AI for Energy: Data-efficient and explainable algorithms to exploit energy flexibility

Chris Develder, et al.
AI4E Team, IDLab, Ghent University – imec

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Self-Introduction – Chris Develder[1]

- Professor at Ghent University, Belgium, since Oct. 2007
  - Research Interests:
    - **AI4E Team: Artificial intelligence for energy applications**:[2] data analysis & machine learning for the energy transition
    - **T2K Team: Natural language processing (NLP)**:[3] information extraction (IE), conversational agents, etc.
    - Past: track record in dimensioning and optimizing **optical networks**
  - Visiting researcher at UC Davis, CA, USA, Jul-Oct. 2007 (optical networks)
  - Visiting researcher at Columbia Univ., NY, USA, 2013-15 (IE & information retrieval)
- Industry Experience: Network planning/design tools
  - Former OPNET Technologies, 2004-2005
- PhD in optical networking, UGent, 1999-2003

[1] http://users.ugent.be/~cdvelder/
[2] https://ugentai4e.github.io/
[3] https://ugentt2k.github.io/

The AI4E team at IDLab, Ghent University

https://ugentai4e.github.io/

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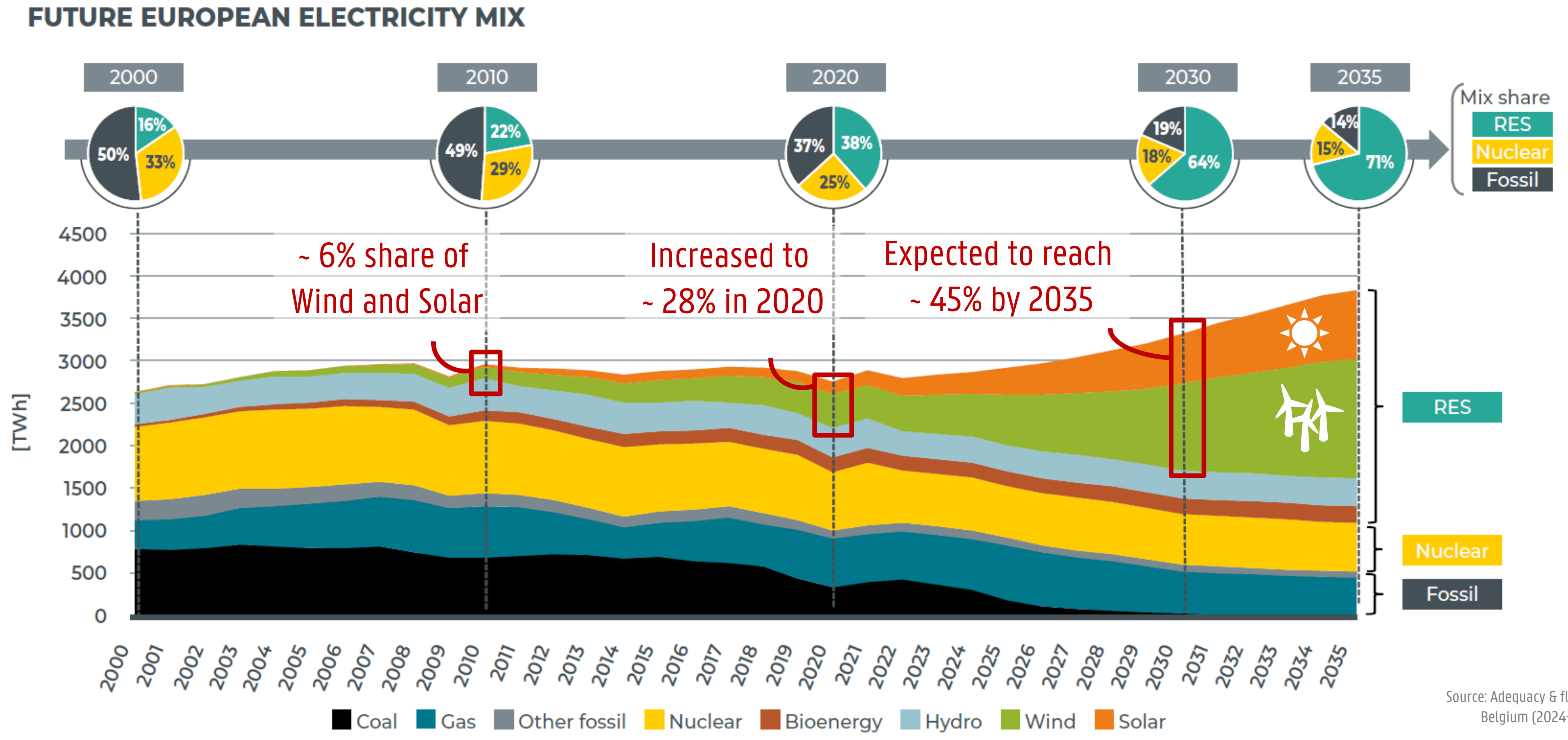
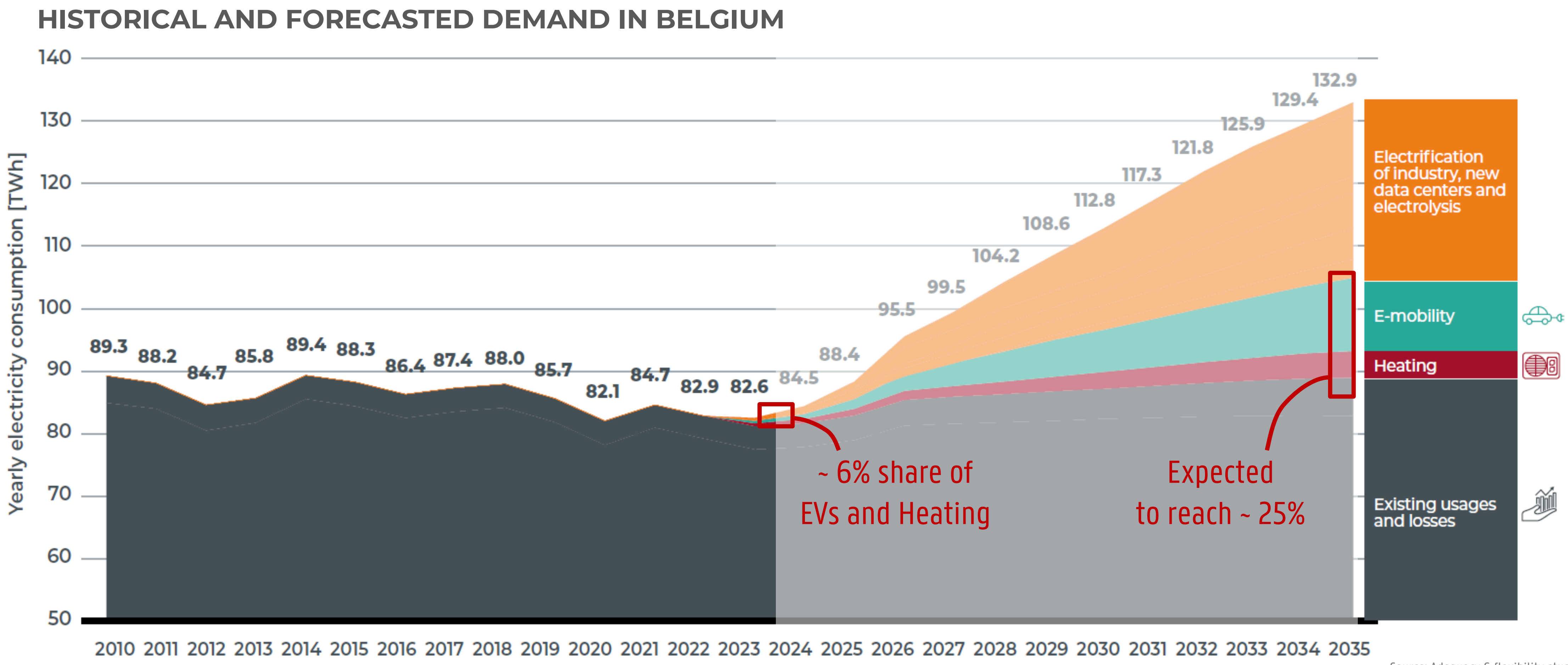
Energy Transition – Supply



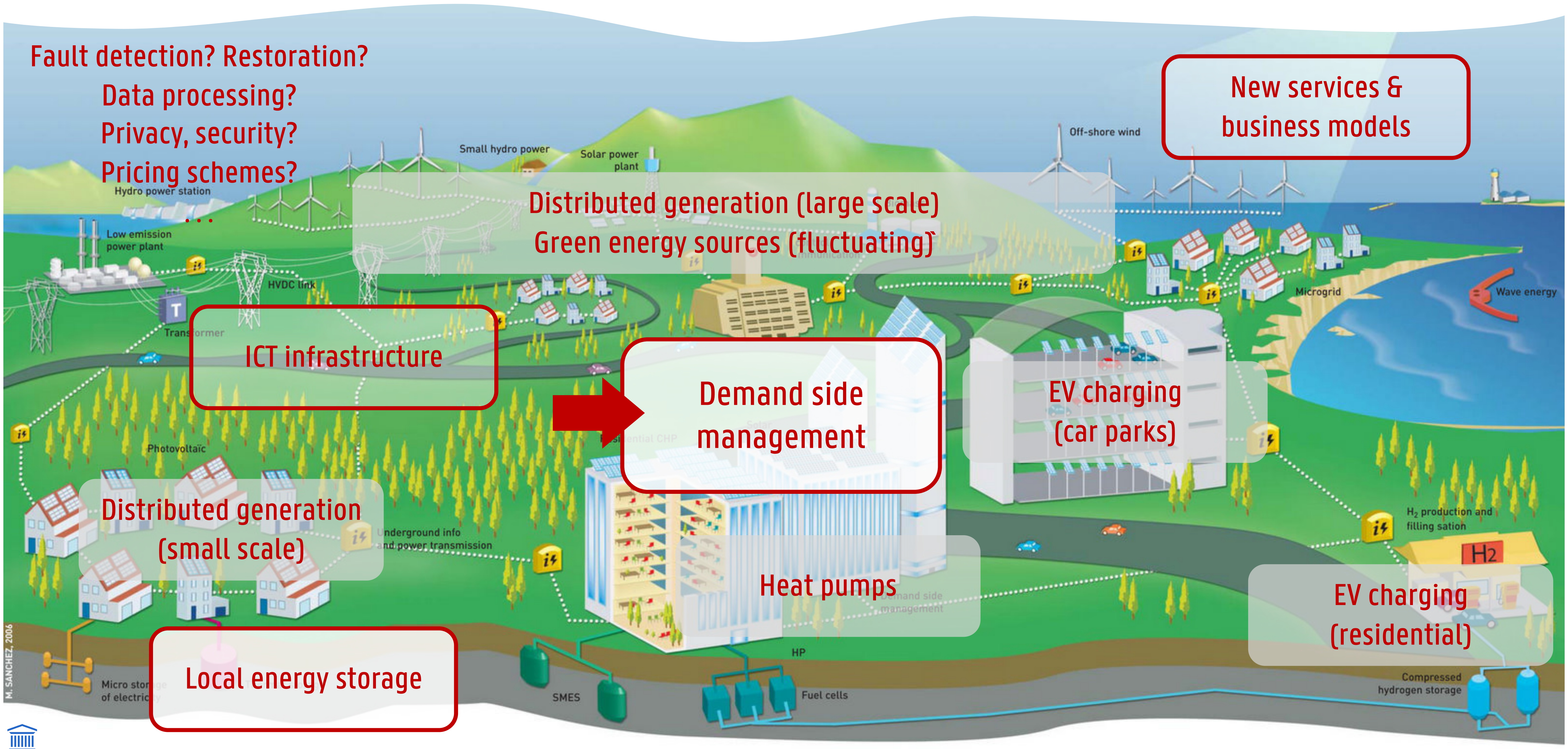
Source: Adequacy & flexibility study for Belgium (2024-2034), ELIA

Energy Transition – Demand



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

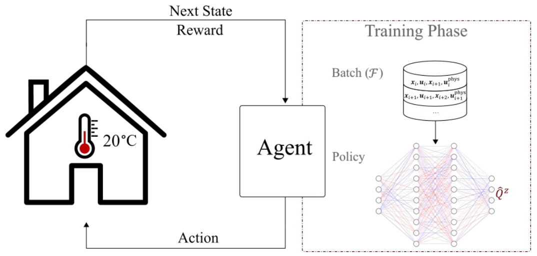
SMART GRID


Fault detection? Restoration?
Data processing?
Privacy, security?
Pricing schemes?
...
New services & business models
Distributed generation (large scale)
Green energy sources (fluctuating)
ICT infrastructure
Demand side management
EV charging (car parks)
Distributed generation (small scale)
Heat pumps
EV charging (residential)
Local energy storage
Hydro power station
Low emission power plant
HVDC link
Small hydro power
Solar power plant
Off-shore wind
Microgrid
Wave energy
Photovoltaic
Underground info and power transmission
H_2 production and filling sation
H2
HP
SMES
Fuel cells
Compressed hydrogen storage
M. SANCHEZ, 2006

Outline

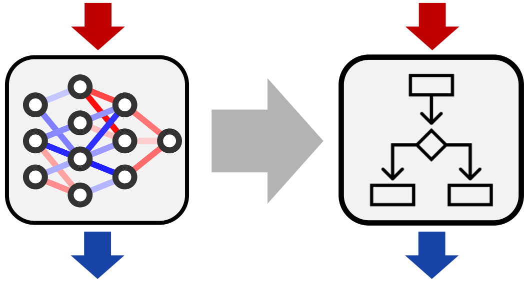
PART I: Physics-informed reinforcement learning

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



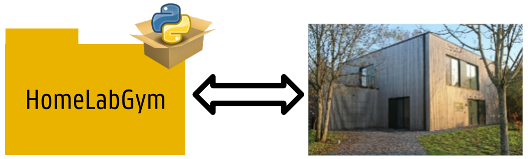
PART II: Interpretable decision trees

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



PART III: Real-world testbed environment

- HomeLabGym: Standardized interface to experiment with real house



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

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

Thanks Gargya!

Residential heat pump control: Problem statement & proposed solution

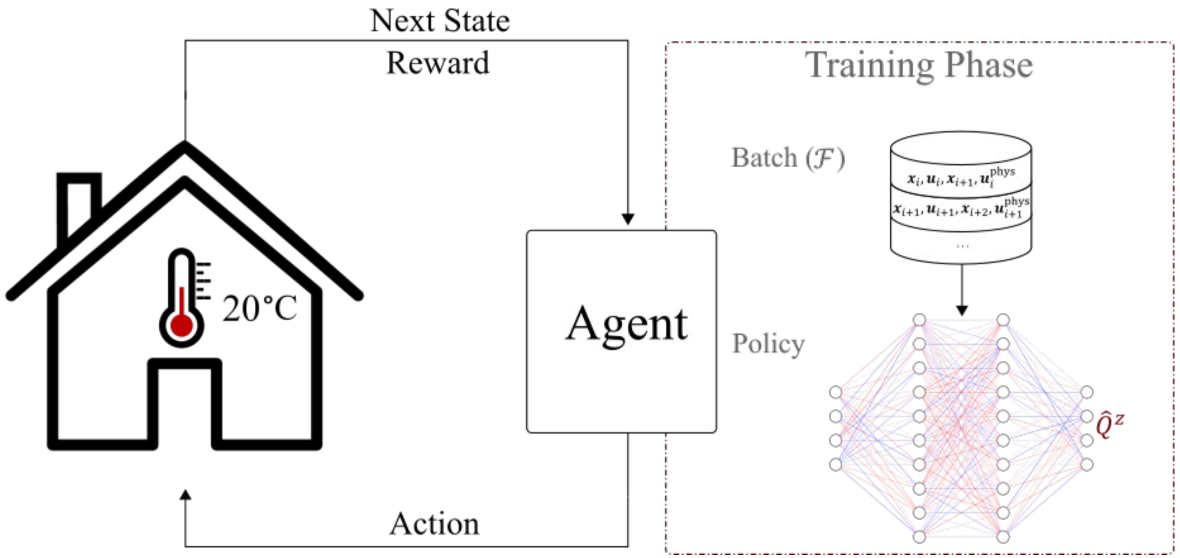
- Objective:

  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:

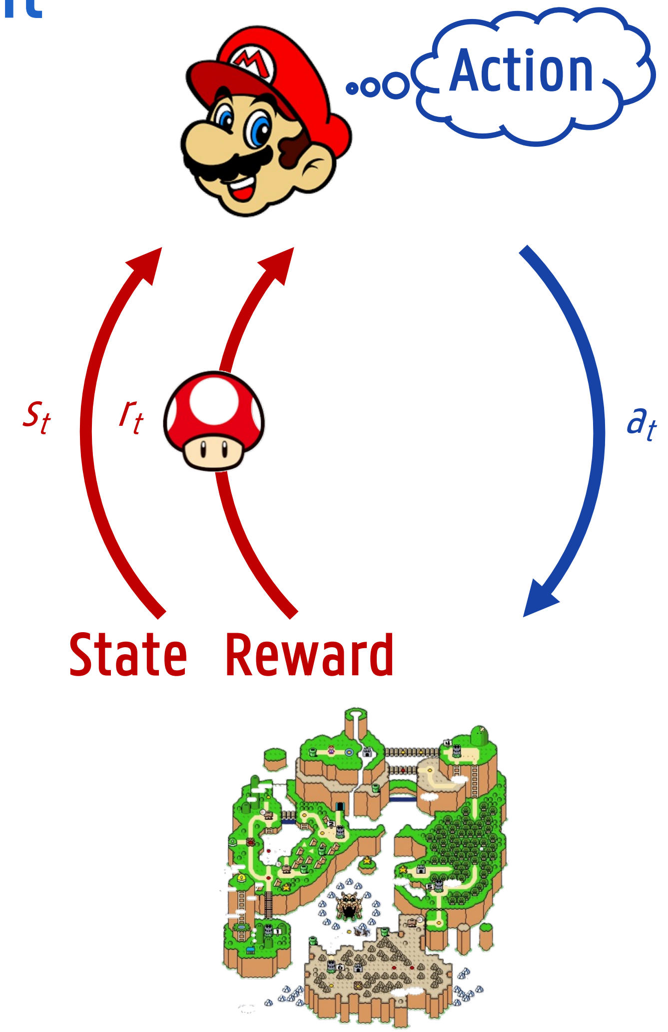
  Off-policy reinforcement learning with physics informed neural networks



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



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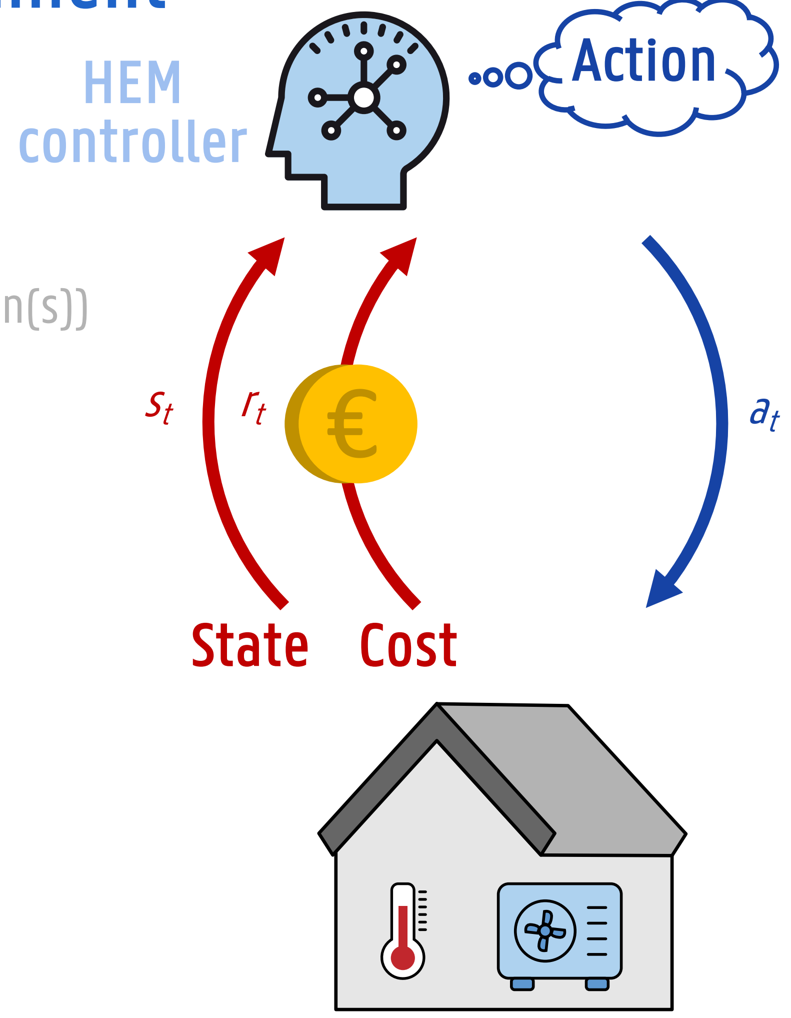
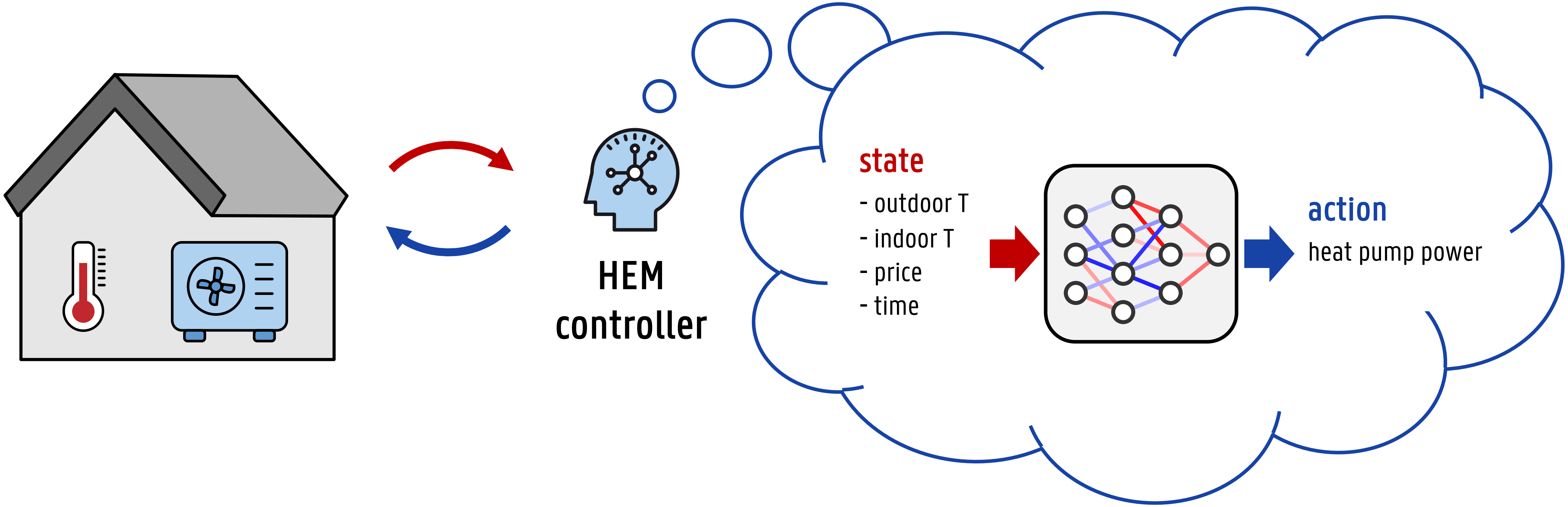


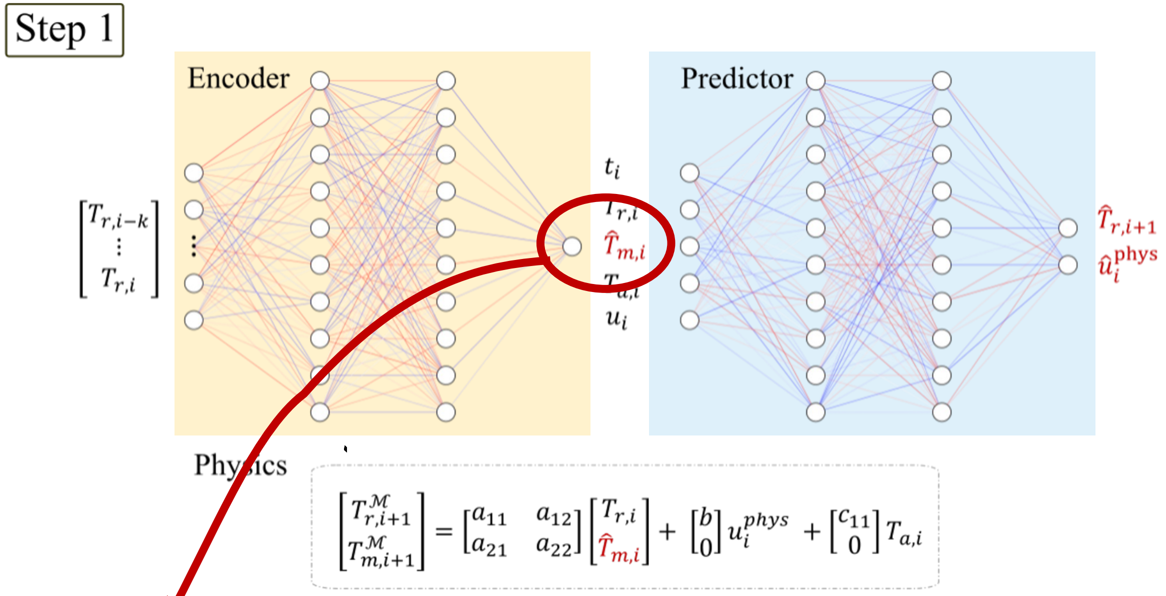
Reinforcement Learning: Heat pump control



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

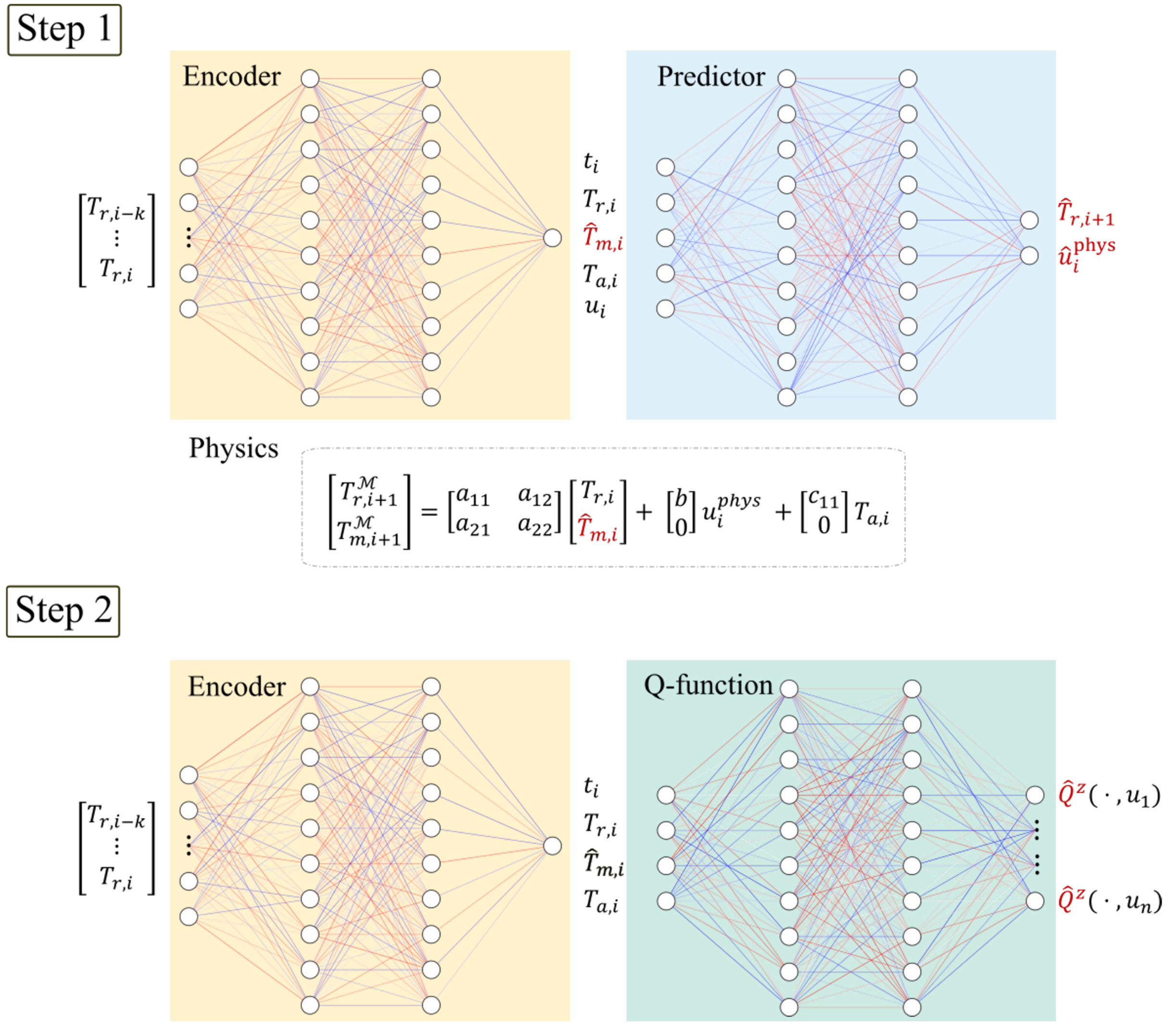
- Two-step Algorithm:
  - **Step 1:** Learn physically relevant representation (bulk temperature T_m), from predicting state transitions



Idea:
- *Include bulk temperature as part of representation, and*
- *Force it to adhere to simplified physical model*

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), from predicting state transitions
  - **Step 2:** Learn a low-dimensional Q-function based on this representation, to perform the actual control



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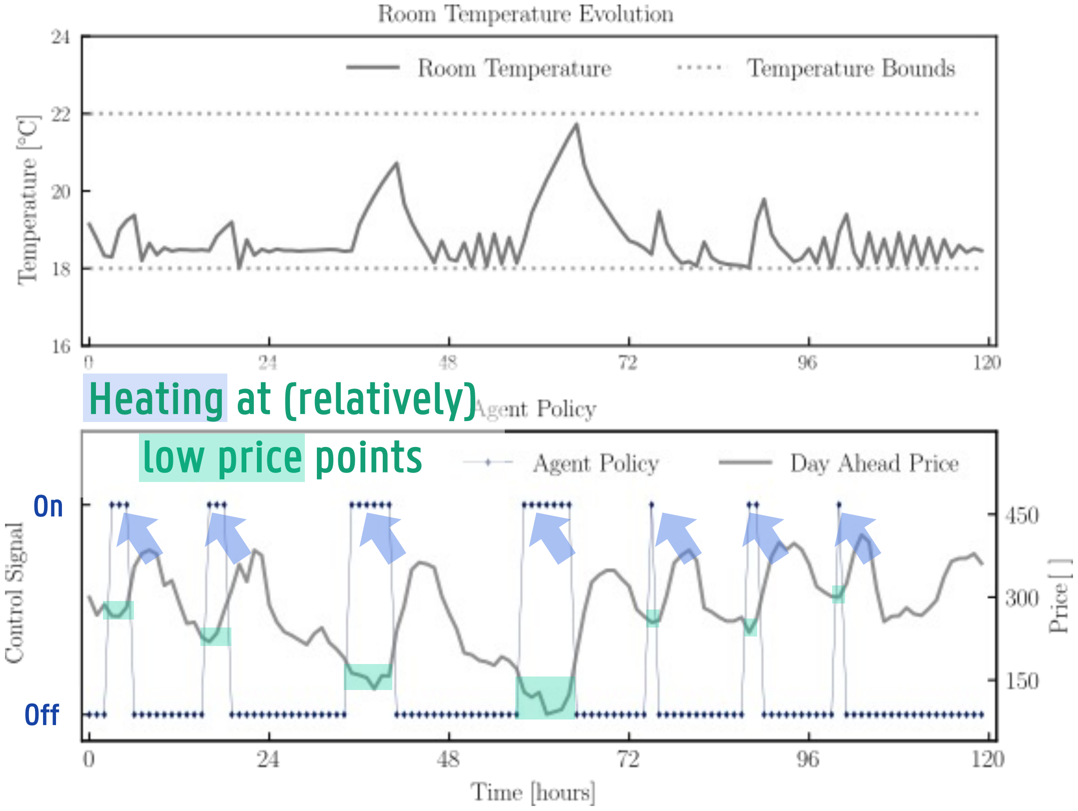
Simulation results

Results for BELPEX prices using a building simulator



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Simulation results

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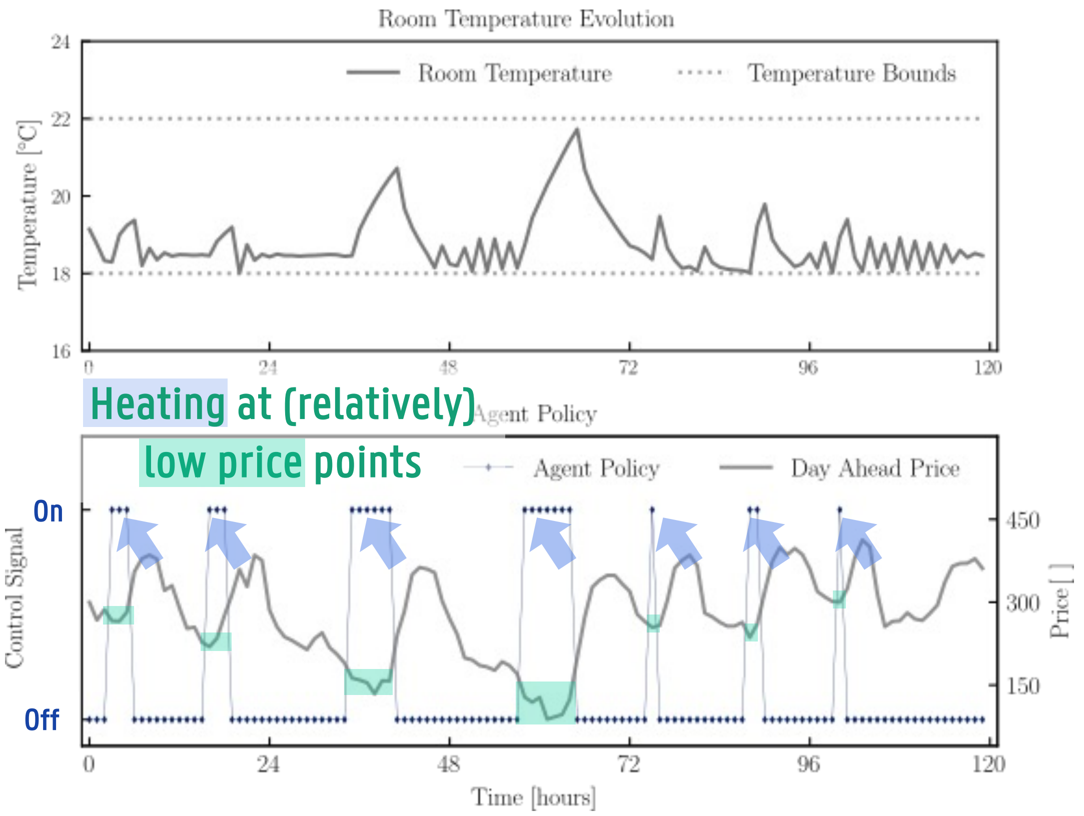
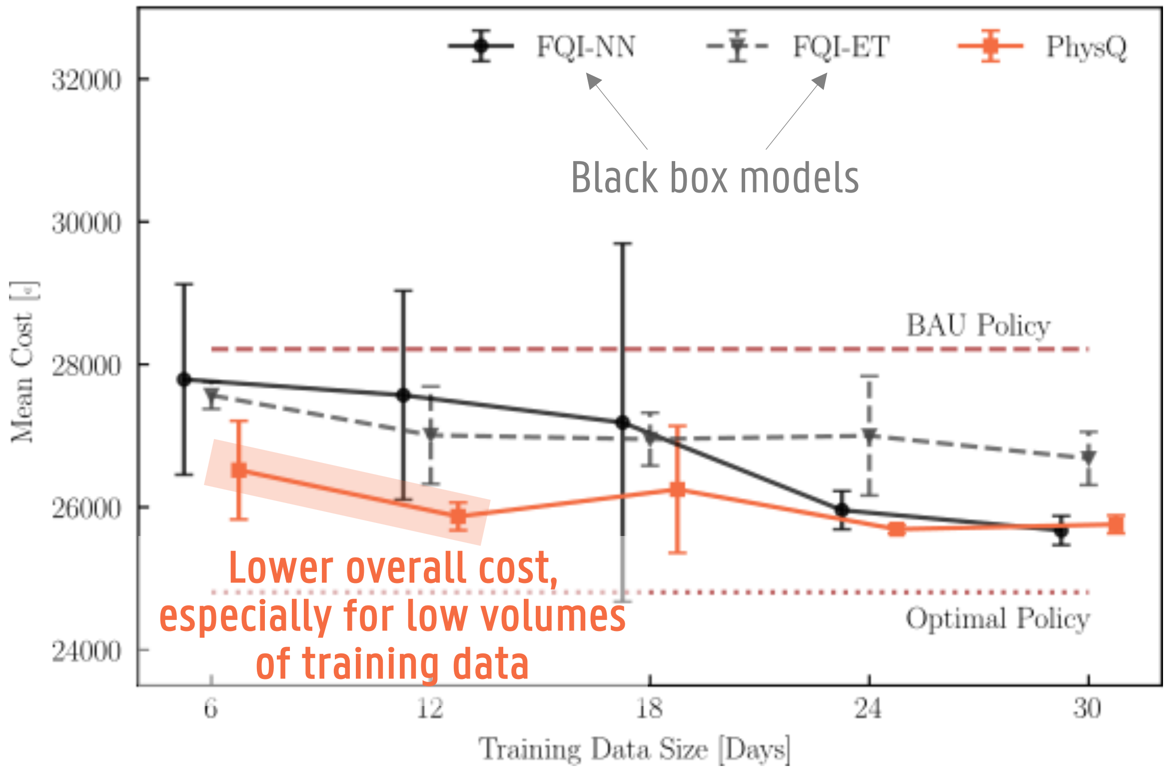


Comparison over different training data sizes and agent types



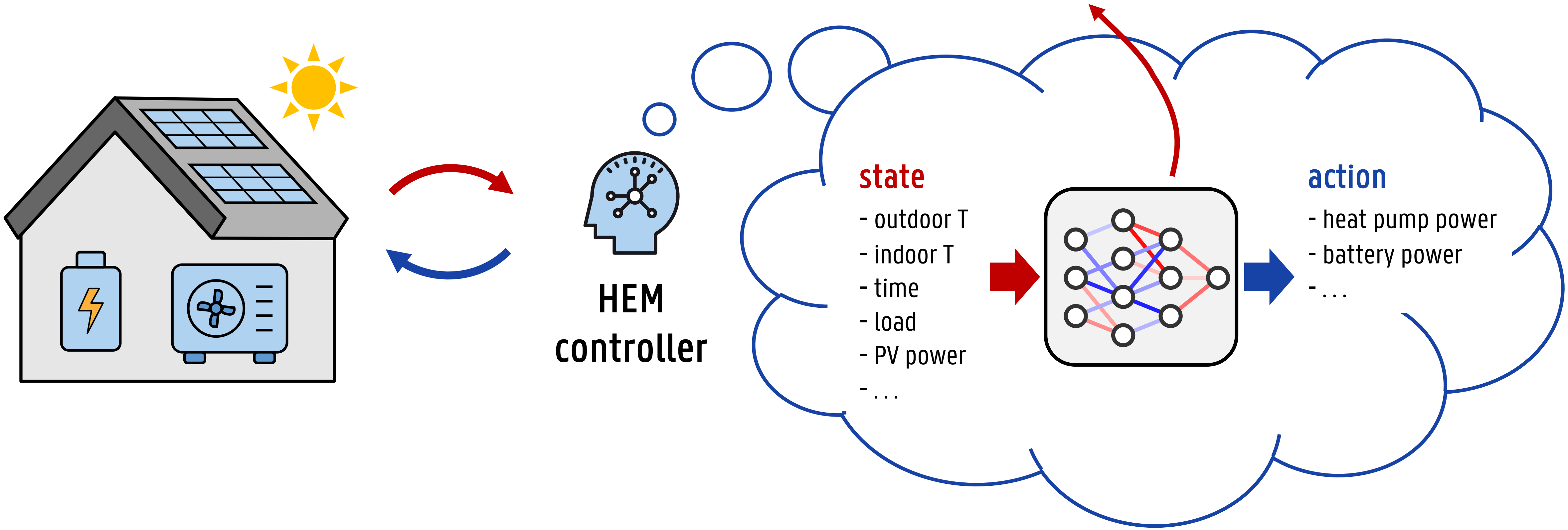
PART II:
Interpretable decision trees distilled from black-box RL policies

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

Thanks Gargya!

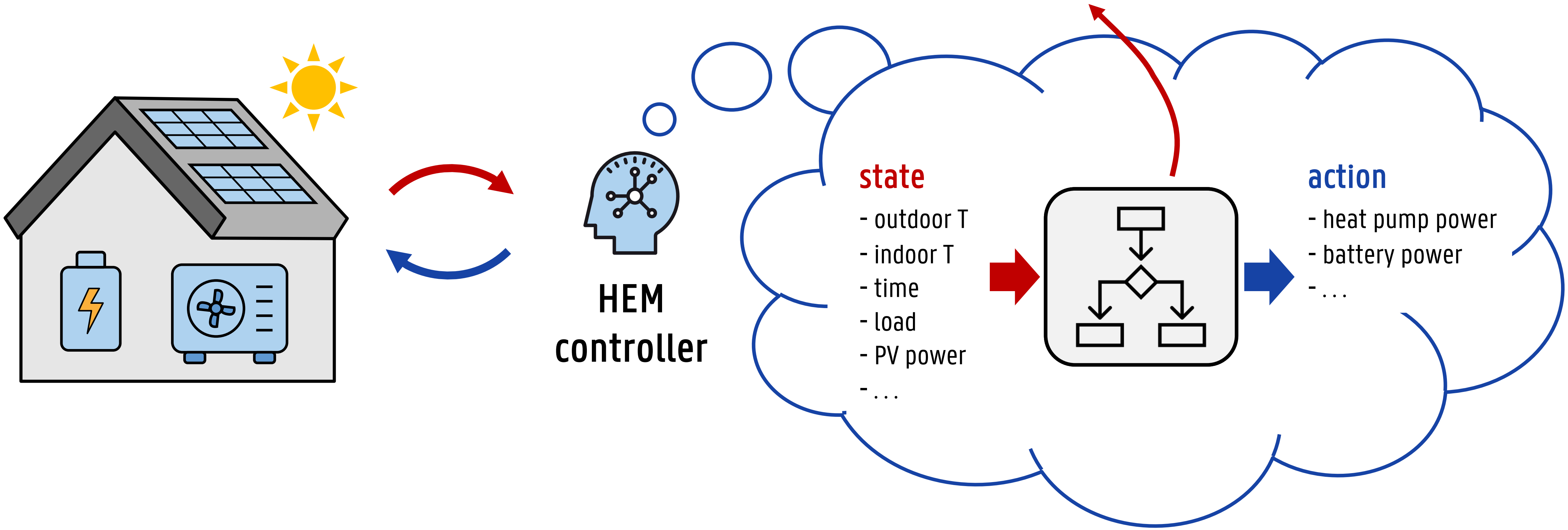
Black-box Reinforcement Learning

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



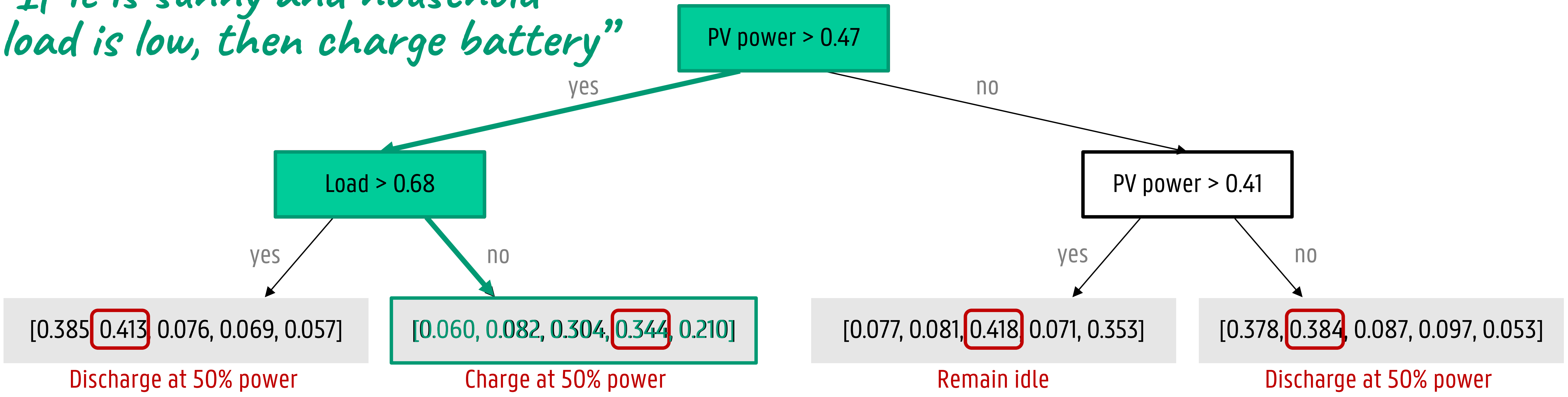
Black-box Reinforcement Learning

Idea: replace neural networks by something more explainable!



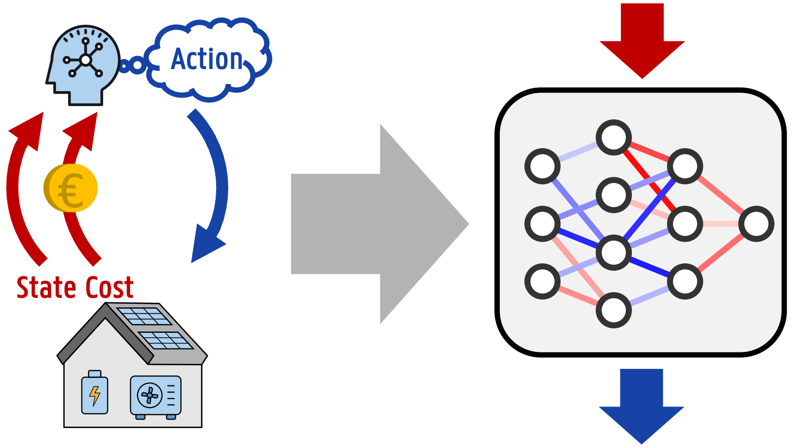
Enhancing explainability: Differentiable Decision Trees

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

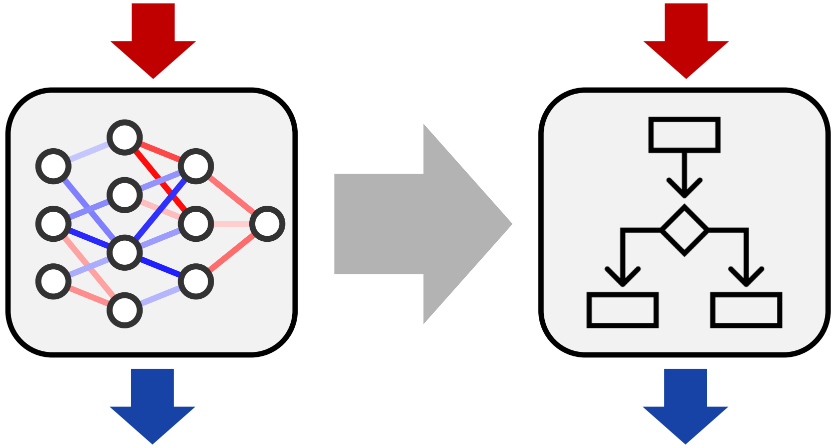


Distill2Explain: Learns the tree from trained RL policy

Step 1: train an RL "teacher" model



Step 2: distill a decision tree "student" model



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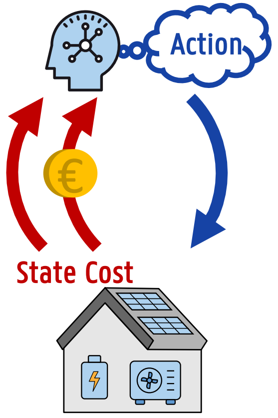

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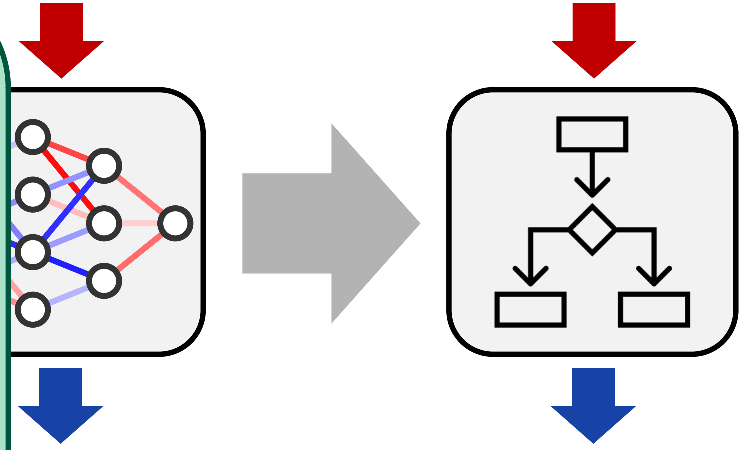
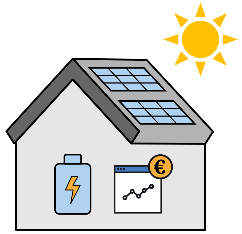


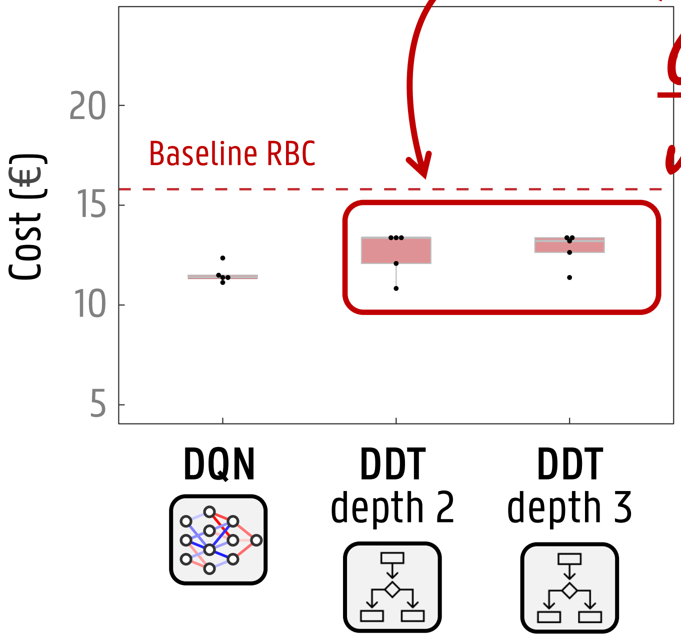
How? E.g., see [1] on how to disill **soft** decision trees.
We learn **deterministic** trees

[1] Y. Coppens, K. Efthymiadis, T. Lenaerts, A. Nowe, 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.

Sample result: Home battery control under time-varying pricing

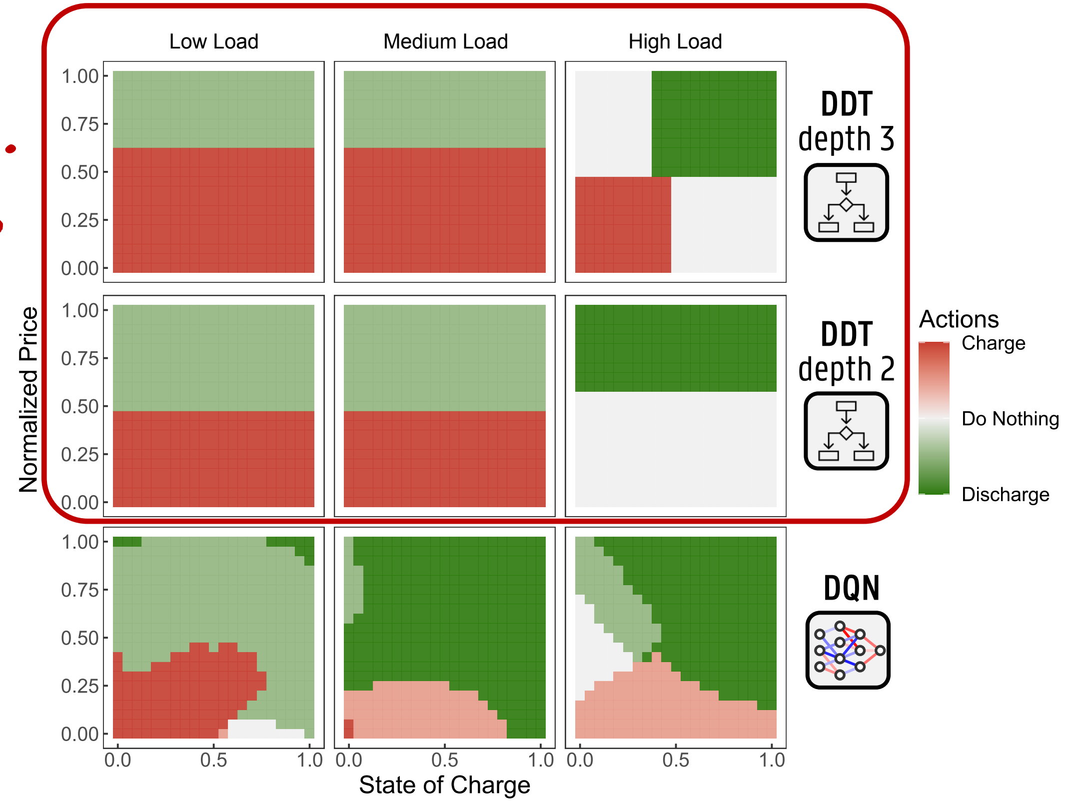
- Household with rooftop PV and battery
- Day-ahead pricing (qh based) and capacity tariff (= based on max. peak load)





Comparable cost . . .

with simpler policies



PART III:
A real-world testbed environment: HomeLabGym

T. Van Puyvelde, M.-S. Verwee, G. Gokhale, M. Zareh Eshdoust and C. Develder, **"HomeLabGym: A real-world testbed for home energy management systems"**, in Proc. 15th ACM Int. Conf. Future Energy Sys. (e-Energy 2024), Singapore, 4-7 Jun. 2024, pp. 1-2. doi:10.1145/3632775.3661974

Thanks Toon!

HomeLab

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Research infrastructure to validate and optimize IoT & AI innovations in real environment

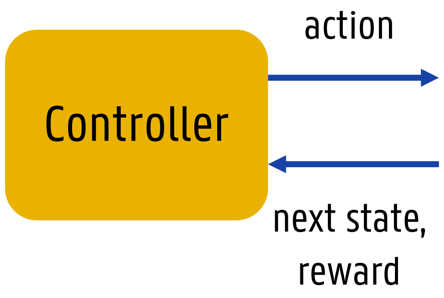
- >300 sensors (temperature, energy, light, occupancy, …)
- HVAC, ESS, PV
- Controllable blinds and windows
- . . .

Energy infrastructure

HomeLabGym

Focus of our research: controllers, based on reinforcement learning, to exploit energy flexibility

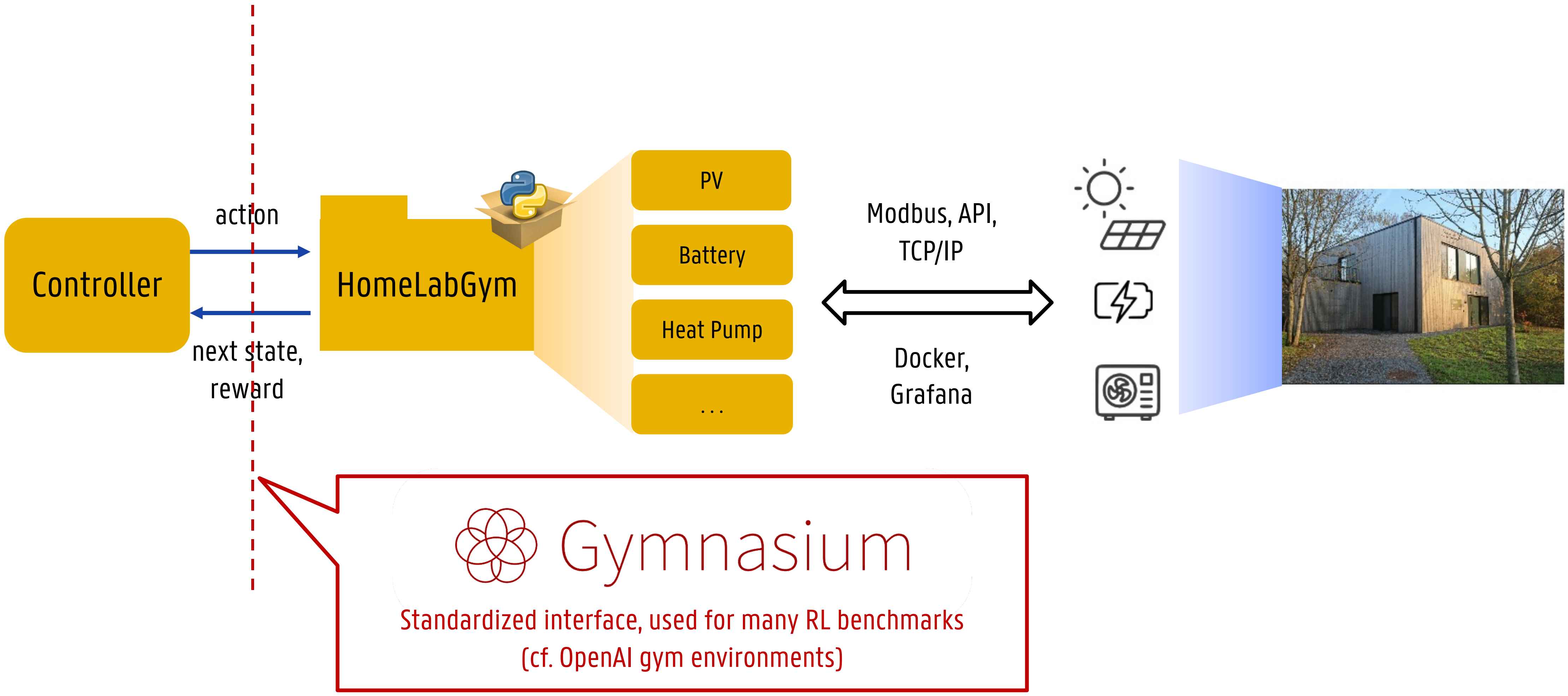
HomeLabGym



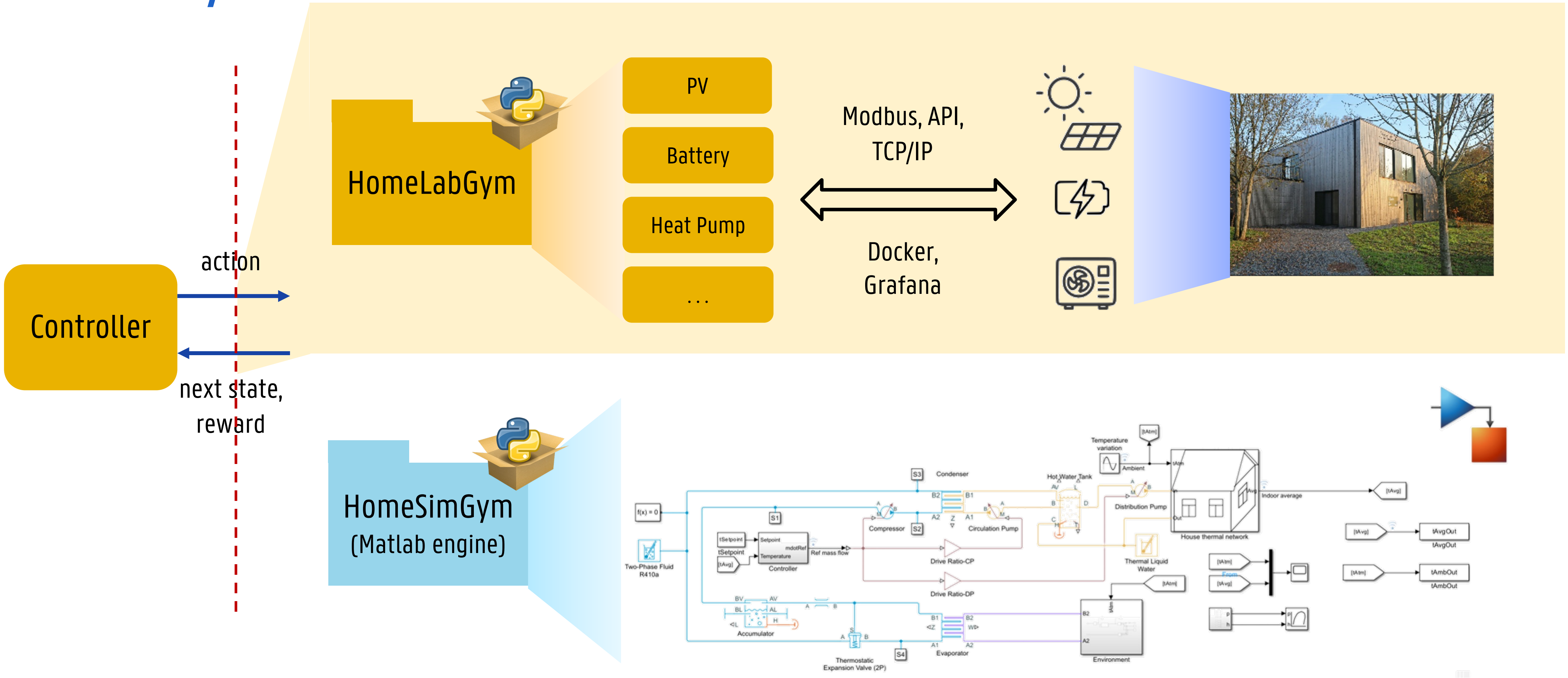
Wishlist:

- Standardized approach
- Plug-and-play
- Extensible solution
- Broad range of communication protocols
- ...

HomeLabGym


action
Controller
next state,
reward
HomeLabGym
PV
Battery
Heat Pump
...
Modbus, API,
TCP/IP
Docker,
Grafana
Gymnasium
Standardized interface, used for many RL benchmarks
(cf. OpenAI gym environments)

HomeLabGym



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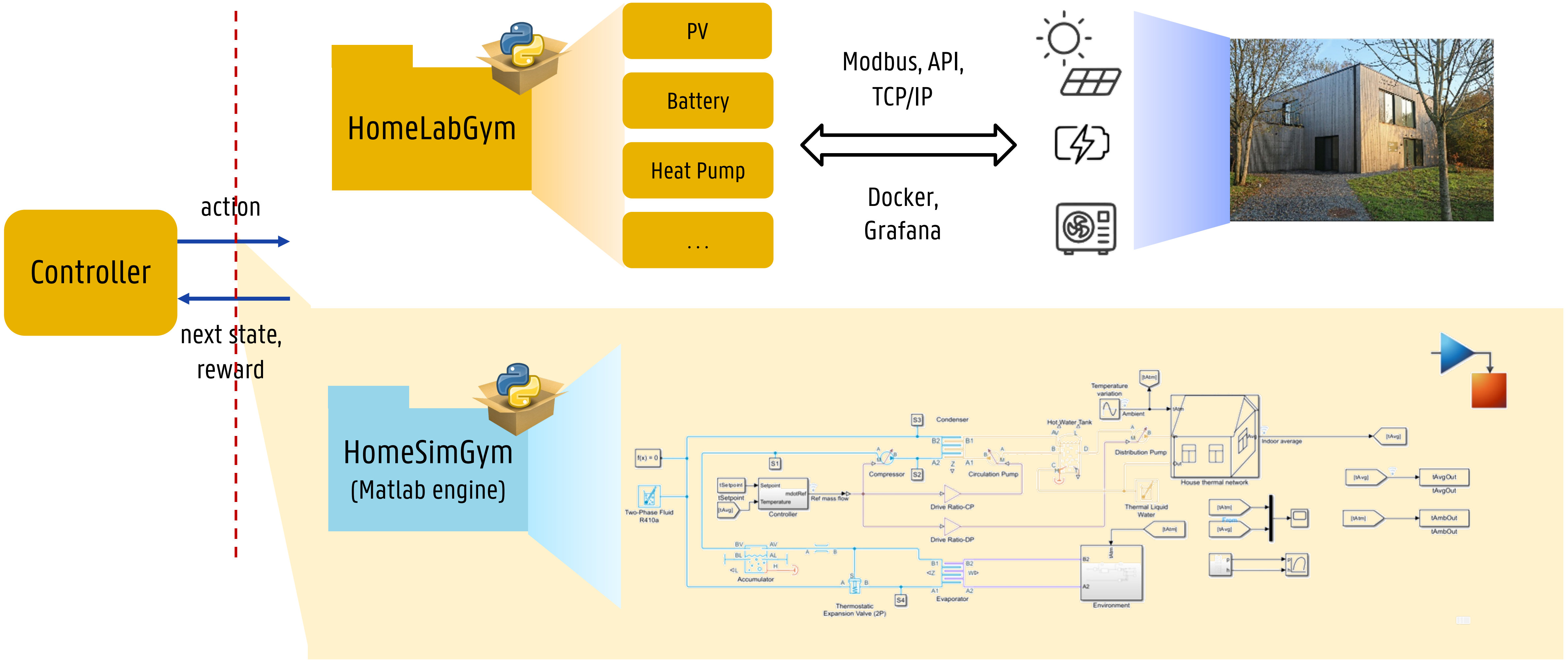
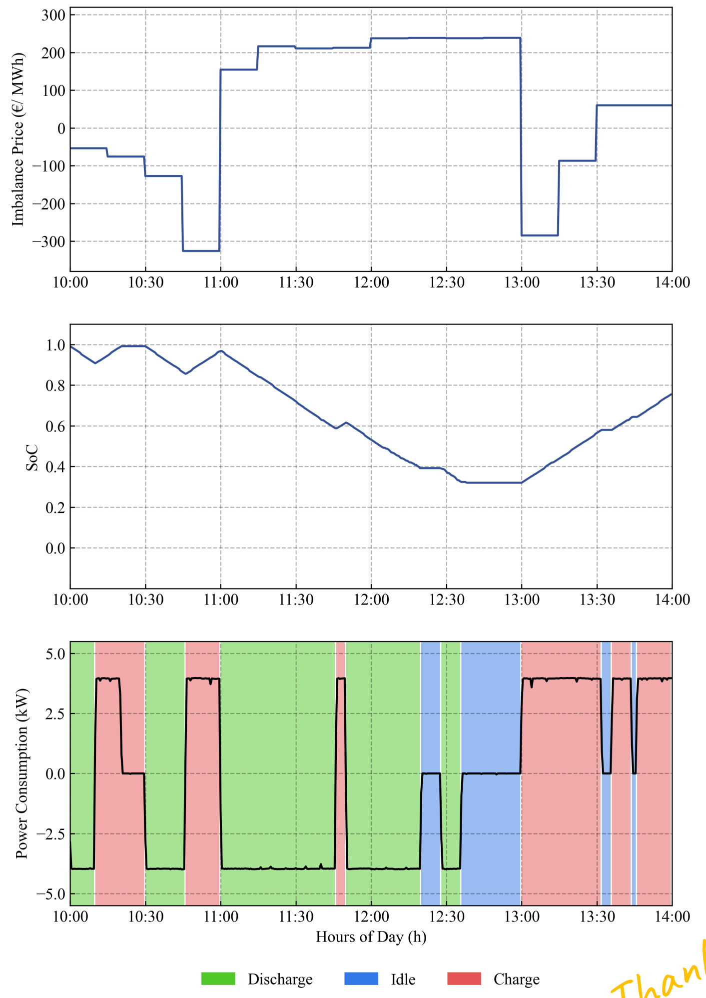
HomeLabGym


Controller
action
next state,
reward
HomeLabGym
PV
Battery
Heat Pump
...
Modbus, API,
TCP/IP
Docker,
Grafana
HomeSimGym
(Matlab engine)

Example use case for HomeLabGym: Validation of RL for energy arbitrage

S.S. Karimi Madahi, G. Gokhale, M.-S. Verwee, B. Claessens and C. Develder, **"Control policy correction framework for reinforcement learning-based energy arbitrage strategies"**, in Proc. 15th ACM Int. Conf. Future Energy Sys. (e-Energy 2024), Singapore, 4-7 Jun. 2024, pp. 1-9.. doi:10.1145/3632775.3661948

- Case study:
  - Home battery
  - Time-varying prices (qh-based)
  - Distributional DQN strategy accounting
- Validation of simulation
  - Real-world battery
  - Using HomeLabGym
- Results
  - **Latency** in communication (~10s)
  - **Battery efficiency** affected by temperature
  - Effect on **daily revenue**: real profit €5.6 vs. simulated €6



Thanks Soroush!

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Thank you!
Any questions?

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

https://ugentai4e.github.io

BLUE BIRD

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the European Union

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