IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

RÉPUBLIQUE FRANÇAISE
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Hybrid Modeling for Smarter Energy System

Physics Meets AI

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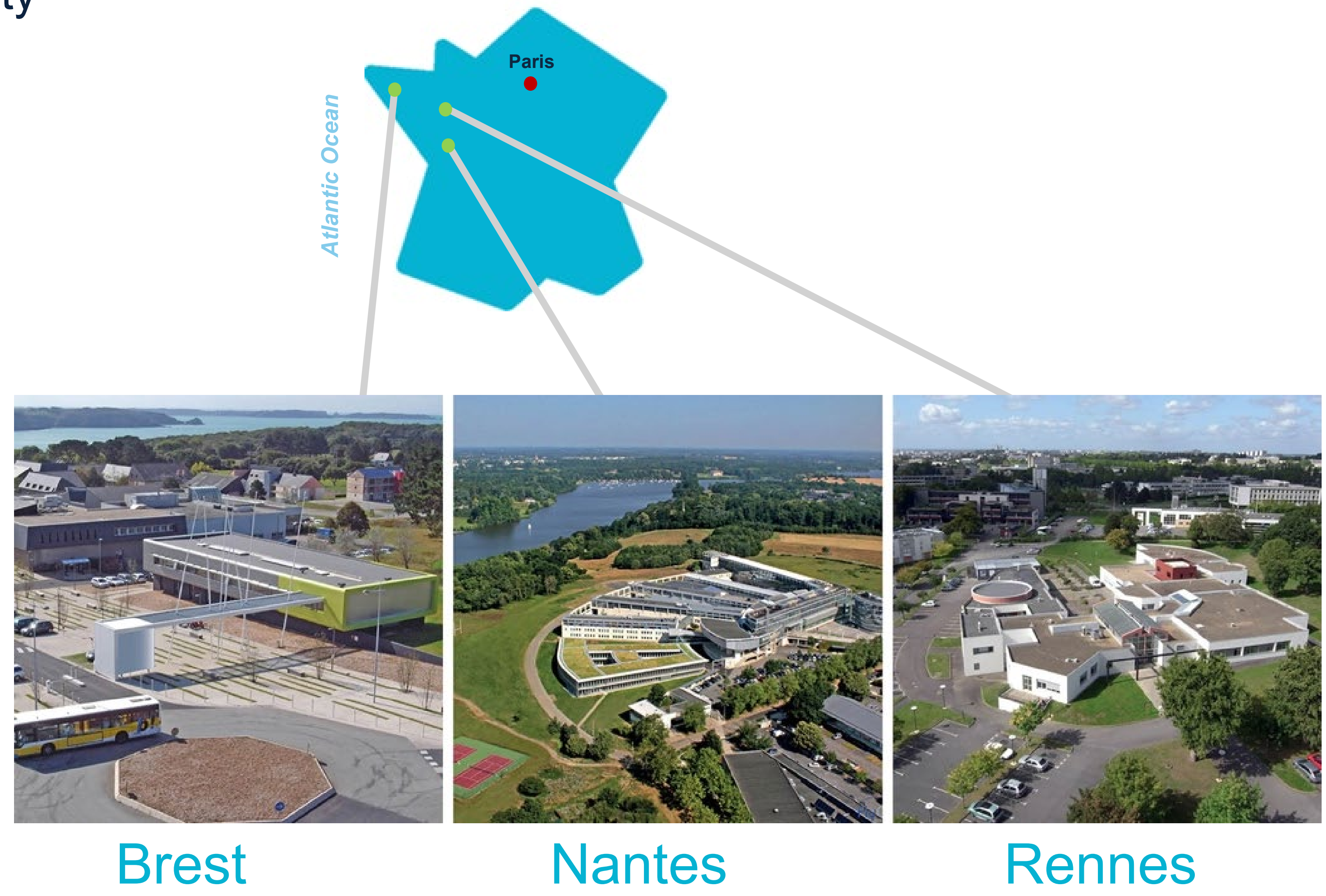
Thanks to all contributors:

Bruno LACARRIERE, Shri Balaji PADMANABHAN, Dubon RODRIGUE, Dessie Tadele EMBIALE, and many others

IMT ATLANTIQUE

A leading technological university



3 CAMPUSES

IMT ATLANTIQUE

Key numbers

2,200
students

650
graduates / year
from MSc to PhD

250
faculty members

750
staff

HELLO
こんにちは
مرحبا

> 30%
international students
+70
nationalities

€ **94,5M** budget

Department of Energy systems and Environment

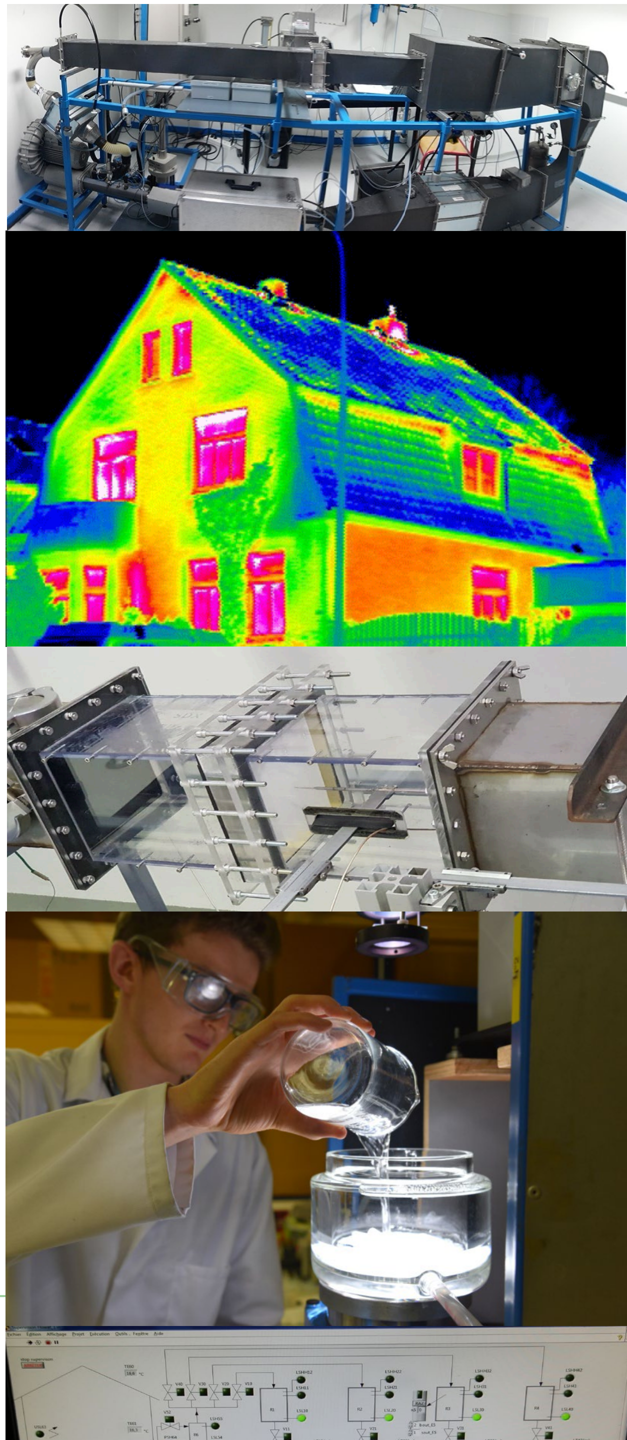
GEPEA
UMR CNRS 6144

DSEE is an integral part of the UMR (joint research unit) CNRS 6144 GEPEA (grouping together the CNRS, Nantes Université, ONIRIS and IMT Atlantique)

Main research field: Ecotechnologies

divided in 3 teams:

TEAM	Water & Air Treatment, Metrology
VERTE	Energy and Resources Recovery from Residues and Emission Treatment
OSE	Optimization - System - Energy



Research focus

Energy systems

Goal

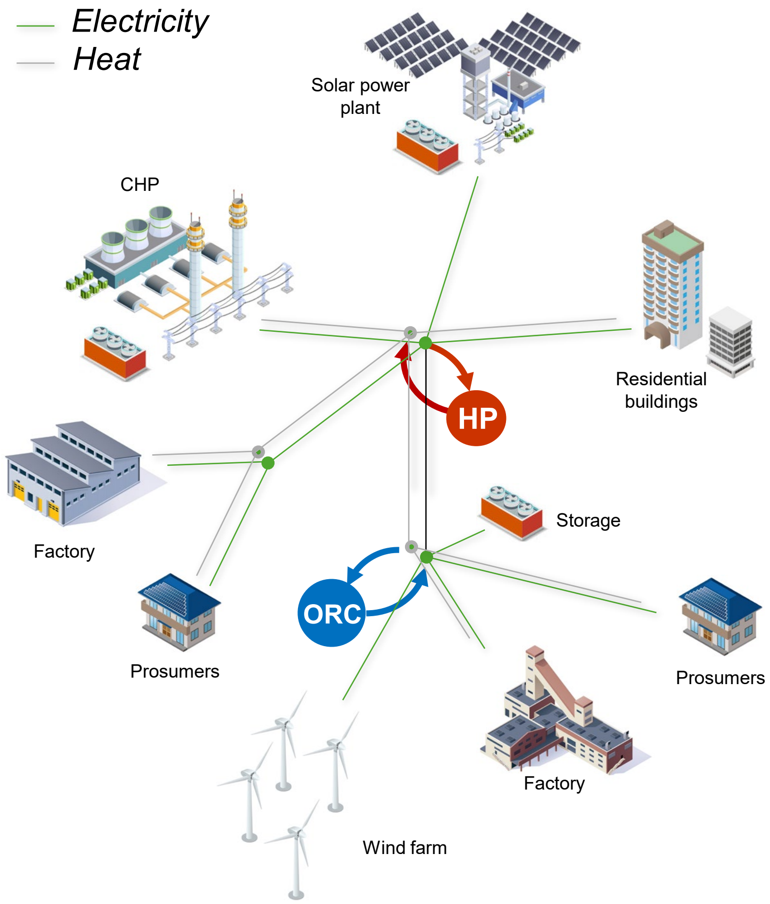
- Developing new methods for modelling energy systems ranging from individual processes to large scale systems.
- Integrate these methods in decision making processes.

Which technologies?

Key technologies for:

- coupling different sectors
- adding flexibility to the system
- efficient integration of different energy sources (renewables and waste energy)

Decentralized and coupled energy system

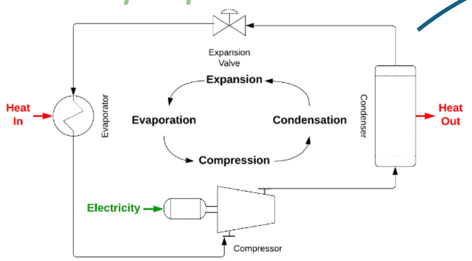


Research focus

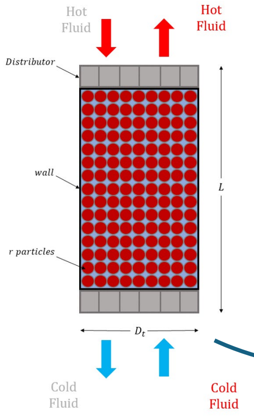
Energy systems

Process Hub Network

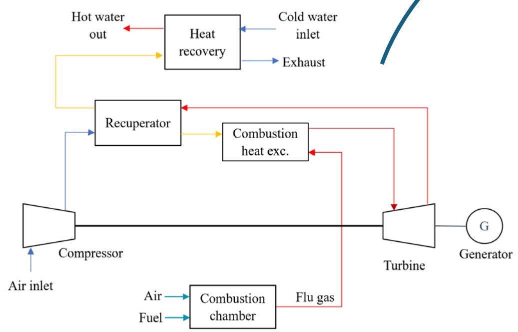
Heat pump

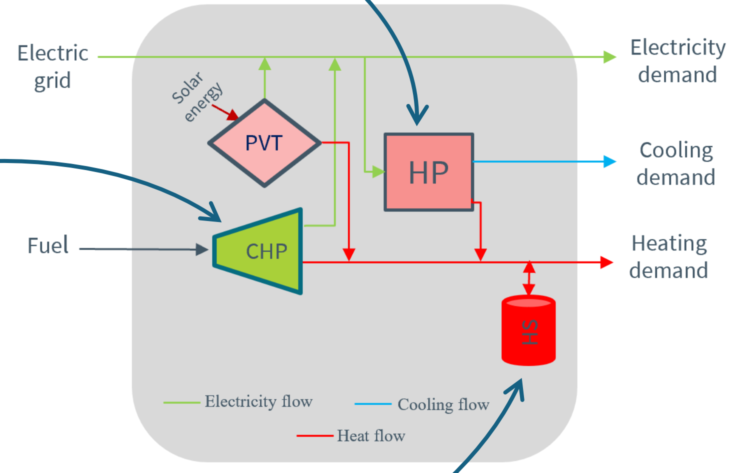


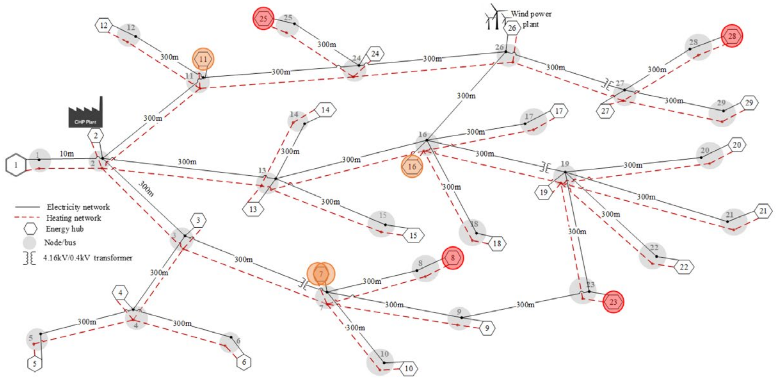
Heat storage

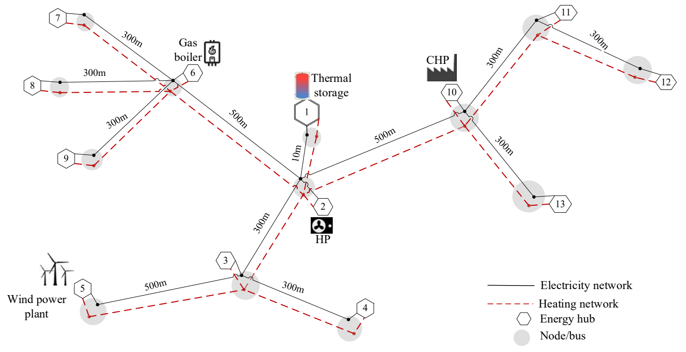


Combined heat & power





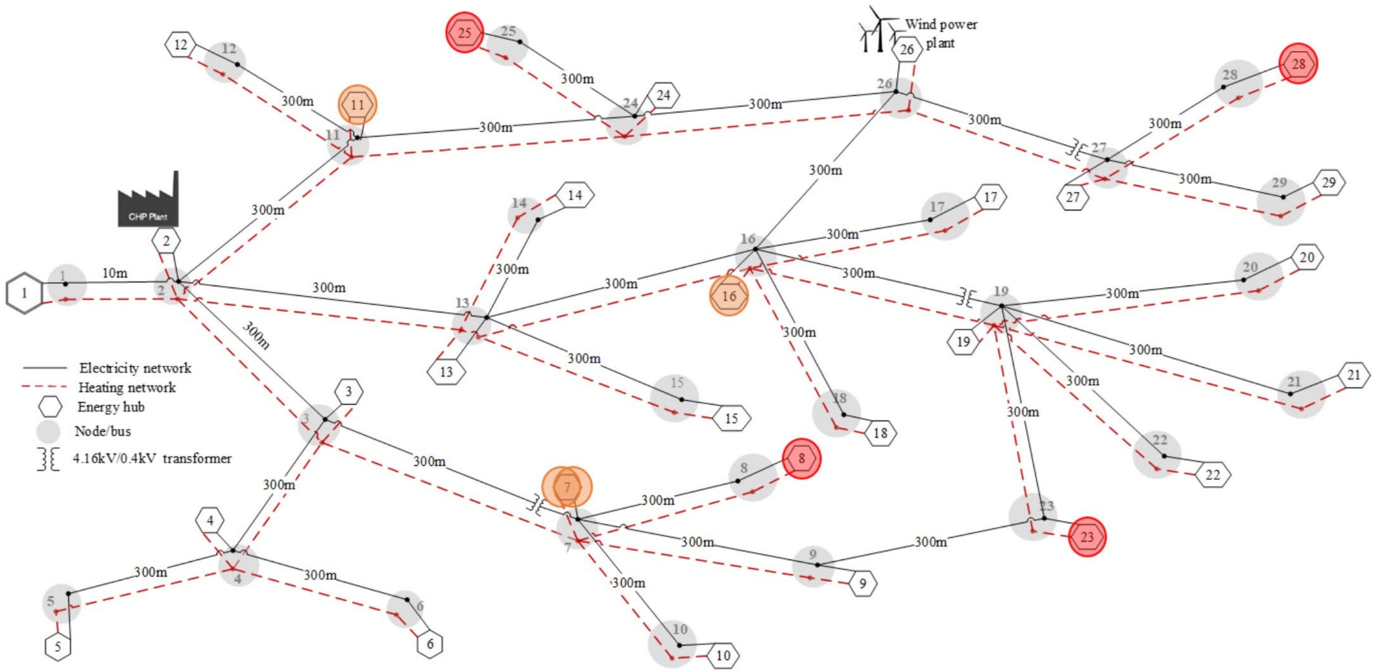




Previous works

Siting and sizing of heat pumps in coupled energy networks[1]

Topology of the coupled electrical and district heating networks



🟥 **Scenario 1**: considering district heating network only

🟧 **Scénario 2**: considering both networks (heating + electricity)

Effect of networks coupling

- **Higher** thermal losses (~3%)
- **Higher** pumping energy (~16%)
- **Lower** electrical losses (~42%)
- **Lower** operational costs (~5%)

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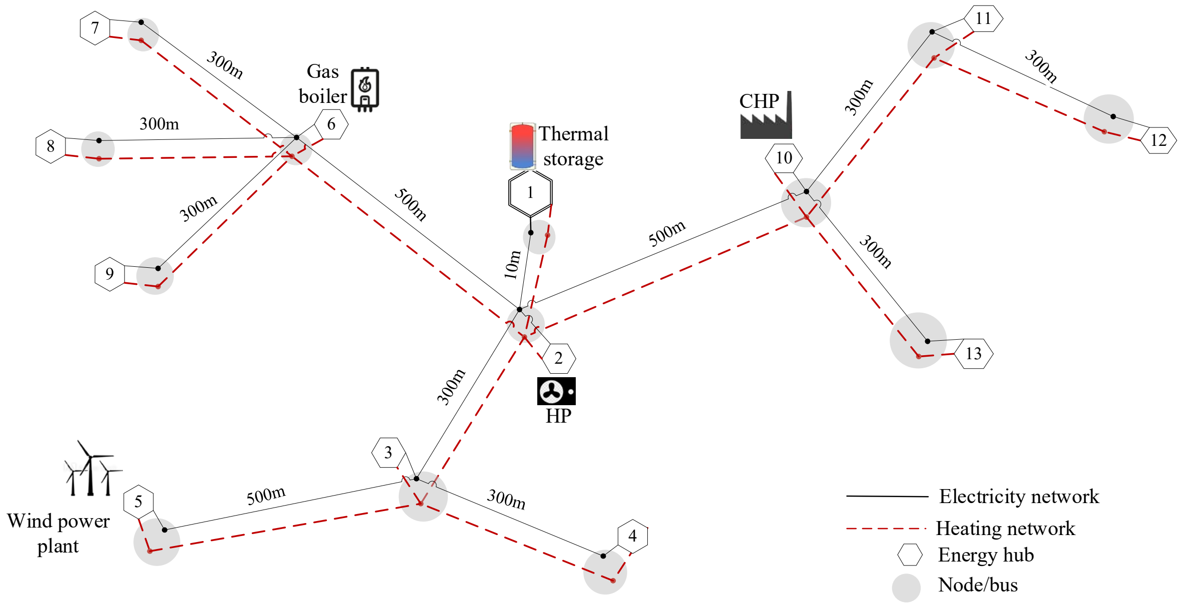
1. Getnet Tadesse Ayele, Mohamed Tahar Mabrouk, Pierrick Haurant, Björn Laumert, Bruno Lacarrière, Optimal placement and sizing of heat pumps and heat only boilers in a coupled electricity and heating networks, Energy, Volume 182, 2019, Pages 122-134

Previous works

Optimal operation of energy production and storage in coupled energy networks[2]

Topology of the coupled networks



- District heating & electrical networks
- Coupling and production technologies (cogeneration, heat pump, gas boiler)
- Thermocline heat storage

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2. Getnet Tadesse Ayele, Mohamed Tahar Mabrouk, Pierrick Haurant, Björn Laumert, Bruno Lacarrière, Optimal heat and electric power flows in the presence of intermittent renewable source, heat storage and variable grid electricity tariff, Energy Conversion and Management, Volume 243, 2021, 114430

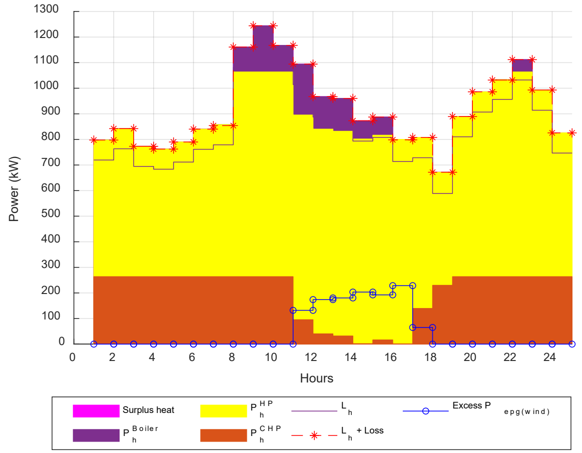
Previous works

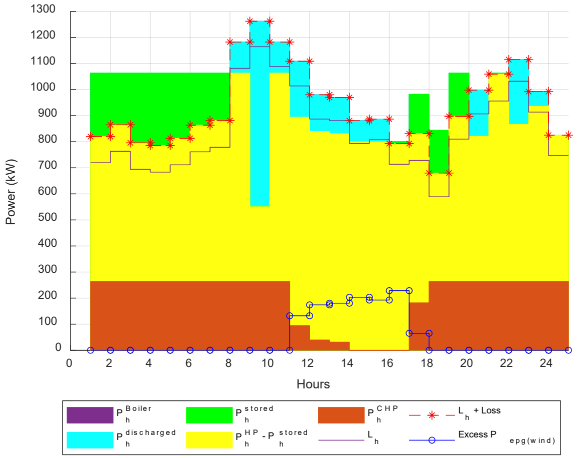
Optimal operation of energy production and storage in coupled energy networks[2]

Without heat storage

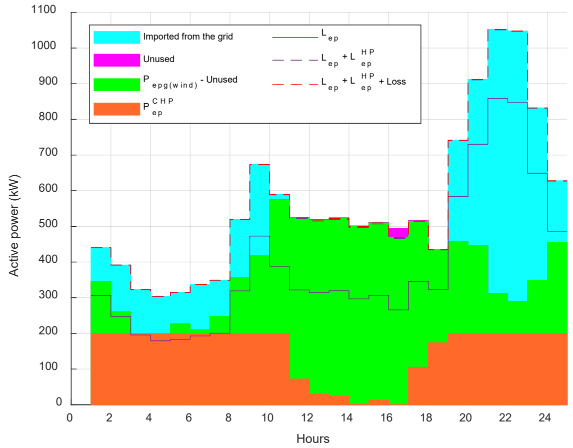
With heat storage

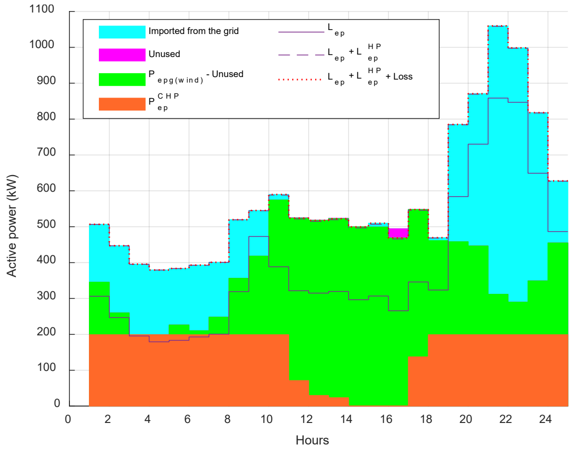
Heat production





Electricity production





Scenario’s compararison

- **Same** electrical losses
- **Higher** thermal losses (~18%)
- **Lower** operational cost(~2%)
- **Lower** CO_2 emission (~9.5%)
- **Lower** pumping energy (~38%)

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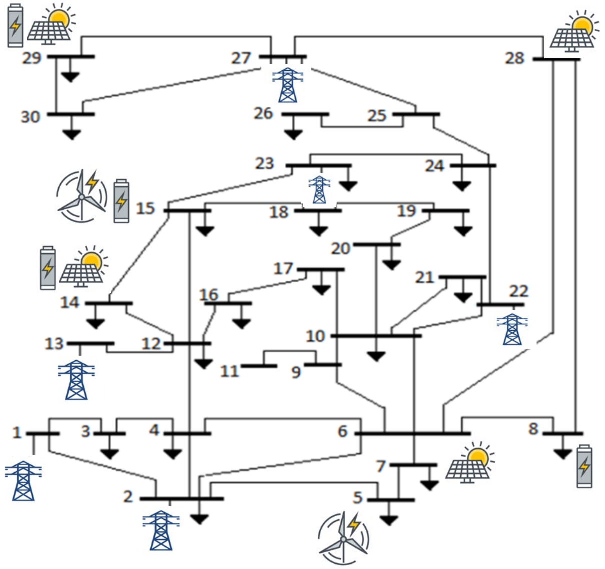
[2] Getnet Tadesse Ayele, Mohamed Tahar Mabrouk, Pierrick Haurant, Björn Laumert, Bruno Lacarrière, Optimal heat and electric power flows in the presence of intermittent renewable source, heat storage and variable grid electricity tariff, Energy Conversion and Management, Volume 243, 2021, 114430

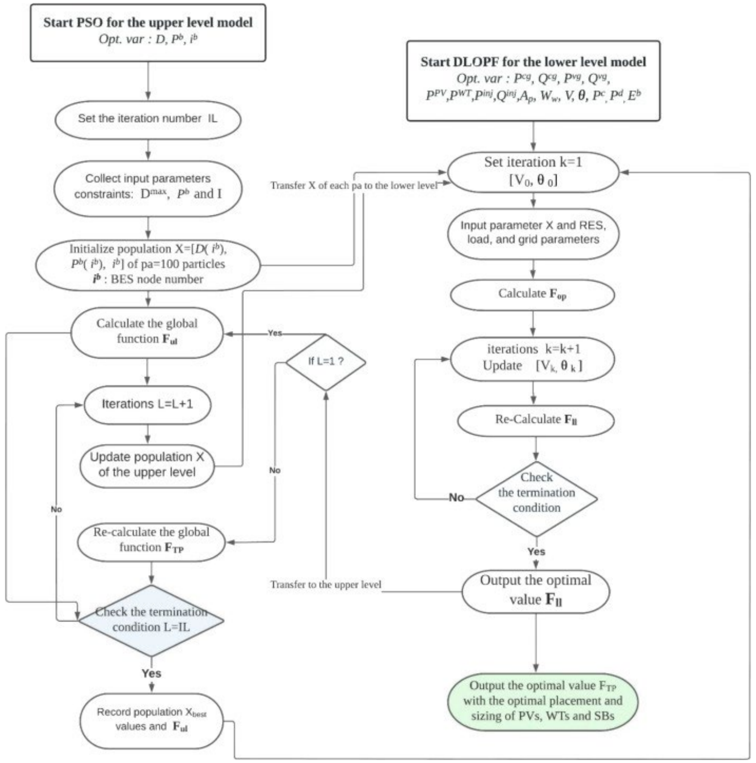
Previous works

Optimal integration of renewables and batteries to support overloaded electricity networks[3]

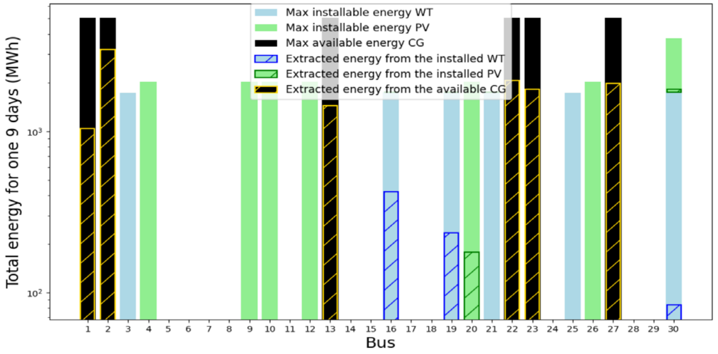
Case-study



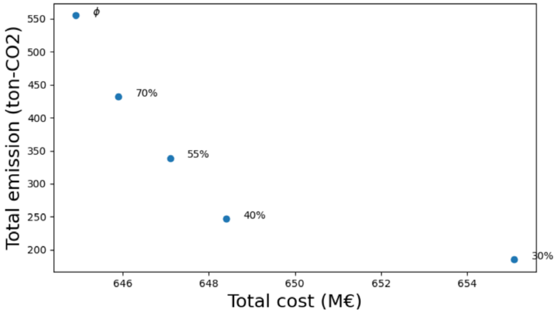
Bi-level optimization



Optimization results (energy)



Multi-objectif optimization (Economic / environmental)



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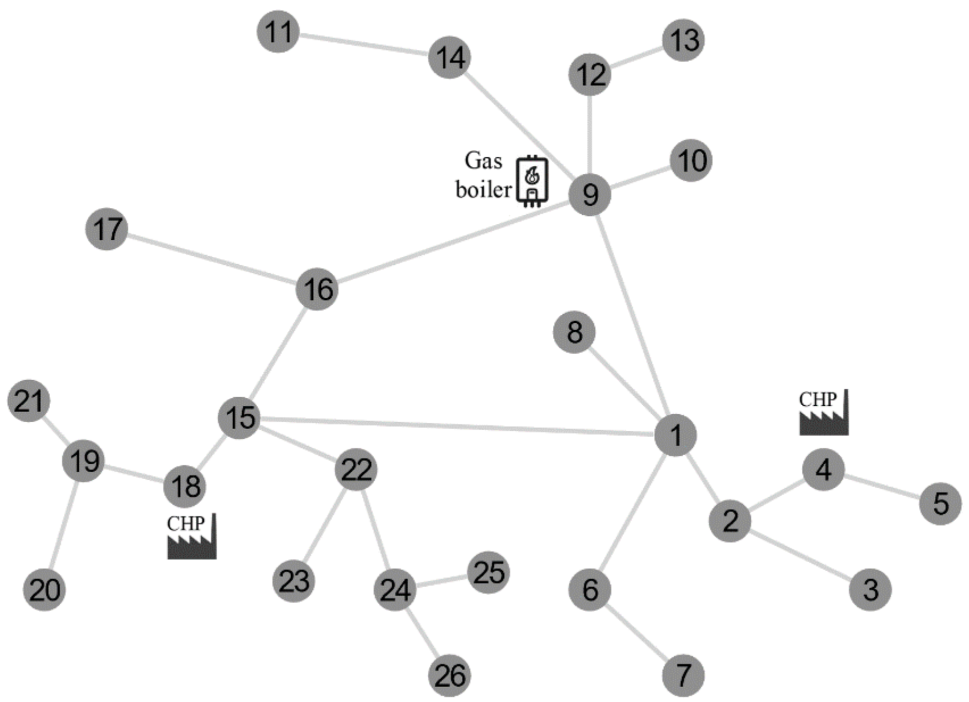
3. Sara Fakih, Mohamed Tahar Mabrouk, Mireille Batton-Hubert, Bruno Lacarriere, Bi-level and multi-objective optimization of renewable energy sources and storage planning to support existing overloaded electricity grids, Energy Reports, Volume 10, 2023, Pages 1450-1466

Previous works

Model-predictive control of heat delivery in district heating networks

Network topology



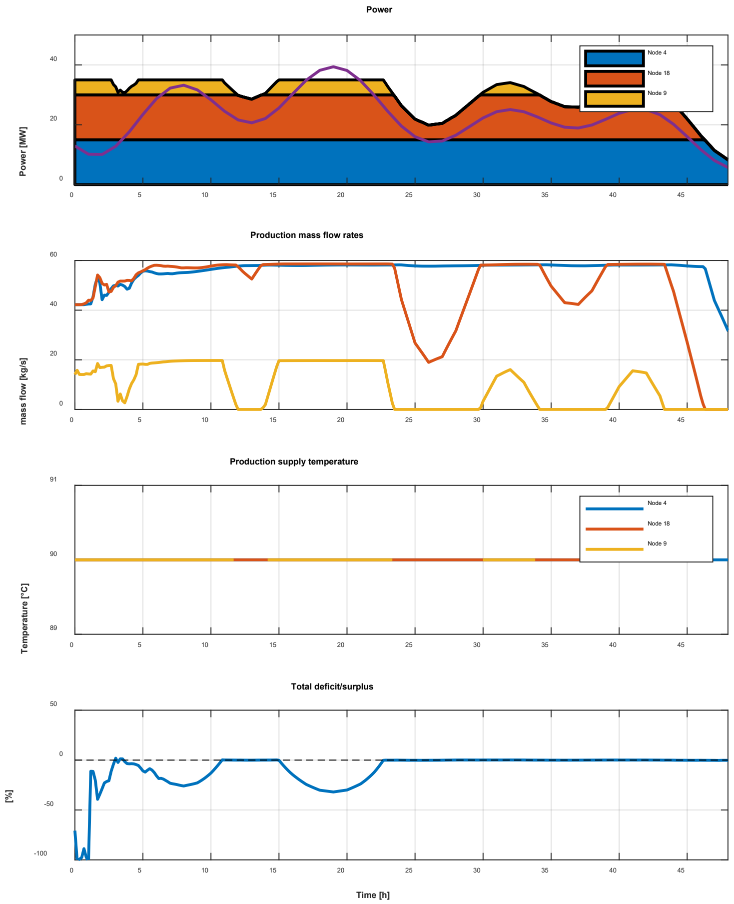
Production units’ characteristics

Node #	Production technology	Maximum capacity (MW)	Cost coefficient (cost units)
4	CHP	15	1
18	CHP	25	1.2
9	Gas boiler	5	1.4

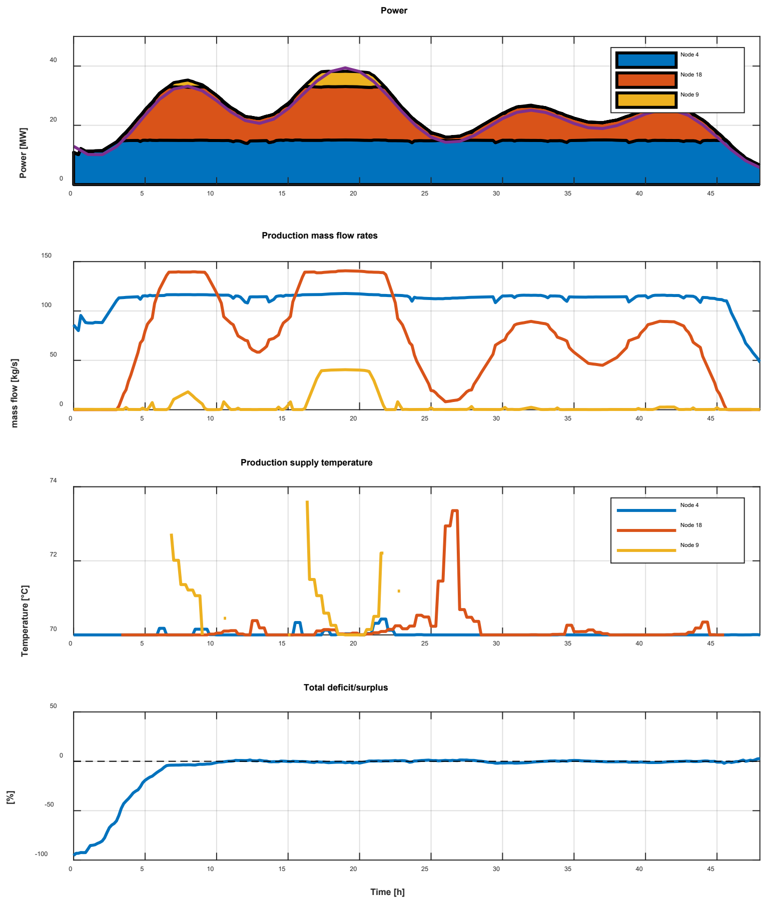
Previous works

Model-predictive control of heat delivery in district heating networks

Reference case

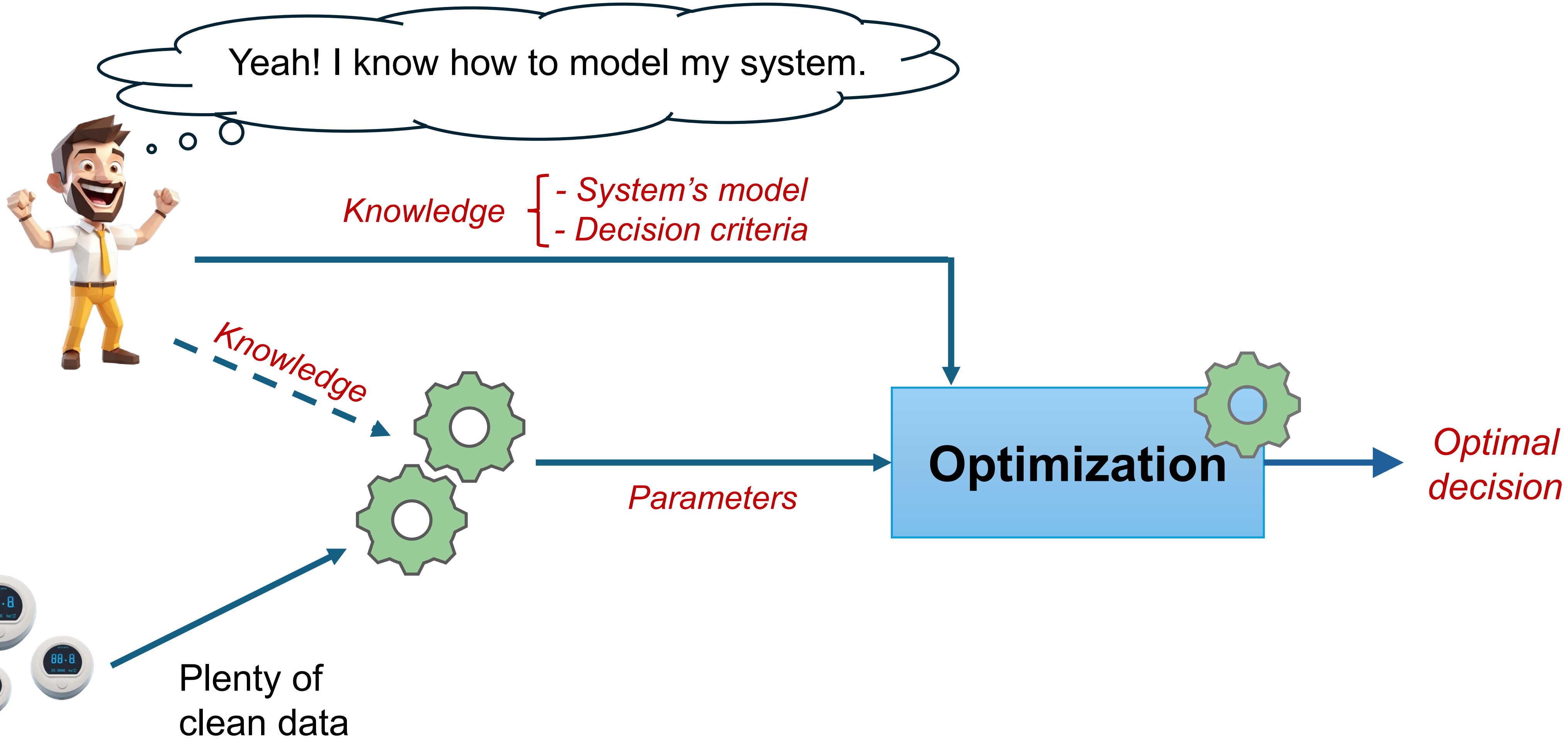


Model predictive control



Model-based energy systems optimization

In a perfect world



Yeah! I know how to model my system.

Knowledge
- *System's model*
- *Decision criteria*

Knowledge

Parameters

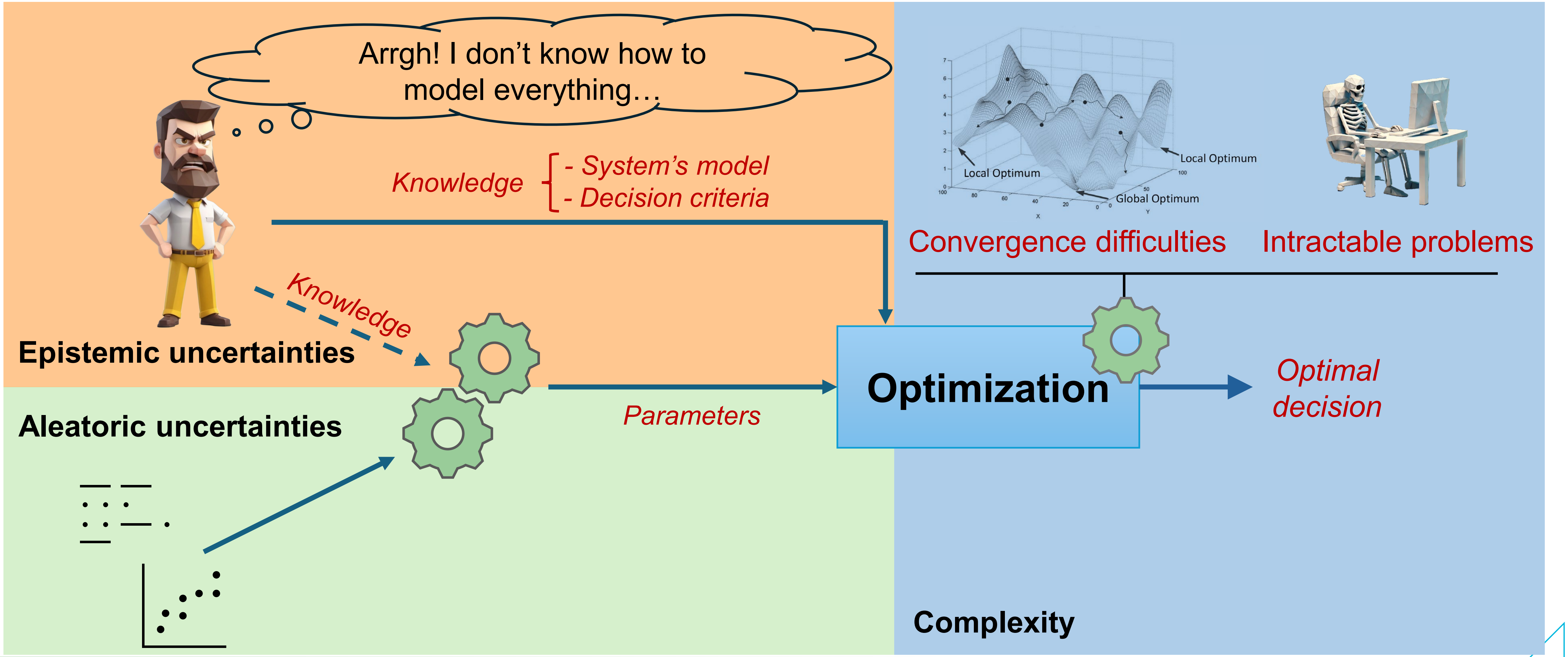
Optimization

Optimal decision

Plenty of clean data

Model-based energy systems optimization

In reality



Arrgh! I don't know how to model everything…

Knowledge { *- System's model* *- Decision criteria*

Knowledge

Epistemic uncertainties

Aleatoric uncertainties

Parameters

Convergence difficulties

Intractable problems

Optimization

Optimal decision

Complexity

Previous works

Conclusion

Previous studies focused on adapting the level of detail of energy system's model and exploiting the structure of the problem to develop scalable optimization routines.

This has limitations:

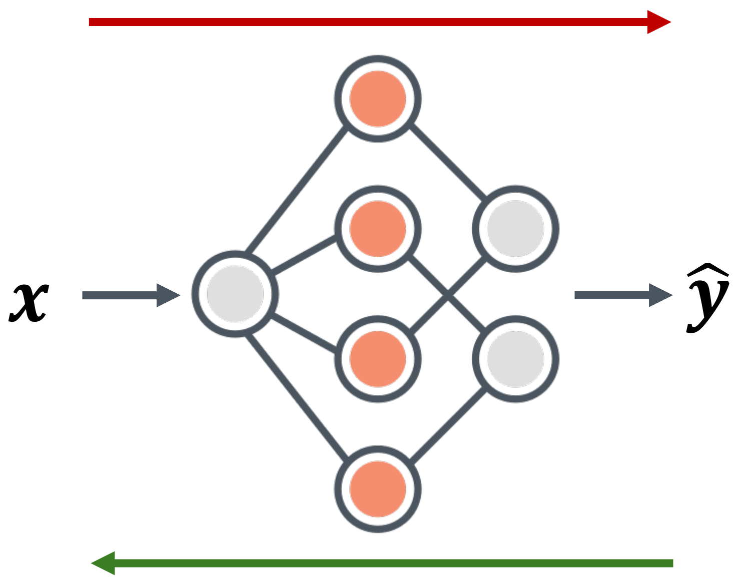
- Case by case
- Over simplifying models and decision problems
- Complexity increases rapidly for real-world systems
- Hard to handle uncertainties

Machine learning

Fundamentals

Forward pass

$$\hat{y} = f(x, \theta_p)$$



Backward pass

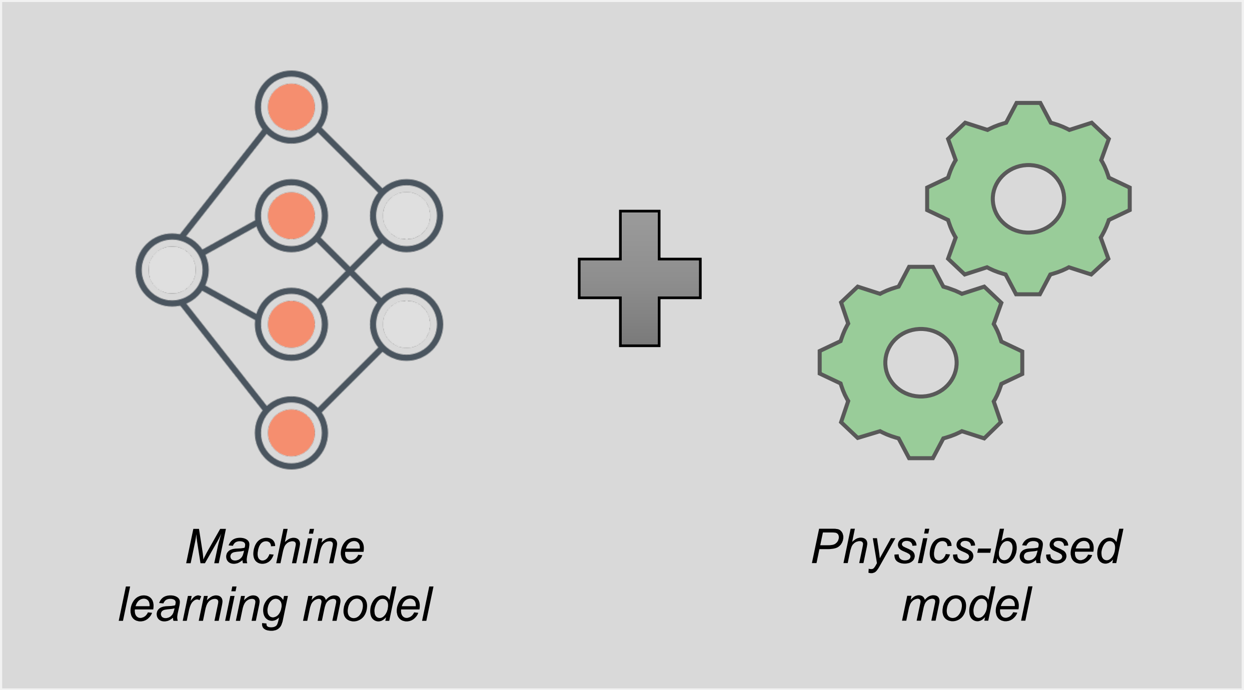
$$\frac{d\hat{y}}{dx}, \frac{d\hat{y}}{d\theta_p}$$

- **Very fast** prediction
- Efficient **pattern recognition**
- Easy to train

  (providing enough data and computational resources)
- **Generalize poorly** to unseen cases
- **Curse of dimensionality**

Hybrid modelling

Definition

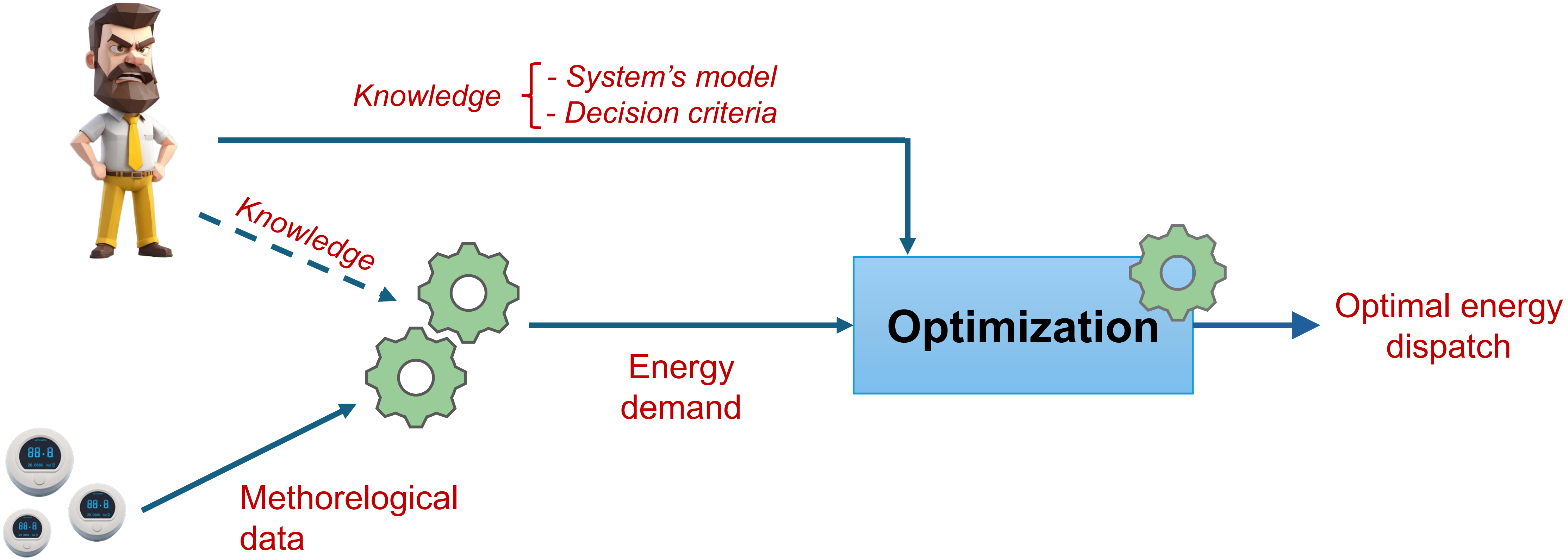

Machine learning model

Physics-based model

Global model

Hybrid modelling

A new concept ?



Knowledge

- System’s model

- Decision criteria

Knowledge

Optimization

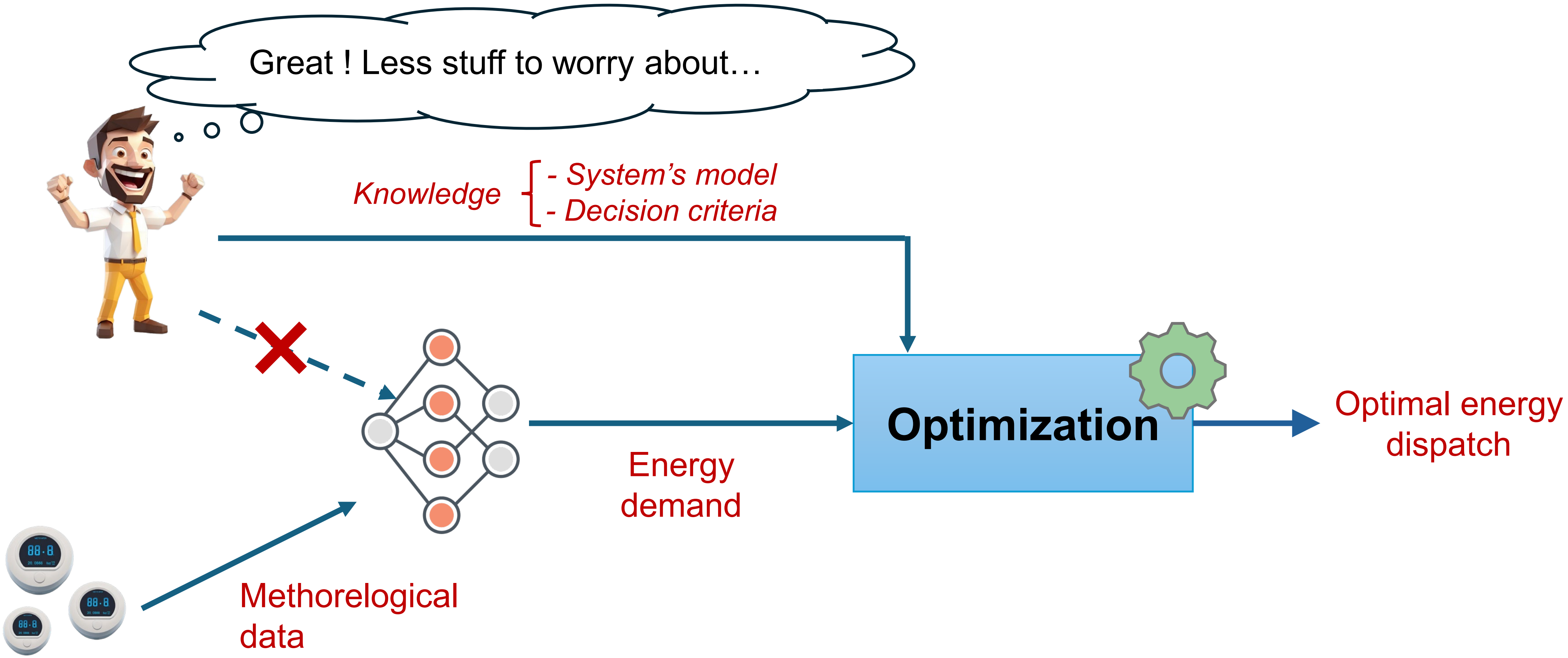
Optimal energy dispatch

Energy demand

Methorelogical data

Hybrid modelling

A new concept ?



Great ! Less stuff to worry about…

Knowledge

- System’s model

- Decision criteria

Optimization

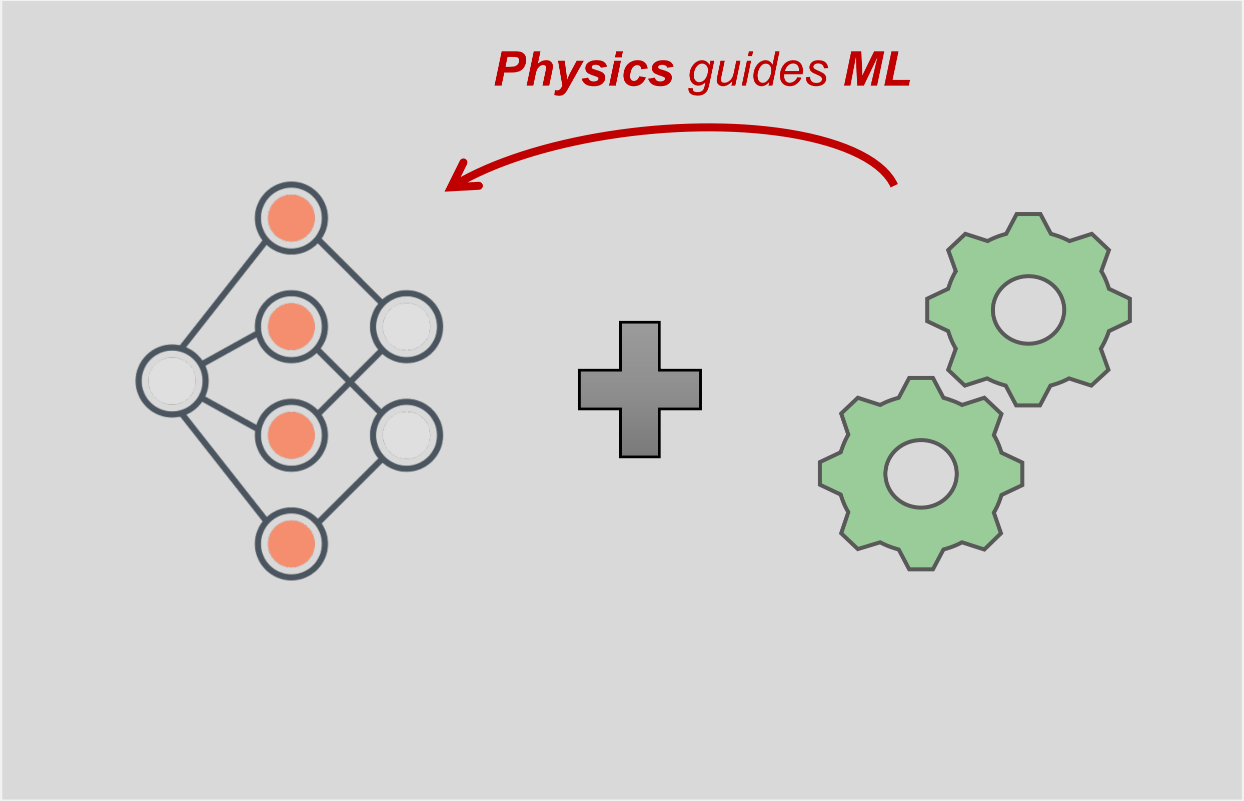
Optimal energy dispatch

Energy demand

Methorelogical data

Hybrid modelling

An evolving concept…



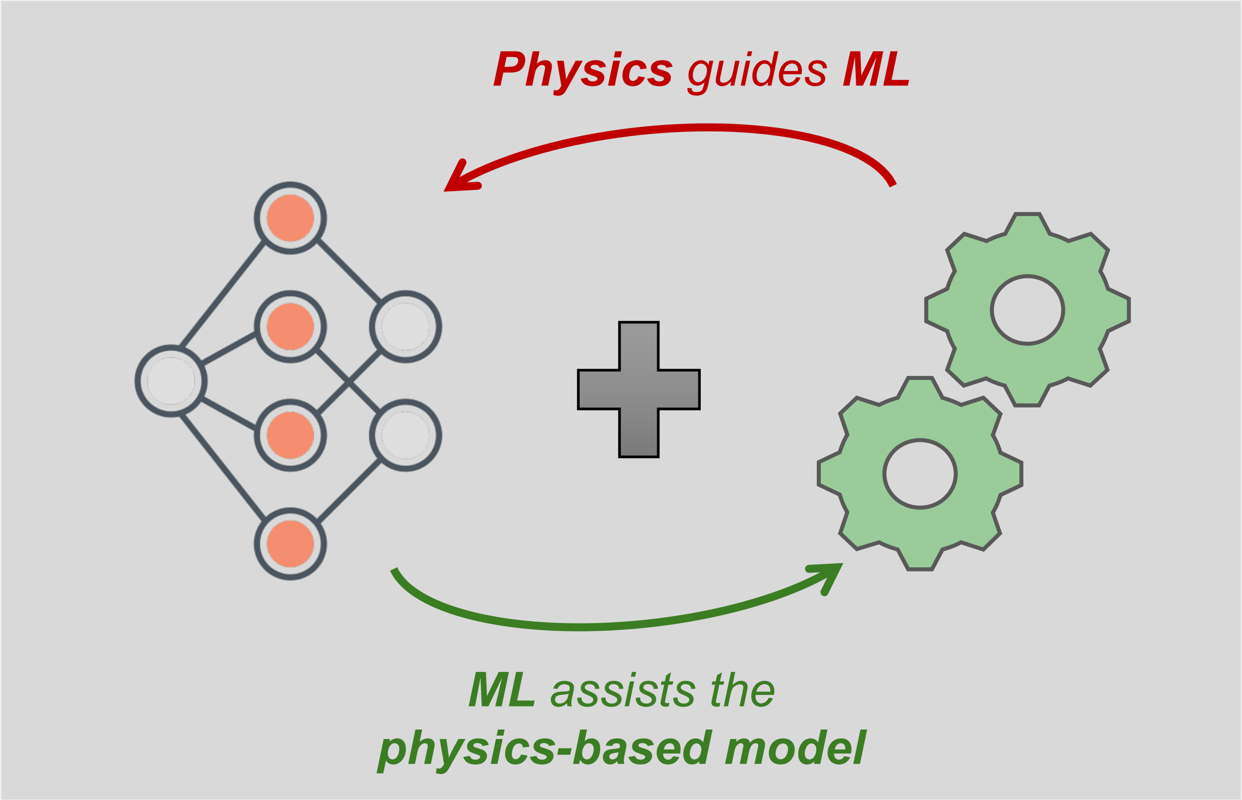
Global model

Physics** guides **ML

- Guiding the **training**
  - Physics-informed Machine learning
  - Physically constrained Machine learning
  - Physics-inspired architectures
- Guiding the **prediction**
  - Providing partial solutions to the ML
  - Providing physical states to the ML

Hybrid modelling

An evolving concept…



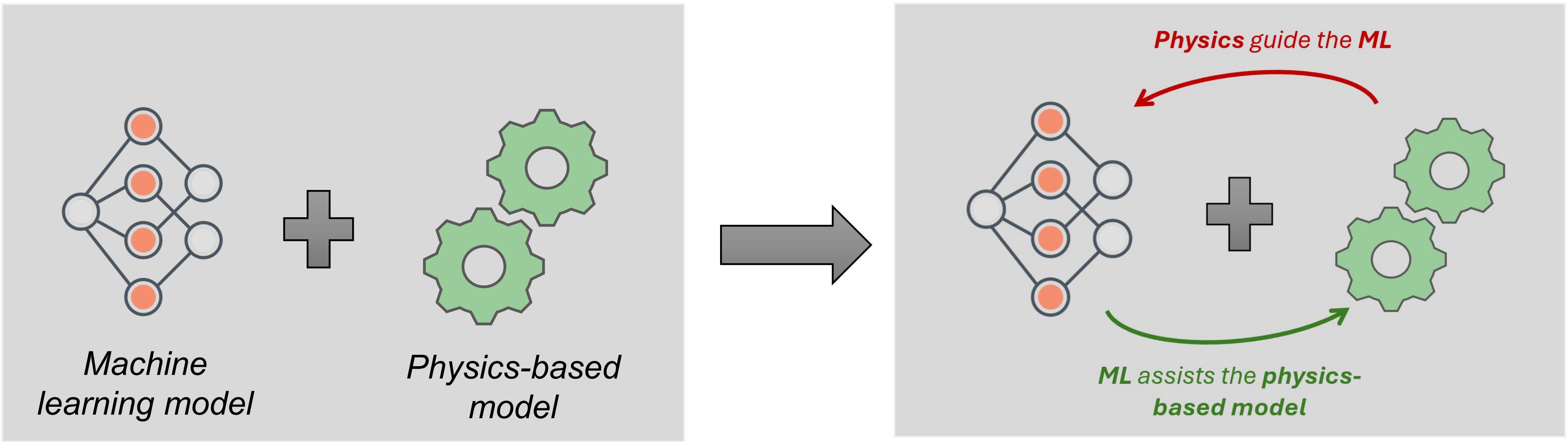
Global model

ML *assists the* ***physics-based model***

- Discovering **unknown physics**
  - Automatic pattern recognition
  - Symbolic regression
- **Accelerate** computation
  - Fast surrogate models of computationally intensive parts

Hybrid modelling

An evolving concept…



Coexisting models

Machine learning model

Physics-based model

Global model

Co-dependent models

Physics *guide the* ***ML***

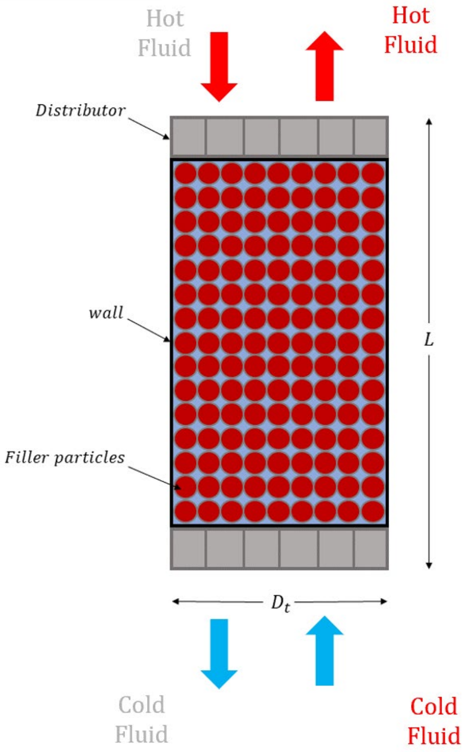
ML *assists the* ***physics-based model***

Global model

Ongoing studies

Hybrid models for heat storage technologies: Sensible heat storage[4]

General layout



Porous medium:
Silica gravel (80%) + Silica sand (20%)
Fluid medium: Therminol 66

Mathematical model

$$\epsilon(\rho C_p)_f \frac{\partial T_f}{\partial t} + \epsilon(\rho C_p)_f U \frac{\partial T_f}{\partial z} = \frac{\partial}{\partial z}\left(k_f \frac{\partial T_f}{\partial z}\right) + h_v(T_s - T_f) - H(T_f - T_{ext}) \qquad \text{(fluid)}$$

$$(1-\epsilon)(\rho C_p)_s \frac{\partial T_s}{\partial t} = k_s \frac{\partial^2 T_s}{\partial z^2} - h_v(T_s - T_f) \qquad \text{(solid)}$$

Boundary conditions:

$$T_f\ (z=0,t) = T_{f\,inlet}\ ; \quad \frac{\partial T_f(z=L\ t)}{\partial z} = \frac{\partial T_s(z=L,t)}{\partial z} = \frac{\partial T_s(z=0,t)}{\partial z} = 0$$

Initial conditions:

$$T_f(z,t=0) = T_{f,0}(z) \qquad T_s(z,t=0) = T_{s,0}(z)$$

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4. Shri Balaji Padmanabhan, Mohamed Tahar Mabrouk, Bruno Lacarrière, A hybrid model for packed bed thermal energy storage system, Journal of Energy Storage, Volume 98, Part B, 2024, 113068

Ongoing studies

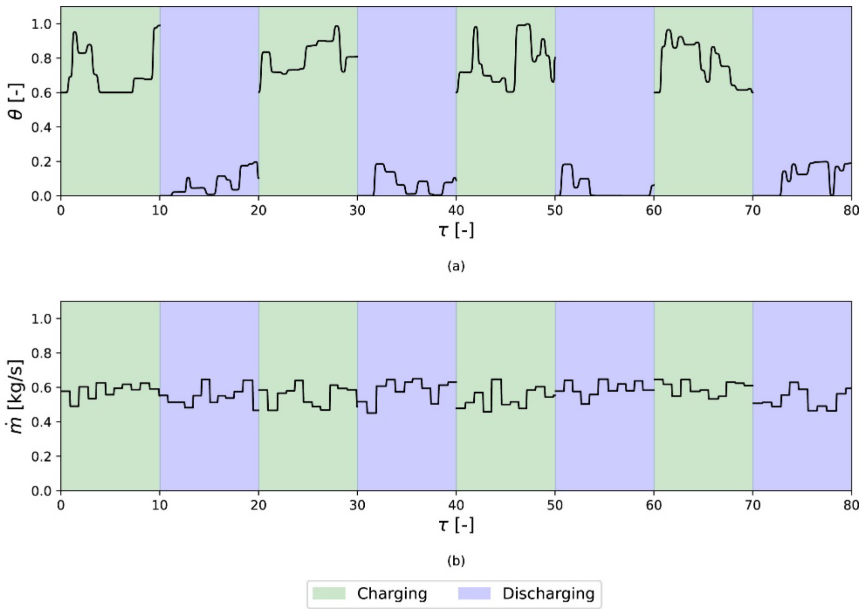
Hybrid models for heat storage technologies: Sensible heat storage[4]

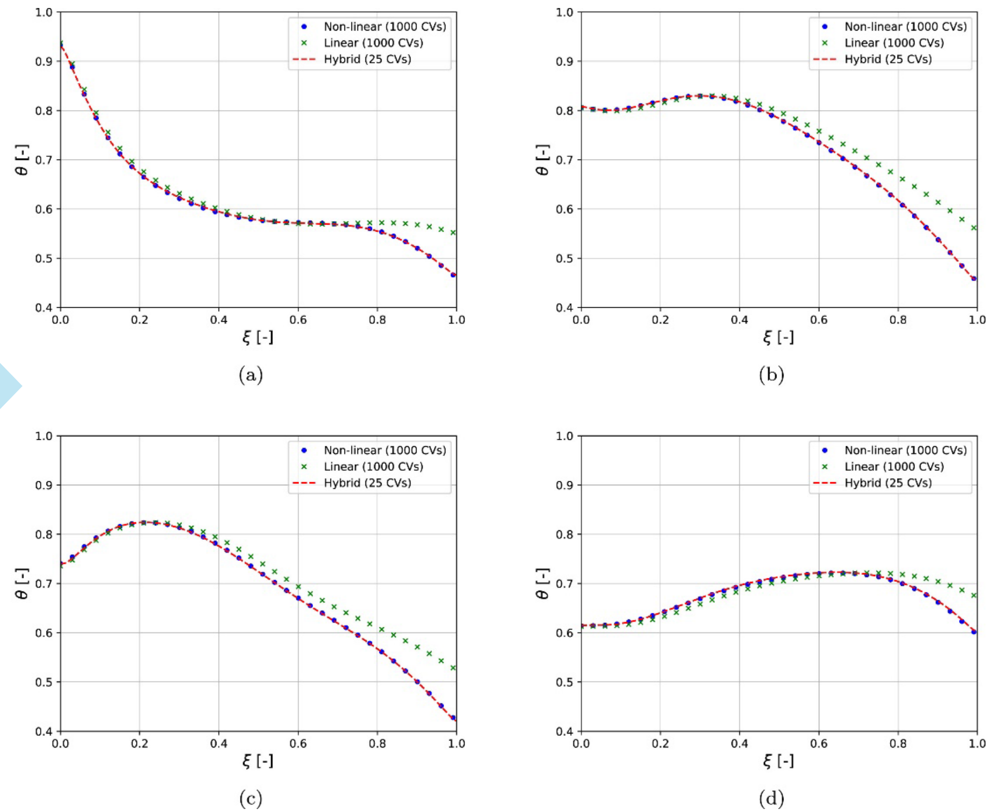
General structure of the hybrid model

4. Shri Balaji Padmanabhan, Mohamed Tahar Mabrouk, Bruno Lacarrière, A hybrid model for packed bed thermal energy storage system, Journal of Energy Storage, Volume 98, Part B, 2024, 113068

Ongoing studies

Hybrid models for heat storage technologies: Sensible heat storage[4]





Input sequences for Validation Simulation 1
(a) Inlet fluid temperature, (b) Inlet fluid mass flow rate

Input sequences for Validation Simulation 1
(a) Inlet fluid temperature, (b) Inlet fluid mass flow rate

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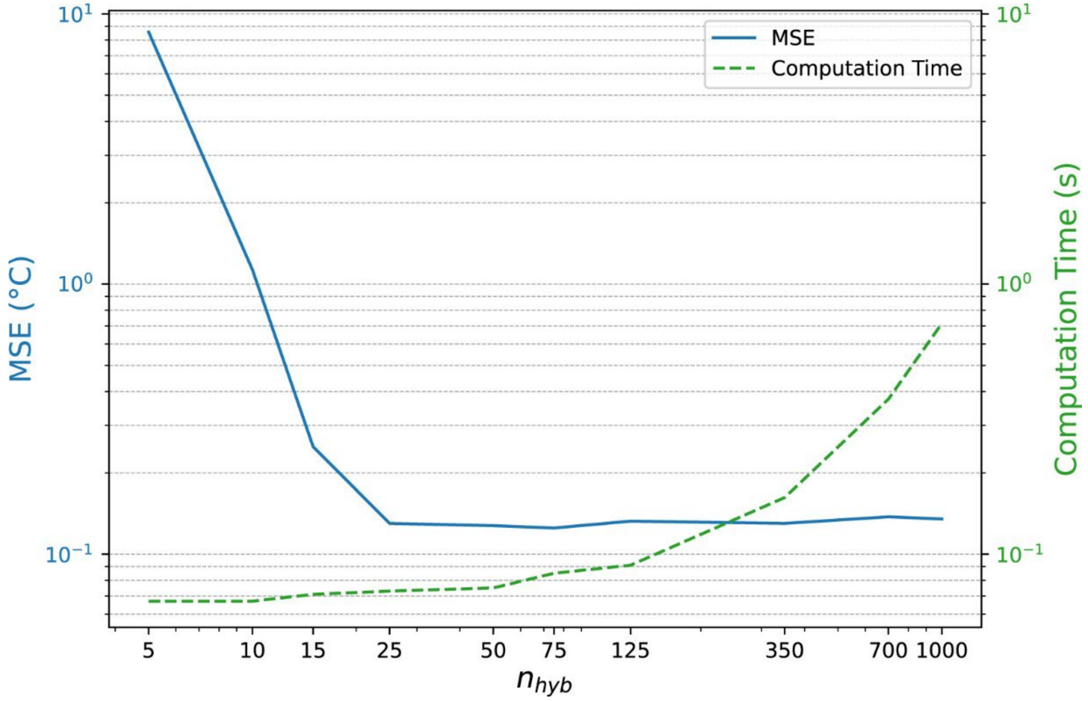
[4] Shri Balaji Padmanabhan, Mohamed Tahar Mabrouk, Bruno Lacarrière, A hybrid model for packed bed thermal energy storage system, Journal of Energy Storage, Volume 98, Part B, 2024, 113068

Ongoing studies

Hybrid models for heat storage technologies: Sensible heat storage[4]

Effect of the hybrid model's coarseness on the performance (time and accuracy)



~350X

acceleration

on the test sequences

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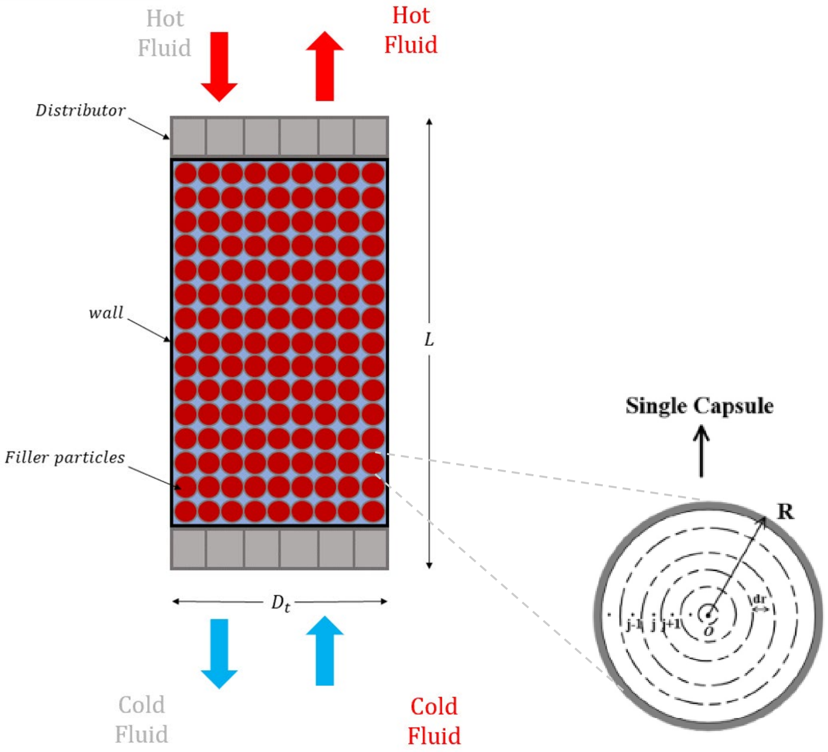
4. Shri Balaji Padmanabhan, Mohamed Tahar Mabrouk, Bruno Lacarrière, A hybrid model for packed bed thermal energy storage system, Journal of Energy Storage, Volume 98, Part B, 2024, 113068

Ongoing studies

Hybrid models for heat storage technologies: latent heat storage[5]

General layout



Porous medium:
Paraffin encapsulated in metallic spheres
Fluid medium: Therminol 66

Concentric dispersion model

High-fidelity model

$$\epsilon(\rho C_p)_f \frac{\partial T_f}{\partial t} + \epsilon(\rho C_p)_f U \frac{\partial T_f}{\partial z} = \frac{\partial}{\partial z}\left(k_f \frac{\partial T_f}{\partial z}\right) + h_v(T_p - T_f) - H(T_f - T_{ext}) \quad \text{(fluid)}$$

$$\rho_p \frac{\partial h_p}{\partial t} = k_p \left(\frac{\partial^2 T_p}{\partial z^2} + \frac{2}{r}\frac{\partial T_p}{\partial z}\right) \quad \text{(PCM)}$$

Continuous-solid phase model

Low-fidelity model

$$\epsilon(\rho C_p)_f \frac{\partial T_f}{\partial t} + \epsilon(\rho C_p)_f U \frac{\partial T_f}{\partial z} = \frac{\partial}{\partial z}\left(k_f \frac{\partial T_f}{\partial z}\right) + h_v(T_p - T_f) - H(T_f - T_{ext}) \quad \text{(fluid)}$$

$$\rho_p \frac{\partial h_p}{\partial t} = -h_v(T_p - T_f) \quad \text{(PCM)}$$

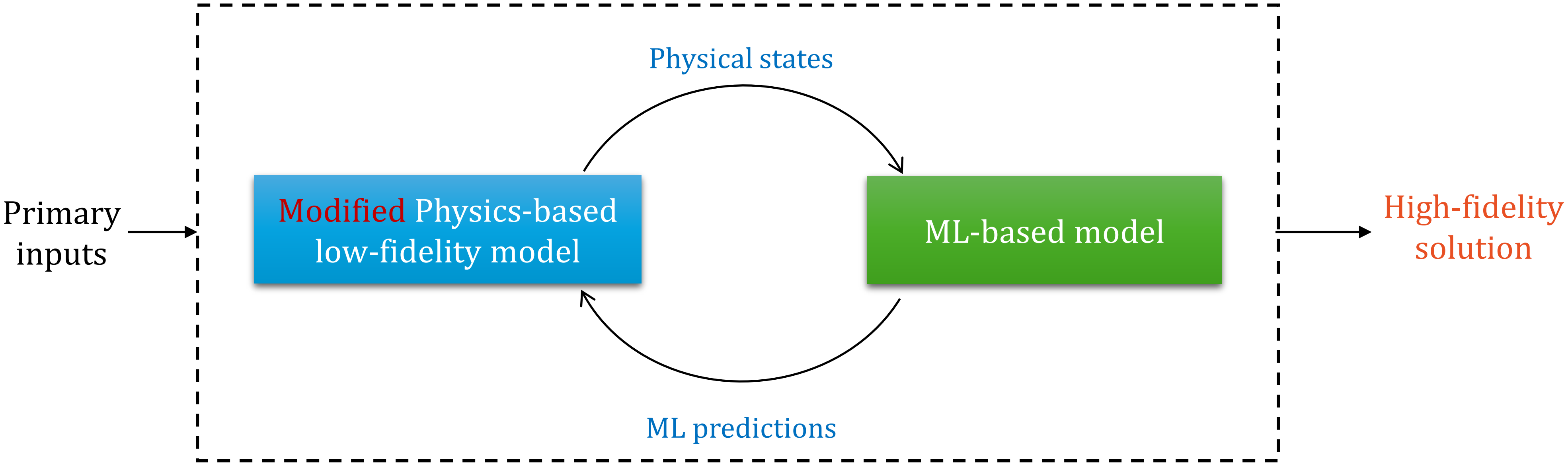
---

5. Dessie Tadele Ayele, Mohamed Tahar Mabrouk, Stéphane Grieu, Bruno Lacarriere, A neural accelerated numerical model for a packed bed latent heat storage system, submitted

Ongoing studies

Hybrid models for heat storage technologies: latent heat storage[5]

General structure of the hybrid model



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Ongoing studies

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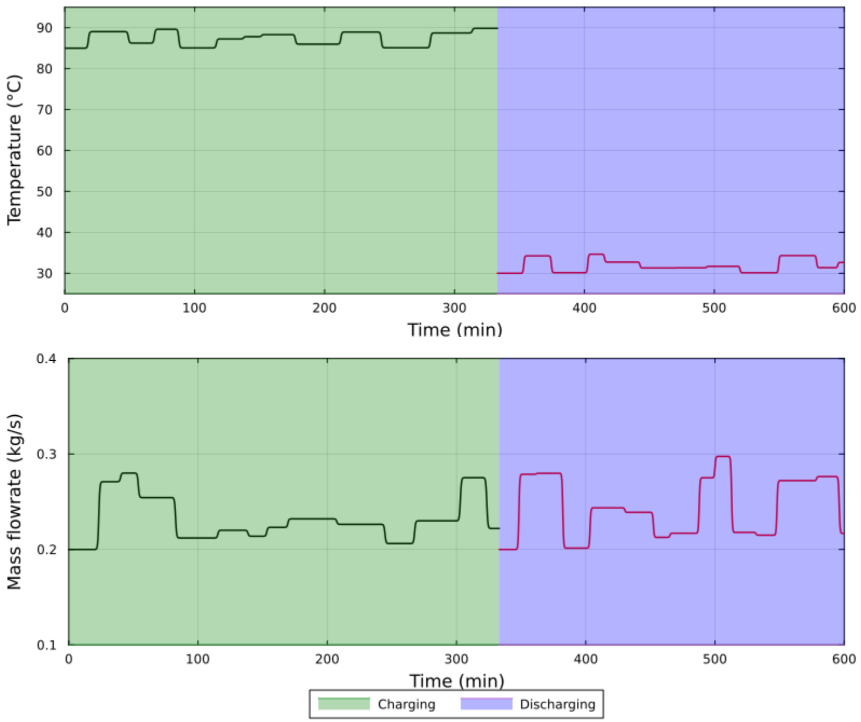

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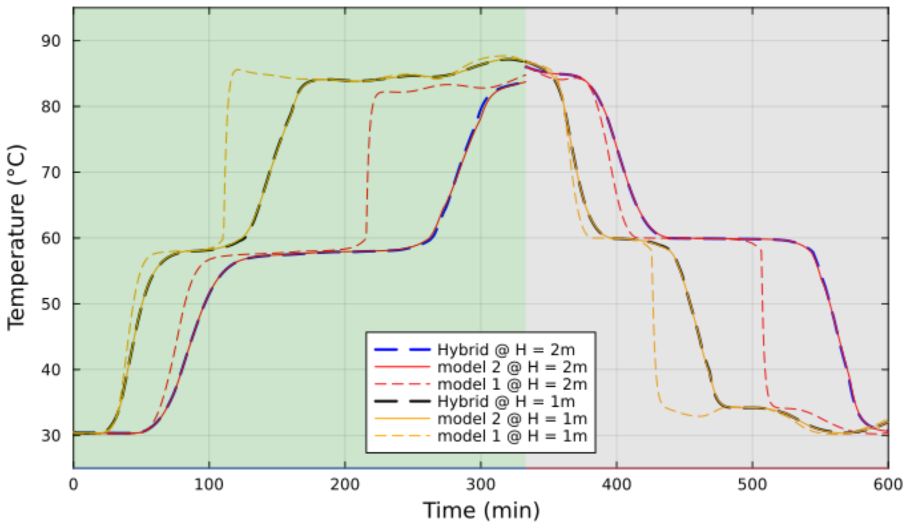

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Ongoing studies

Hybrid models for heat storage technologies: latent heat storage[5]

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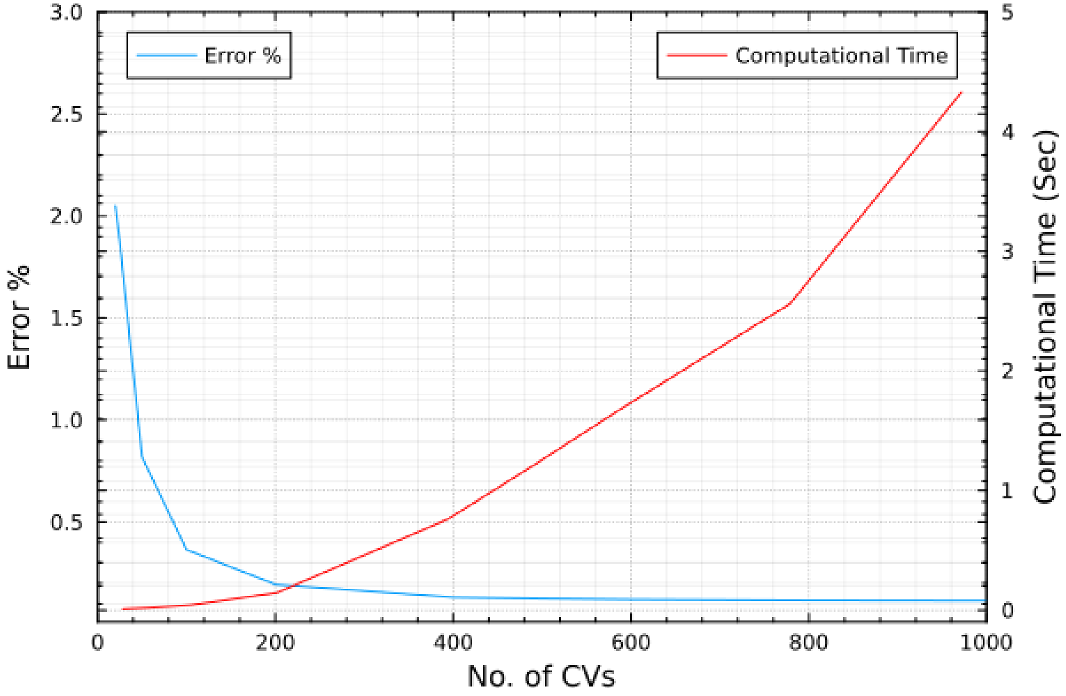

~750X

acceleration

on the test sequences

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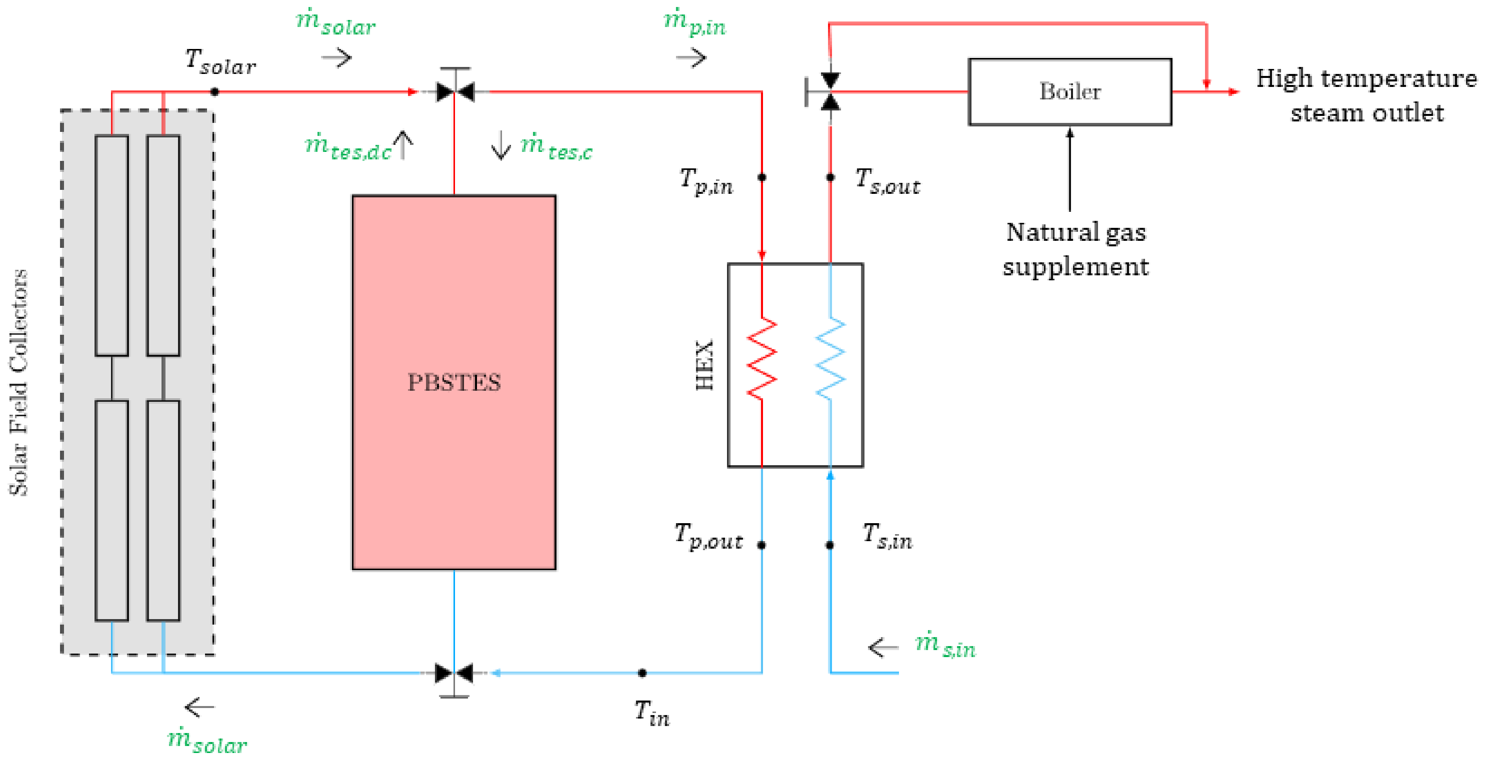
Ongoing studies

Hybrid models for optimal operation: sensible heat storage optimal operation

Use case general layout

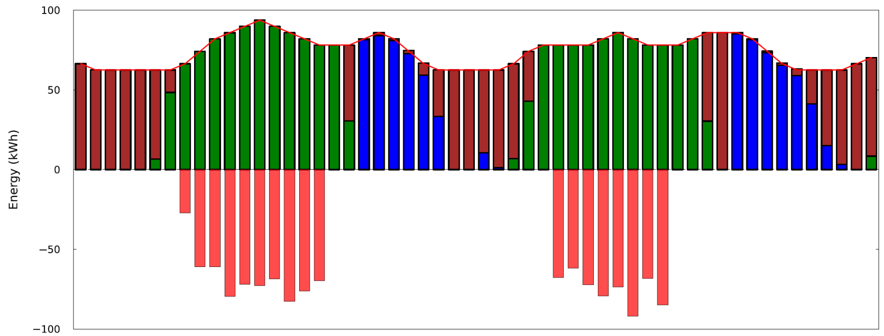


Ongoing studies

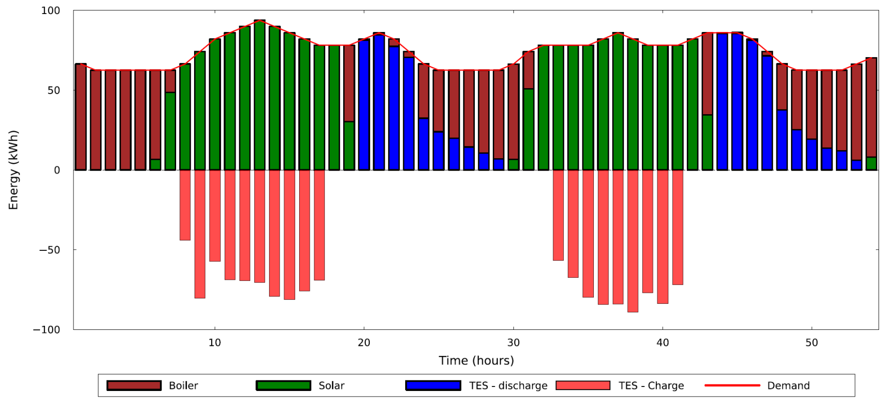
Hybrid models for optimal operation: sensible heat storage optimal operation

Optimal energy dispatch (2 days)

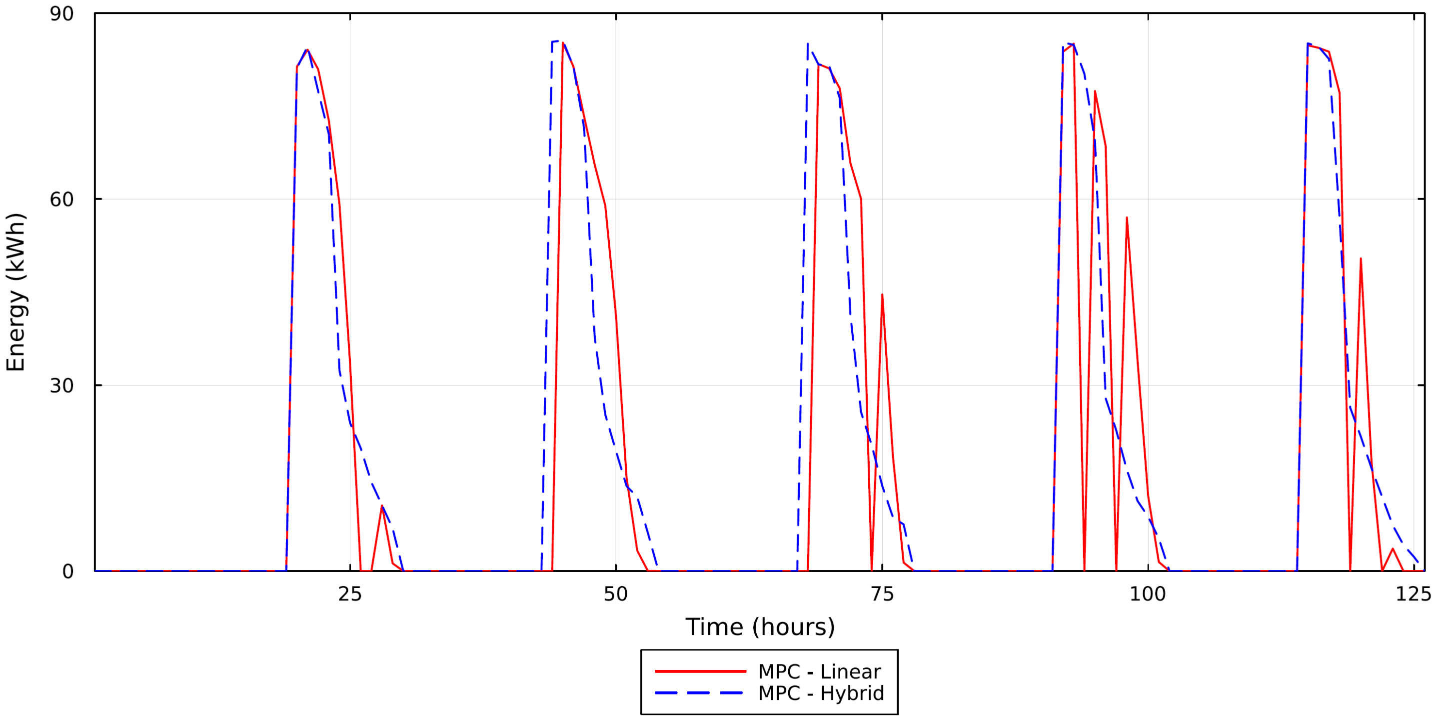
(a) MPC - Linear



(b) MPC - Hybrid



Energy discharge (5 days)



Conclusions

Hybrid modelling concept

Old concept but evolving towards more intricated modelling

Hybrid modelling for model reduction and acceleration

- Proven to be very efficient to adapt detailed models for real time decision.

- Applied with success to different energy systems: Heat storage (sensible, latent) but many others too (heat pumps, district heating networks, power grids).

- Substantial model acceleration: from 300X to 10,000X

Decision making

Suitability for real-time optimal operation is demonstrated

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RÉPUBLIQUE
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THANK YOU

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