Hybrid control for next generation of heating and cooling networks

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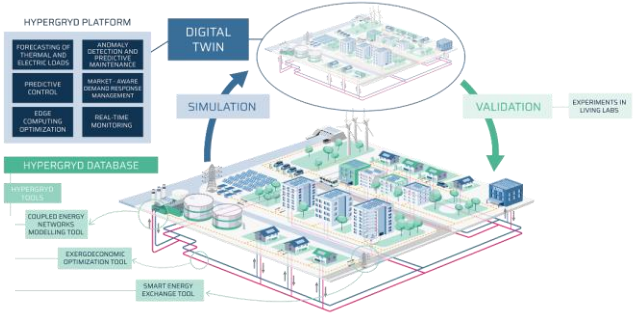
In partnership with

HYPERGRYD



Background

Transitions of EU district heating/cooling network

(EU FitFor 55 packages)

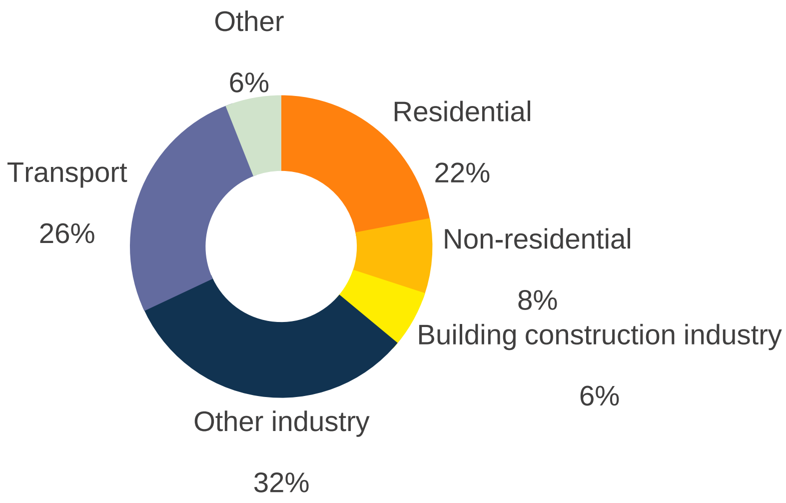


Figure: Share of buildings and construction in global final energy consumption and by end use, Worldwide

- District heating/cooling transition towards 4th-6th generation;
- EPBD recast, ”smart readiness” for buildings;
- The increasing needs of integrating renewables in combination with storage toward releasing the power grid pressure;
- Traditional control methods face challenges when energy networks become increasingly complex and coupled.

Vision of the project

Understand Load

General (not case-by-case) thermal-electric load prediction

Accurately understand/predict load flexibility

Advanced Control

Technical and semantic interoperability
Integrate distributed energy sources with existing district heating (TES, RES…)

Digital Twin

Smart control strategy
Virtual-to-Physical
A representational model with bi-directional flow

Data-driven approach co-developed with stakeholders

Selected pilot

SONNEPLATZ
Location: Großschönau, Austria
LiL Type: Biomass-based local heating networks with RES integrated

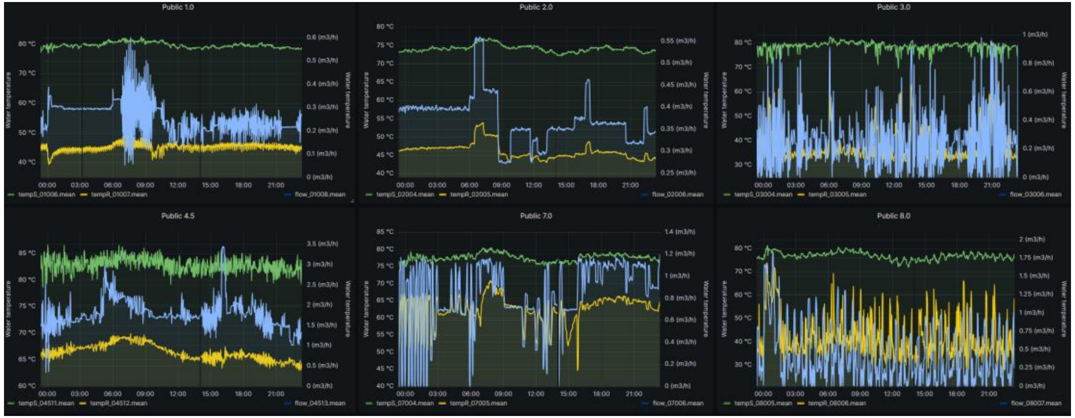


Figure: District Heating network real-time data monitoring

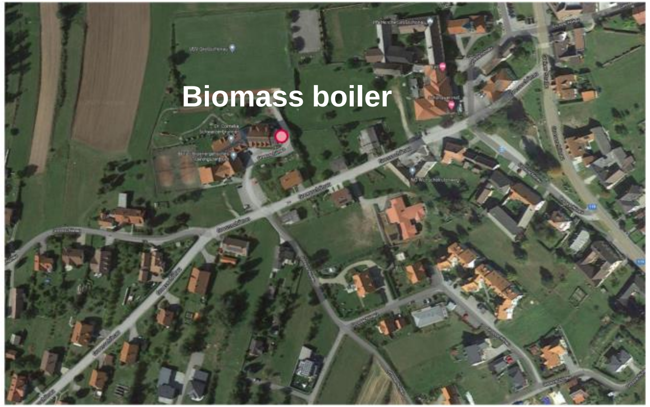


Figure: The testbed in Sonneplatz, Austria

Load flexibility using machine learning (I)

Artificial Neural Network (ANN)

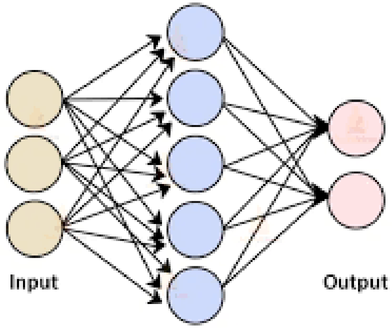


Figure: ANN architecture

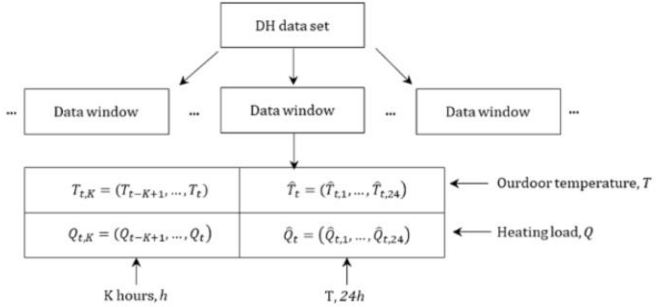


Figure: The logic of short-term prediction model

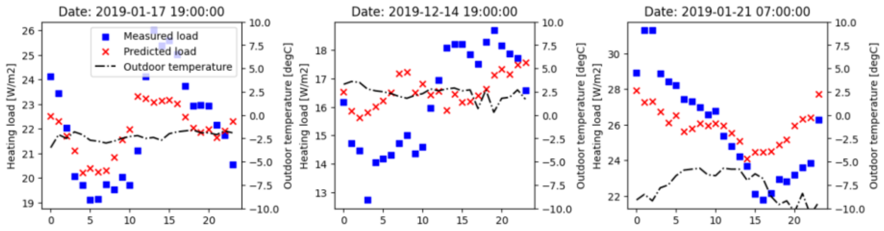


Figure: Predicted heating load for the 24-hour period

Ohlson Timoudas, T., Ding, Y., & Wang, Q. (2022). A novel machine learning approach to predict short- term energy load for future low-temperature district heating. CLIMA 2022 Conference. https://doi.org/10.34641/clima.2022.319

Load flexibility using machine learning (II)

**ANN + Clustering:
deal with varying quality of measurements**

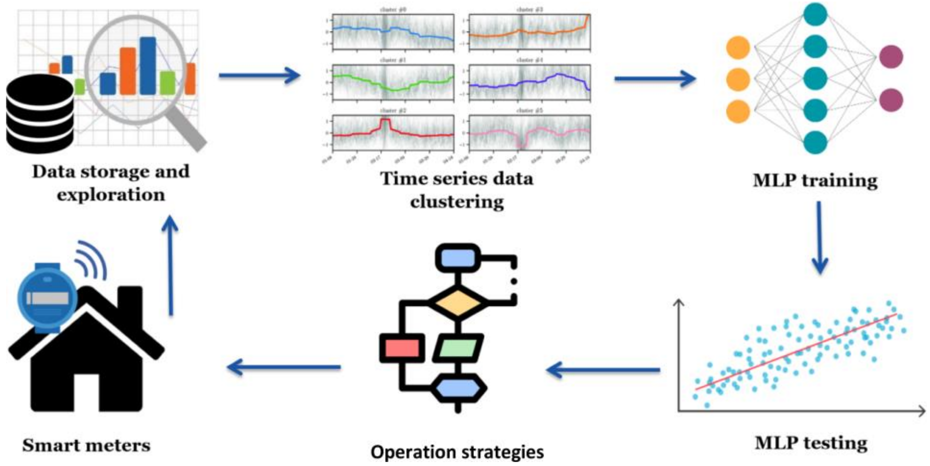


Figure: Data transfer and analysis flowchart

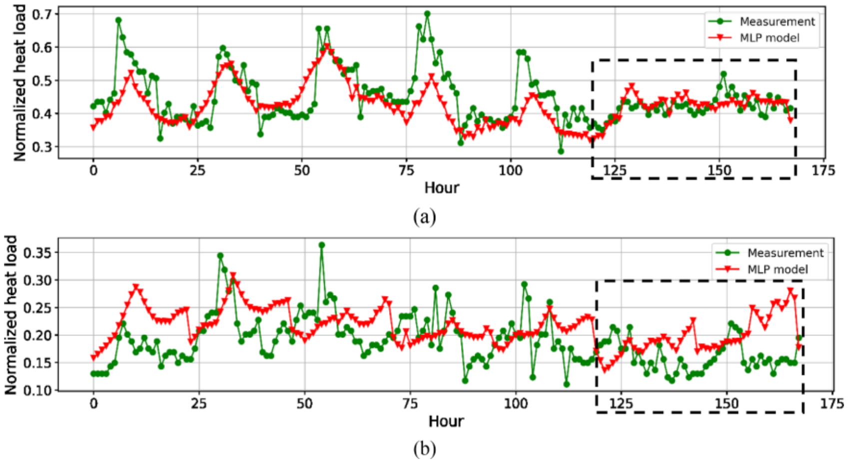


Figure: Prediction performance for a school dataset (a) in winter (b) in summer

Mustapha Habib, Thomas Ohlson Timoudas, Yiyu Ding, Natasa Nord, Shuqin Chen, and Qian Wang. A hybrid machine learning approach for the load prediction in the sustainable transition of district heating networks. Sustainable Cities and Society, page 104892, 2023. ISSN 2210-6707. doi: https://doi.org/10.1016/j.scs.2023.104892.

Load flexibility using machine learning (III)

(Work in progress)

Expand the training dataset: enable model with more generalization

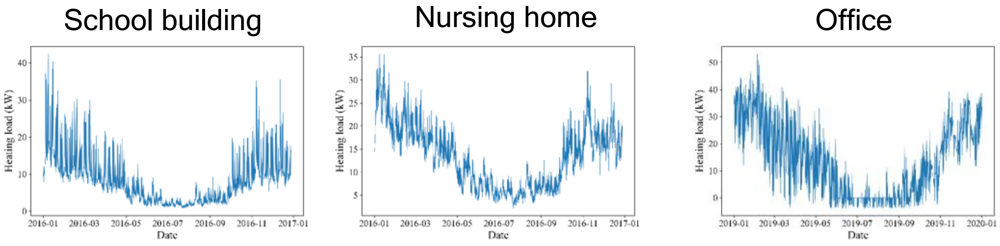


Figure: Part of the training load data

2 Validations

Parallel validation: if the model is robust enough to predict the load for the same building but different years.

Vertical validation: if the model is generalized enough when predicting load of untrained buildings.

Years	Trained building	Untraine d building
2019	…	…
2020	…	…
2021	…	…

Training set

Parallel validation

Vertical validation

Load flexibility using machine learning(III)

Energimyndigheten

(Ongoing)

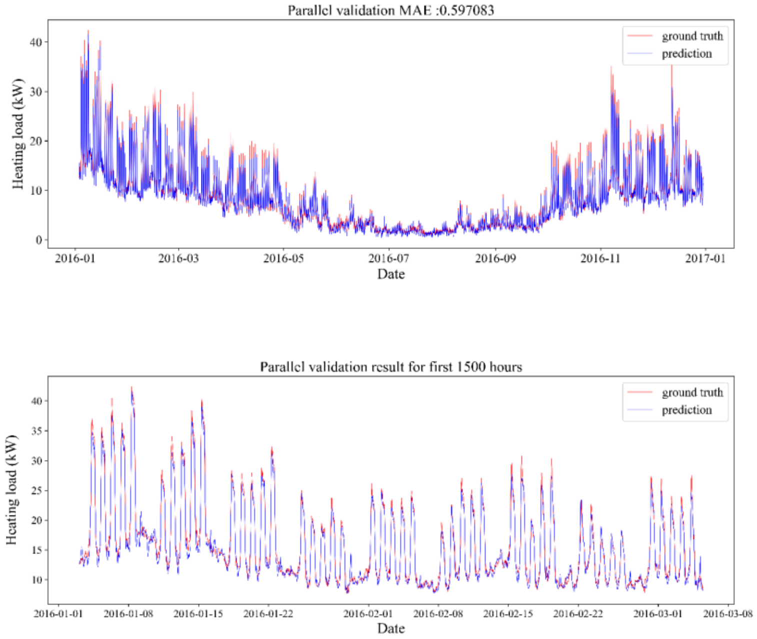


Figure: Prediction results on a school building

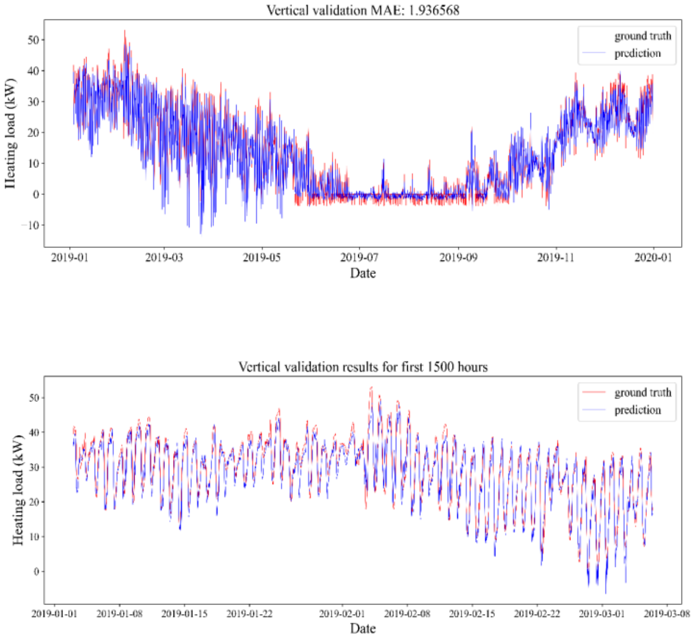
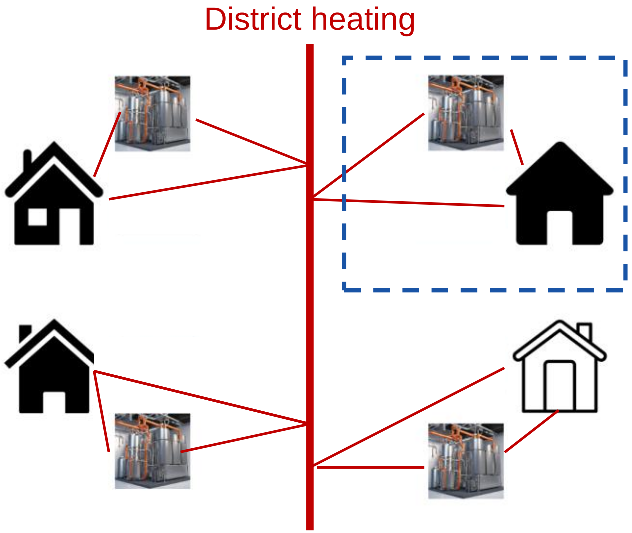
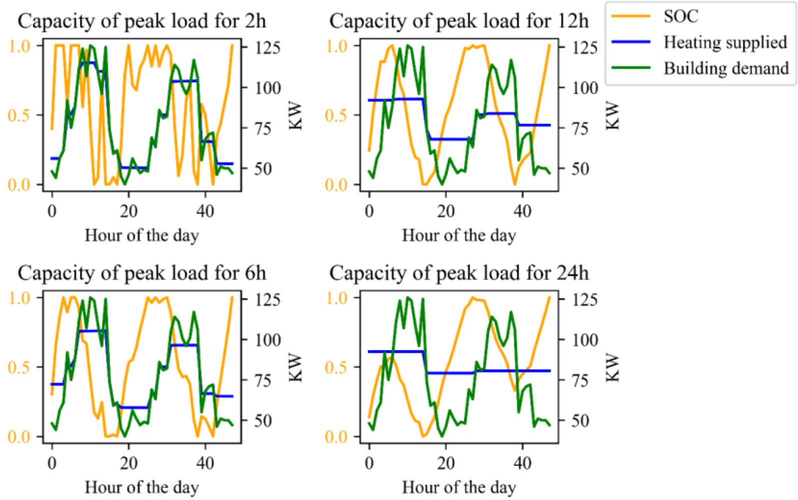


Figure: Prediction results on a office building

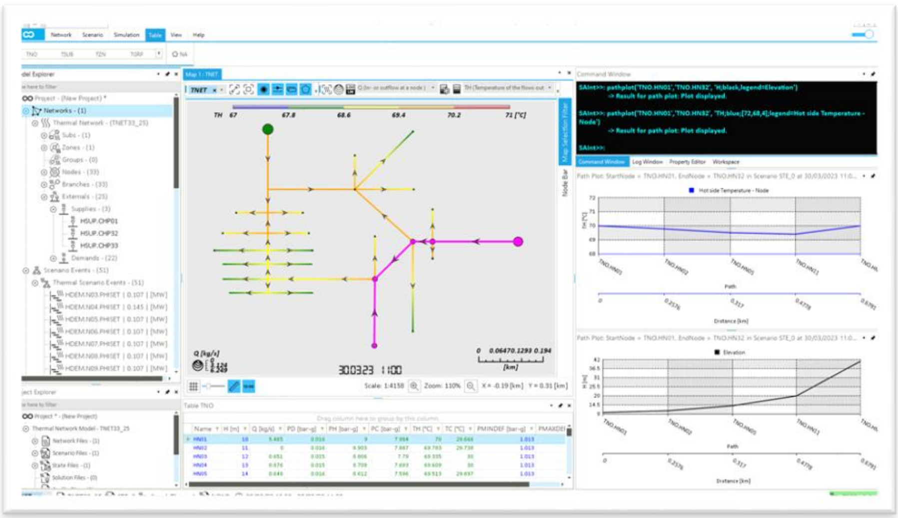
Example results: rather good agreements are reached so far of the developed ML models

Flexibility analysis (individual building)



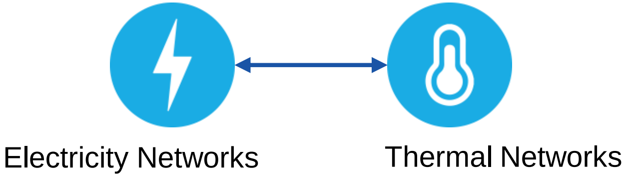


Coupled network optimization and co-simulation (Aggregated)



Thermal network simulation

- Steady state thermal network simulation
- Quasi-dynamic Thermal Network Simulation
- Coupled electricity & thermal network simulation (integrate HP with storage)



Digital twinning architecture (DT)

Digital Twin

with

Ontology

1. Basic system and energy flow representation

2. Ontology framework, semantic interoperability, and data exchange

3. Data-driven co-simulation and control

Figure: Comprehensive Brick Schema of a Building

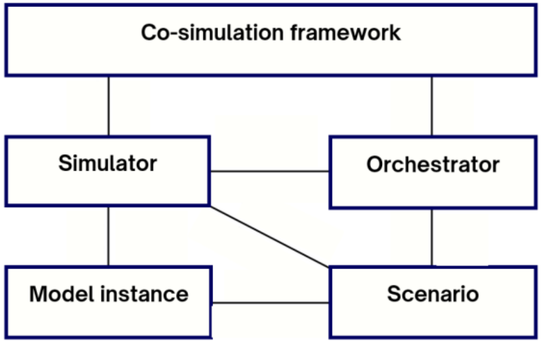


Figure: Component schema of a general co-simulation framework

DT-driven Interoperability validations

1. System and energy flow representation:

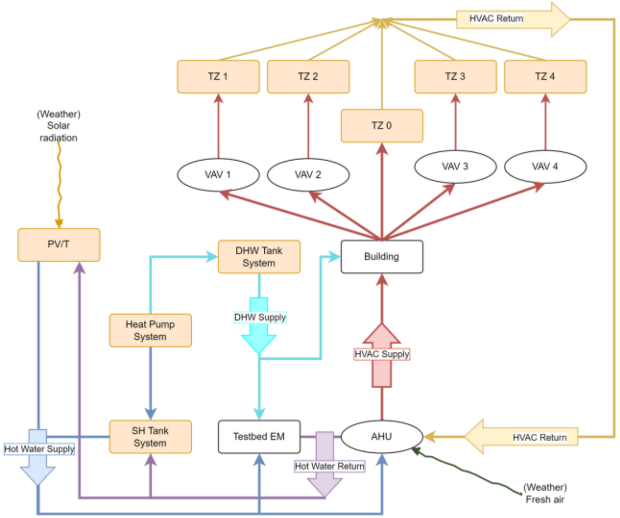


Figure: Energy flow diagrams of heat pump-FTX heating network

2. Implementation of the ontology:

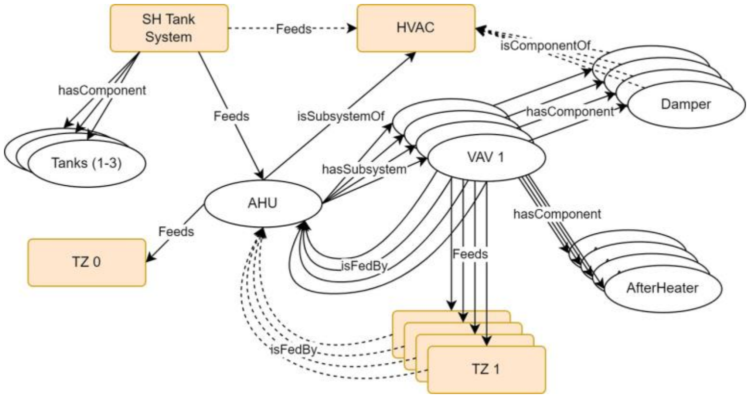


Figure: Example of studied ontology of the heating network

Conventional control

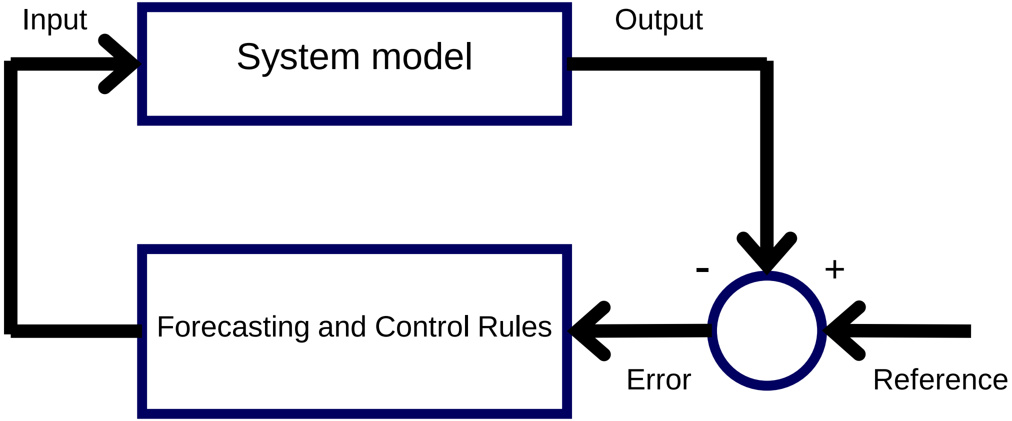


Figure: Architecture of the rule-based control system

1. Fixed rules regardless of real condition.
2. Cannot integrate with other systems.
3. Less efficiency.

Potentials of integrating Reinforcement learning (RL)

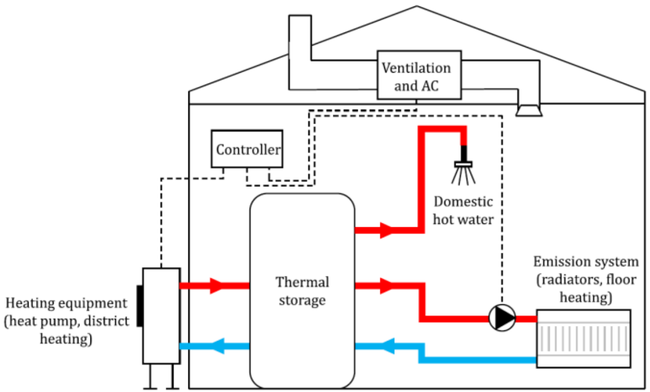


Figure: A generic illustration of a BES, and the associated measurement and control system.

RL in single buildings

- Real buildings generate data too slowly for traditional RL
- With simulated data RL learns the simulation model
- Hard to trust RL to explore strategies in operation

RL in building clusters

- Use data from many buildings – but innovative methods needed to learn from buildings with different characteristics.
- Multi-agent learning

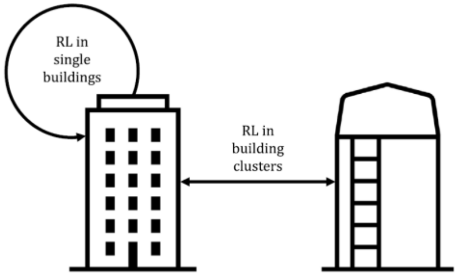


Figure: RL in building clusters concerns the transfer of information between buildings

David Weinberg, Qian Wang, Thomas Ohlson Timoudas, Carlo Fischione, A Review of Reinforcement Learning for Controlling Building Energy Systems From a Computer Science Perspective, Sustainable Cities and Society, Volume 89, 2023, 104351, ISSN 2210-6707, https://doi.org/10.1016/j.scs.2022.104351.

Next step research

Imitation learning along with systematic empirical studies of pre-training

Combine transfer learning with other learning methods (e.g., RL)

Theoretical analysis of the problems encountered in thermal storage integrated control algorithm

Theoretical development

Development of interoperability and co-simulations

Combine control algorithm with coupled network optimizations

Testing, validation and demonstrations in various LiL environments with thermal storage solutions

Engineering implementation and validations

Thank you!