A framework for hybrid control of thermal storage connected energy systems – A preliminary study

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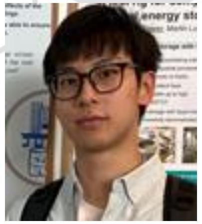
Acknowledgement



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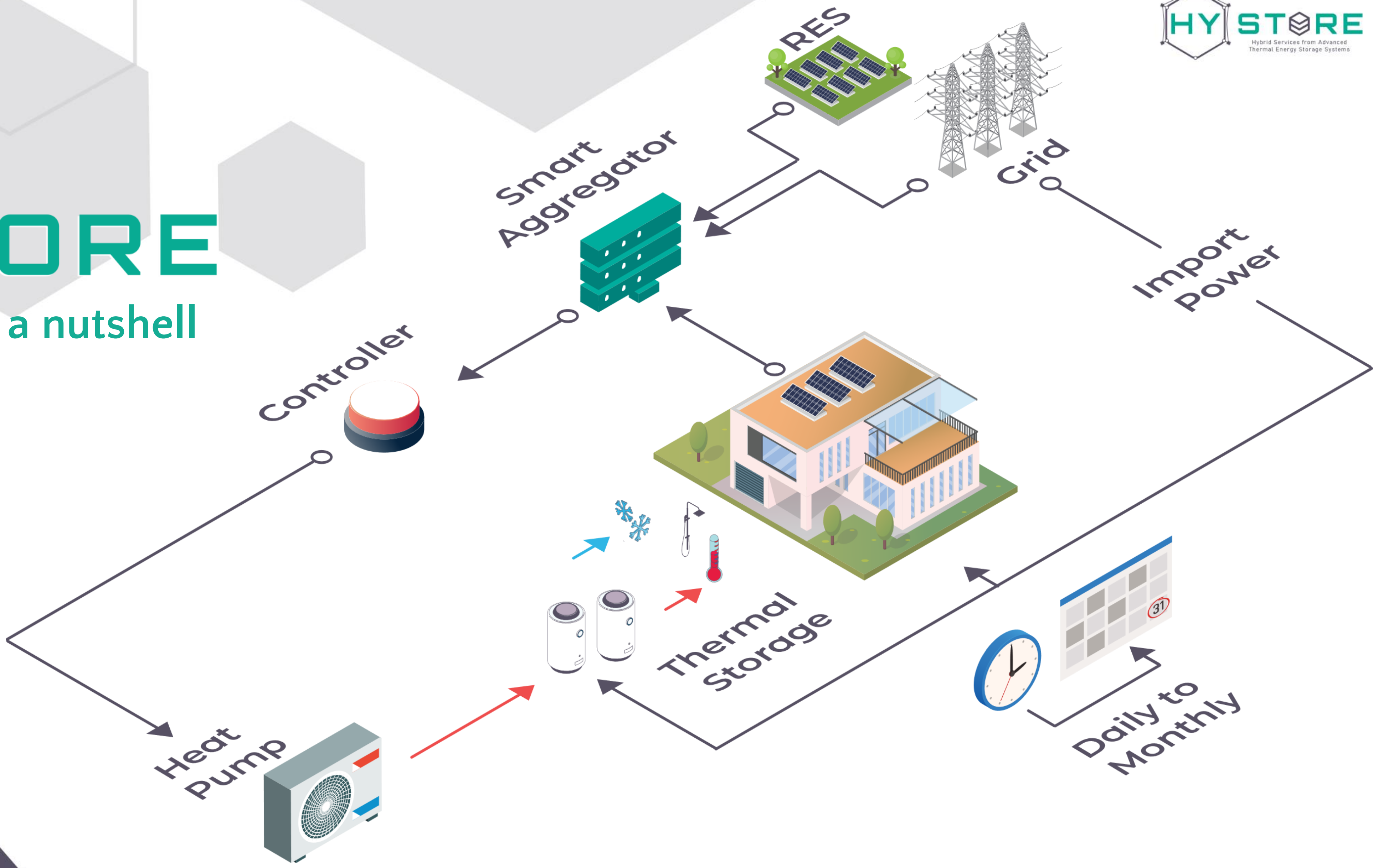
The motivation of controlling thermal storage in energy network complex

Background

- **Thermal storage** critical to unlocking **demand flexibility at scale**
  - Utilize excess electricity without batteries
  - Reduce environmental footprint
- Integrate **thermal storage** with **low-temperature district heating** to mitigate fluctuations in energy supply and demand
- **Data-driven methods** autonomously learn models of components and patterns of energy use
- AI-enabled control to **optimise and adapt to dynamic energy systems** at multiple scales (buildings, communities, grid)

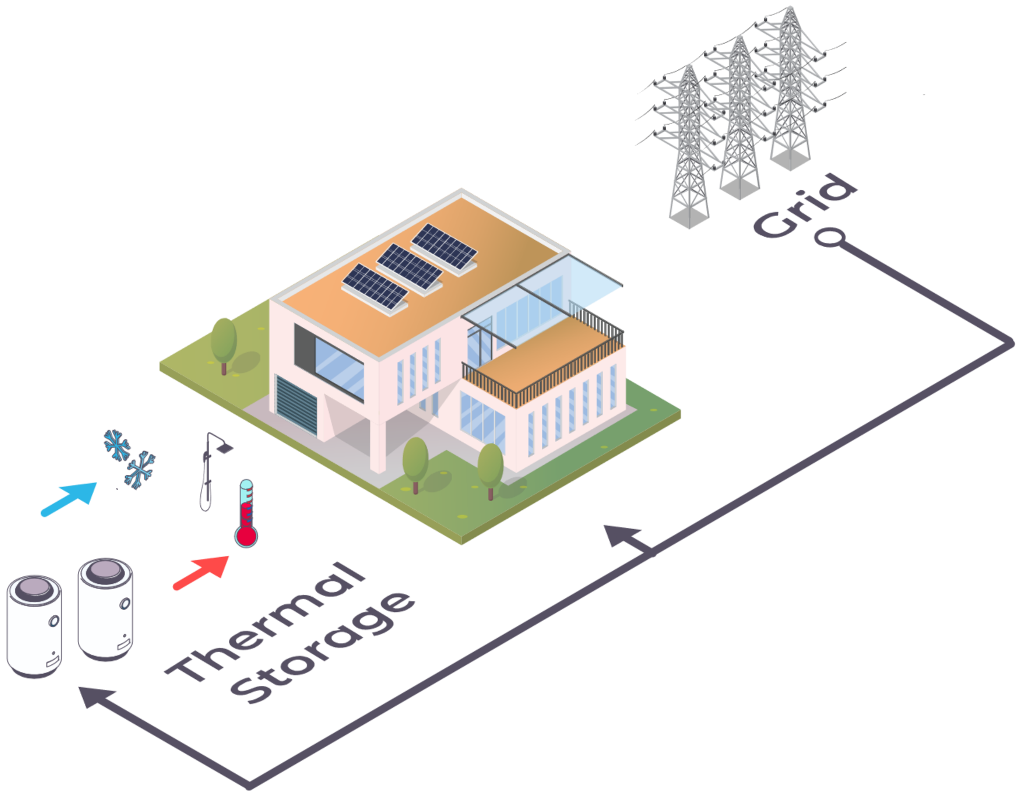
HYSTORE

In a nutshell



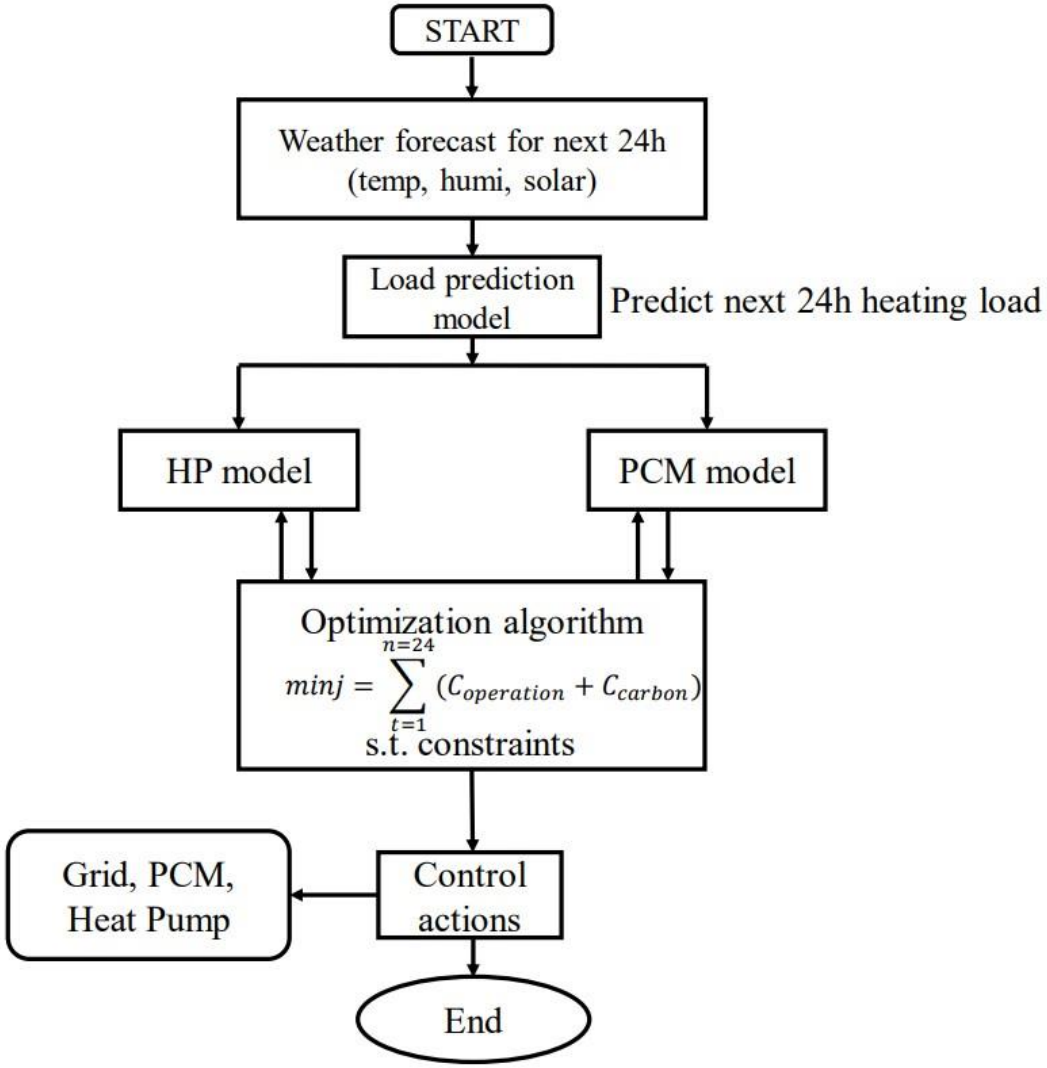
Goal

- Integrate machine-learning (ML) models and components at **system-level**
- **Scalable ML models** for predicting thermal load complex
- **General ML models** at the component level
- Optimization can **combine multiple objectives,** e.g., energy cost, carbon emission, thermal comfort, etc.



Scope

- Within the optimization algorithm, **all the prediction will be considered** holistically and output the optimal result to each component **from cloud with IoT equipment**
- The outputs include grid actions, phase-change materials (PCM) actions and HP actions for the control horizon
- **The combination of ML and advanced control** enables the building to optimally deal with energy demand and supply



Load Prediction Model

- To better control the building energy system, **load prediction is essential** to smart building control (e.g. load shifting)
- ML method is widely adopted (ANN, CNN…) for both thermal demand and electricity with relatively accurate results

Research gaps:

1. The prediction models developed by most of the research are not general enough;

2. The correlation is approximately linear to the outdoor temperature, so deep layer models may cause overfitting.

Load Prediction Model

Outdoor Temp

Calender data

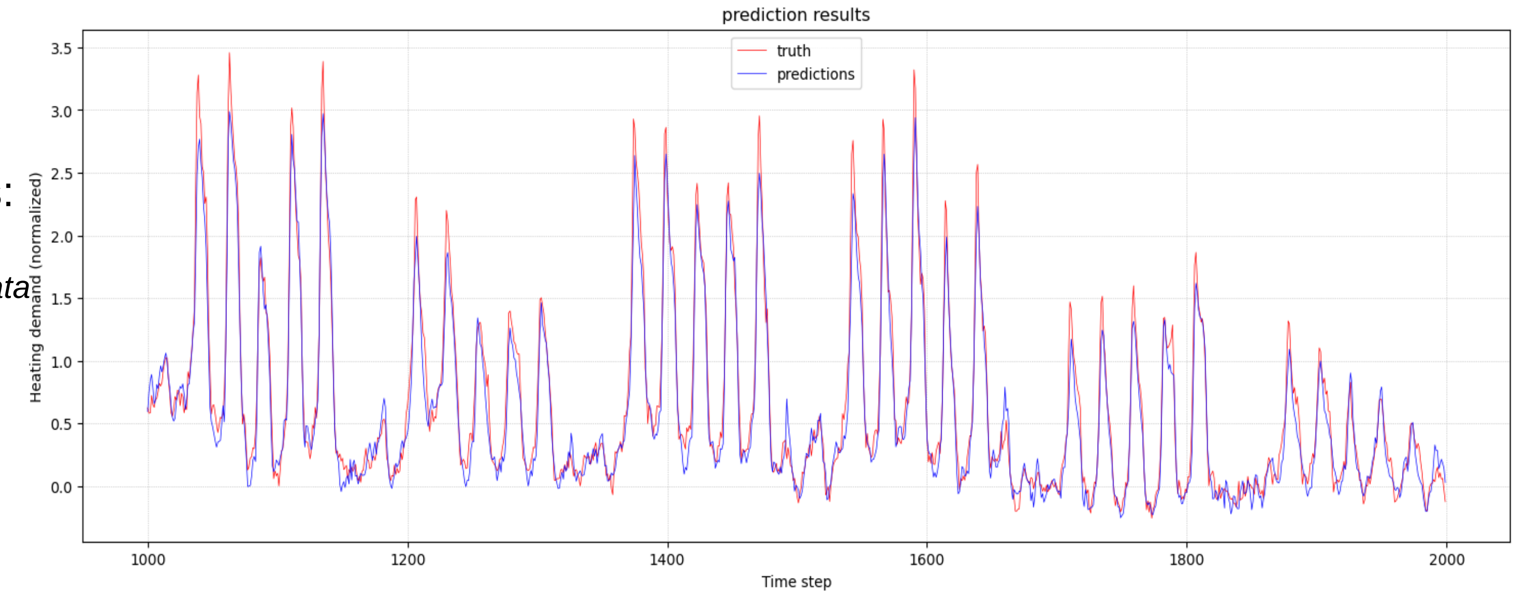
Historical values for past 24 or 48 h

Prediction model

Thermal demand for next 6h or 12h

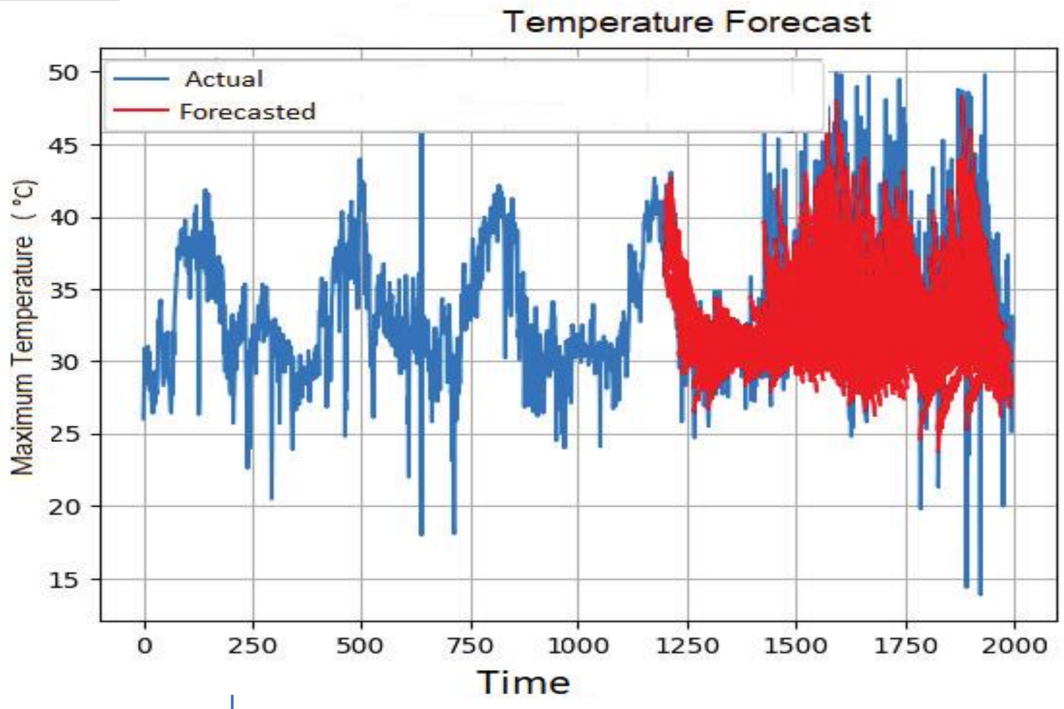
Validation on an untrained school buildings:
Mean Squre error of 0.01

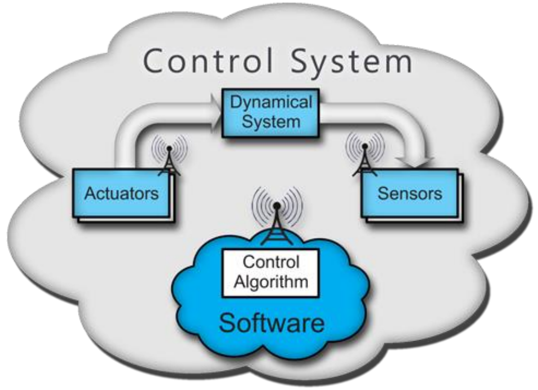
Data source: [HYPERGRYD] pilot data



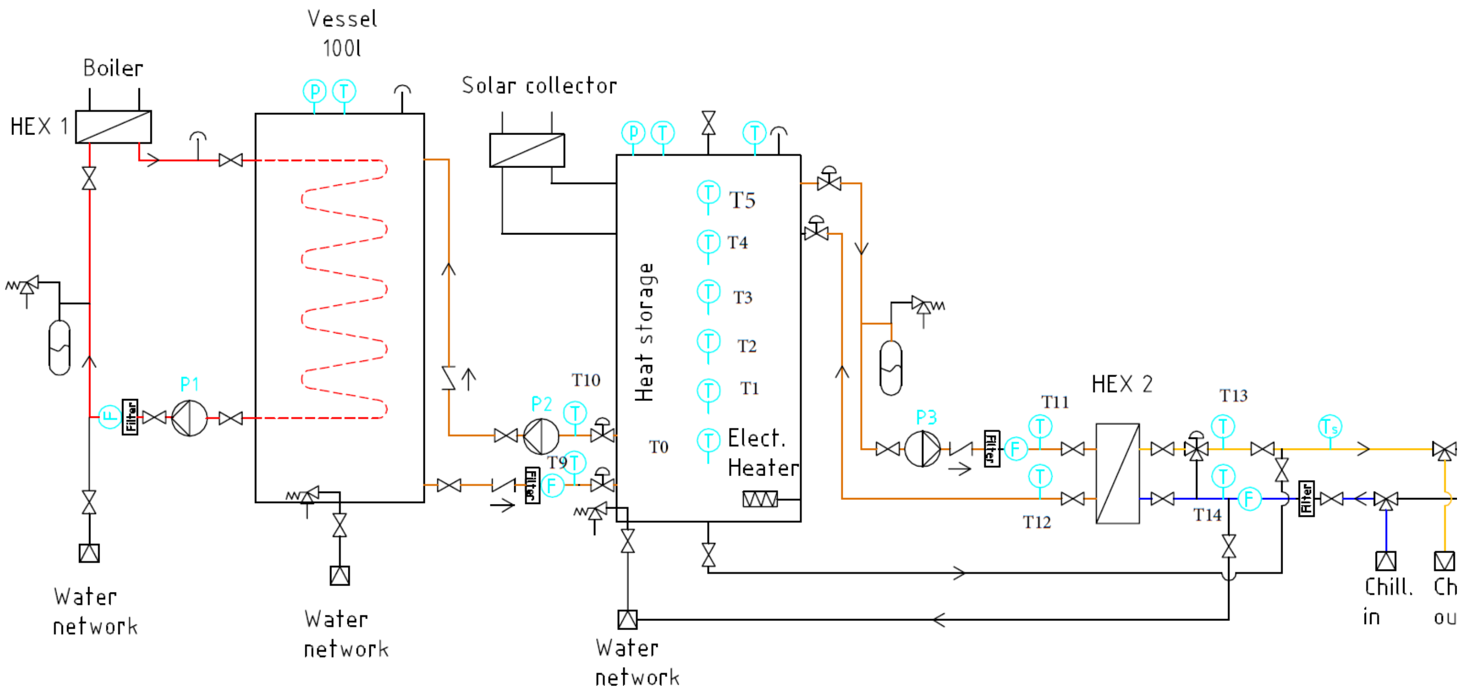
System co-simulation

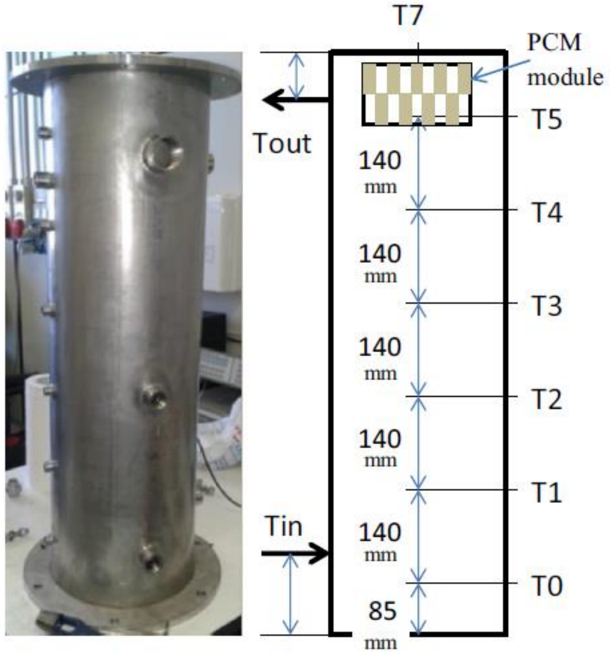
- **Predict the temporal trajectory of a set of a set of dependent variables**
- **Combine thermal storage framework with optimal control framework**
- **Plug in these predictions into the control algorithm**





Thermal storage model

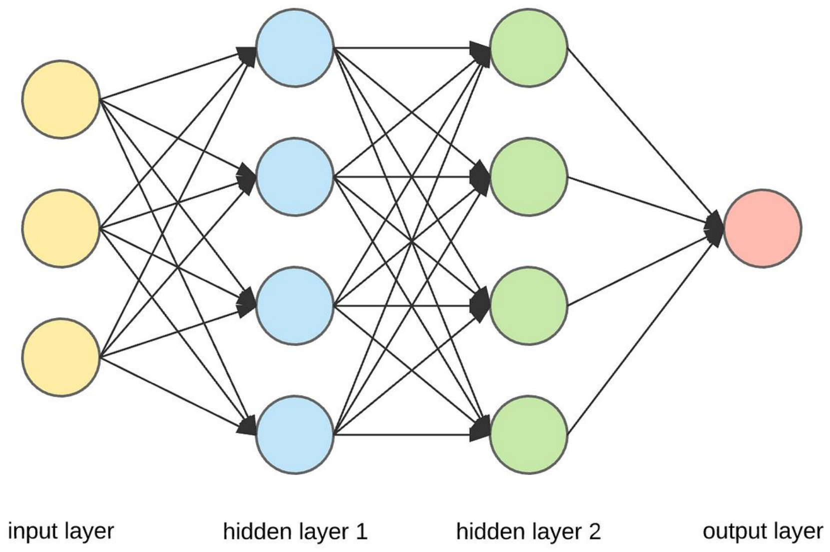




Reference: *Frazzica, A., Manzan, M., Sapienza, A., Freni, A., Toniato, G., & Restuccia, G. (2016). Experimental testing of a hybrid sensible-latent heat storage system for domestic hot water applications. Applied Energy, 183, 1157-1167.*

Physics-based and data-driven modelling of thermal storage using ML techniques

- **Objective**: Predict the temporal trajectory of a set of dependent variables (e.g., outlet temperatures, heat content) in response to a set of independent variables (e.g., inlet temperatures, flow rates)



NNs are universal function approximators

Customize the loss function according to physics

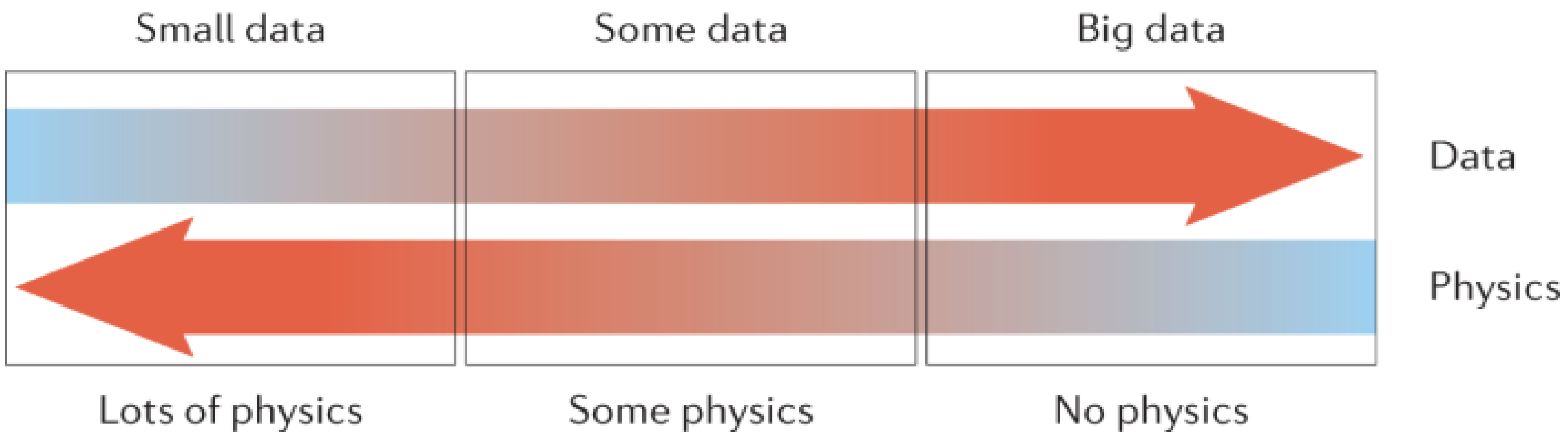
Comparison with other methods

- **Our data-driven approach:**

- Less costly
- Requires significantly less data
- Combines physics and data

- **Numerical methods and standard NN approach:**

Computationally heavy
Requires a lot of data



Comparison to FEM and standard ML approach

- Finite elements modeling (FEM) methods are the standard solvers in the industry
- FEM methods display limitations such as computational cost for large industrial problems
- Also issues in leveraging external data sources, e.g. sensors data, to drive the solution of the PDEs
- Our approach is a promising alternative to FEM methods covering some of these limitations
- Our approach is also different from the standard supervised ML

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