

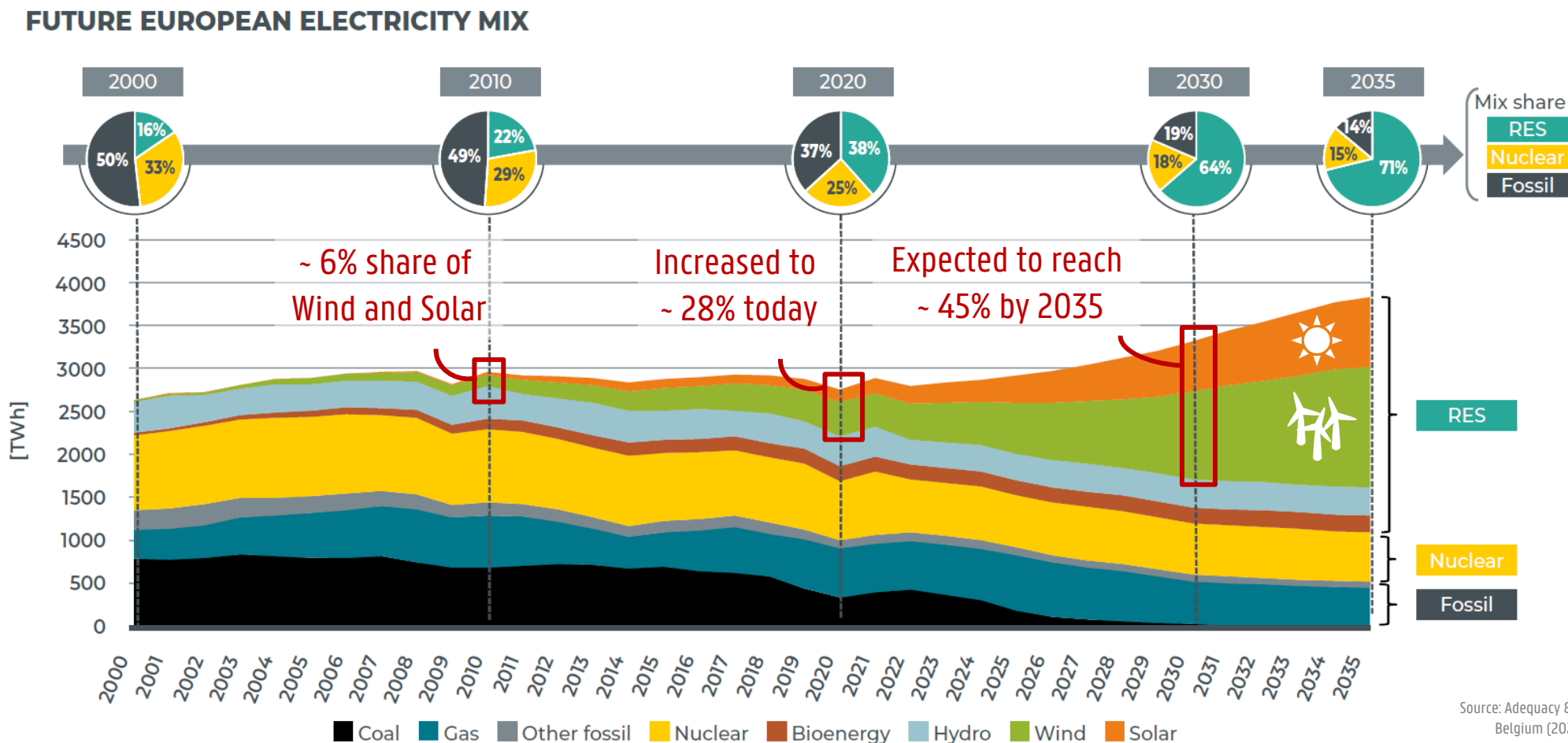
AI for Energy:

Reinforcement Learning for data-efficient and
explainable control algorithms to exploit
energy flexibility

Chris Develder, et al.

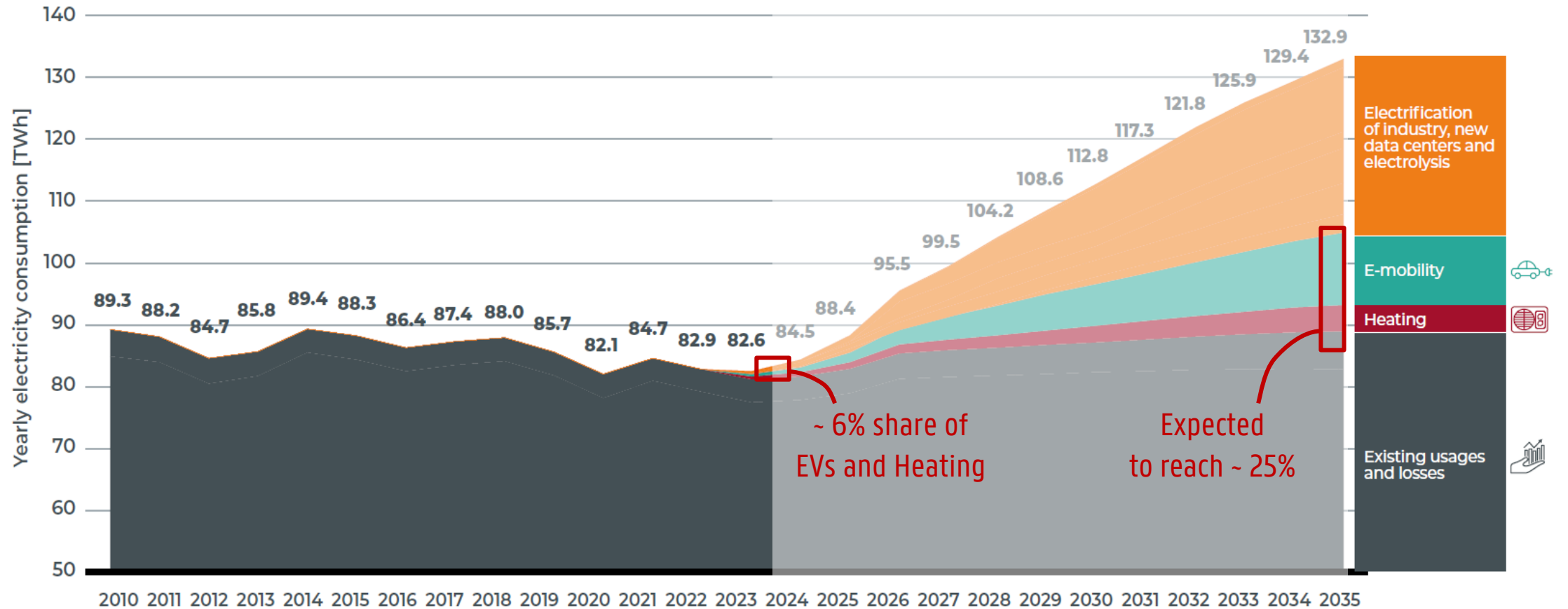
AI4E Team, IDLab, Ghent University – imec

Energy Transition – Supply



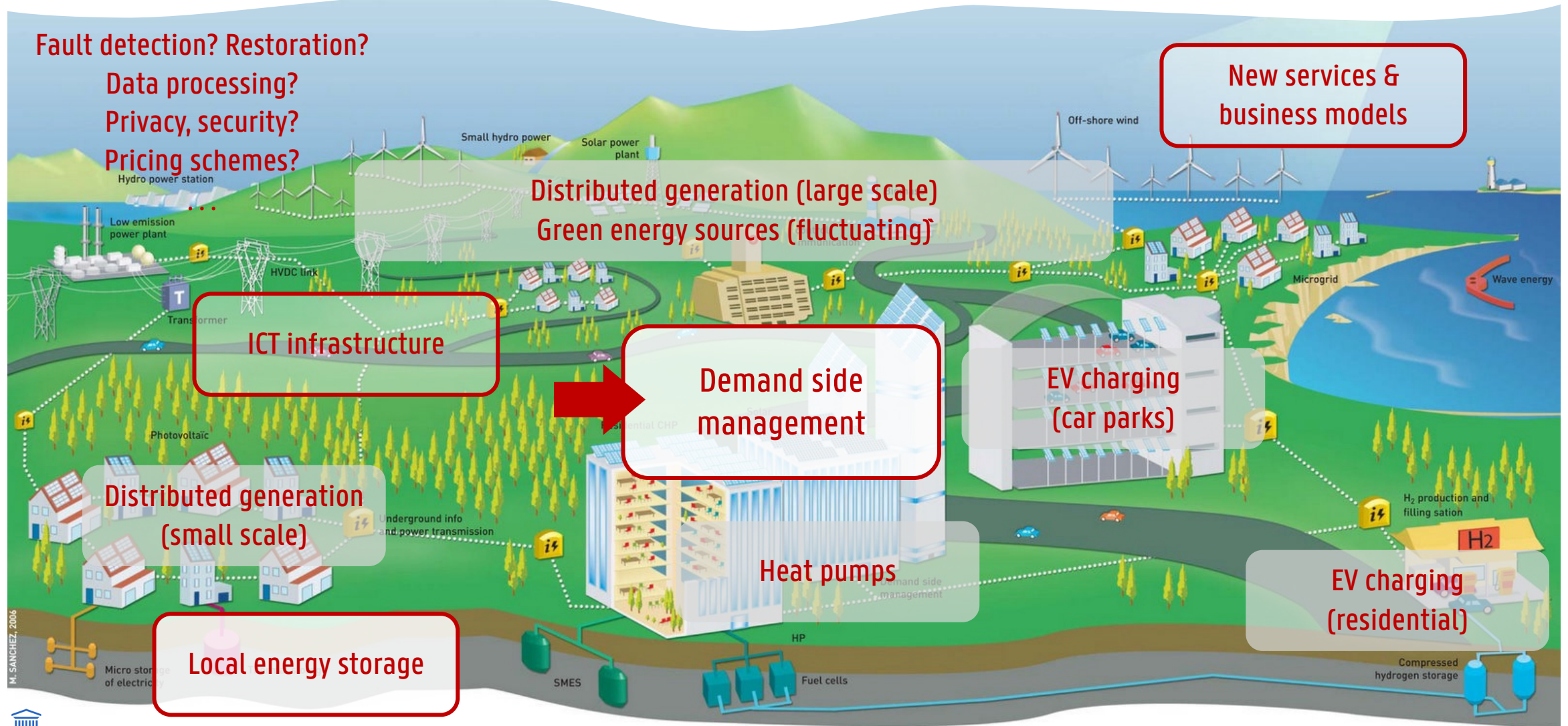
Source: Adequacy & flexibility study for Belgium (2024-2034), ELIA

Energy Transition – Demand



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

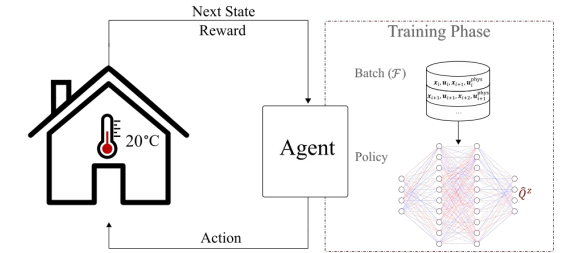
SMART GRID



Outline

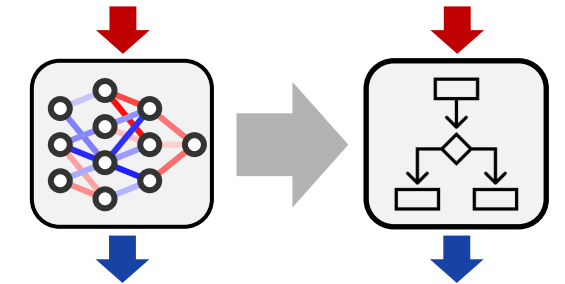
PART I: Physics-informed reinforcement learning

- Challenge: Learn suitable control policy from limited data
- Solution: Infuse a priori physics knowledge into neural network model



PART II: Interpretable decision trees

- Challenge: Policies from RL are black-box and non-trivial to deploy
- Solution: Distill a learned policy into decision tree



PART I:

Physics-informed reinforcement learning for residential heat pump control

G. Gokhale, B. Claessens, and C. Develder, "Physics-informed neural networks for control-oriented thermal modeling of buildings", Appl. Energy, Vol. 314, 15 May 2022, pp. 1-10. [doi:10.1016/j.apenergy.2022.118852](https://doi.org/10.1016/j.apenergy.2022.118852)

G. Gokhale, B. Claessens, and C. Develder, "PhysQ: A physics-informed reinforcement learning framework for building controls", Arxiv preprint, 21 Nov. 2022, [arXiv:2211.11830v1](https://arxiv.org/abs/2211.11830v1)

Thanks
Gargya!



Residential heat pump control: Problem statement & proposed solution

■ Objective:

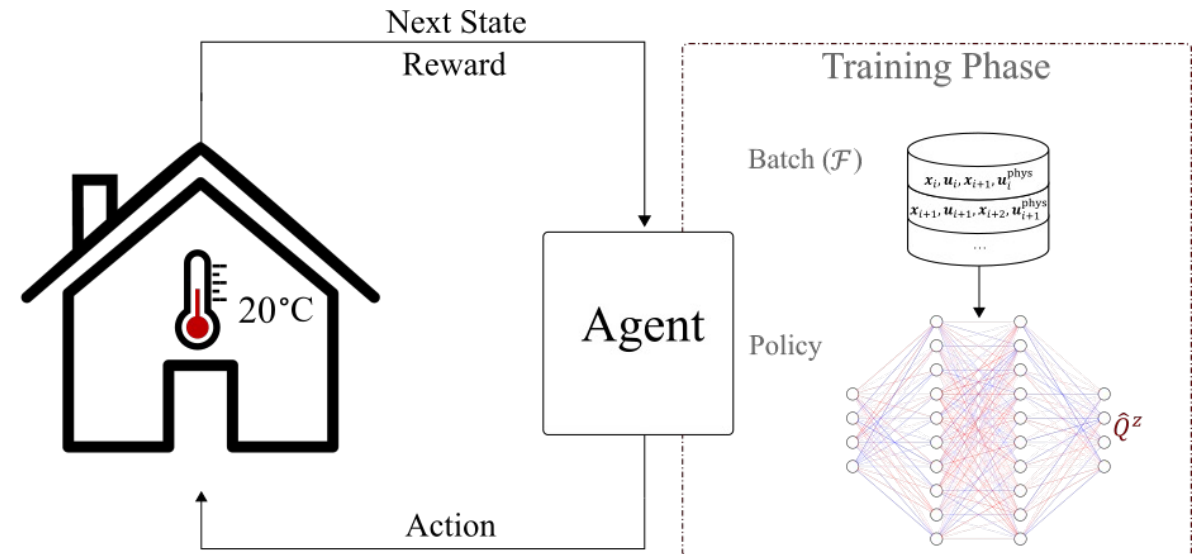
Minimize cost of energy consumed by a household while maintaining thermal comfort

■ Controller should:

- Use data efficiently
- Scale across different households
- Yield high-quality control policies

■ Proposed Solution:

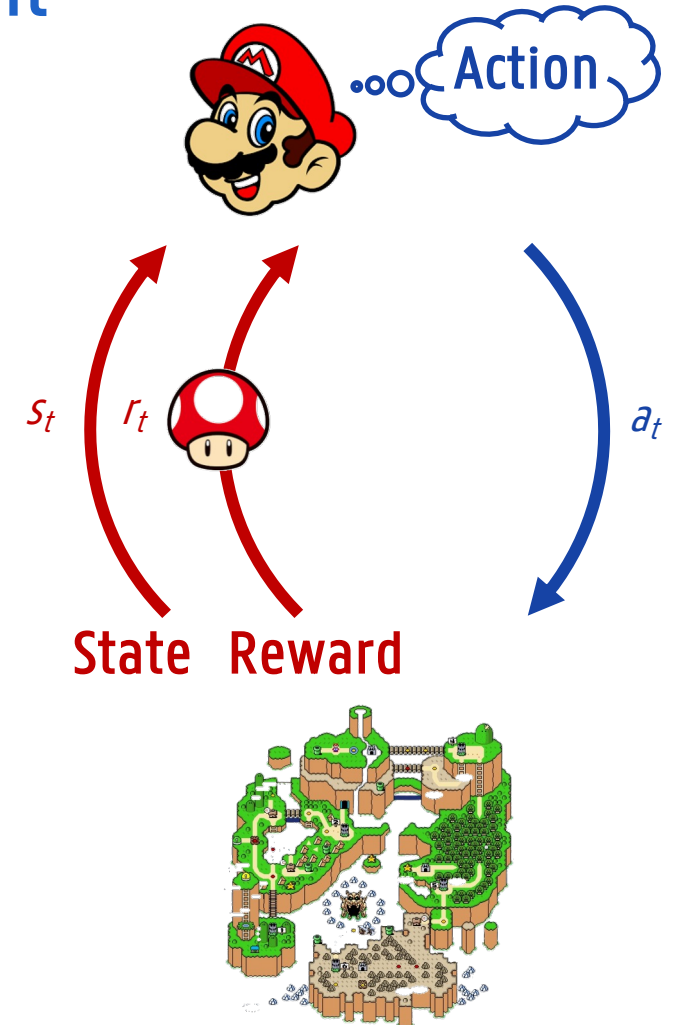
Off-policy reinforcement learning with physics informed neural networks



Reinforcement Learning: Agent acts in an environment

- At each timestep t the agent
 - Gets **state** observation s_t
 - Gets scalar **reward** r_t (depending on current state and thus previous action(s))
 - Decides to take **action** a_t
- The environment
 - Receives action a_t
 - Emits **state** s_{t+1} (which will depend on action)
 - Emits scalar **reward** r_{t+1}

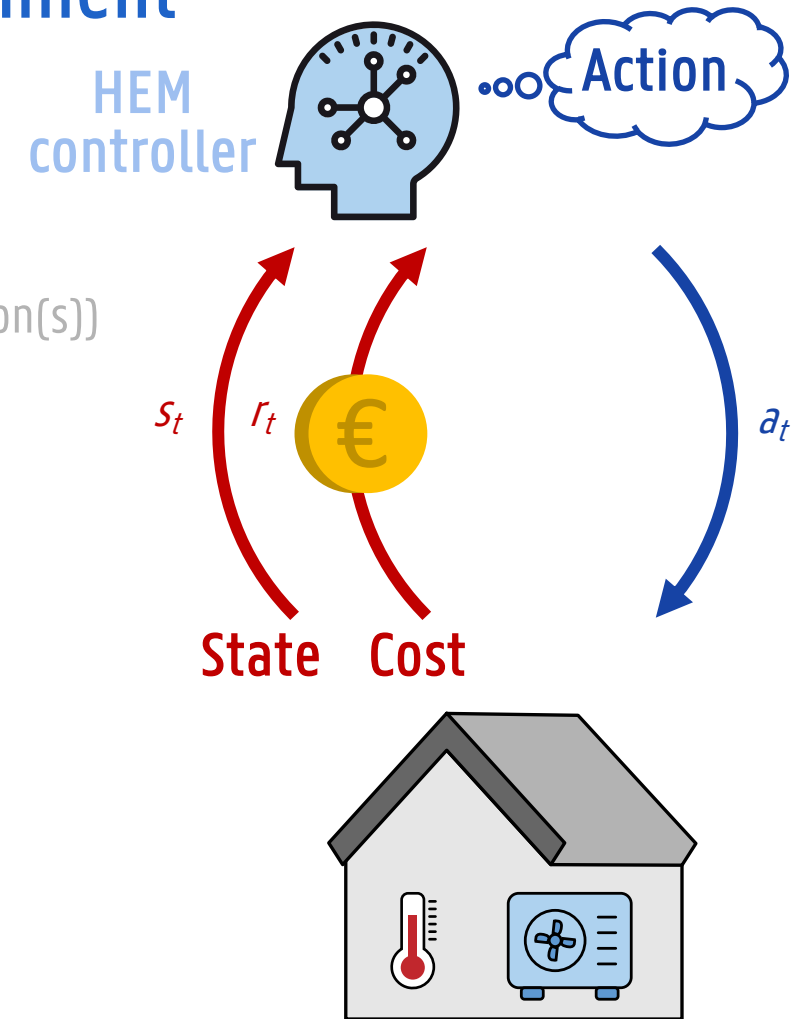
RL idea: learn a policy that maps state s_t to action a_t , such that long-term reward $\sum r_t$ is maximized



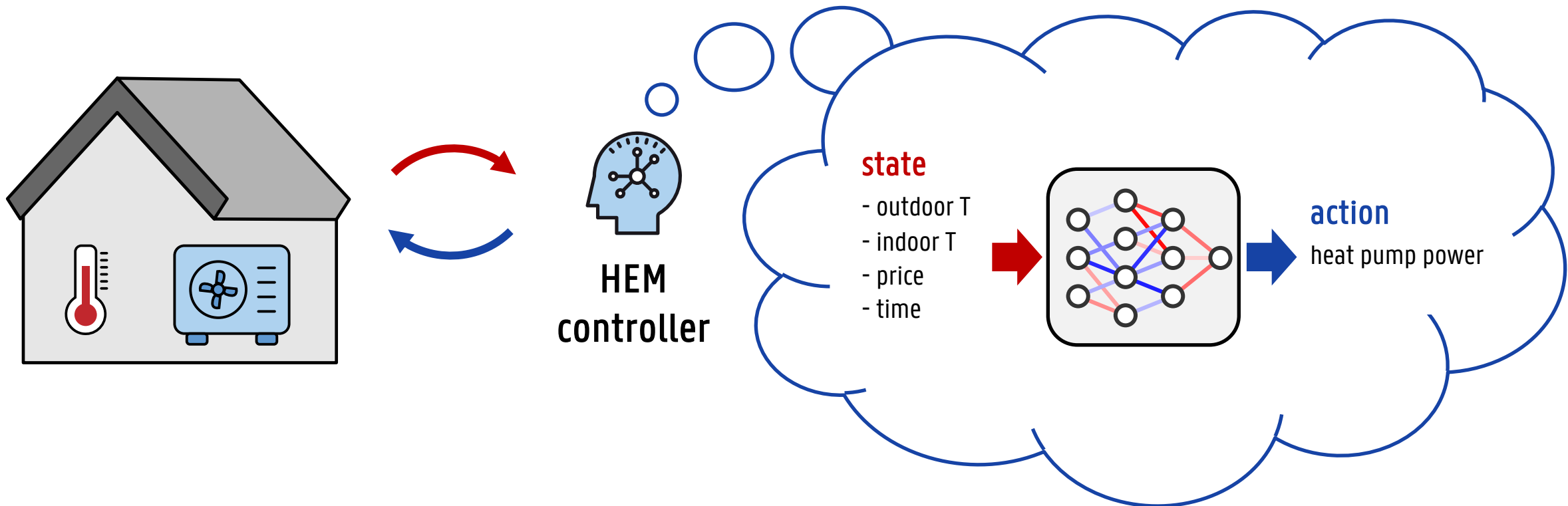
Reinforcement Learning: Agent acts in an environment

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RL idea: learn a policy that maps state s_t to action a_t , such that long-term reward $\sum r_t$ is maximized



Reinforcement Learning: Heat pump control



PhysQ: A physics-informed reinforcement learning framework

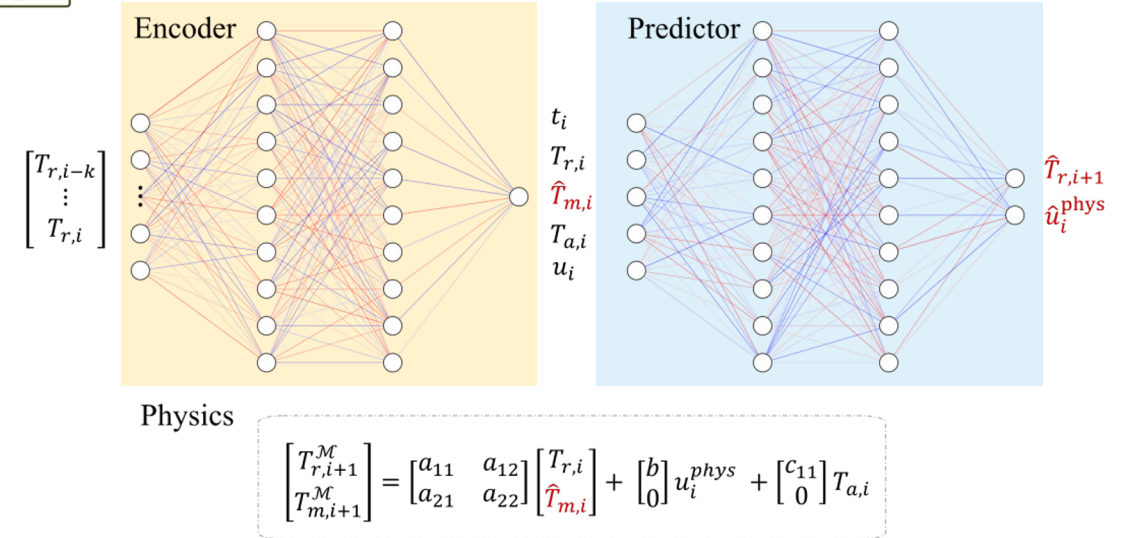
■ PhysQ:

- Physics informed RL framework
- Leverages prior physics to learn physically relevant **latent representations**
- Learns a control policy using this latent representation

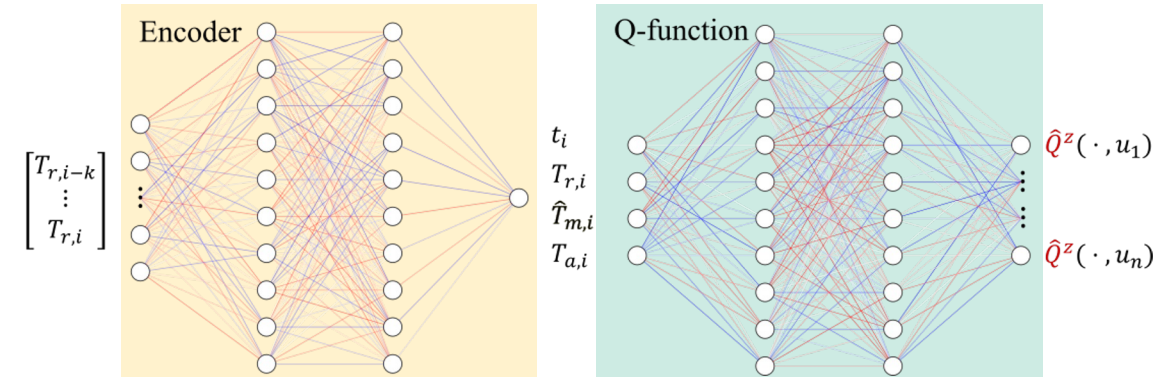
■ Two-step Algorithm:

- **Step 1:** Learn physically relevant representation (**bulk temperature T_m**)
- **Step 2:** Learn a low-dimensional **Q-function** based on this representation

Step 1 Learn to **predict temperature** evolution

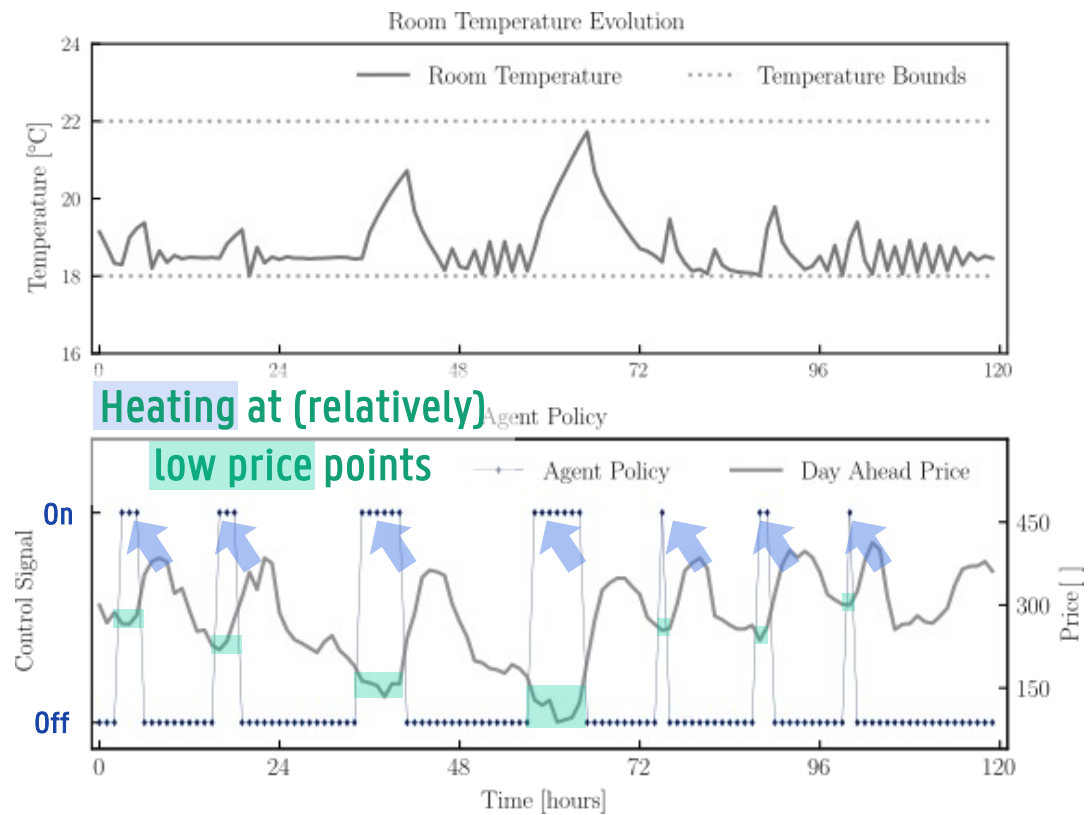


Step 2 Learn to **control the heat pump**



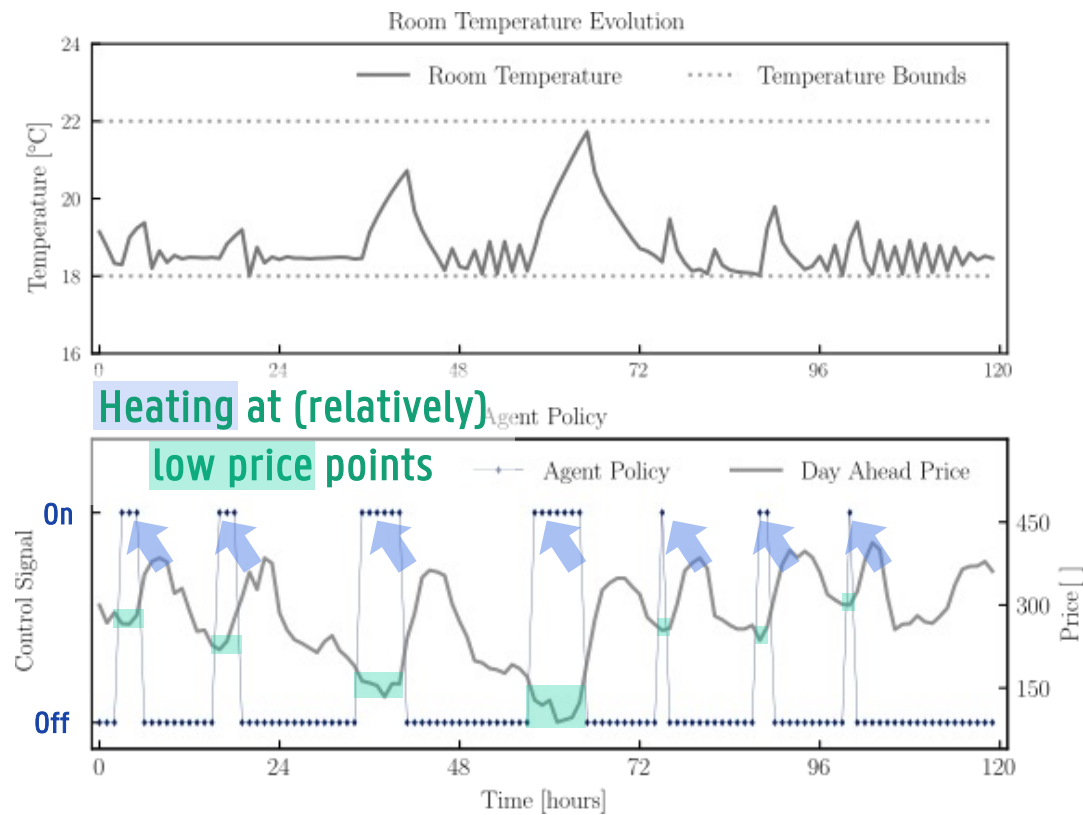
Simulation results

Results for BELPEX prices using a building simulator

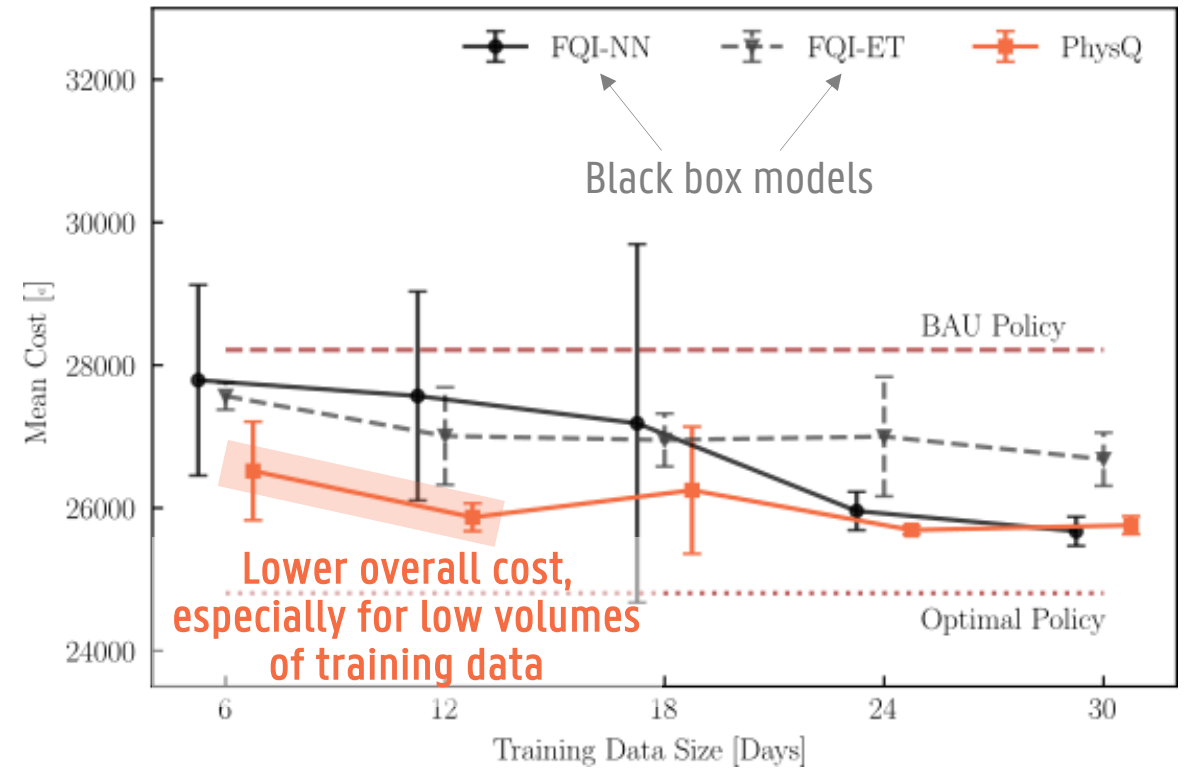


Simulation results

Results for BELPEX prices using a building simulator



Comparison over different training data sizes and agent types



PART II:

Interpretable decision trees distilled from black-box RL policies

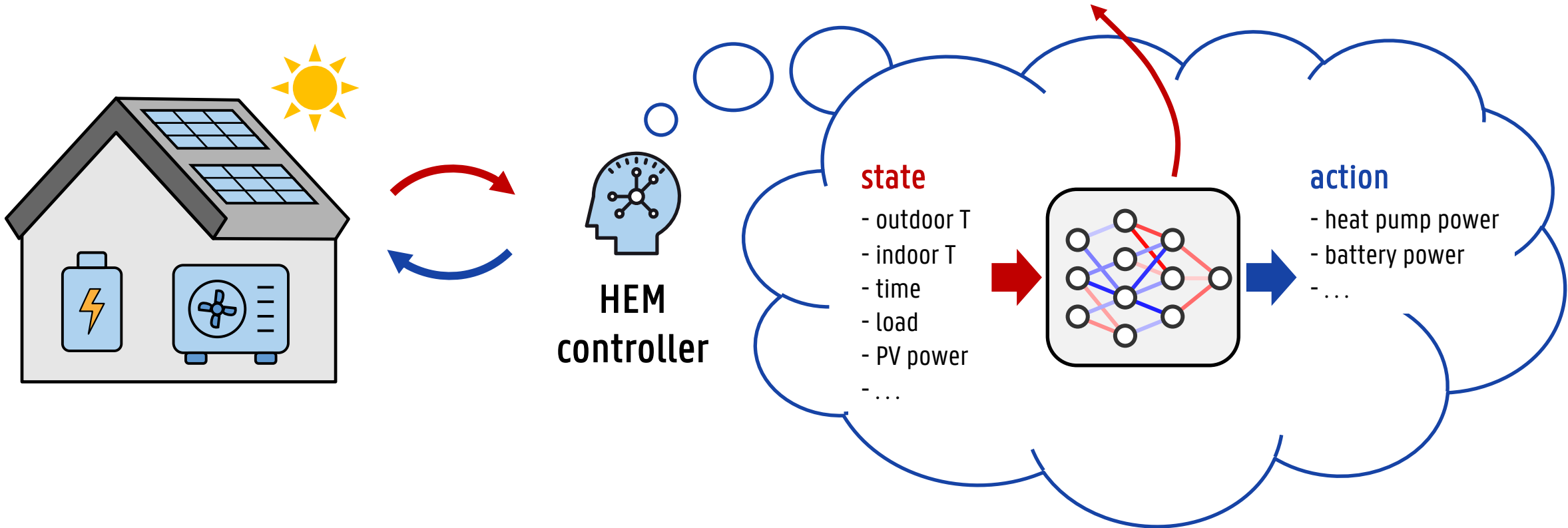
G. Gokhale, S.S. Karimi Madahi, B. Claessens and C. Develder, "**Distill2Explain: Differentiable decision trees for explainable reinforcement learning in energy application controllers**", in Proc. 15th ACM Int. Conf. Future Energy Sys. (e-Energy 2024), Singapore, 4-7 Jun. 2024, pp. 1-8. [doi:10.1145/3632775.3661937](https://doi.org/10.1145/3632775.3661937)

Thanks
Gargya!



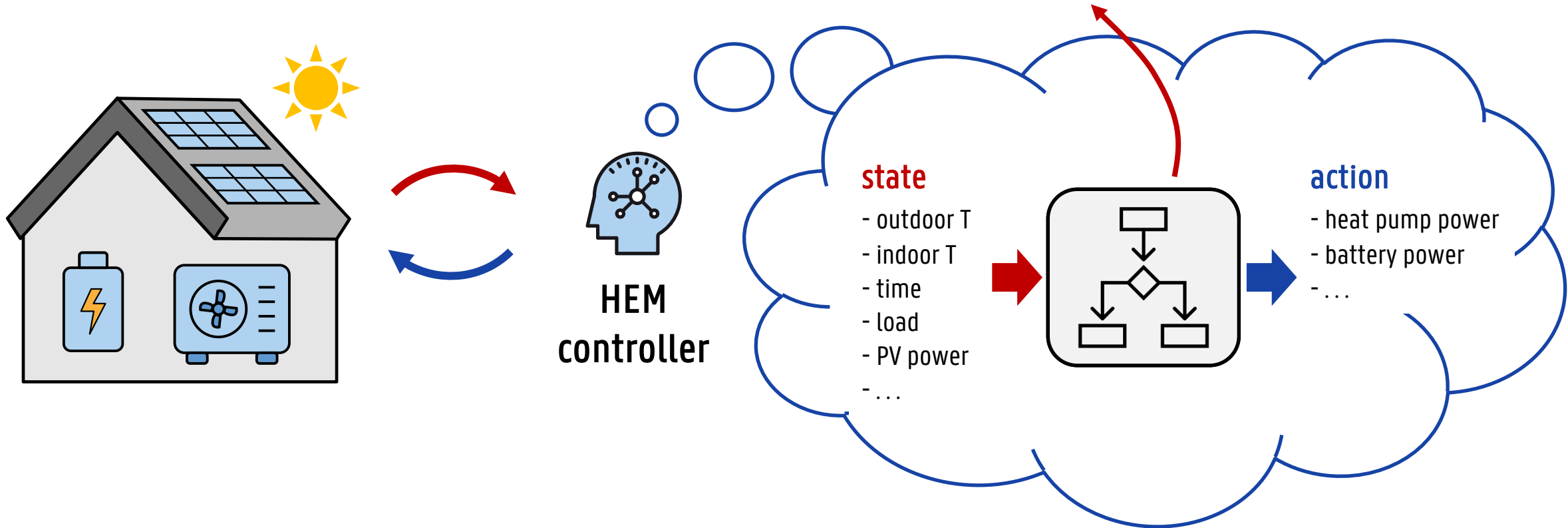
Black-box Reinforcement Learning

Black-box model: cannot explain why a given action is chosen . . .



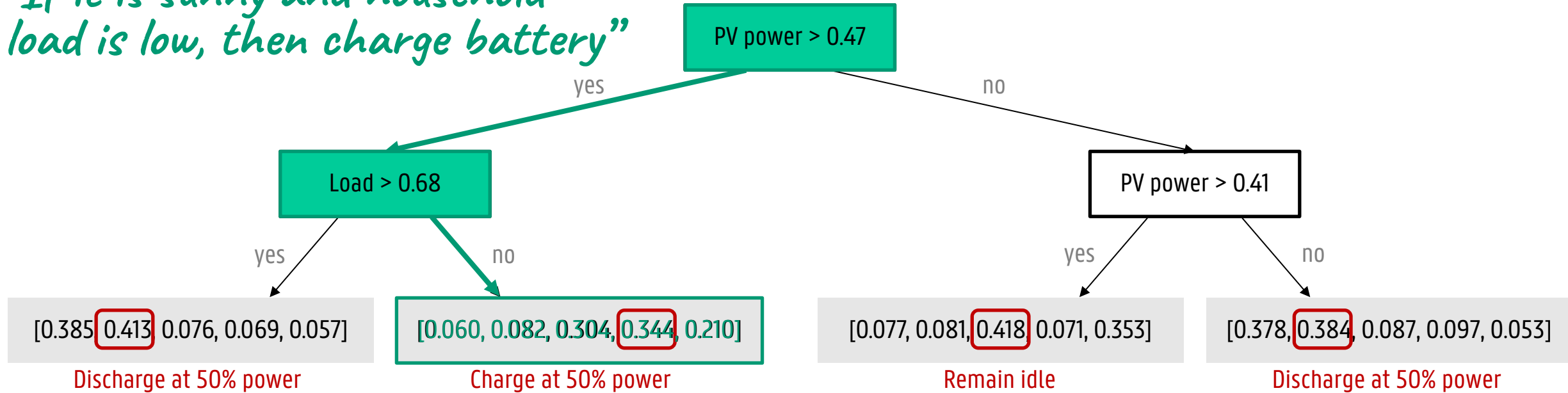
Black-box Reinforcement Learning

Idea: replace neural networks by something more explainable!



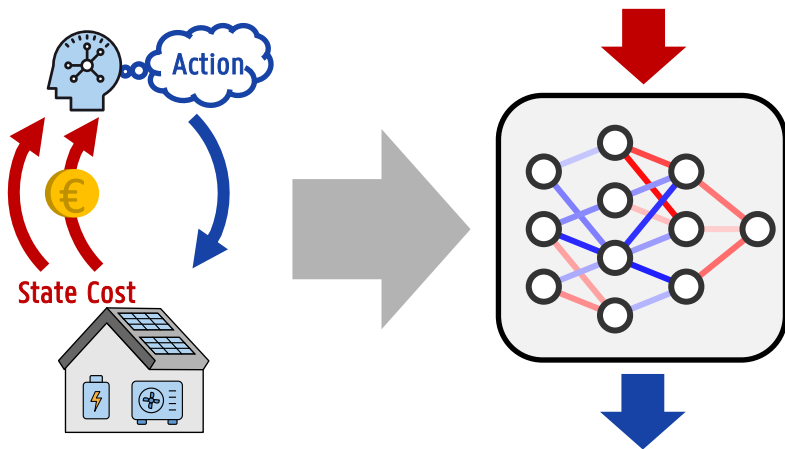
Enhancing explainability: Differentiable Decision Trees

“If it is sunny and household load is low, then charge battery”

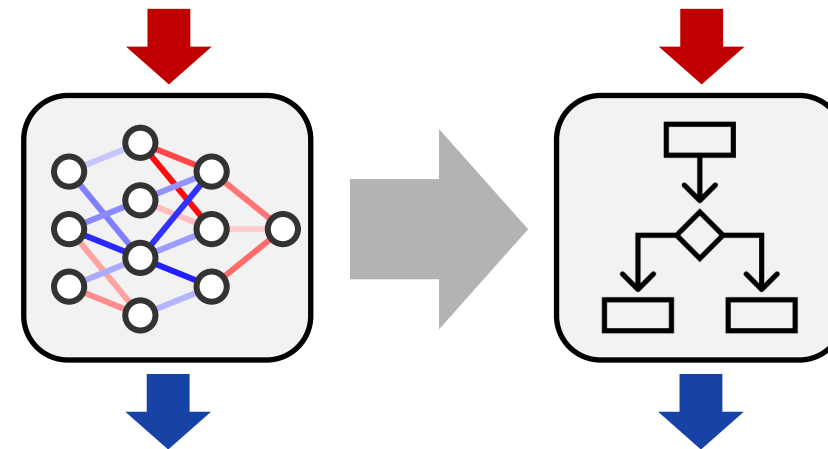


Distill2Explain: Learns the tree from trained RL policy

**Step 1: train an RL
“teacher” model**

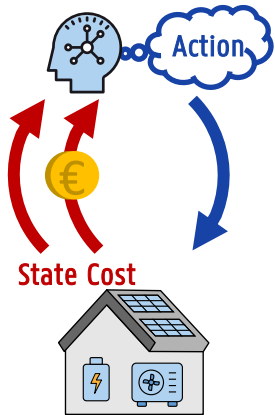


**Step 2: distill a decision
tree “student” model**



Distill2Explain: Learns the tree from trained RL policy

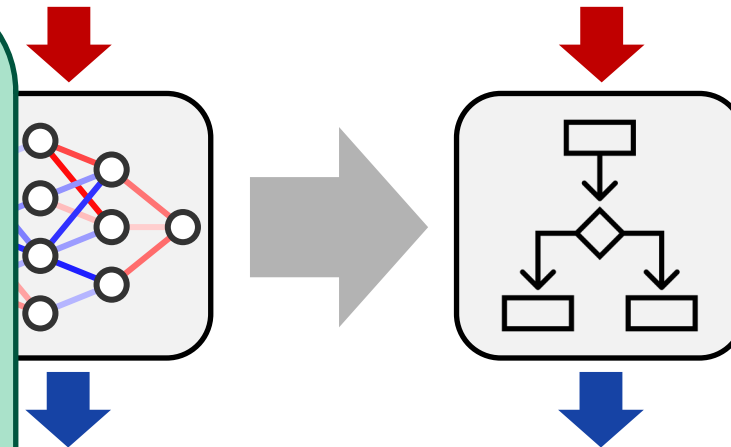
Step 1: train an RL
“teacher” model



How? E.g., see [1] on how to
distill soft decision trees.
We learn deterministic trees

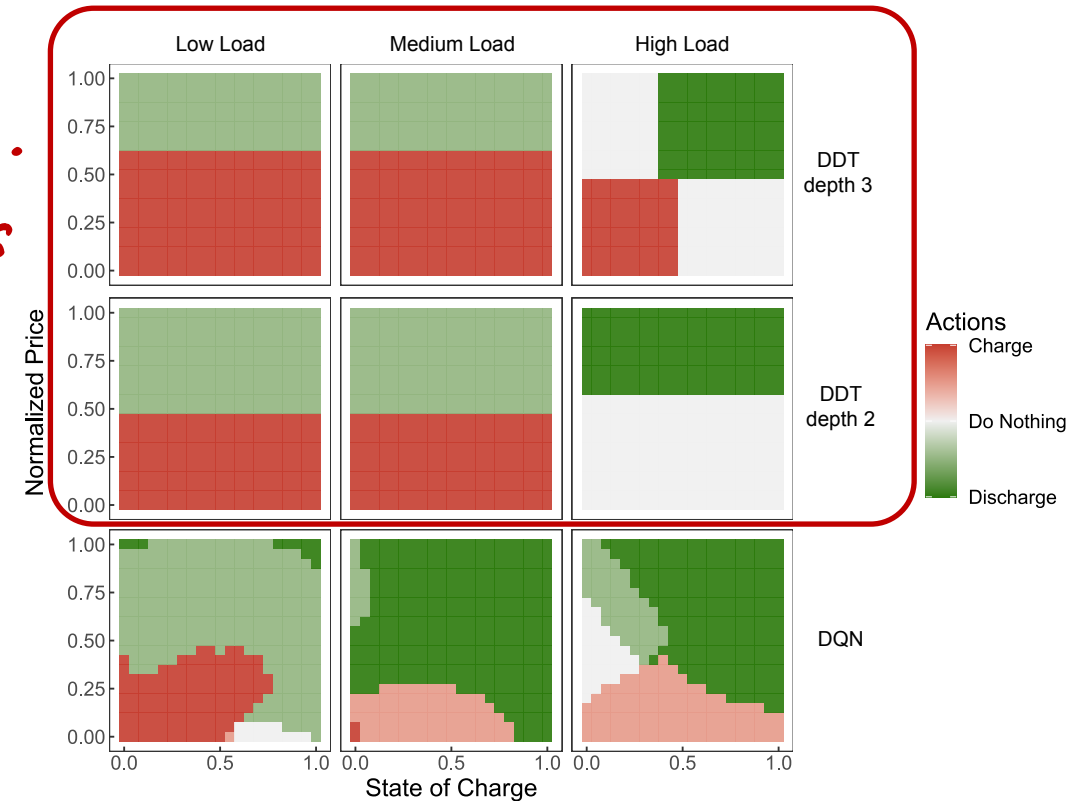
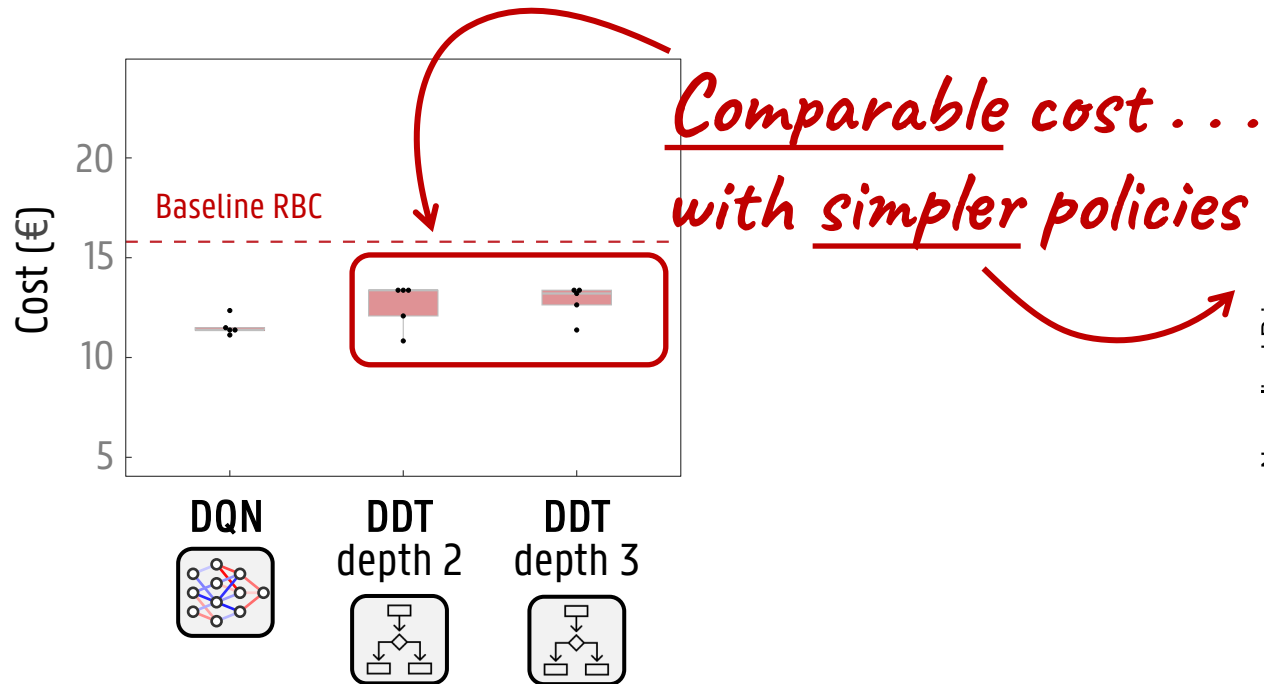
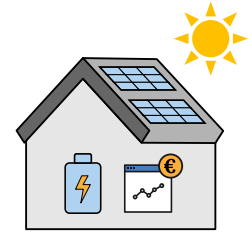
[1] Y. Coppens, K. Efthymiadis, T. Lenaerts, A. Nowé, T. Miller, R. Weber, and D. Magazzeni, “Distilling deep reinforcement learning policies in soft decision trees”, In Proc. IJCAI 2019 Workshop on Explainable AI, pp. 1–6.

Step 2: distill a decision
tree “student” model



Sample result: Home battery control under time-varying pricing

- Household with rooftop PV and battery
- Day-ahead pricing (qh based) and capacity tariff (= based on max. peak load)



Thank you! Any questions?

chris.develder@ugent.be

<http://users.ugent.be/~cdvelder>

*It's not easy
being green ...*



The AI4E team at IDLab, Ghent University



<https://ugentai4e.github.io/>