for asset pool
2. Proof-of-principle validation for EV charging case

Attention-Based RL



Attention-based state representations for scalable RL

Idea:

- Construct state representation combining own asset + relative to other assets + global state
- Use state representation as input representation in conventional RL (e.g., to map to Q-value, action, …)

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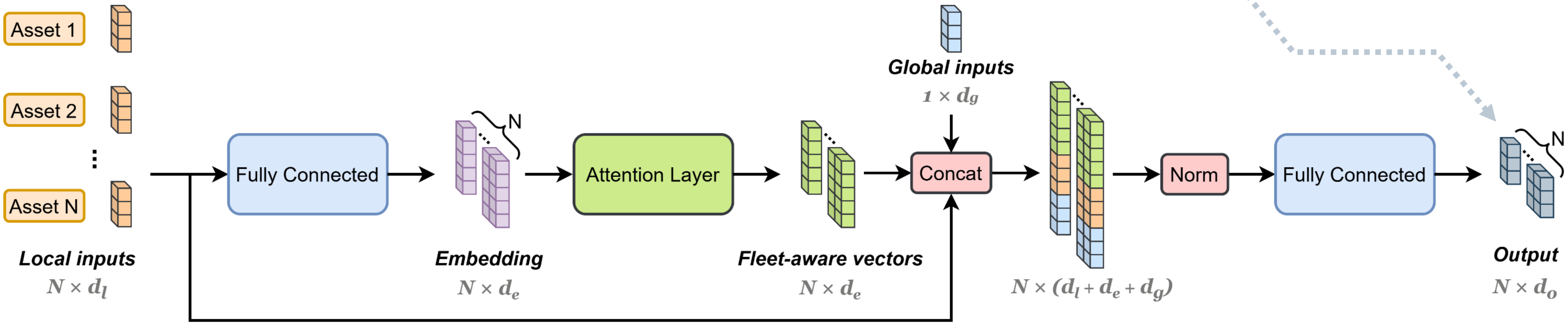

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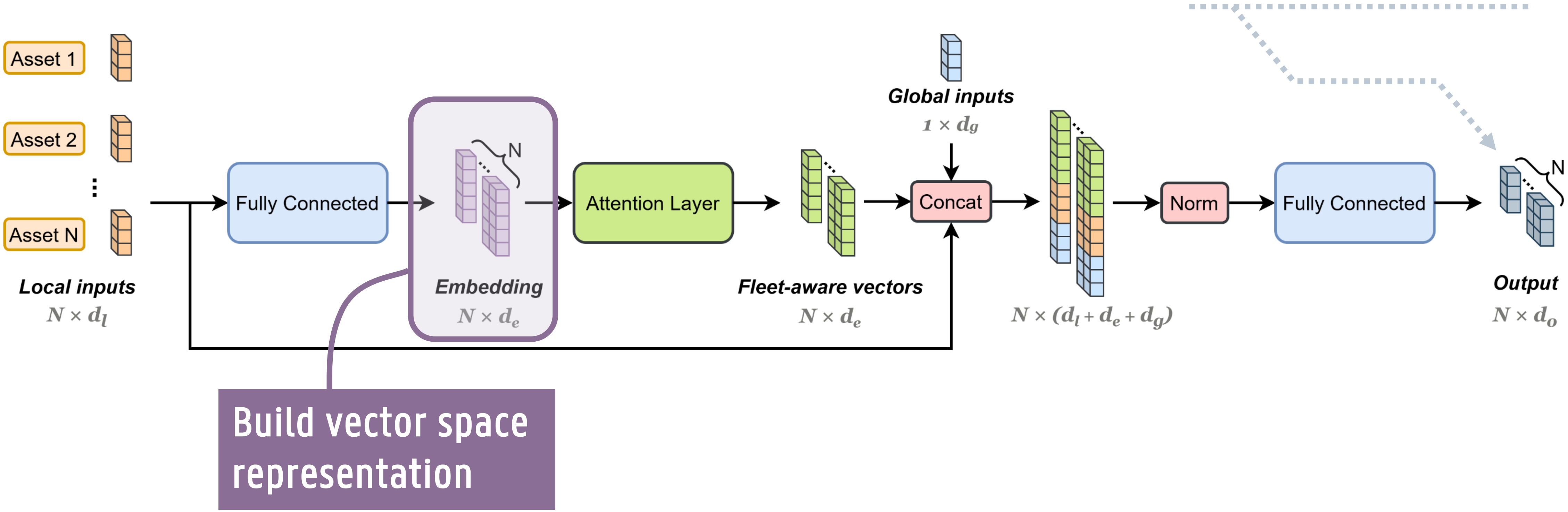

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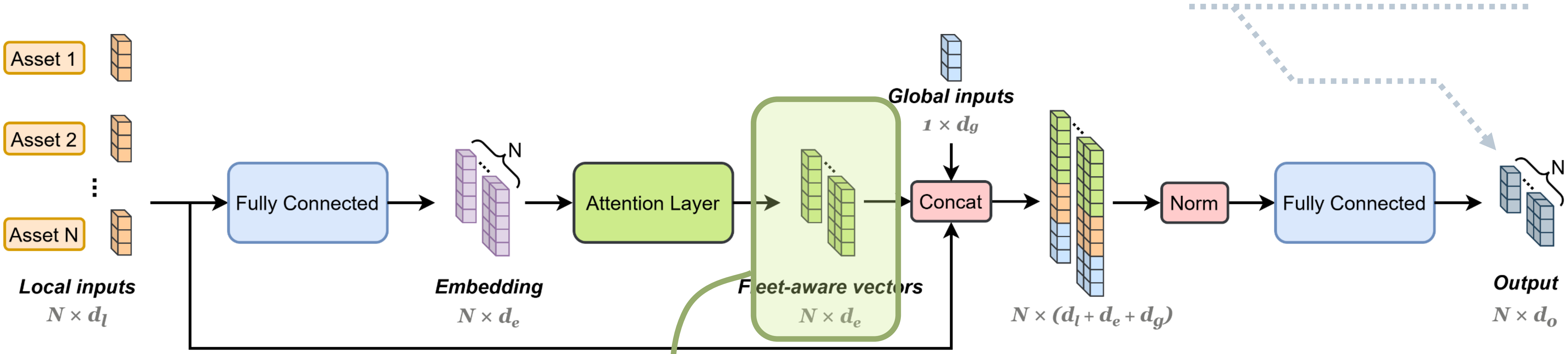

Adjust representation in light of other assets

Note: Attention layer can deal with varying number of assets involved!

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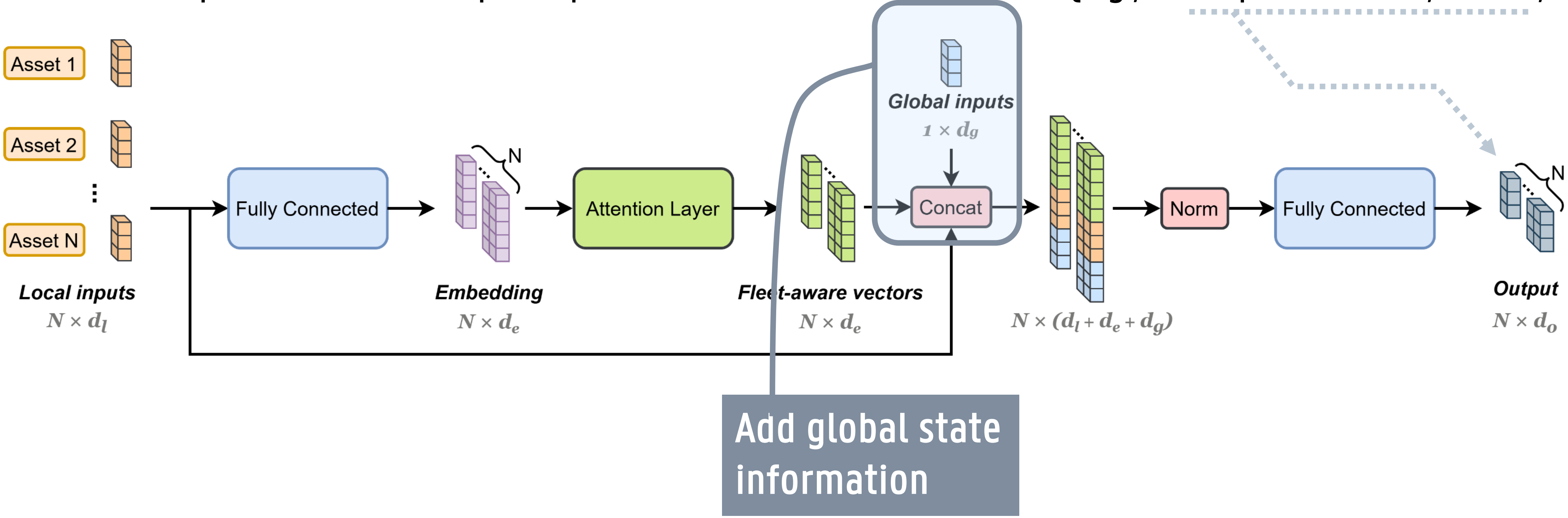

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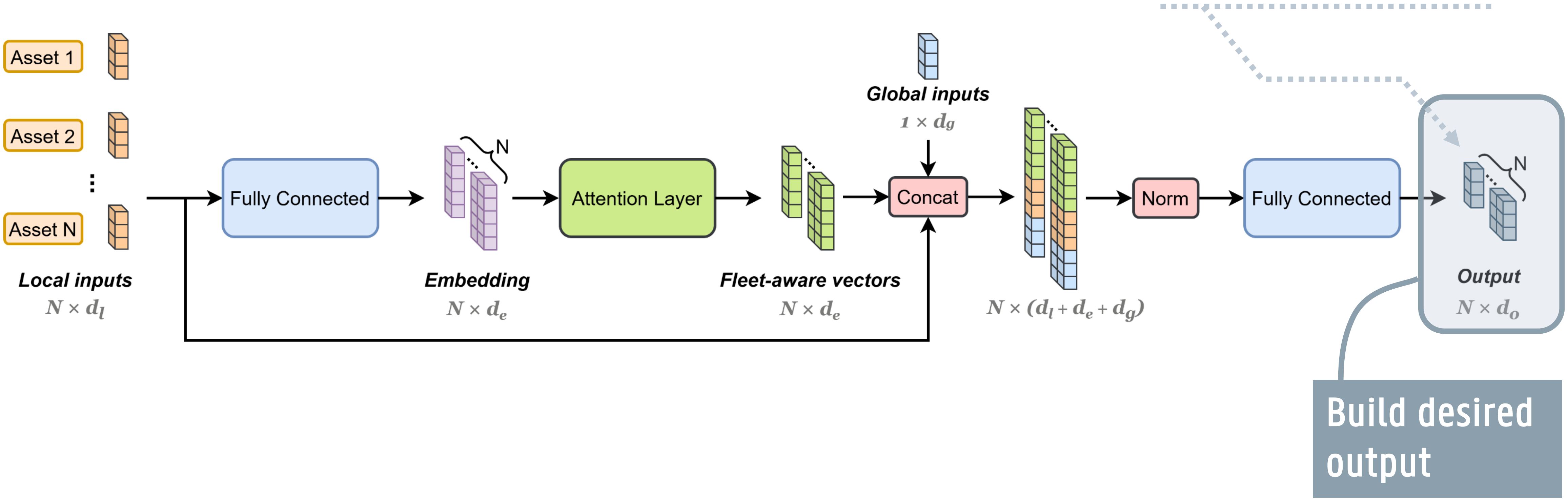

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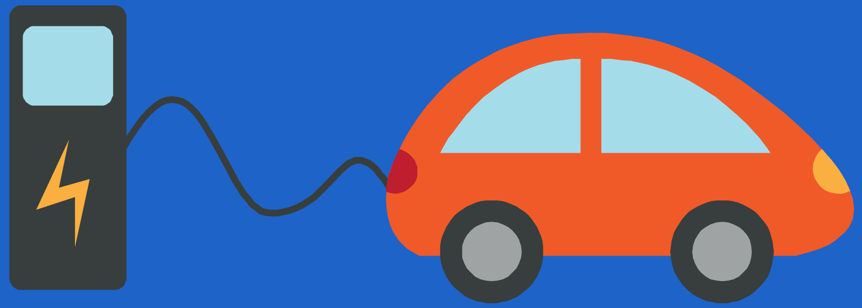
Case study: EV charging



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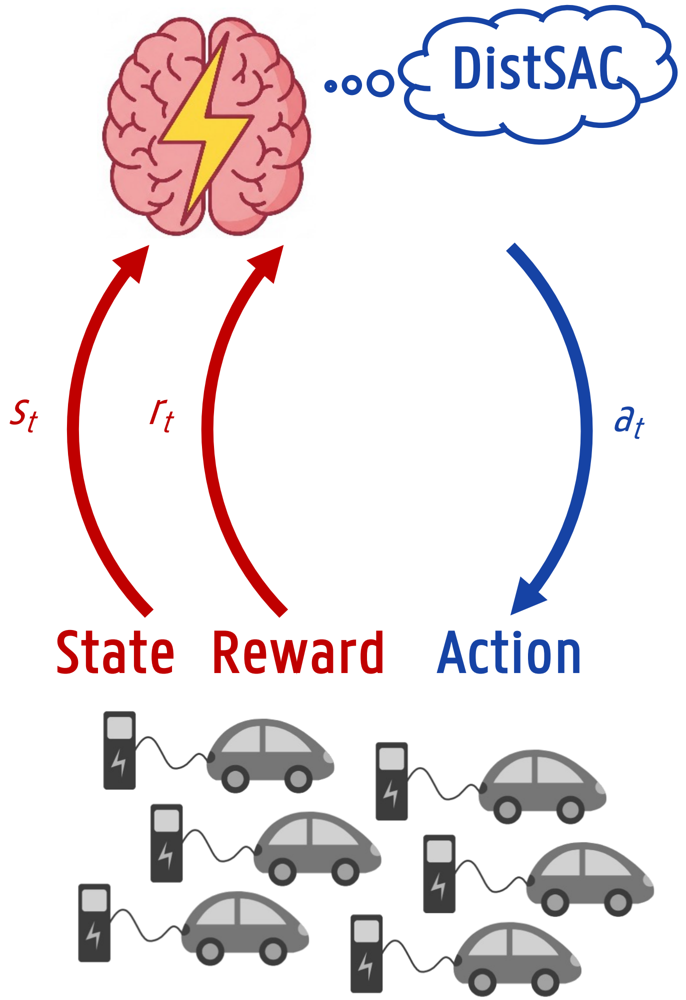
MDP Formulation for EV Problem

- At each timestep t the agent
  - Gets **state** observation $s_t = \bigoplus_{i=1}^{N_t} (\underbrace{t_{i,t}^{\text{arr}}, t_{i,t}^{\text{dep}}, E_{i,t}^{\text{req}},}_{\text{local info}} \underbrace{t, N_t}_{\text{global info}})$
  - Decides to take **action** $a_t = \bigoplus_{i=1}^{N_t} a_{i,t}, \quad a_{i,t} \in \{0, P_i^{\max}\}$
- The environment
  - Receives action a_t
  - Transitions to **state** s_{t+1}
  - Returns scalar **reward**

$$r_t = \underbrace{-\left(\sum_{i=1}^{N_t} a_{i,t}\right)^2}_{\text{load flattening}} \underbrace{- \alpha \sum_{i=1}^{N_t} \mathbb{1}\left\{E_{i,t}^{\text{req}} > t_{i,t}^{\text{dep}} \cdot P_i^{\max}\right\}}_{\text{penalty for unfinished charging}}$$

RL goal: learn policy to flatten the load of the whole parking, while satisfying the needs of EV users



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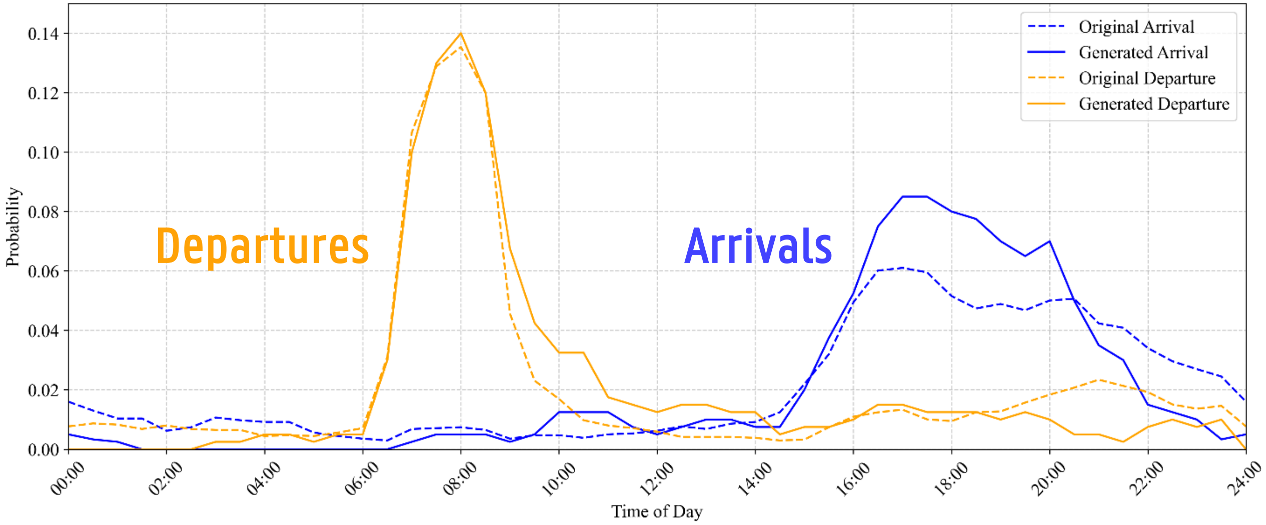
Simulation Setup

Datasets

- Historical real-world dataset from 20 EVs
  - Belgian residential charging sessions
  - Data split: 40d train / 5d eval / 5d test
- Scaled dataset from 100 EVs
  - Fit Gaussian mixture model on historical dataset
  - Data split: 30d train / 7d eval / 7d test



Benchmark controllers

- Business-as-usual (BAU): Start charging upon arrival
- Optimal: MPC optimization with perfect foresight over full day

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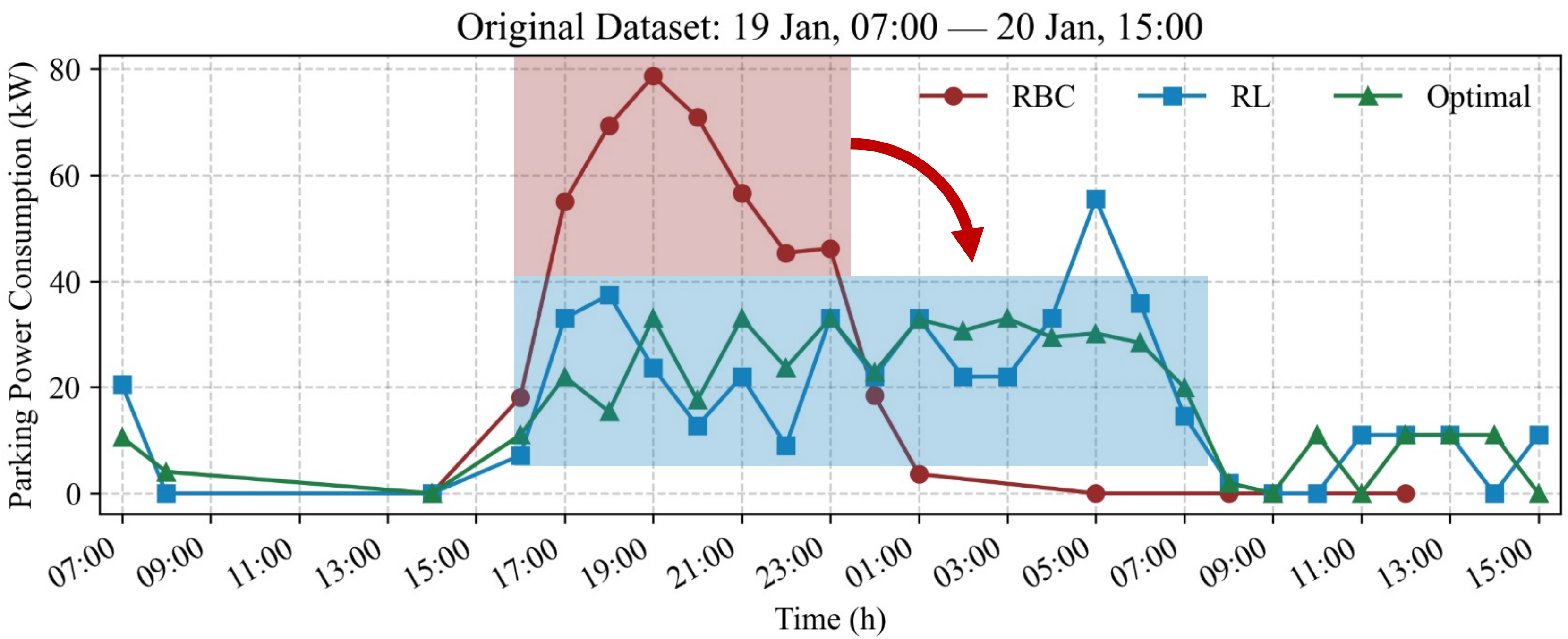
Simulation Results – Our RL outperforms BAU



Attention-based RL

- Flattens load (peak reduced by 27%)*

*: 27% is the average over full test set

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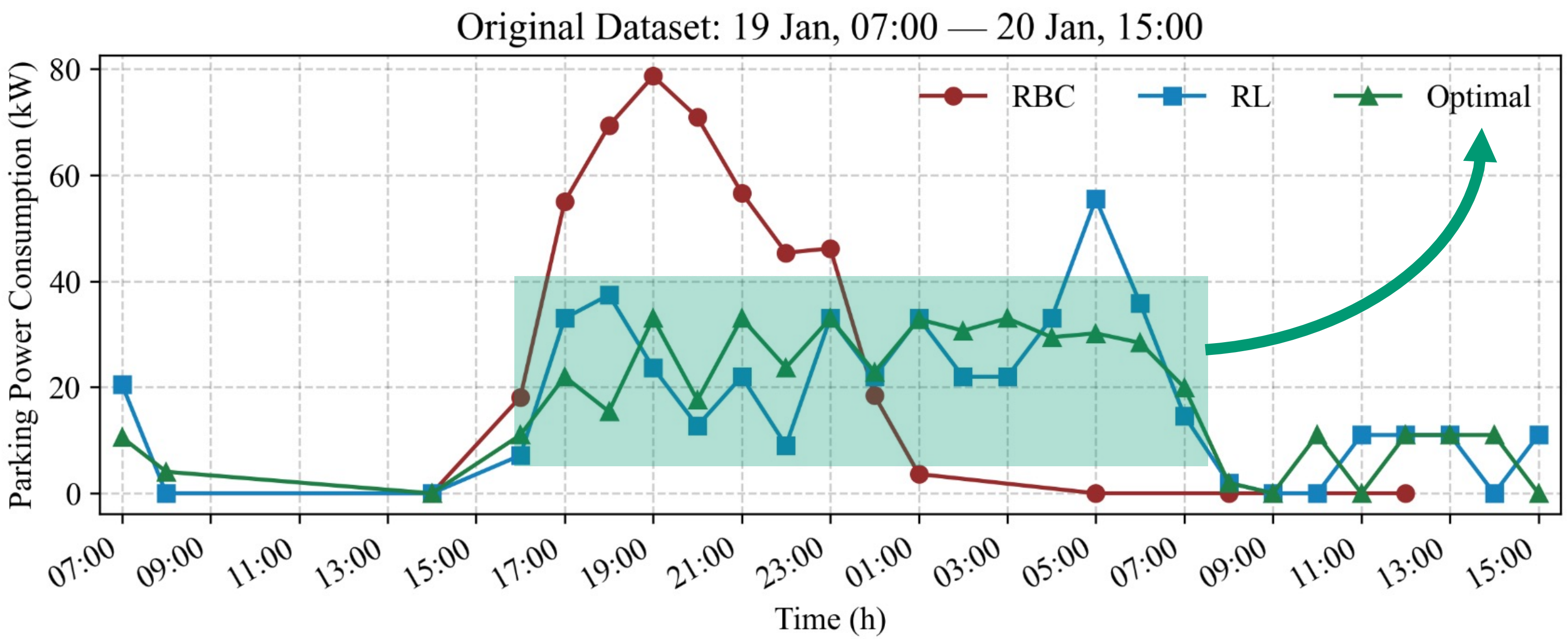

Attention-based RL

- Flattens load (peak reduced by 27%)*
- Performs close to optimization based on perfect foresight

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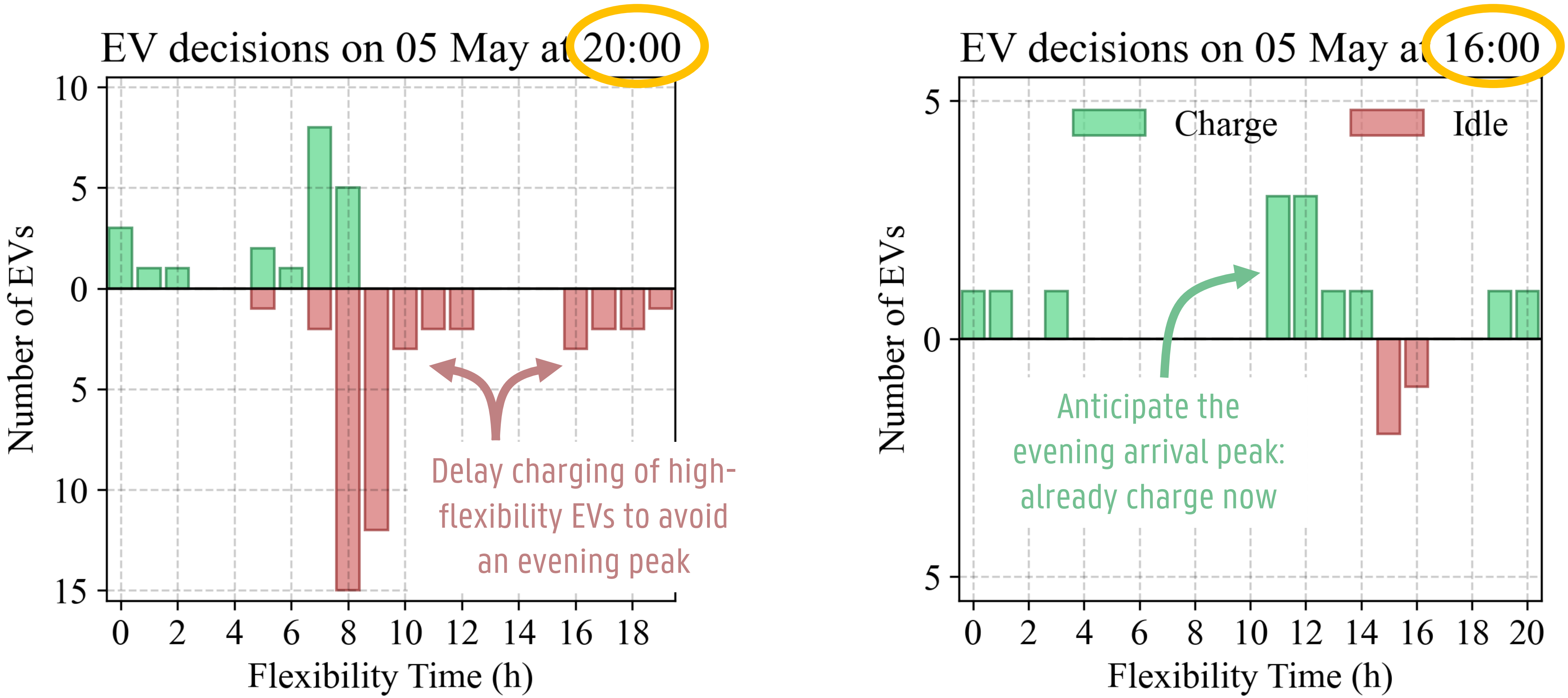
Simulation Results – Our RL learns to prioritize EVs correctly



Wrap-up

Conclusion

- Introduced a **scalable centralized** RL method to jointly control a fleet of flexible assets
    - Asset-specific info aggregation using attention layer
    - Model parameter size independent of number of assets
- Case study: load flattening of EV parking lot
    - Outperforms BAU by 28%
    - Average peak reduction of 27%

Future work

- Application to other asset types in multi-agent energy problems
- Joint control of a fleet of <u>heterogeneous</u> flexible assets

Thank you!
Any questions?

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Thank you!
Any questions?

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