ETH zürich

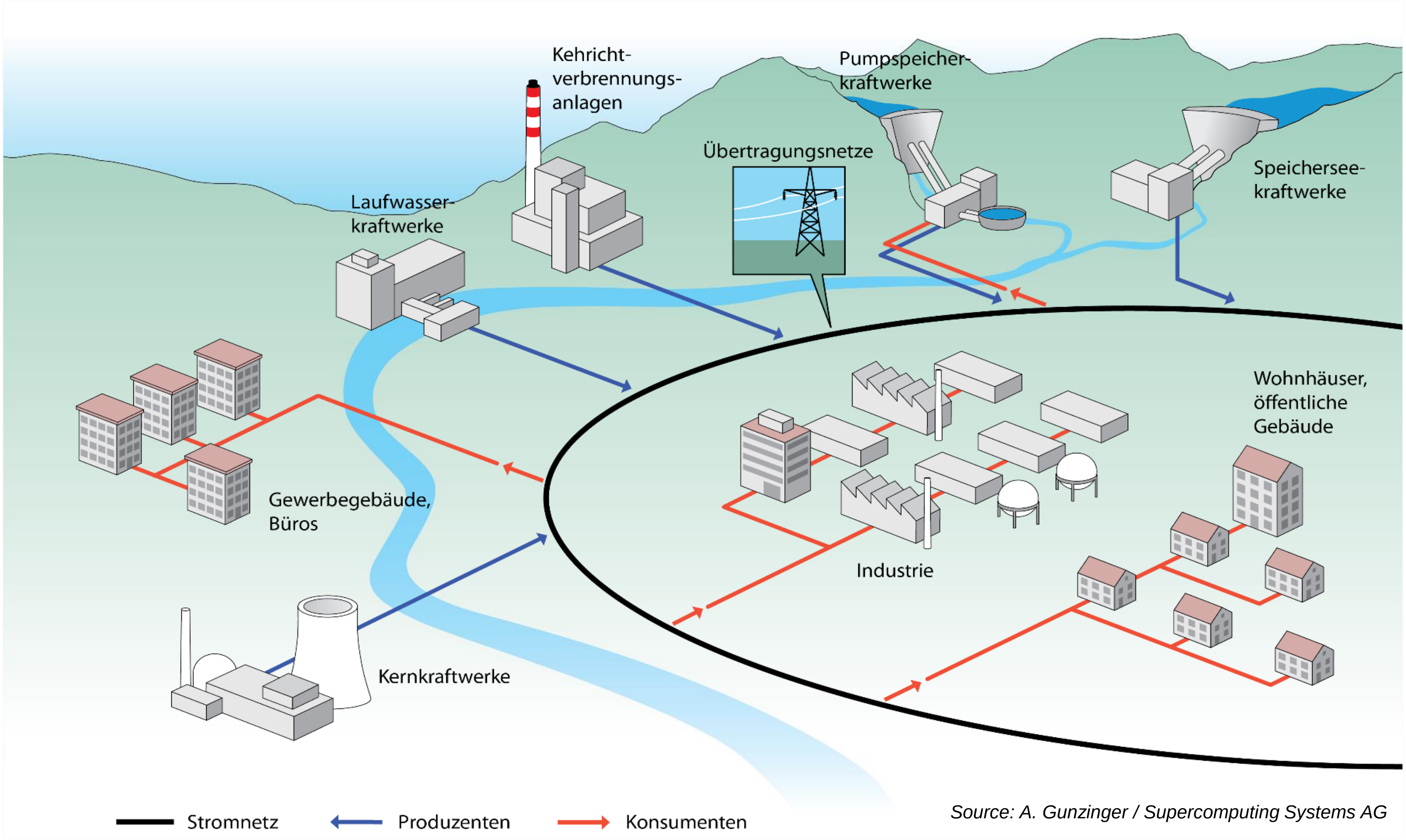
D-MAVT

Design of integrated multi-energy systems with novel conversion technologies and seasonal storage

Paolo Gabrielli, Matteo Gazzani, Marco Mazzotti

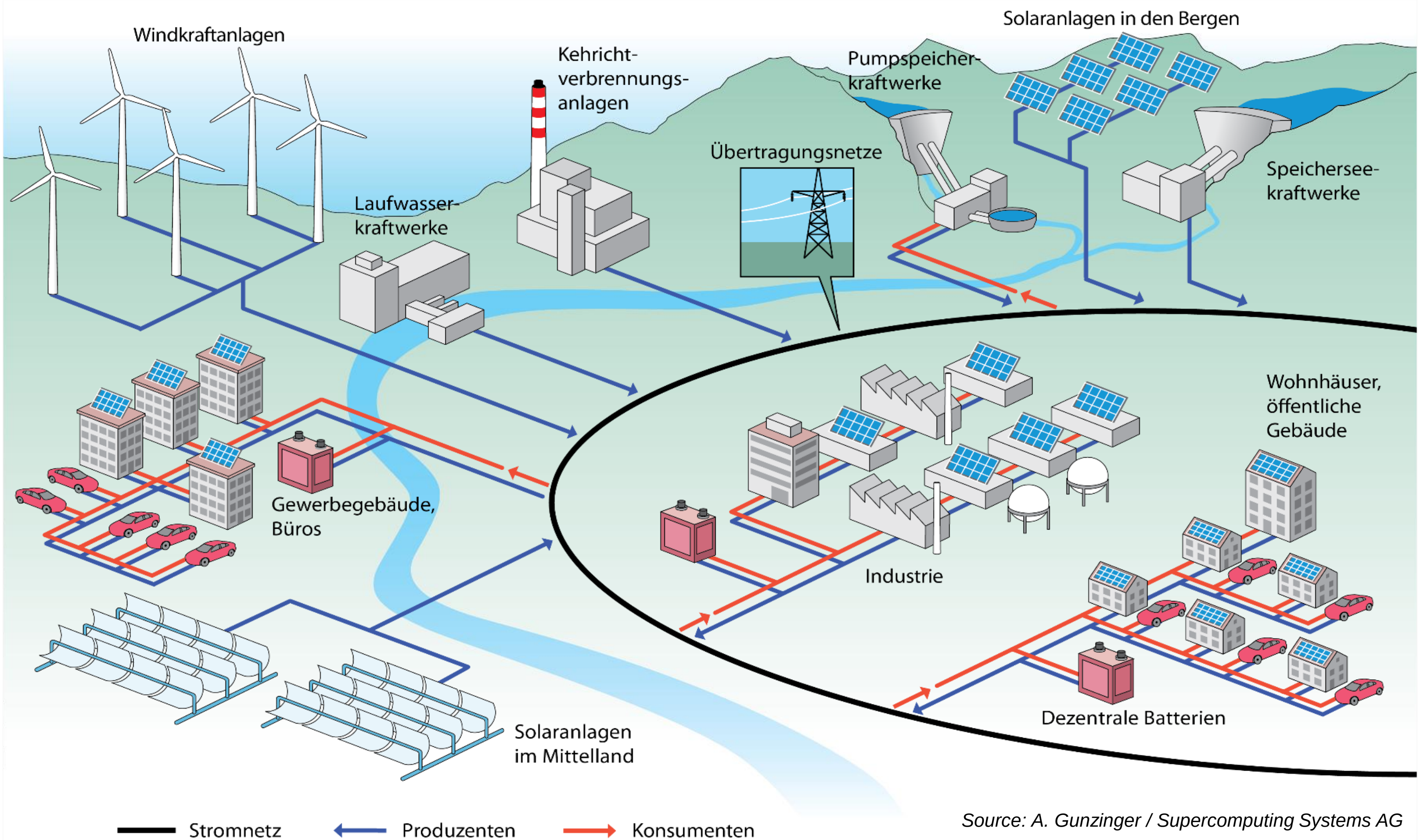
Separation Process Laboratory - Institute of Process Engineering

Motivation: from centralized energy generation ...



Source: A. Gunzinger / Supercomputing Systems AG

… to decentralized energy generation



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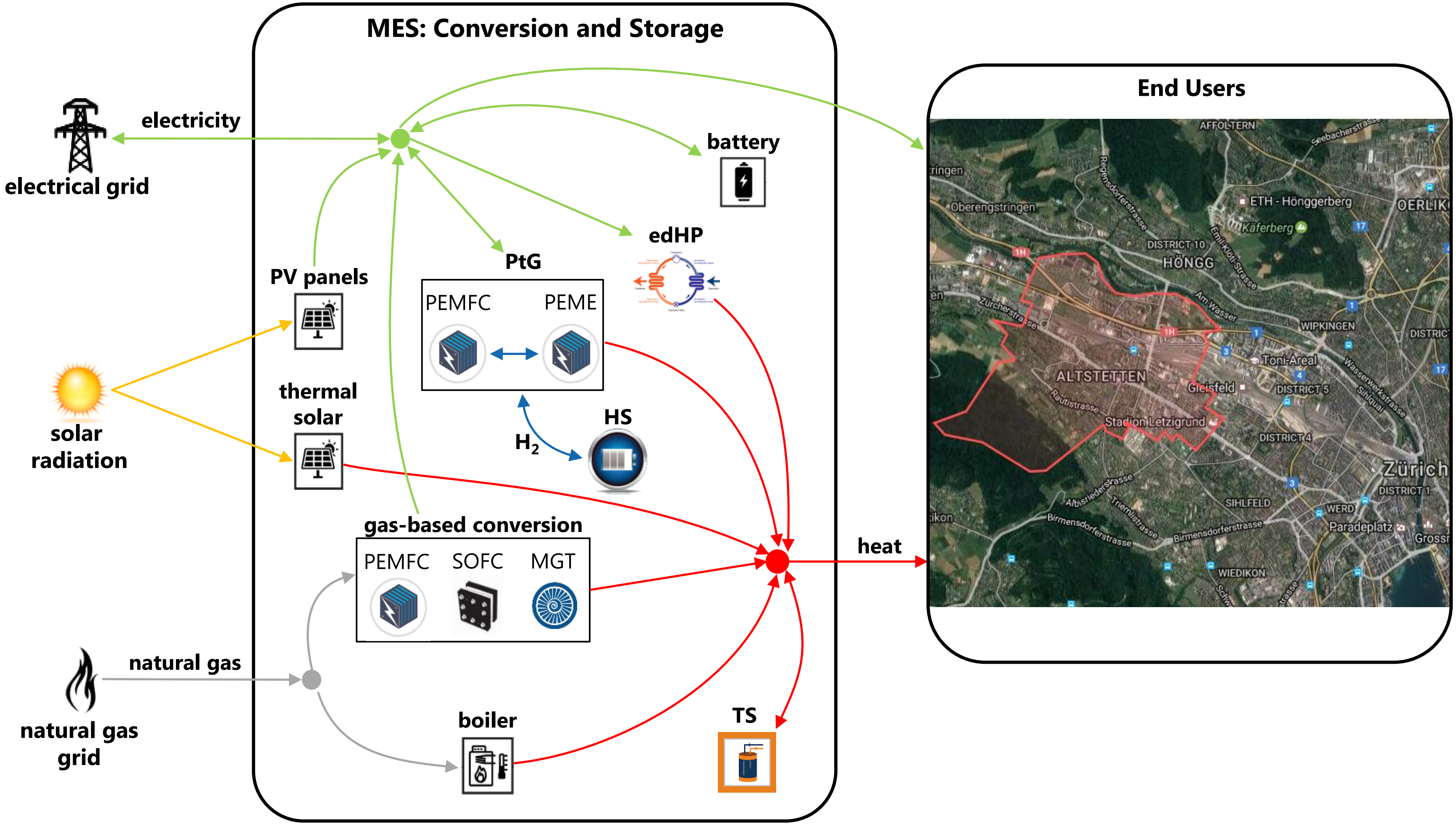
What is a multi-energy system (MES)

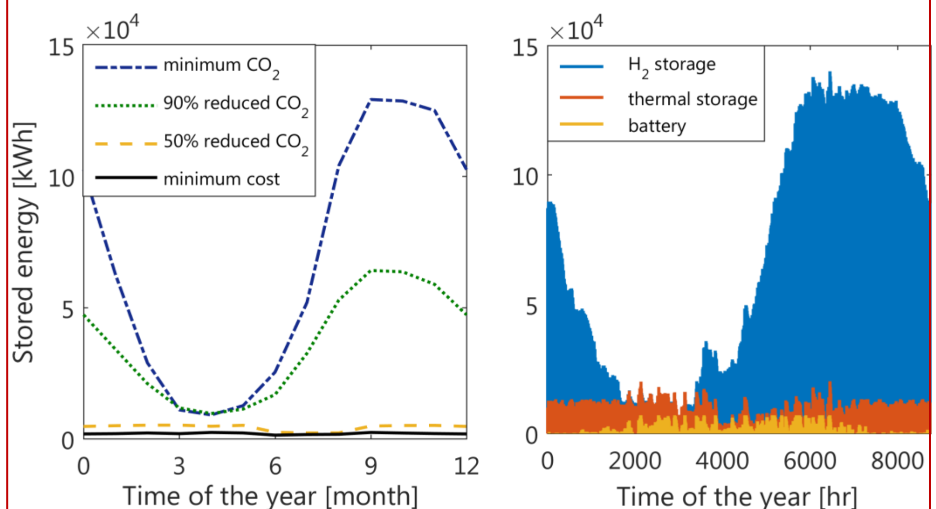


Main goal: design and analysis of MES with novel conversion technologies and seasonal storage

Conversion technologies

- Current approaches perform the design of integrated MES with a quite simplified description of the conversion technologies
- We want to provide more realistic models for such technologies within the design of MES

Seasonal storage



- Current approaches do not allow to consider the seasonal operation of complex multi-energy systems
- We want to enable the design and analysis of complex MES including seasonal storage with low computational complexity

Agenda

1. Modeling of fuel cell and electrolyzer devices
   a. Thermodynamic models
   b. Linear approximation methods

2. Formulation of the optimization problem
   a. Proposed methods for designing long-term storage systems
   b. Methods validation

3. Application of the proposed framework to design and analysis of integrated MES

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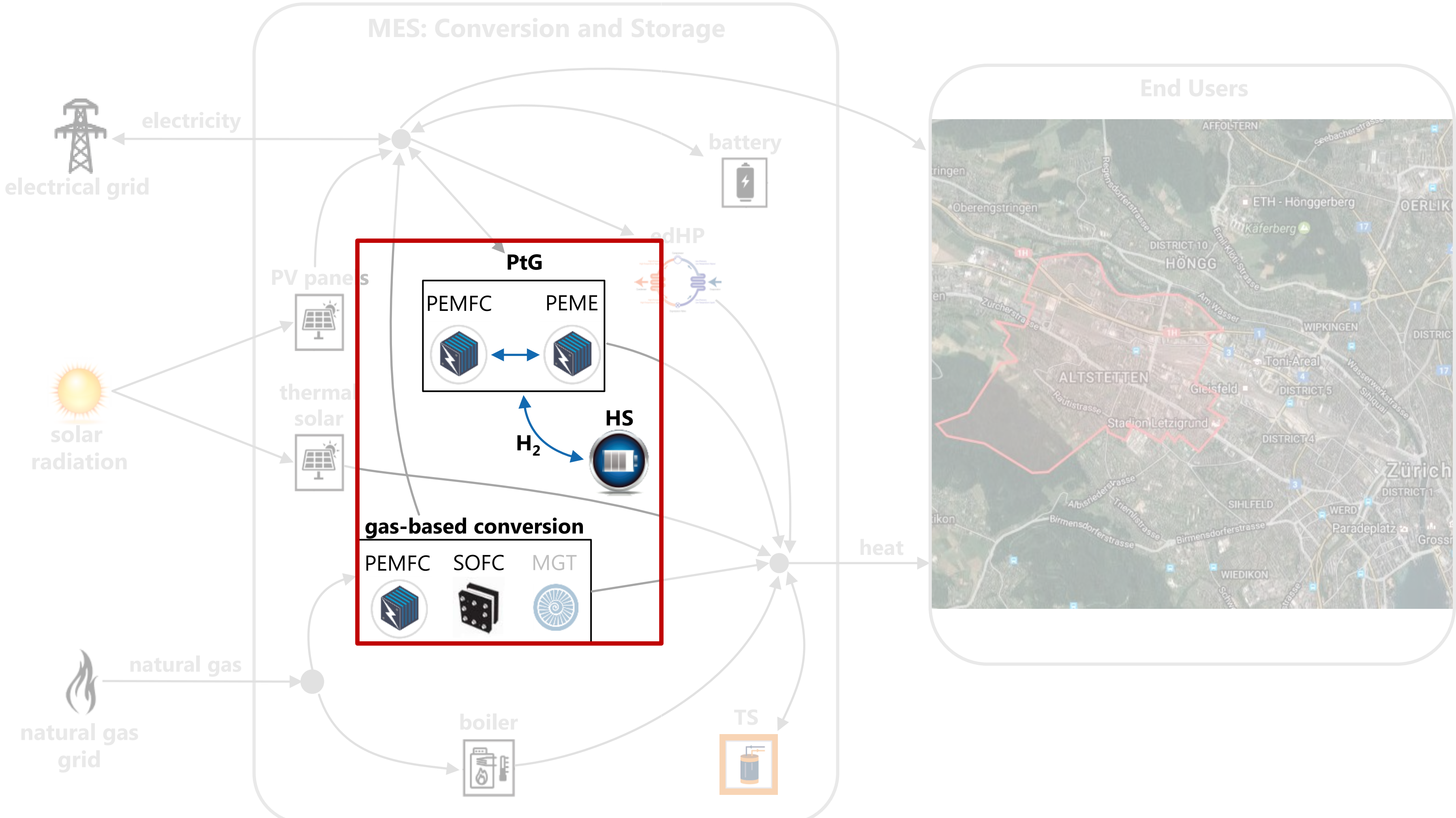
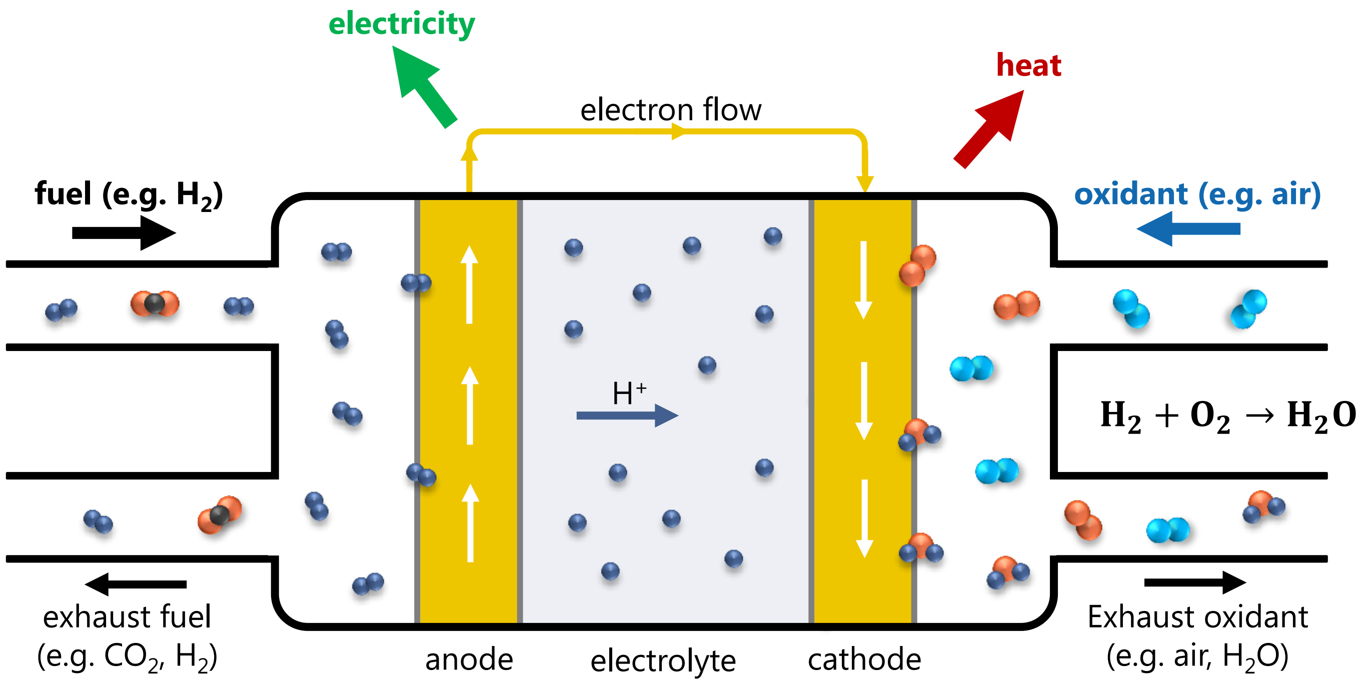
Modeling electrochemical conversion devices



Electrochemical conversion devices: Fuel cells

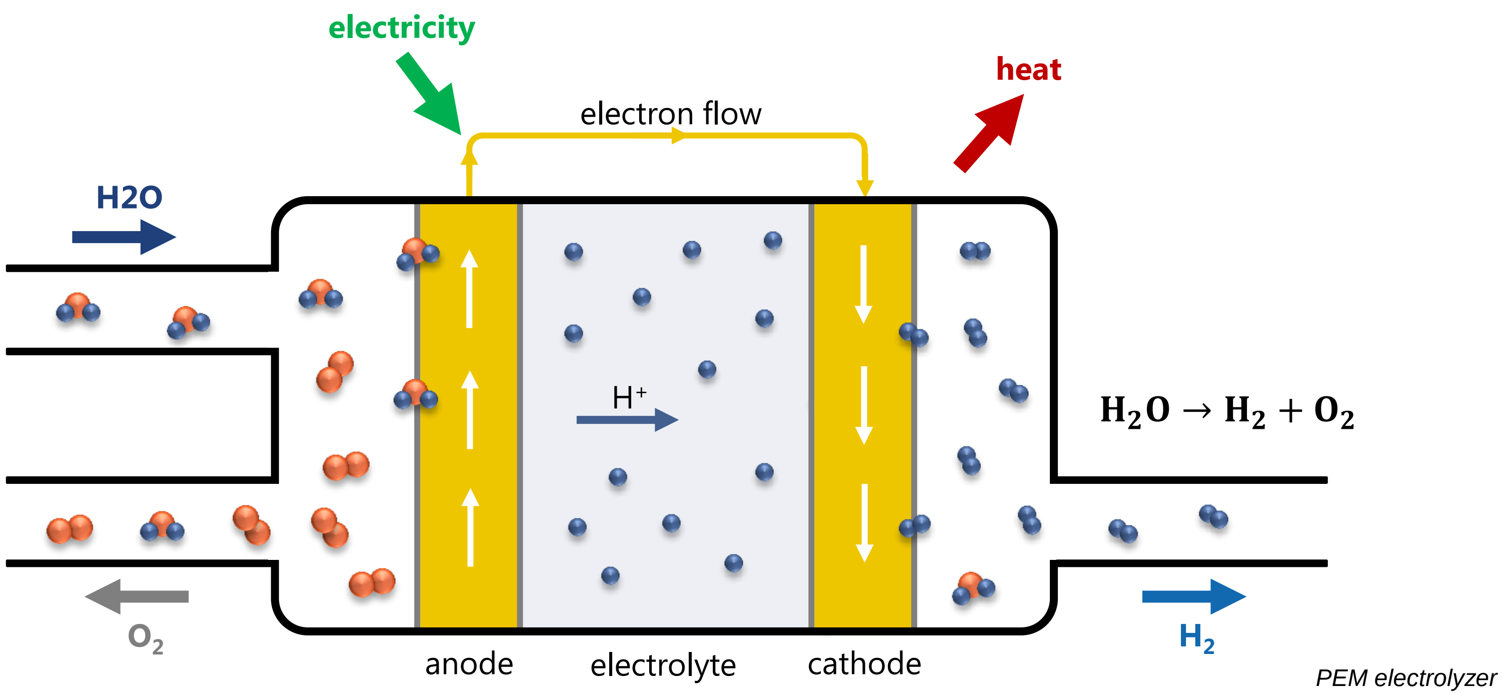


PEM fuel cell, external methane reforming

Fuel cells (FCs) are electrochemical devices that simultaneously generate electricity and heat through the electrochemical reaction of a fuel (e.g. H_2 or natural gas) with an oxidant (e.g. O_2 or air).

Various types of FCs are considered: NG-SOFC, NG-PEMFC, H_2-PEMFC

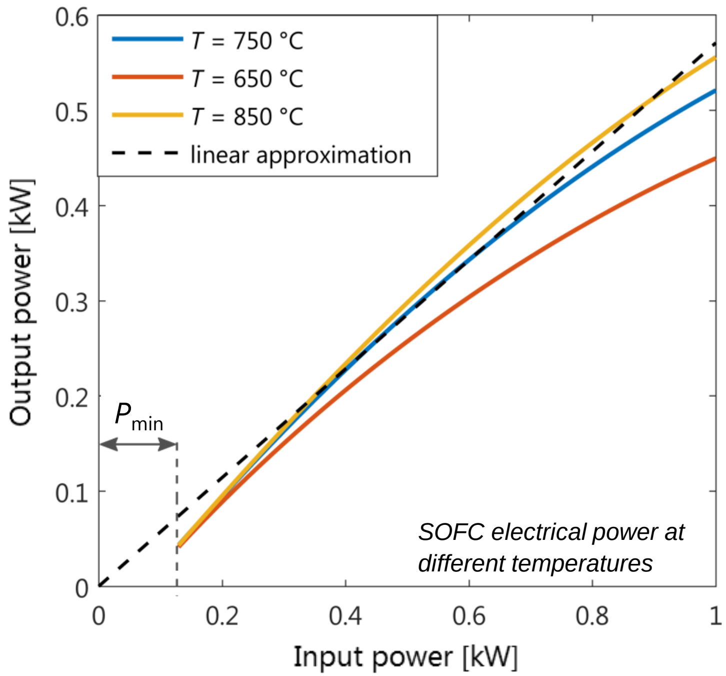
Electrochemical conversion devices: Electrolyzers

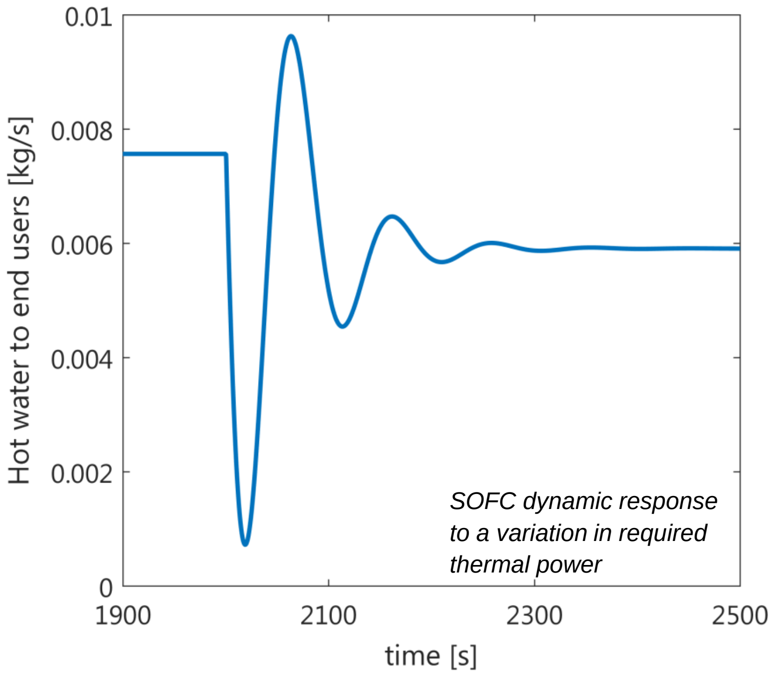


Electrolyzers are electrochemical devices that generate hydrogen and oxygen by absorbing electricity through the splitting of deionized water.

High pressure PEM electrolyzers are considered, generating H_2 and O_2 at 40 bar.

Why first-principle models and how to use them

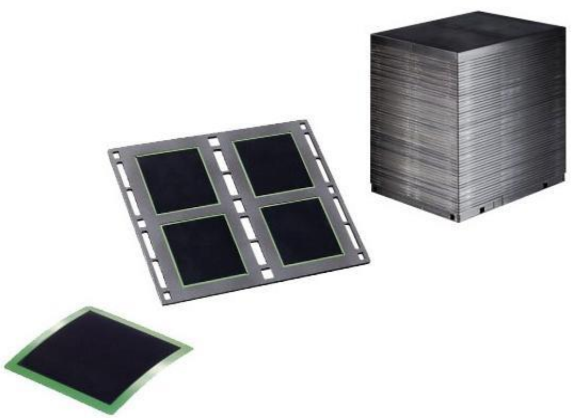


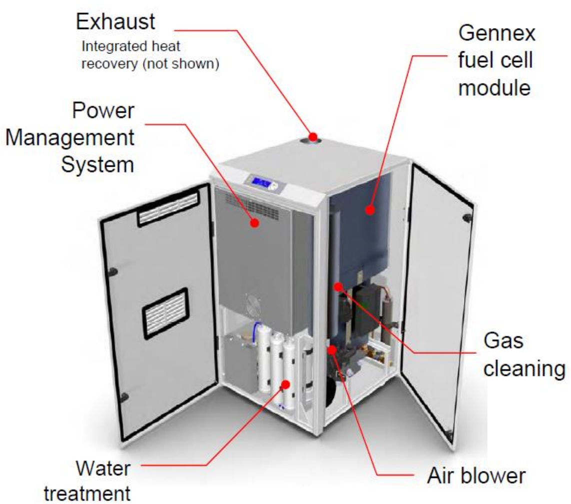


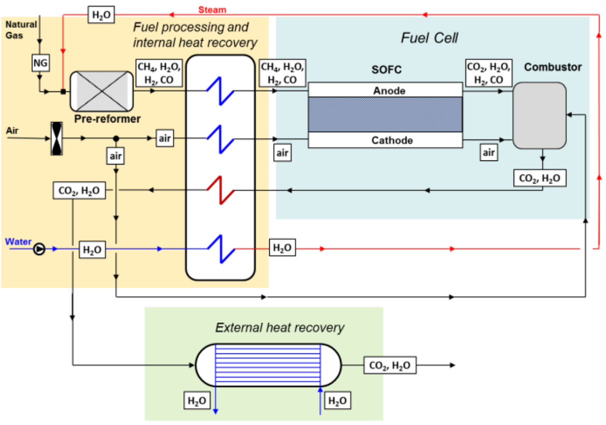
- Thermodynamic first-principle models are used to describe the nonlinear conversion performance and the dynamic features of the conversion technologies
- Computationally efficient approximations suitable for optimization framework

Modeling methodology

CELL STACK	ENTIRE PRODUCT	ENTIRE PRODUCT
Electrochemical model to describe cell performance	Energy and mass balances to describe the overall conversion performance	dynamic modeling to describe the overall transient behavior
MATLAB	ASPEN	SIMULINK







Modeling methodology

CELL STACK

Electrochemical model to describe cell performance

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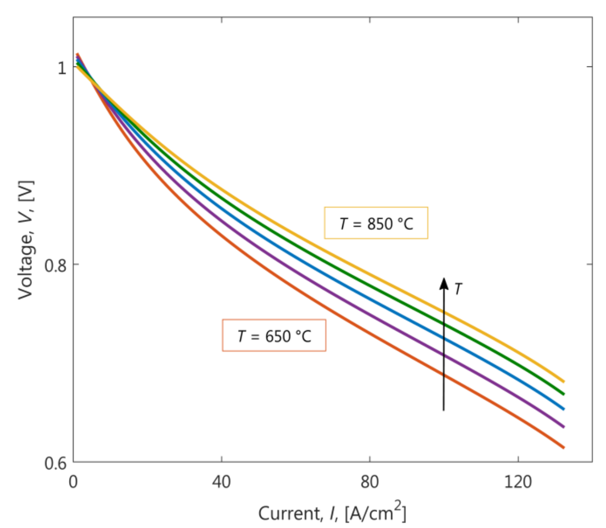

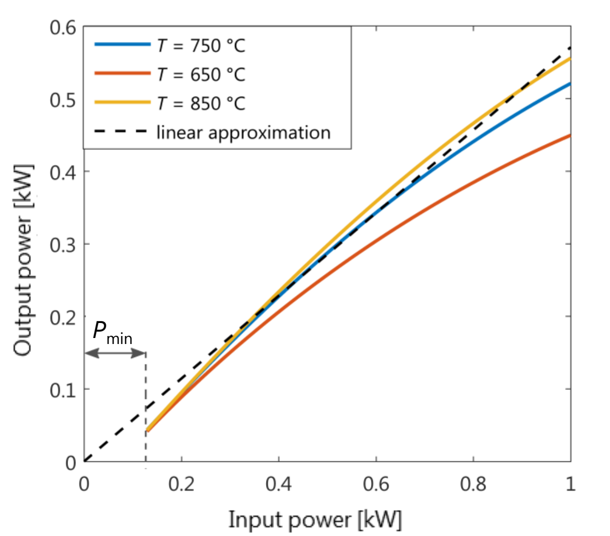

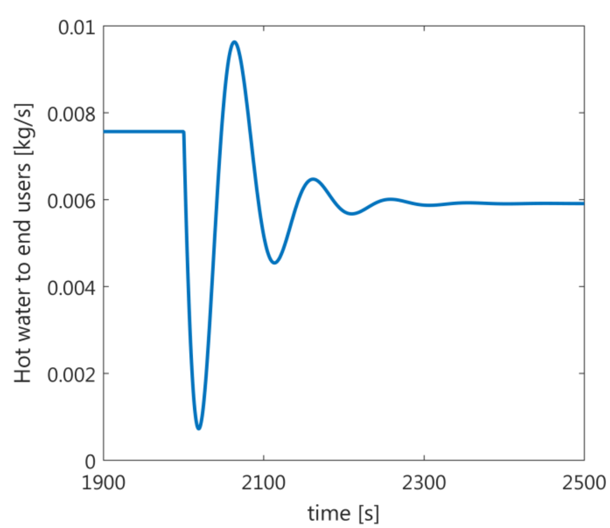

Modeling methodology

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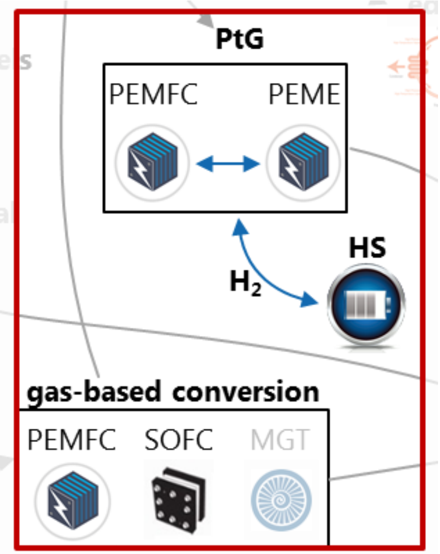
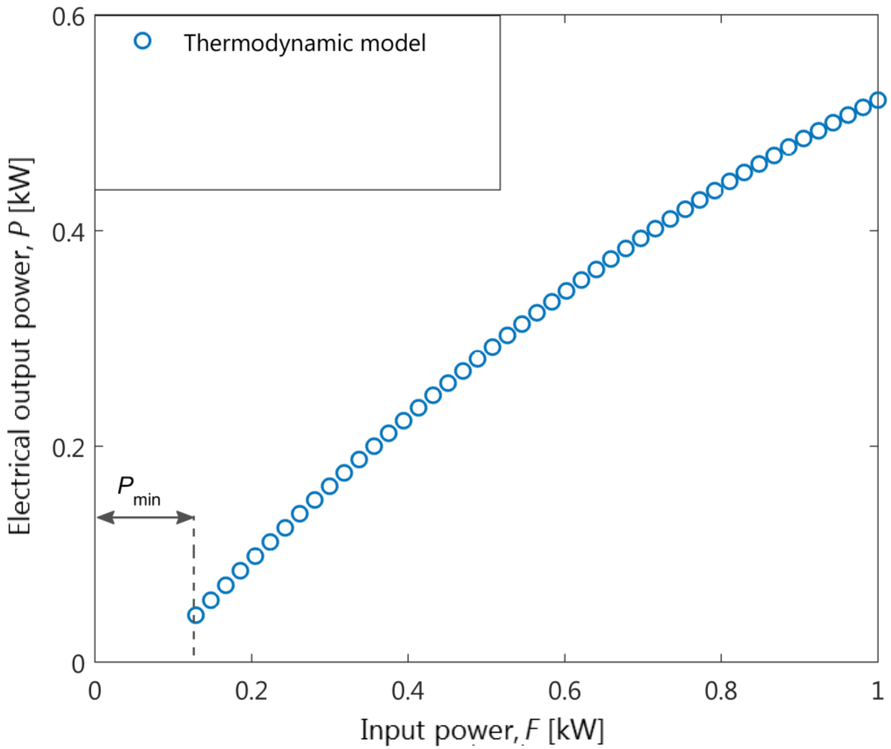
- Solid oxide fuel cell (SOFC) using natural gas and air
- Proton exchange membrane (PEM) fuel cell using natural gas and air
- PEM fuel cell using hydrogen and air
- PEM electrolyzer generating hydrogen and oxygen

Power to gas

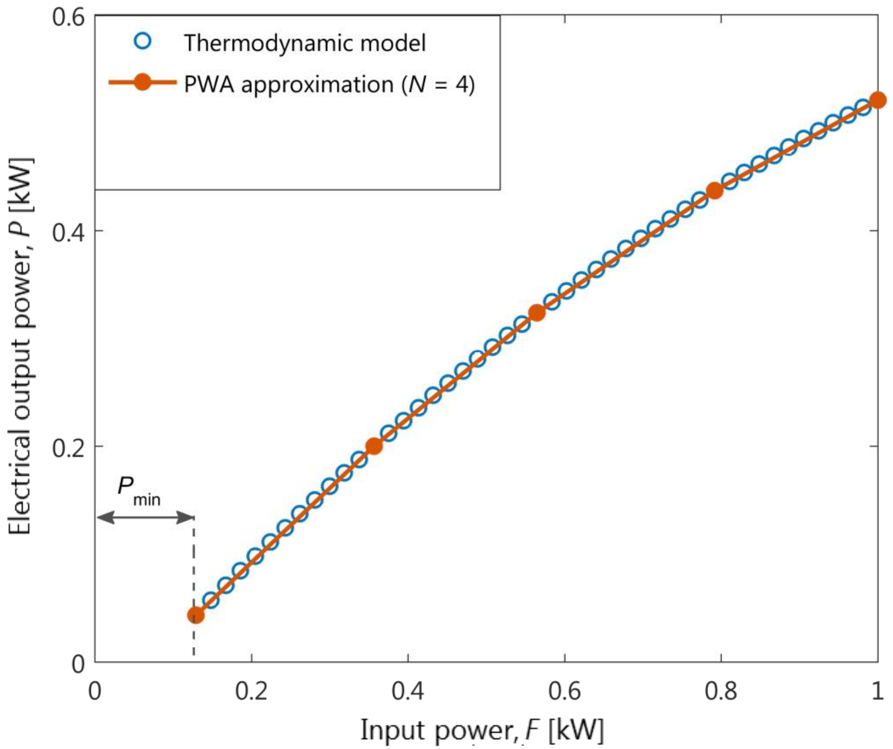


Linear approximation: conversion performance



- Steady-state behavior of conversion performance
- Conversion performance at reference conditions
- The thermodynamic model needs to be linearized to be used in an optimization framework

Linear approximation: conversion performance



Piecewise affine (PWA) approximation

$$P \leq \alpha_i F + \beta_i S + \gamma_i,$$

$$\forall i = 1, \dots, N$$

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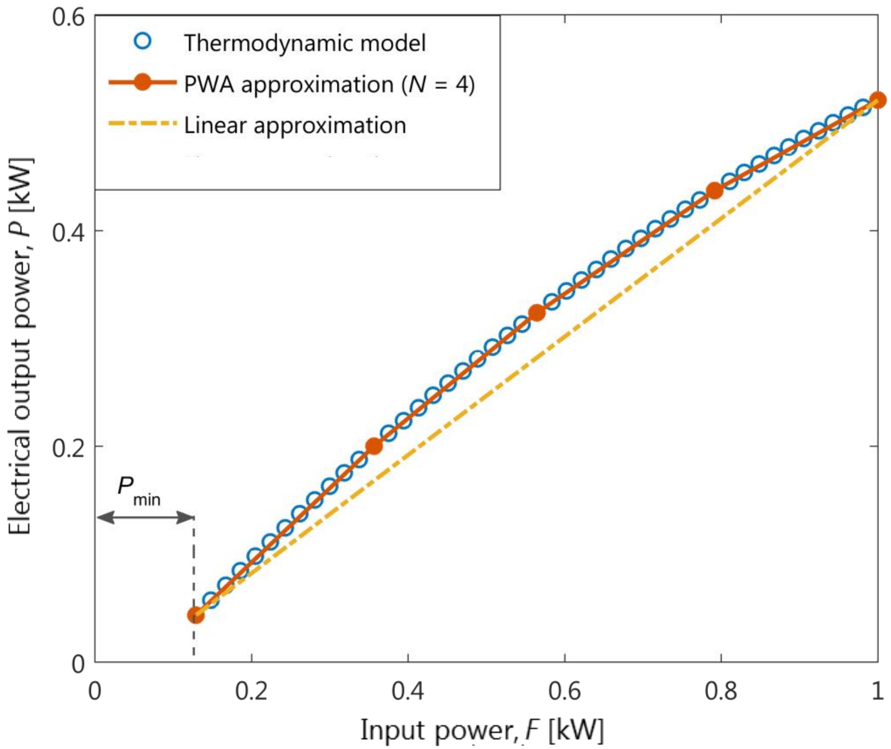
Linear approximation: conversion performance



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Piecewise affine (PWA) approximation

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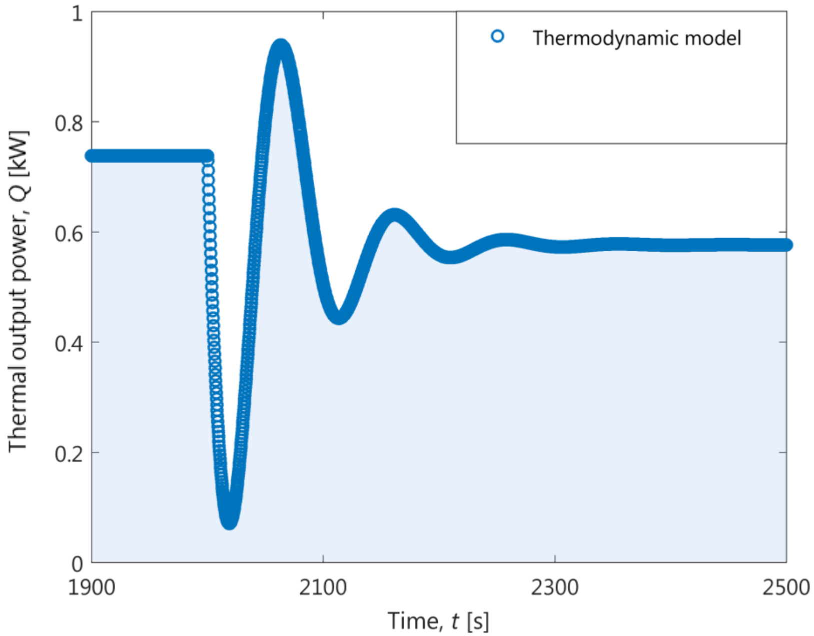
Affine approximation

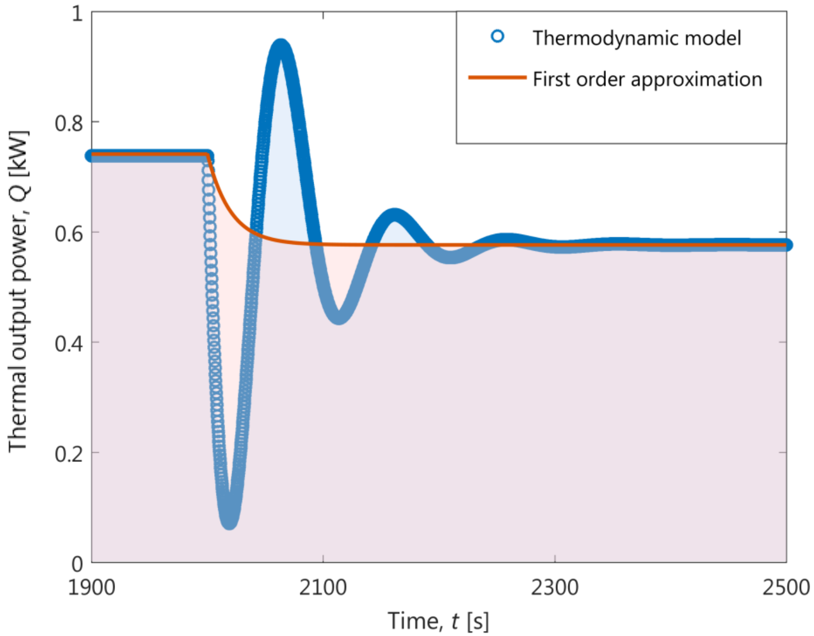
$$P = \alpha F + \beta S + \gamma$$

Linear approximation: dynamic behavior



- Dynamic behavior of the conversion performance

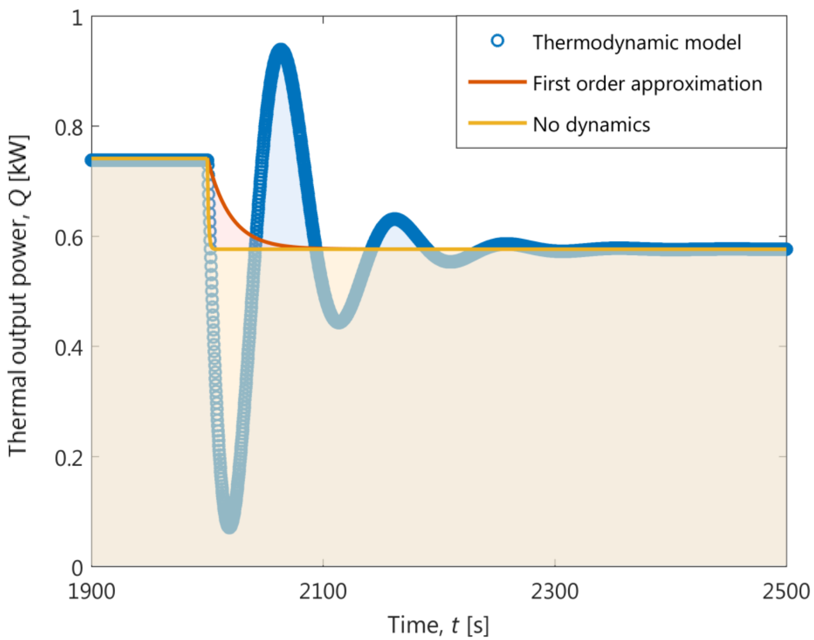
Linear approximation: dynamic behavior



- Dynamic behavior of the conversion performance
- First order approximation of the generated power:

$$\frac{\mathrm{d}Q(t)}{\mathrm{d}t} = \alpha Q(t) + \beta$$

Linear approximation: dynamic behavior



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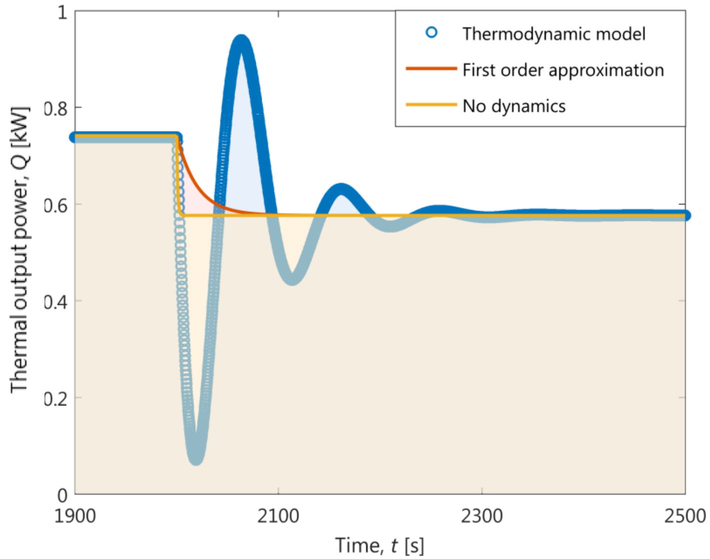

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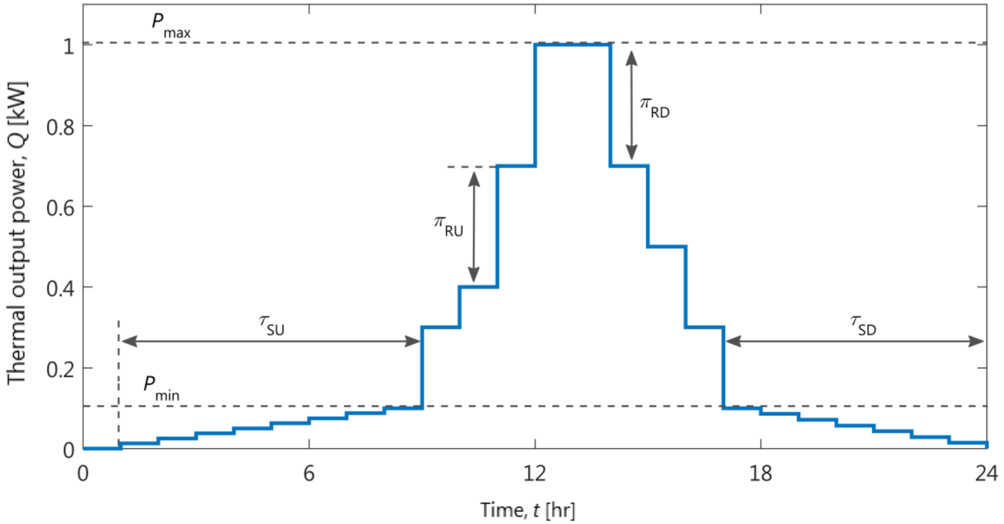
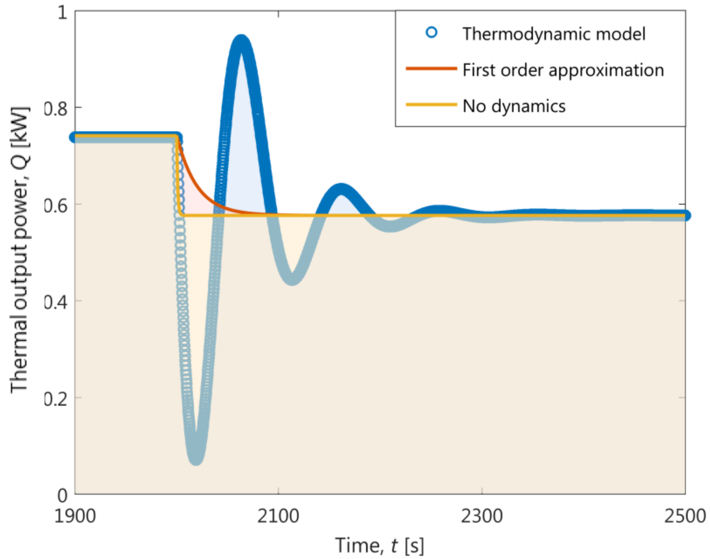


Literature data:

- Start-up and shut-down times
- Ramp-up and ramp-down limitations

In the form of constraints suitable for an optimization framework

Linear approximation: dynamic behavior



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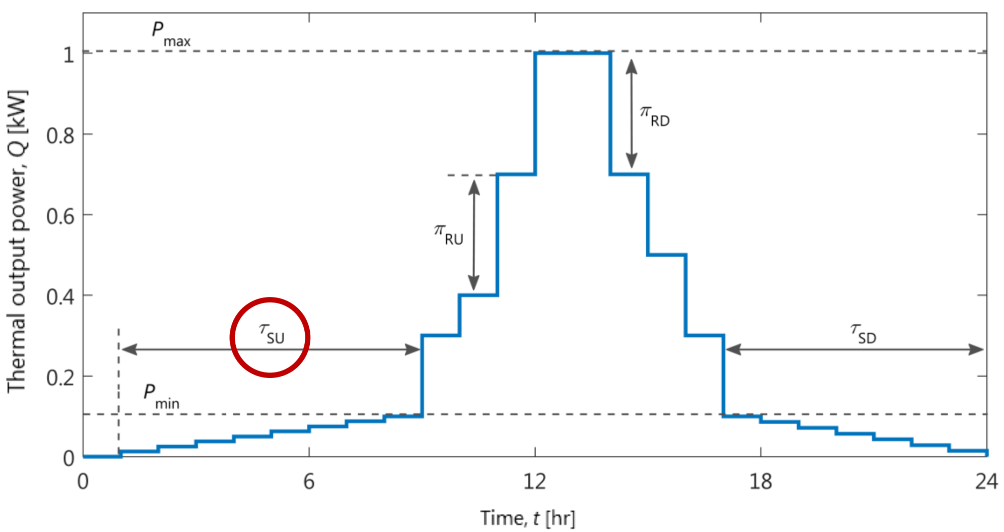

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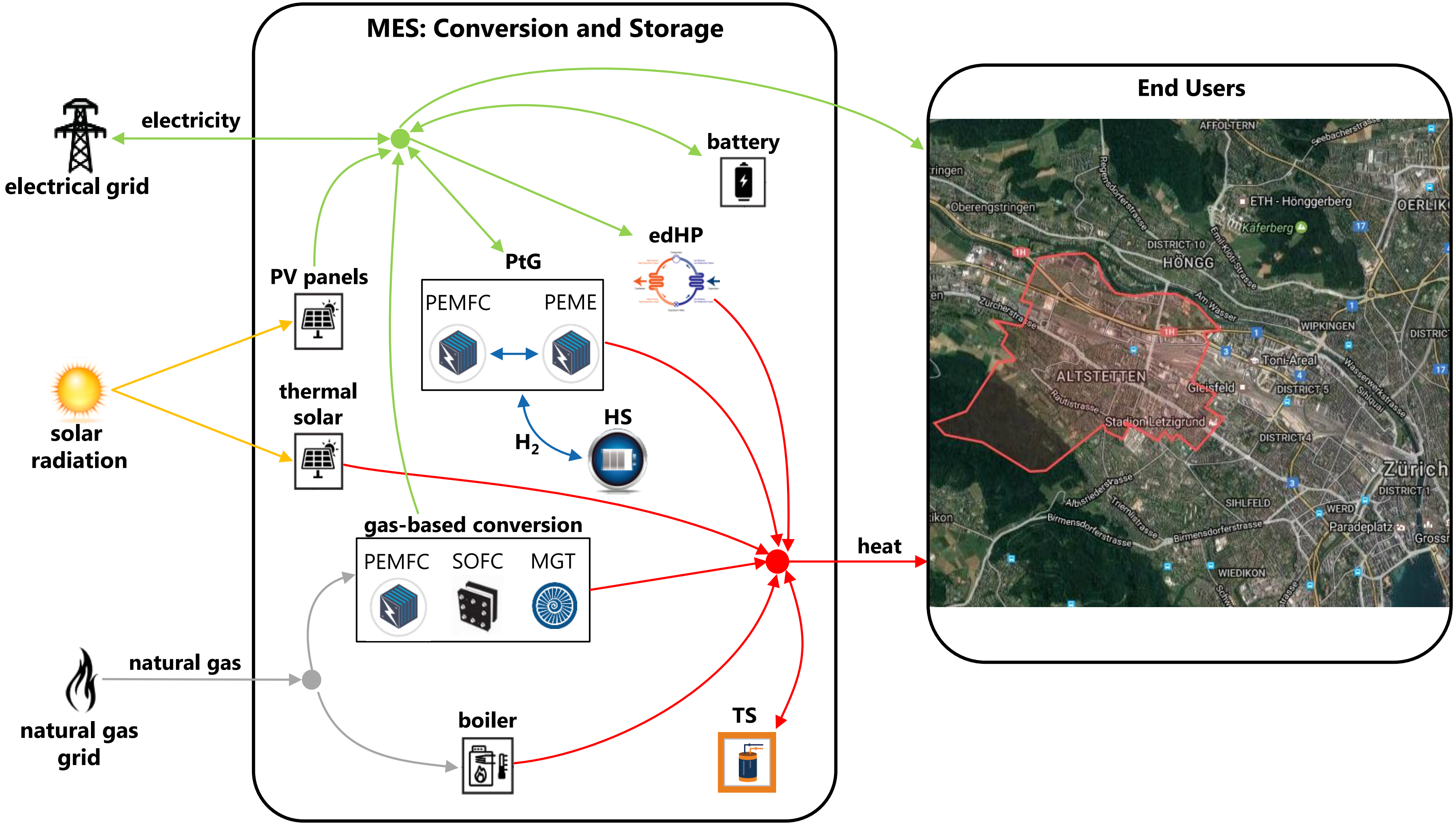
Optimal design of the multi-energy system



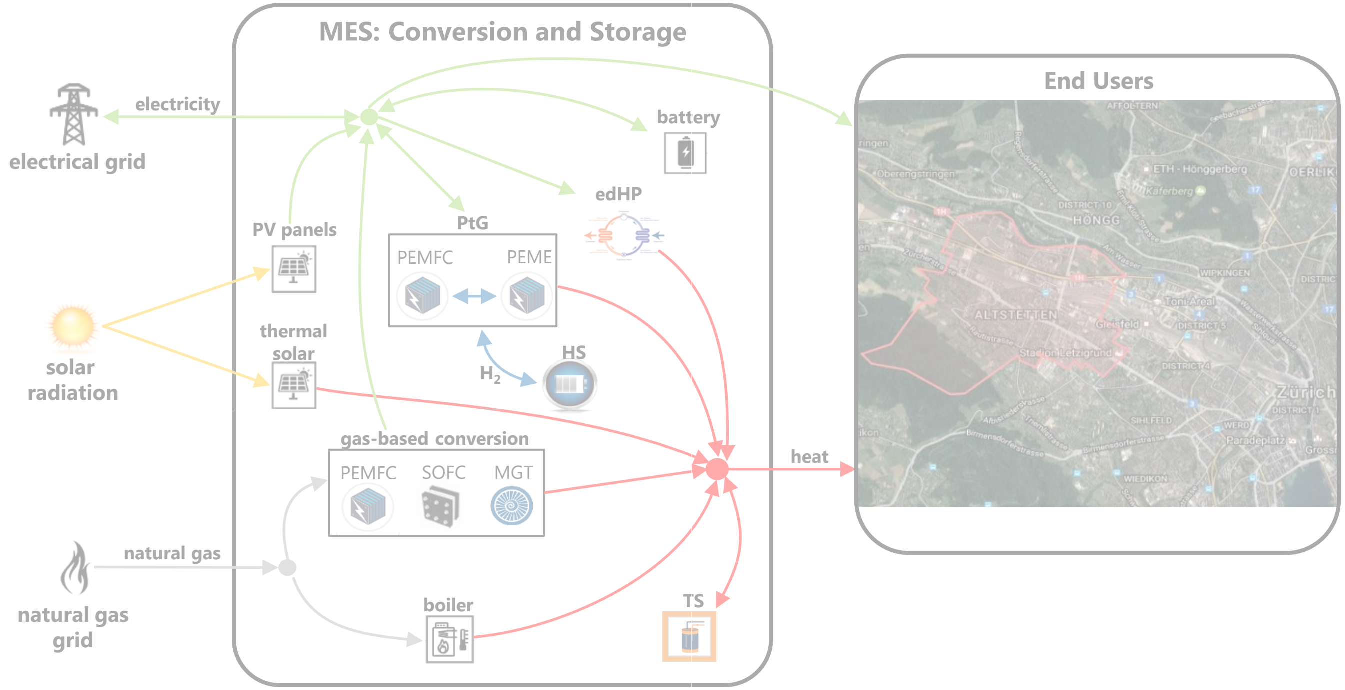
Optimization prob: mixed integer linear program

$$\min_{x,y} \left(c^T x + d^T y\right)$$

subject to

$$Ax + By = b$$

$$x \geq 0, y \in \{0,1\}$$



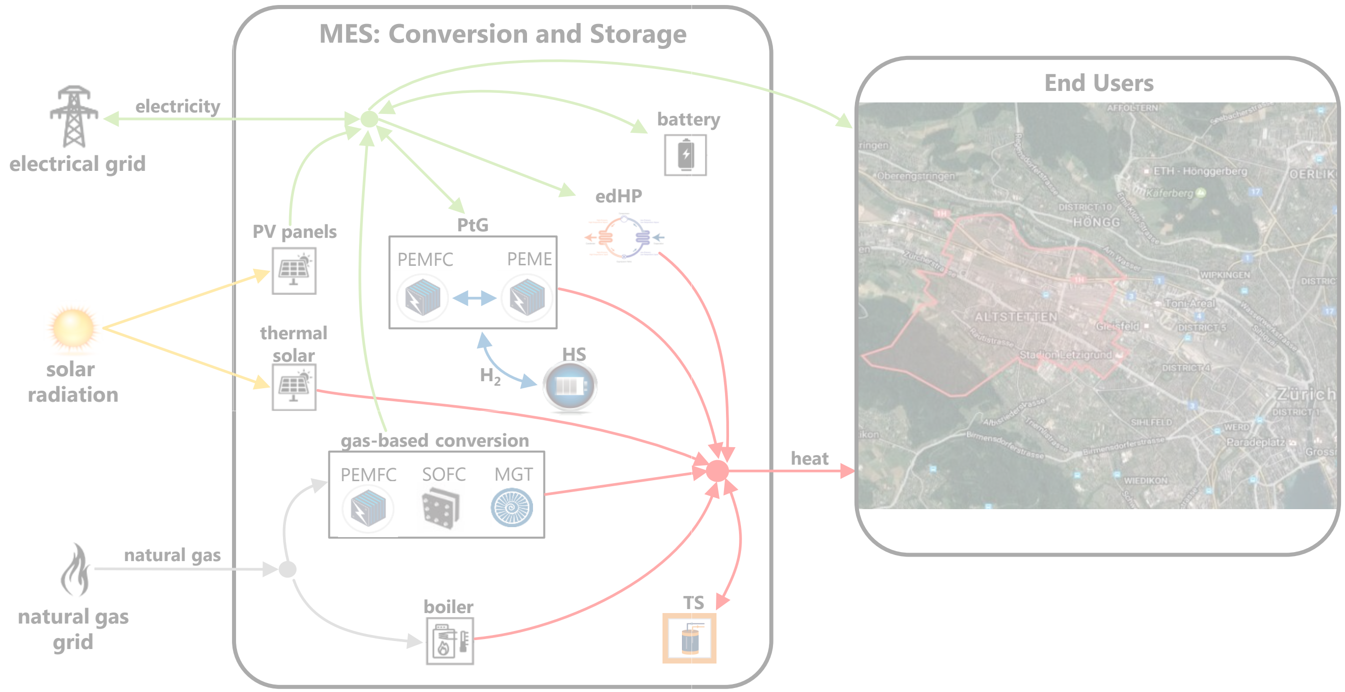
Optimization prob: mixed integer linear program

$$\min_{x,y} \boxed{(c^T x + d^T y)}$$ objective function

decision variables input data

subject to

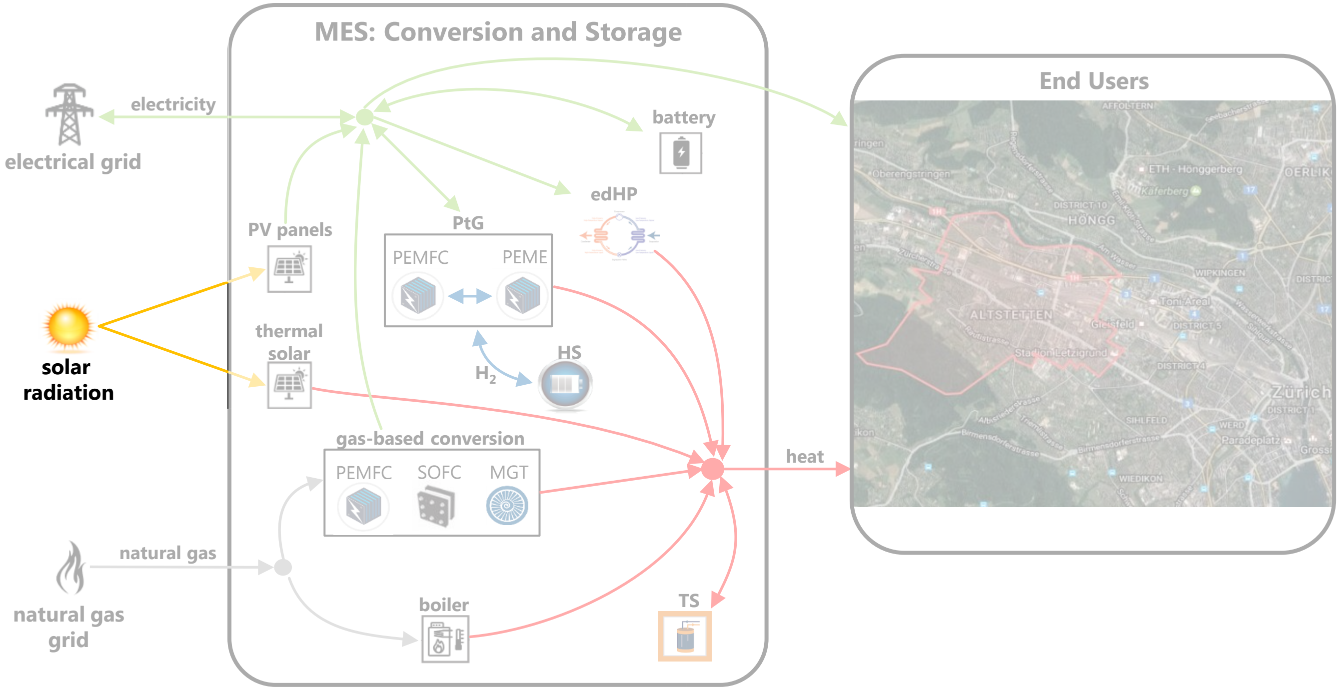
$$\boxed{\begin{array}{l} Ax + By = b \\ x \geq 0, y \in \{0, 1\} \end{array}}$$ constraints



Optimal design problem: input data

1

Environmental conditions: solar irradiance and air temperature



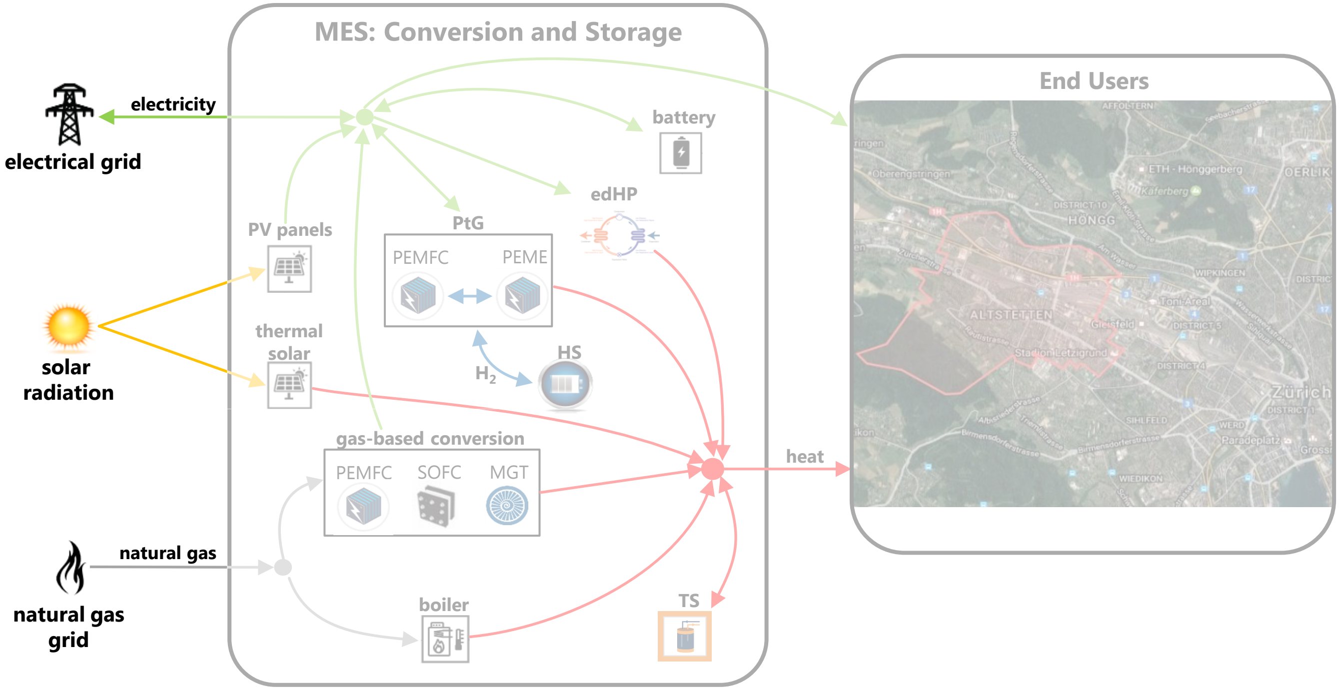
Optimal design problem: input data

1

Environmental conditions: solar irradiance and air temperature

2

Energy prices: electricity and gas prices



Optimal design problem: input data

1

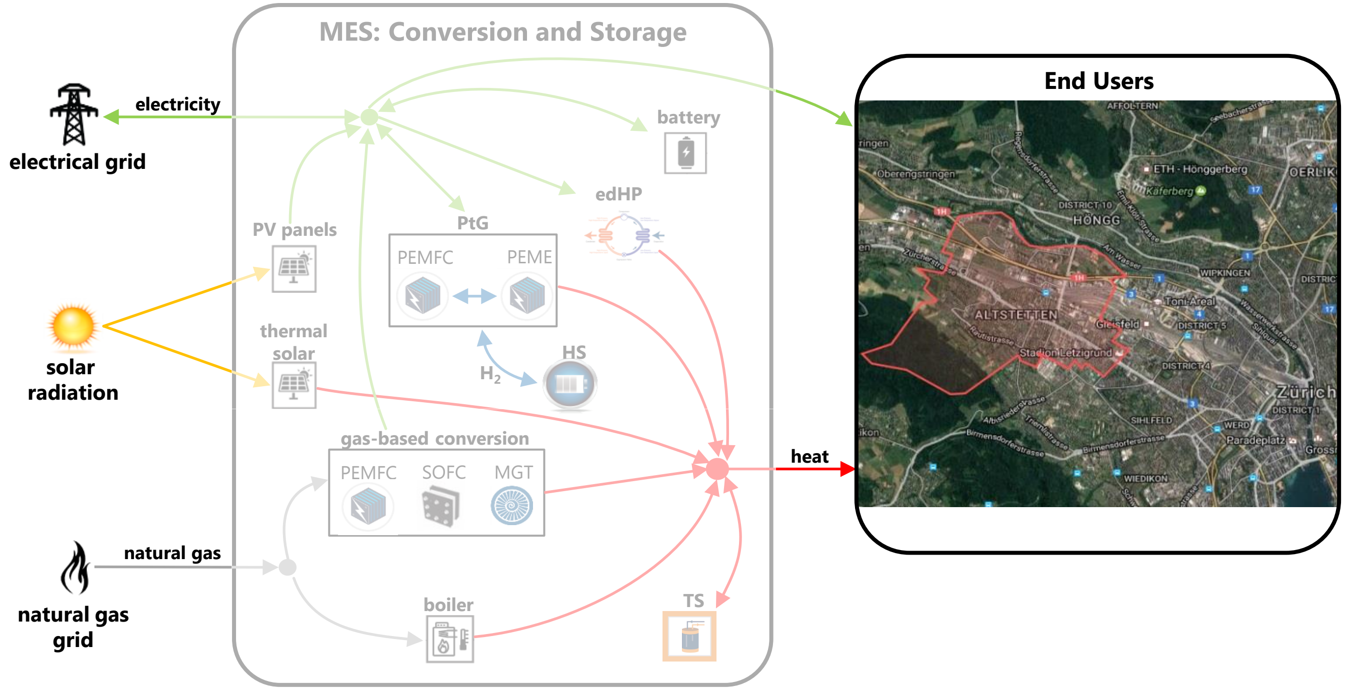
Environmental conditions: solar irradiance and air temperature

2

Energy prices: electricity and gas prices

3

Load demands: electricity and heat demands



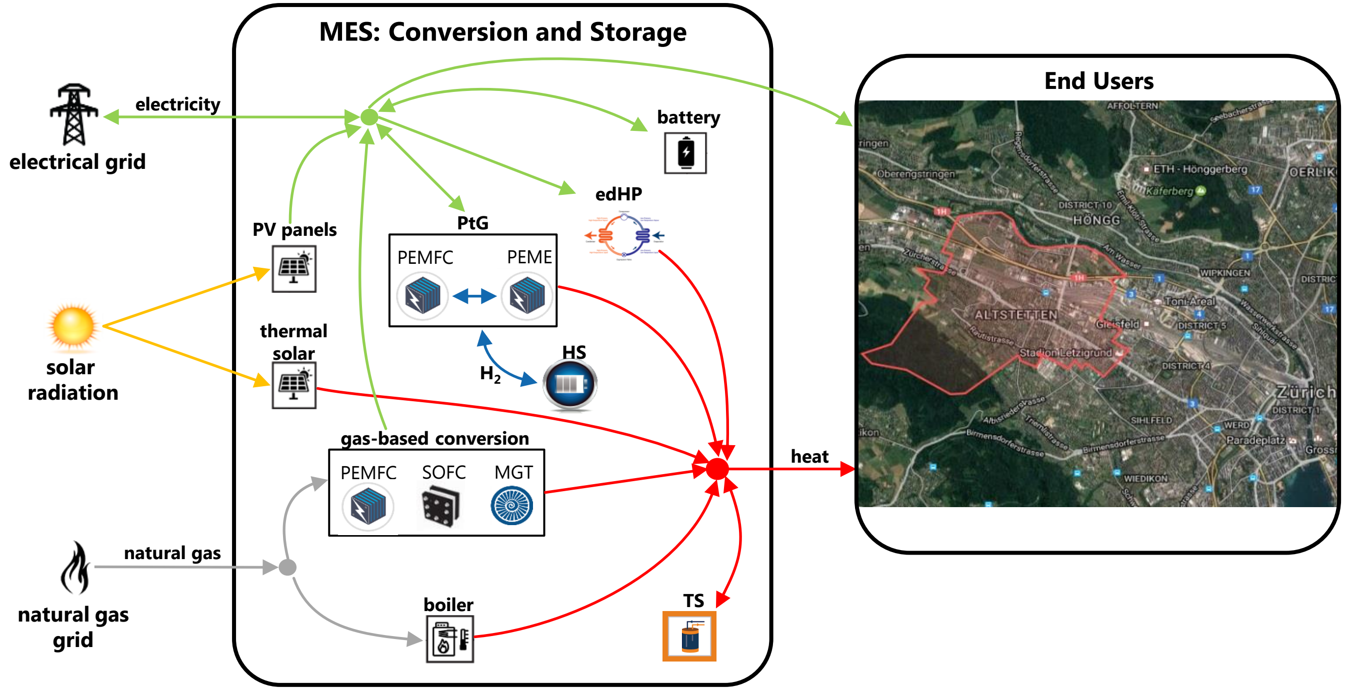
Optimal design problem: input data

1 **Environmental conditions**: solar irradiance and air temperature

2 **Energy prices**: electricity and gas prices

3 **Load demands**: electricity and heat demands

4 **Set of available technologies**: cost and performance coefficients



Optimal design problem: input data

1
Environmental conditions: solar irradiance and air temperature

2
Energy prices: electricity and gas prices

3
Load demands: electricity and heat demands

4
Set of available technologies: cost and performance coefficients

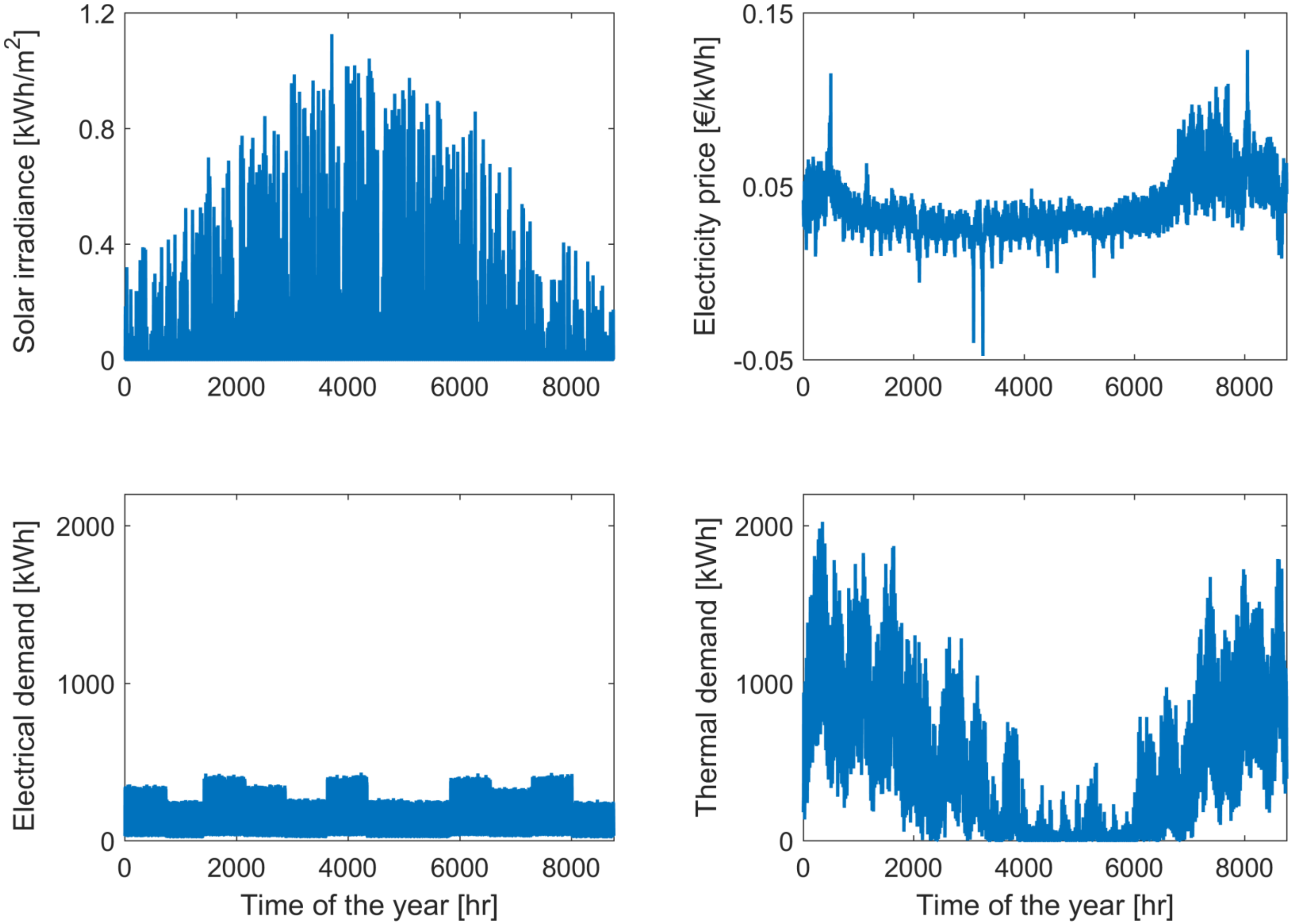
Assumptions

Input data 1-3 are assumed to be known without uncertainty at every time instant *t* of the time horizon, based on past realizations.

Therefore, the following hypotheses are implied:

i. No evolution of input data occurs during following years
ii. All the possible realizations of the uncertainty are included in historical data.

Optimal design problem: input data



Optimal design problem: decision variables

I. Selection and size of the installed technologies

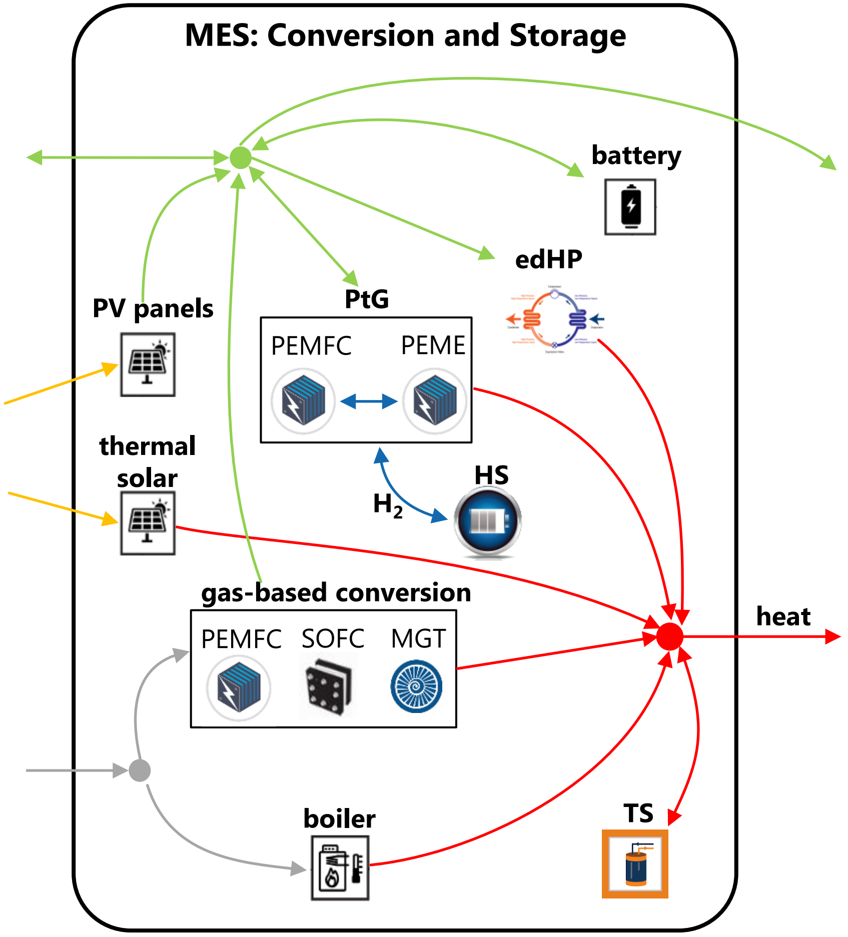
II. Scheduling (ON/OFF status) of the conversion technologies

III. Input and output power of the conversion technologies

IV. Energy stored, charged/discharged by the storage technologies

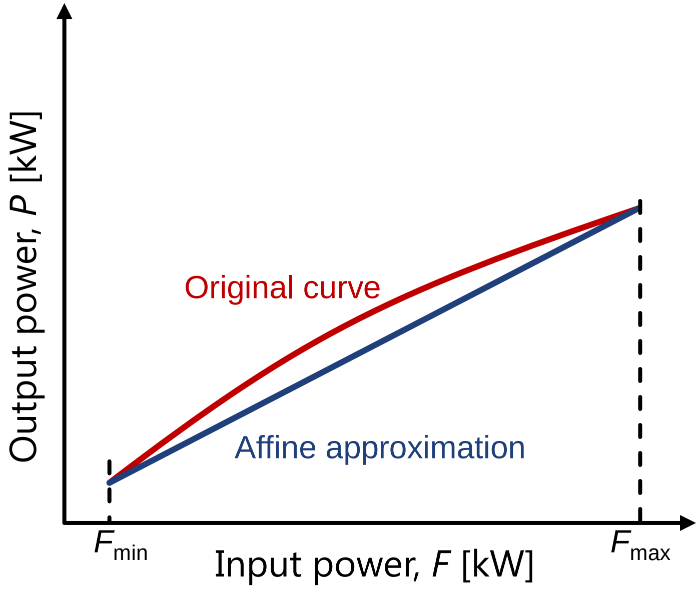
V. Imported/exported power from the grid

Operation variables II-V are determined at every hour of the year.



Optimal design problem: constraints

I. Performance of **conversion technologies**:
affine or piecewise affine (PWA) approximations



$$P_t = \alpha F_t + \beta S x_t + \gamma x_t\ , \ \forall t = \{1, \dots, T\}$$

$$F_t^{\min} x_t \leq F_t \leq F_t^{\max} x_t\ , \ \forall t = \{1, \dots, T\}$$

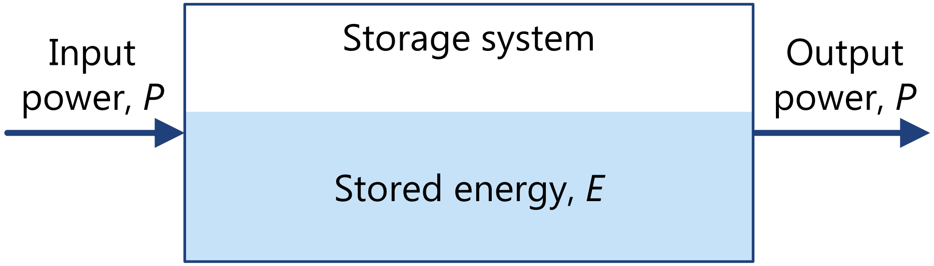
Binary variable $\boldsymbol{x} \in \{0,1\}^T$ to model ON/OFF status.

Additional binary variables $\boldsymbol{y}, \boldsymbol{z} \in \{0,1\}^T$ to model start-up/shut-down dynamics.

Optimal design problem: constraints

I. Performance of **conversion technologies**:
affine or piecewise affine (PWA) approximations

II. Performance of **storage technologies**:
simple linear dynamics



$$\boxed{E_t = E_{t-1}(1 - \lambda\Delta t) + \eta P_t \Delta t \,, \forall t = \{1, \dots, T\}}$$

$$\boxed{E_0 = E_T}$$

$$0 \le E_t \le S \,, \forall t = \{1, \dots, T\}$$

$$-\frac{S}{\tau} \le P_t \le \frac{S}{\tau}, \forall t = \{1, \dots, T\}$$

Optimal design problem: constraints

I. Performance of conversion technologies: affine or piecewise affine (PWA) approximations

II. Performance of storage technologies: simple linear dynamics

III. Hub **energy balances**: the sum of imported and generated power must equal the sum of exported and used power

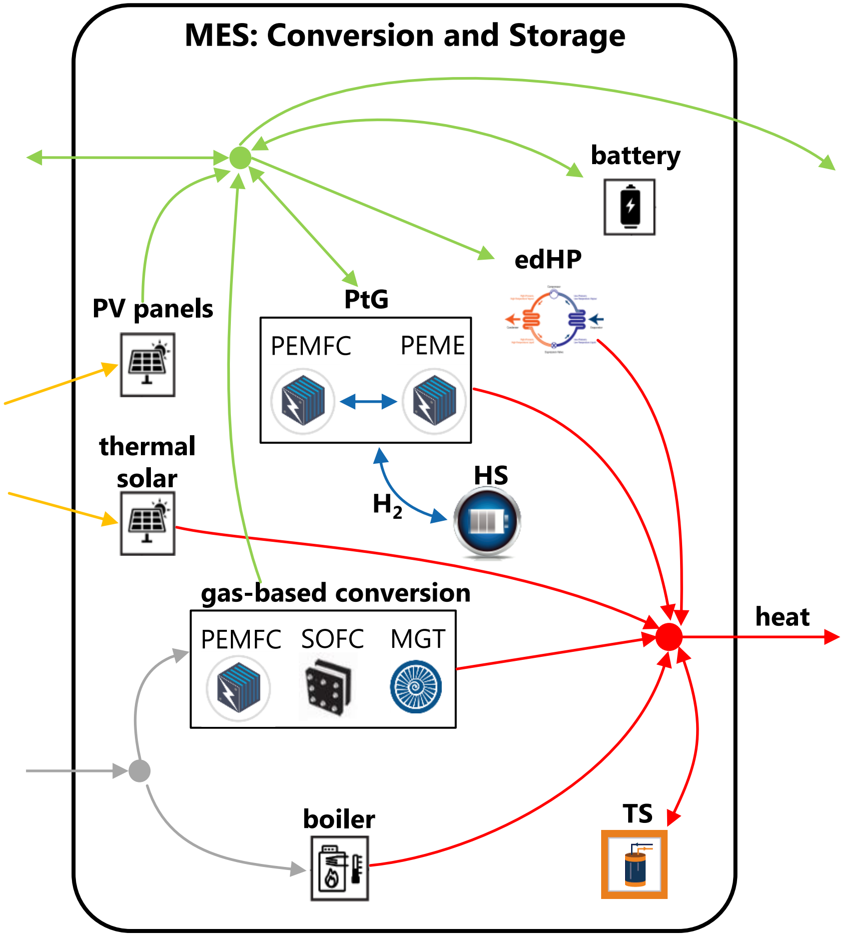
Optimal design problem: objective function

I. Total annual cost of the system:

   I. Capital cost, modeled through a PWA function of the unit size
   II. Operation cost, function of the overall imported/exported energy along the year
   III. Maintenance cost, fraction of the capital cost

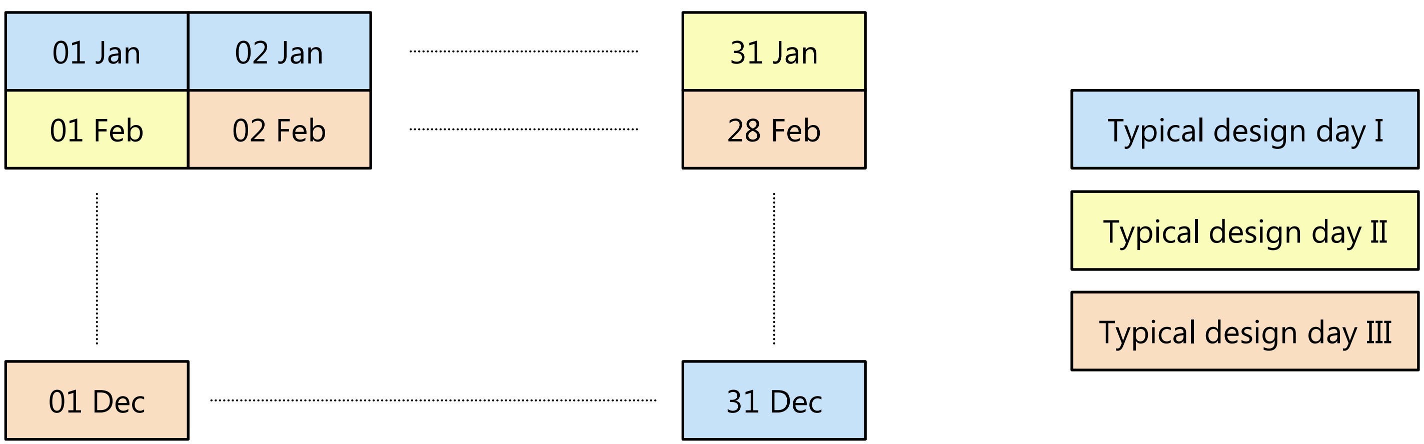
II. Annual CO_2 emissions, function of the overall imported energy

The multi-objective optimization is performed through the ε-constraint method.



Modeling challenge: time horizon

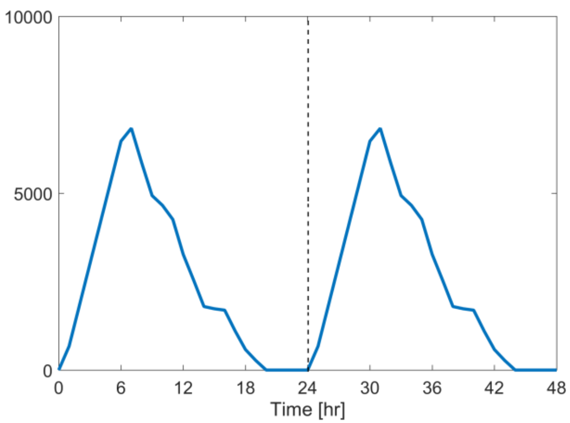
- The possibility of seasonal operation cycles translates in a long time horizon, with high resolution, which implies very large optimization problems
- Based on input data 1-3, the overall year is modeled through a set of *D* typical design days determined through a clustering procedure
- Traditionally, the design problem is solved for the design days, significantly reducing the computational complexity



Modeling the time horizon: novel methods

Traditional method (M0)

- Typical input data
- **Daily periodicity constraints**
- Same stored energy for each design day
- Same stored energy variation at each design day
- Unit scheduling through design days



Coupling design days (M1)

Detailed input data (M2)

Modeling the time horizon: novel methods

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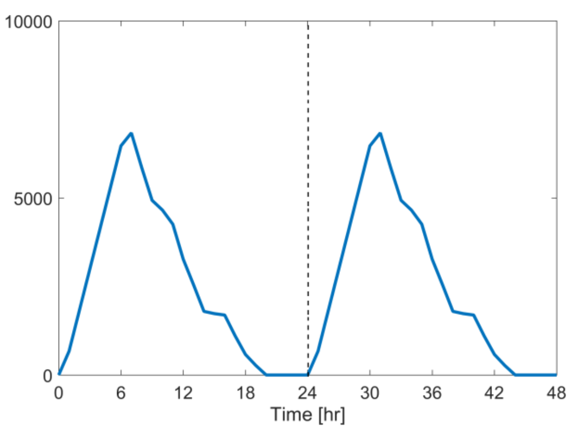
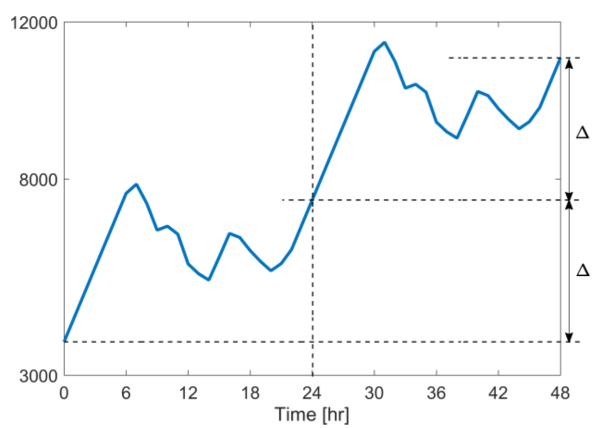


Coupling design days (M1)

- Typical input data
- **Coupling constraints between different design days, using their sequence along the year**
- **Yearly periodicity constraints**
- **Free stored energy along the year**
- Same stored energy variation at each design day
- Unit scheduling through design days

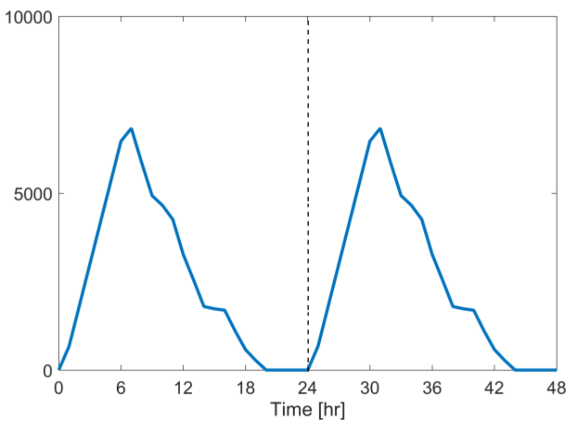


Detailed input data (M2)

Modeling the time horizon: novel methods

Traditional method (M0)

- Typical input data
- **Daily periodicity constraints**
- Same stored energy for each design day
- Same stored energy variation at each design day
- Unit scheduling through design days



Coupling design days (M1)

- Typical input data
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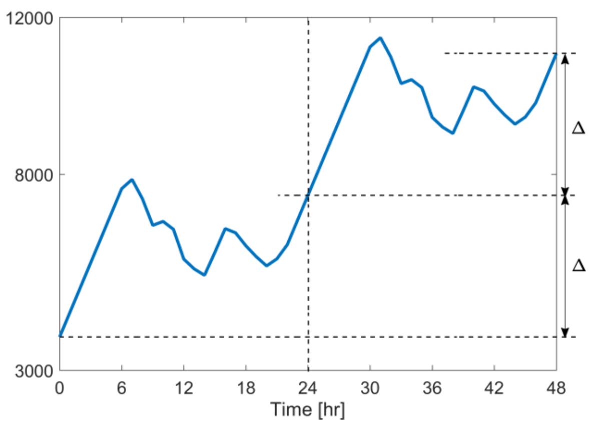
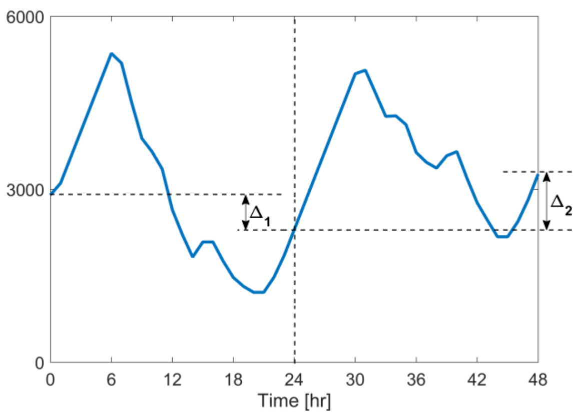
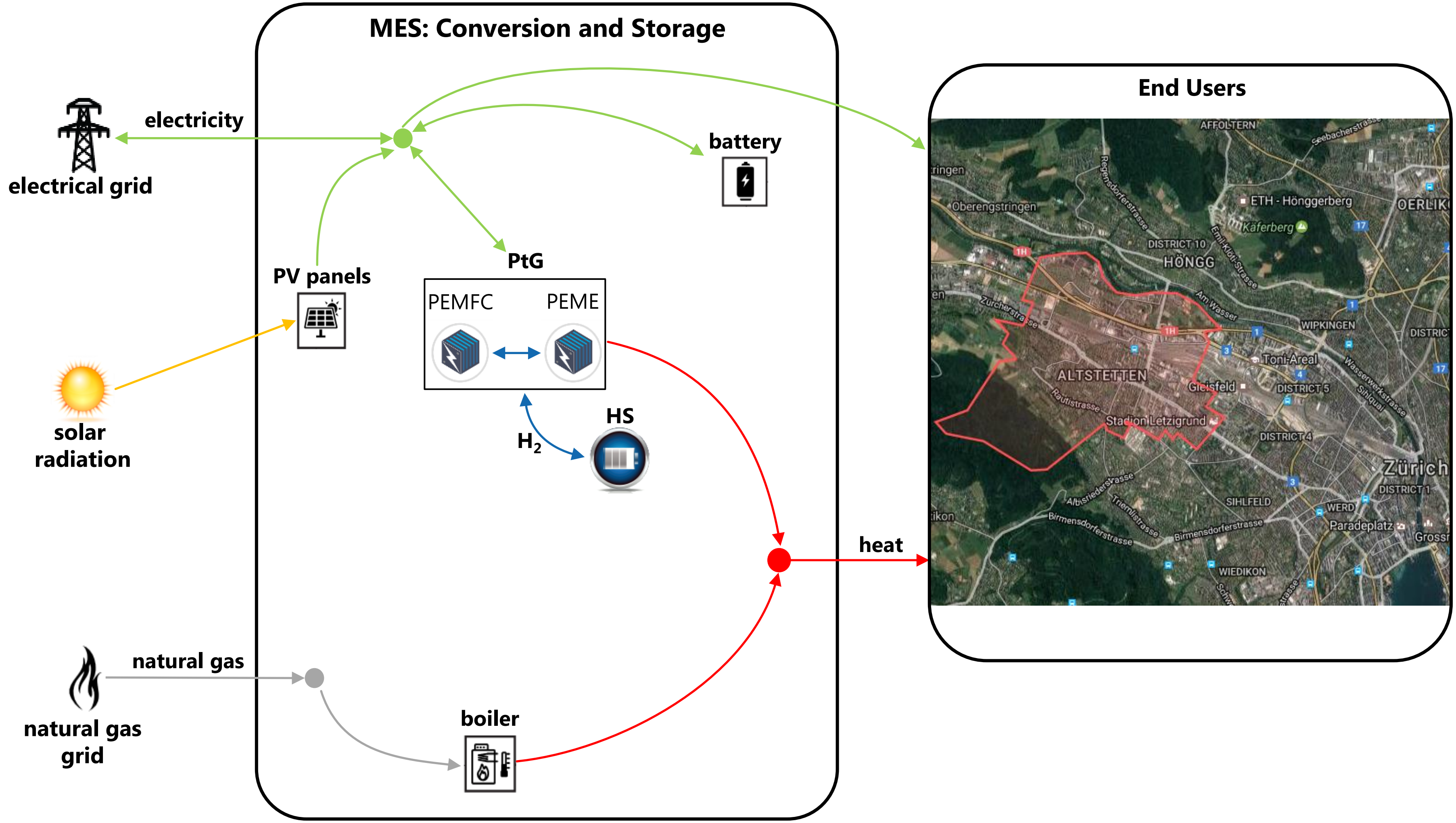


Detailed input data (M2)

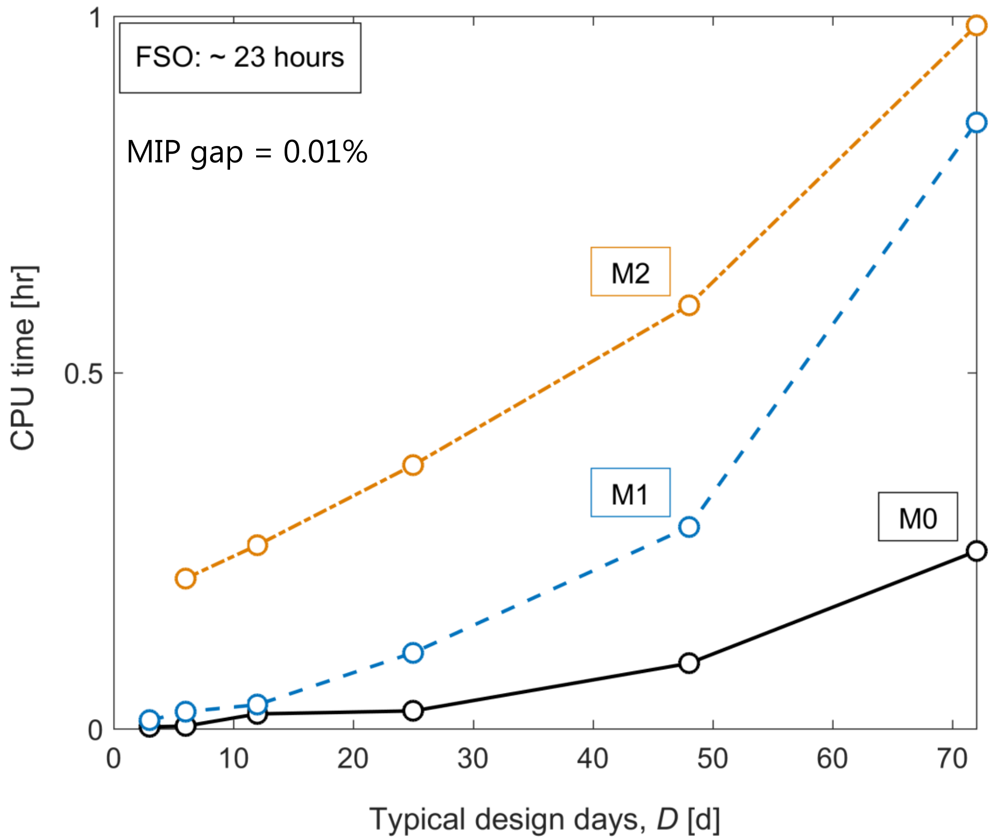
- **Detailed input data**
- **Coupling constraints between different design days, using their sequence along the year**
- **Yearly periodicity constraints**
- **Free stored energy along the year**
- **Free stored energy variation along the year**
- **Unit scheduling through design days only for some technologies**



Model validation: simple MES

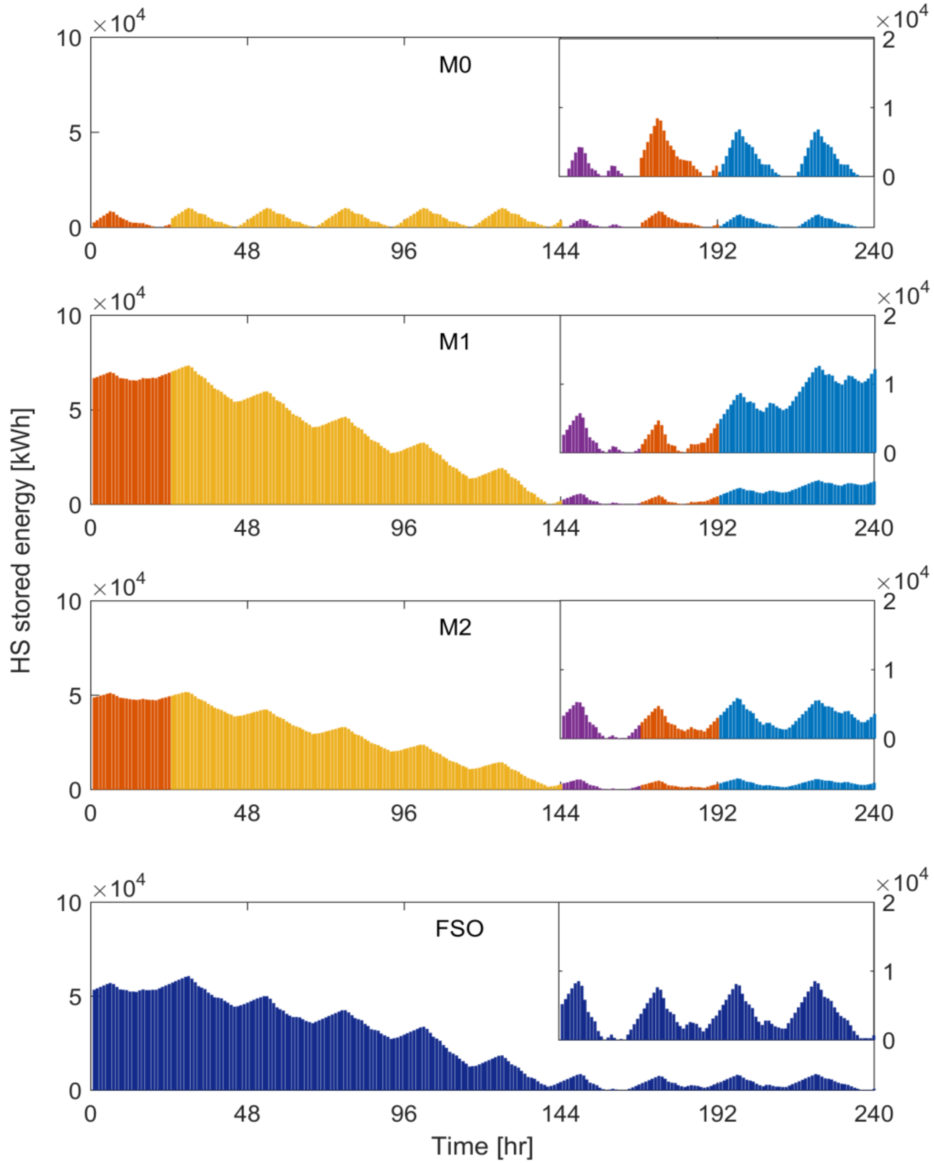


Model validation: computational time



- The full scale optimization (FSO) requires about 23 hours to complete
- All the proposed methods require less than 1 hour for D = 3-72

Model validation: long-term operation (*D* = 48)

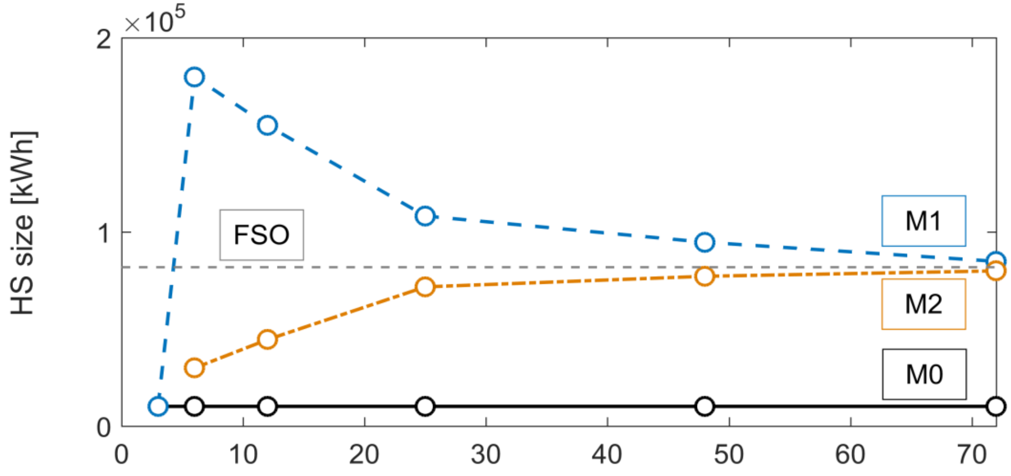


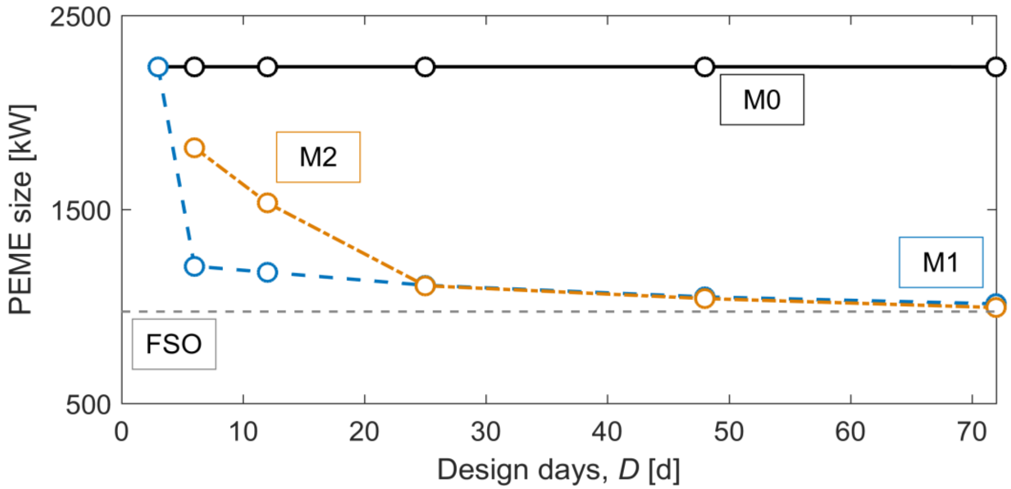
- M0 determines a daily policy for storage operation, different for different design days

- M1 and M2 determine a long-term operation similar to that provided by the full scale optimization (FSO)

10.01.16 – 20.01.16

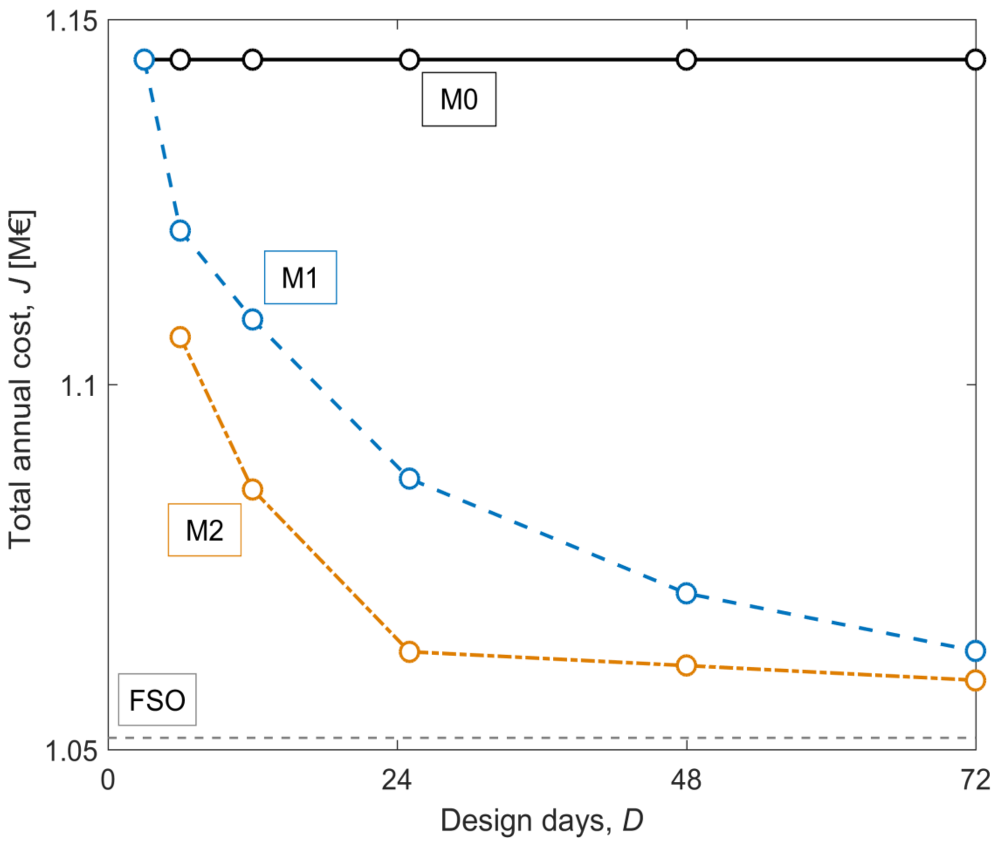
Model validation: system size





- M0 significantly underestimates the size of the storage system and overestimates the size of the conversion technologies, independently of the number of design days
- M1 and M2 provide a more accurate system design when increasing the number of design days (D > 25)

Model validation: total annual cost of the system



Full scale optimizations featuring approximate system design:

- The design provided by M0 translates into significantly higher costs (~9%).
- The design provided by M1 and M2 translate into a lower cost (closer to the optimal value) when increasing the number of design days.
- M2 approaches the FSO value faster than M1 (~1% for *D* = 25-72).

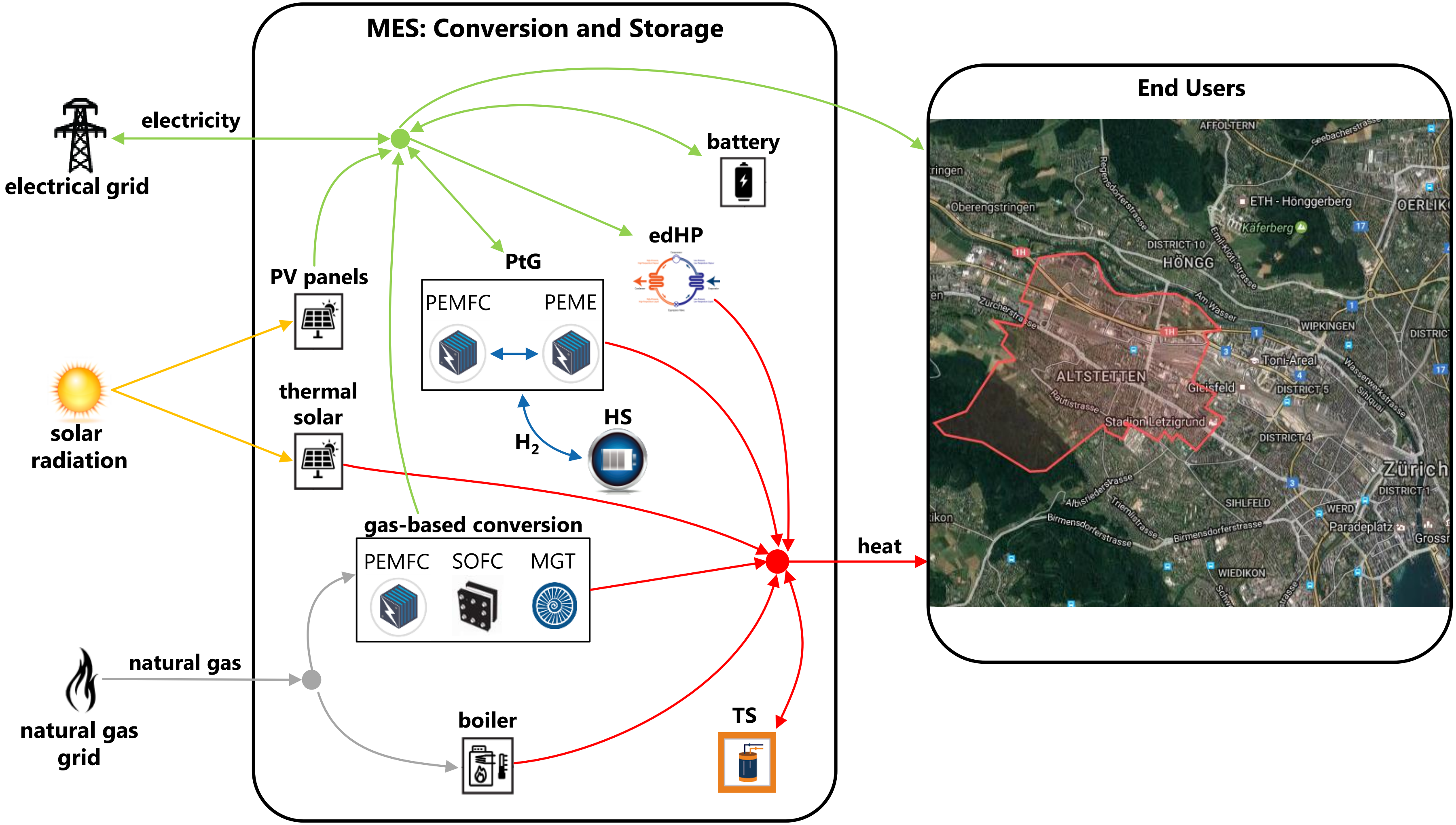
Agenda

1. Modeling of fuel cell and electrolyzer devices
   a. Thermodynamic models
   b. Linear approximation methods

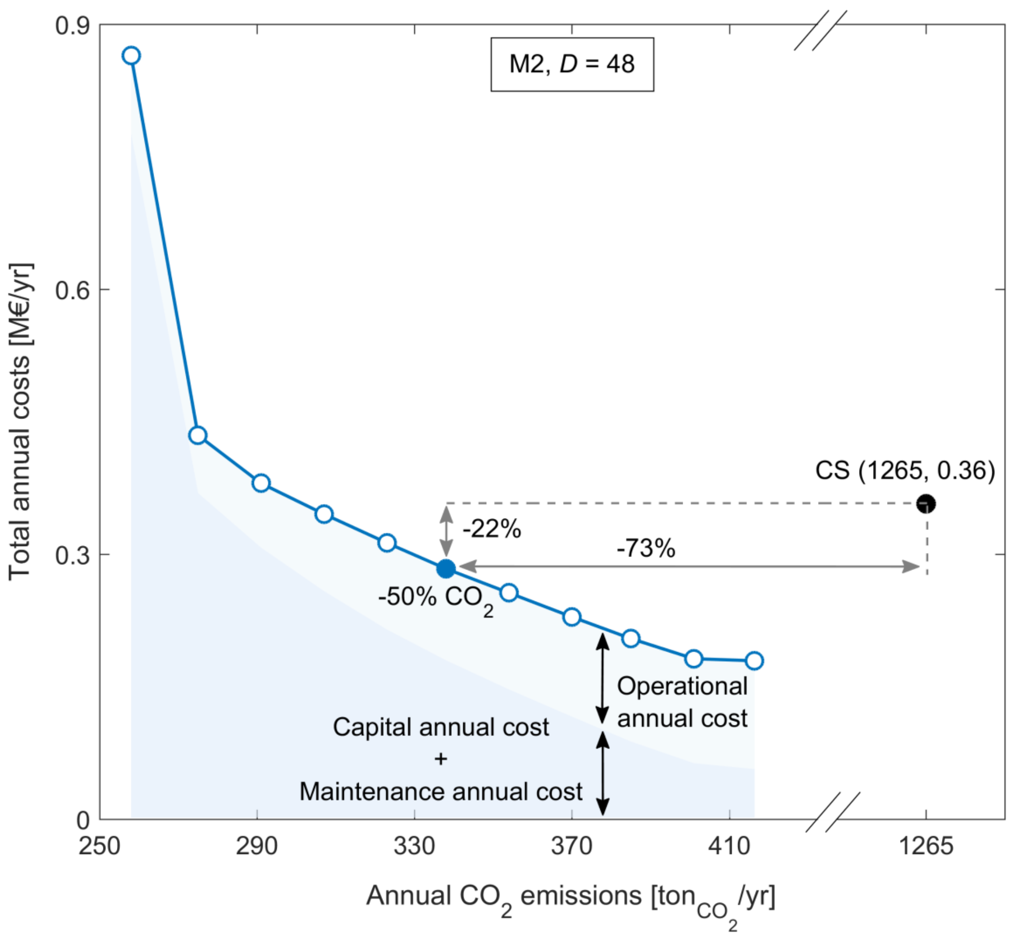
2. Formulation of the optimization problem
   a. Proposed methods for designing long-term storage systems
   b. Methods validation

3. Application of the proposed framework to design and analysis of integrated MES

Model application to a MES of interest

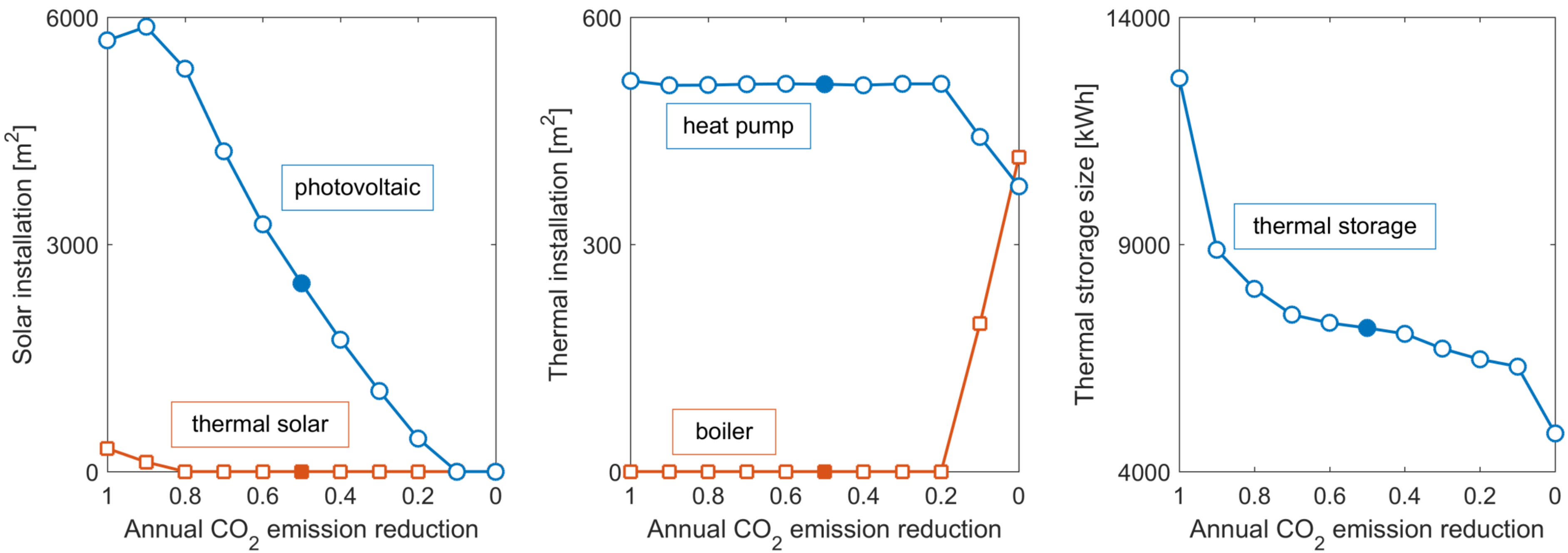


Cost-emission Pareto front



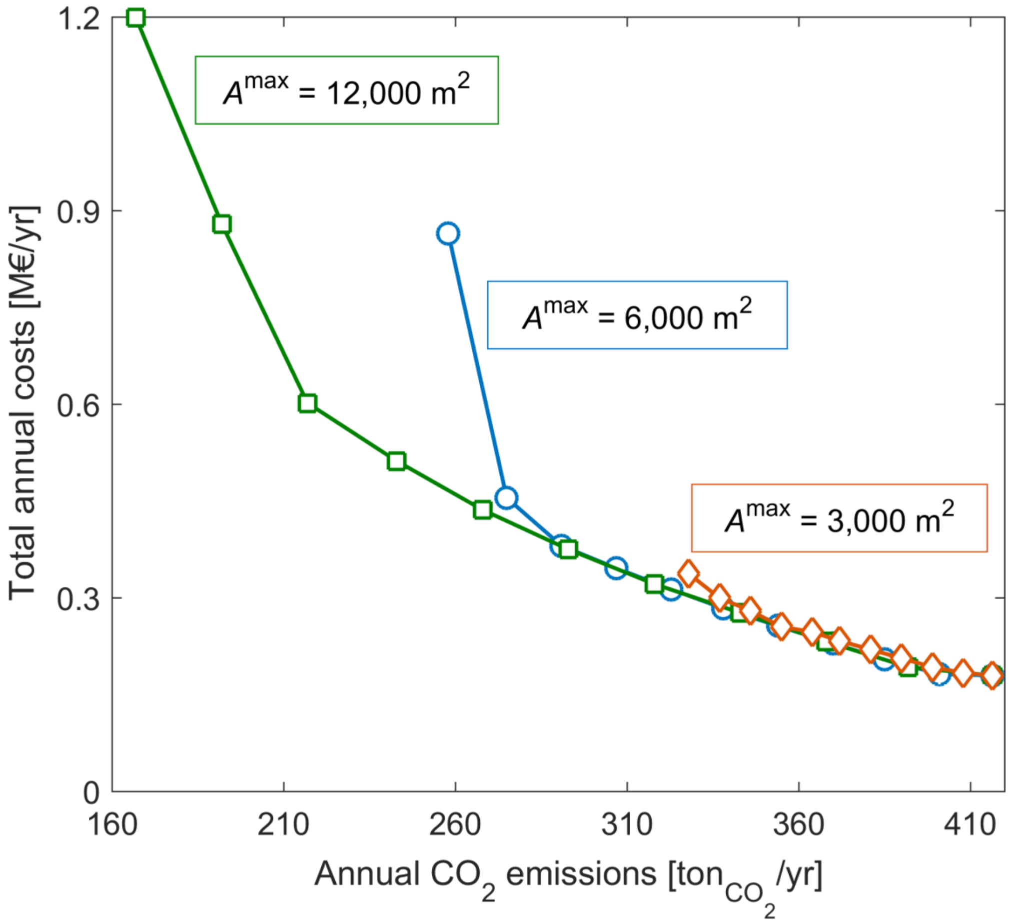
- The full scale optimizations did not complete in 5 days, whereas M2 with *D* = 48 was solved in less than 12 hours
- Tradeoff between capital and operational cost
- A reduction in both cost and emissions can be achieved with respect to a conventional scenario where electricity is bought from the grid and heat is generated with a boiler

Cost-emission Pareto front



The reduction in both cost and emissions is mainly achieved through photovoltaic installation, replacement of boilers with heat pumps and utilization of thermal storage.

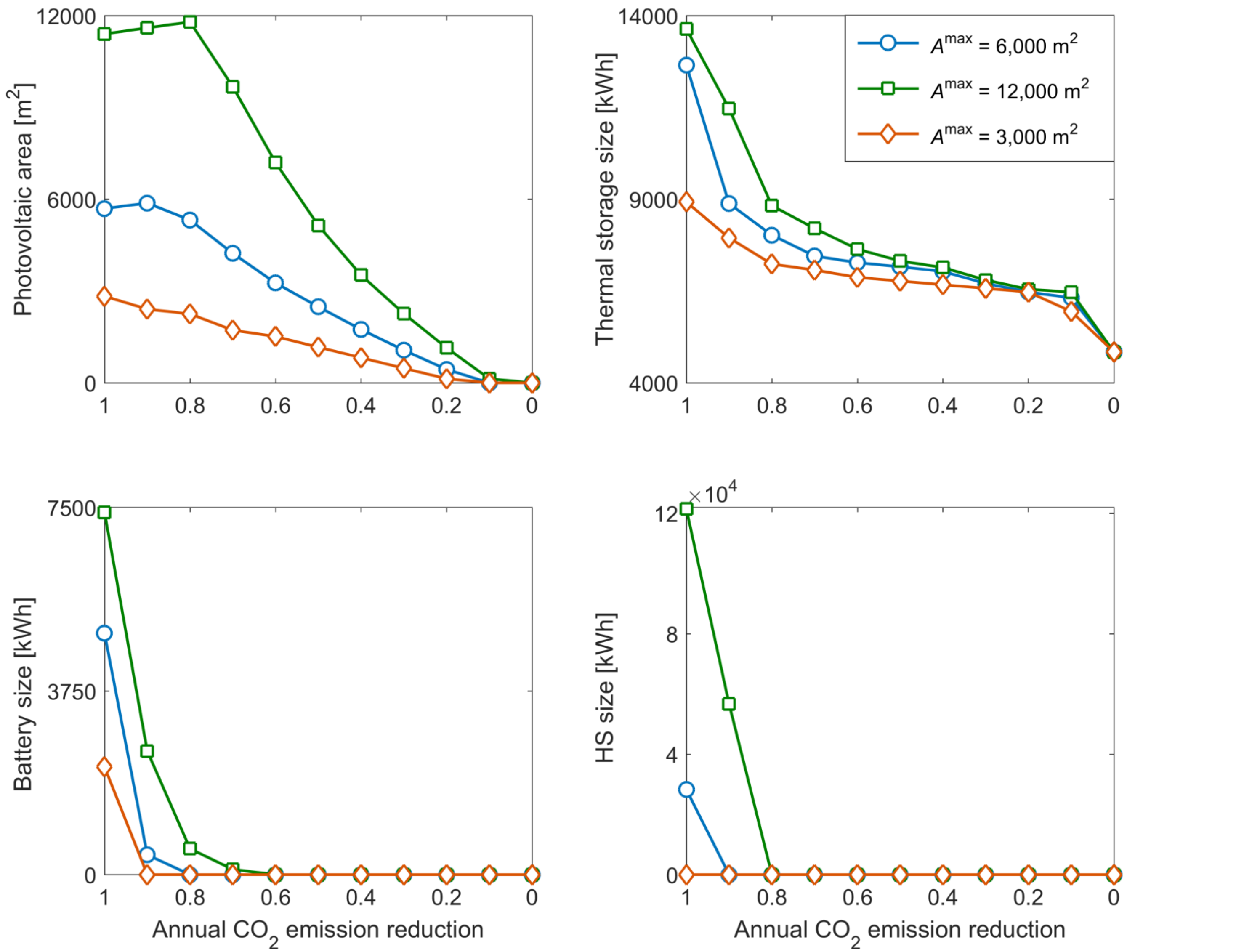
Sensitivity of Pareto fronts: solar installation



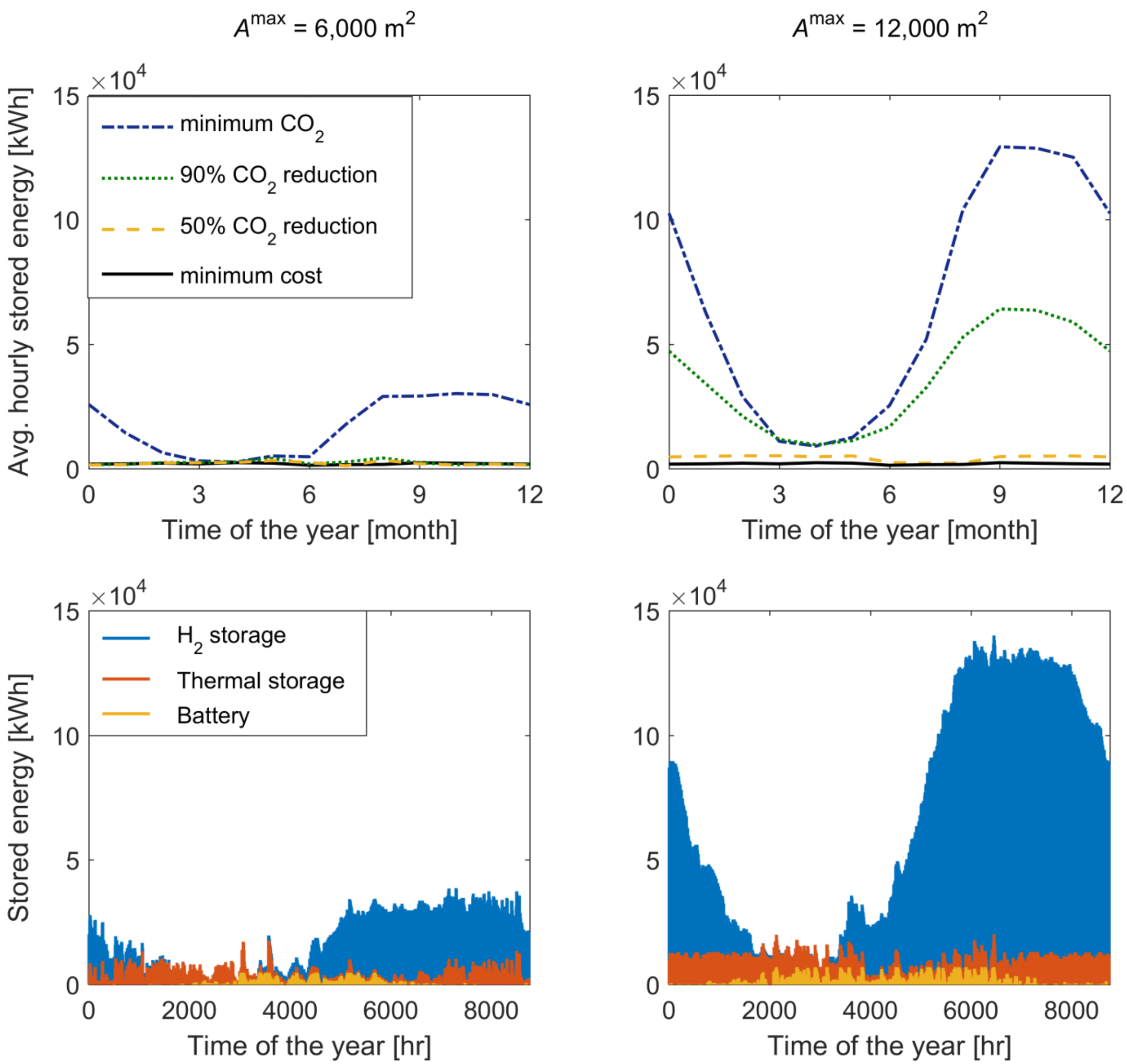
Sensitivity analysis on the area available for solar installation:

- The level of minimum emissions depends on the amount of renewable energy installed
- All the Pareto sets coincide at low annual cost and then are separated at low emissions (high renewable and storage installations)

Sensitivity of Pareto fronts: solar installation



Sensitivity of Pareto fronts: solar installation

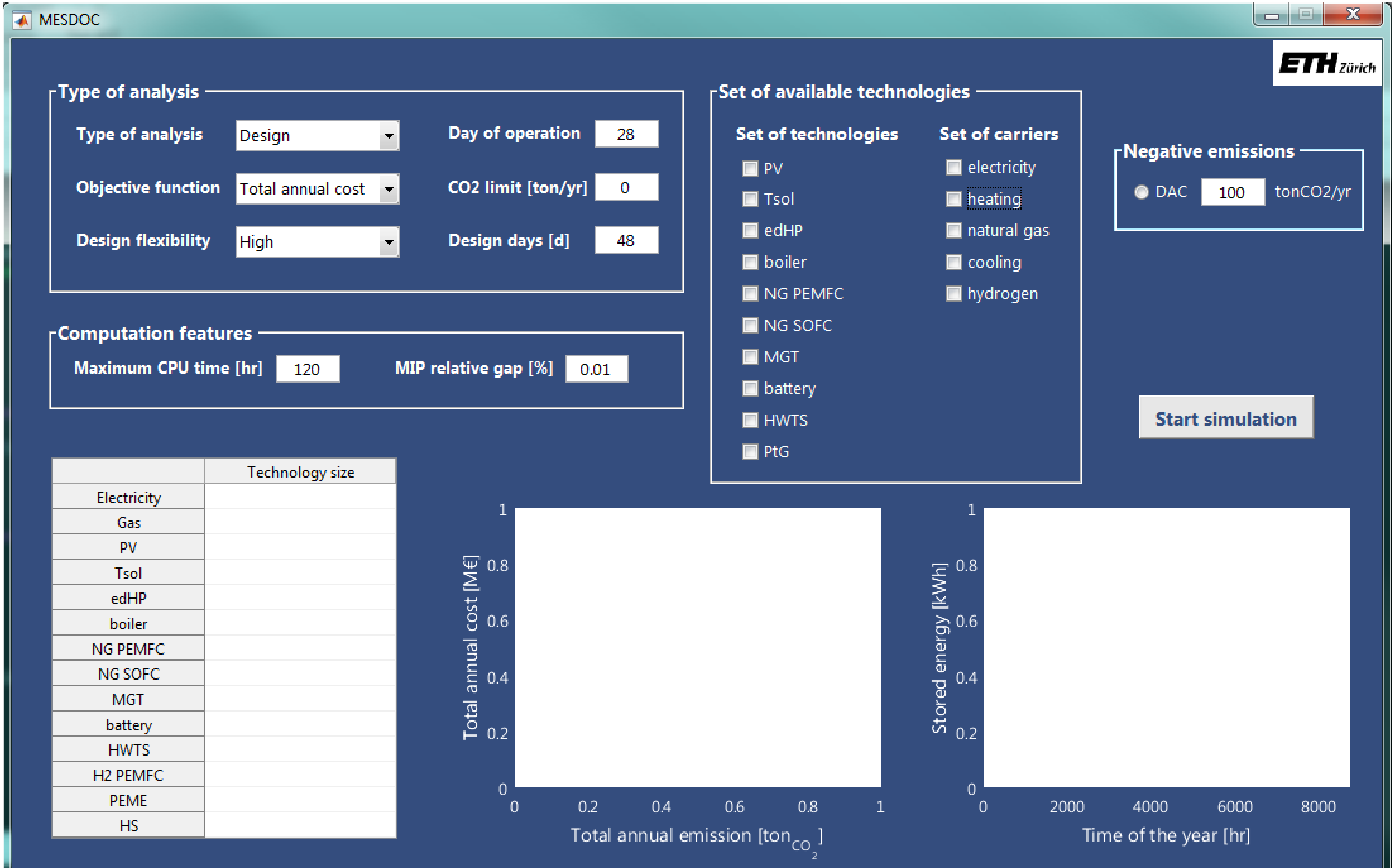


Take-home message

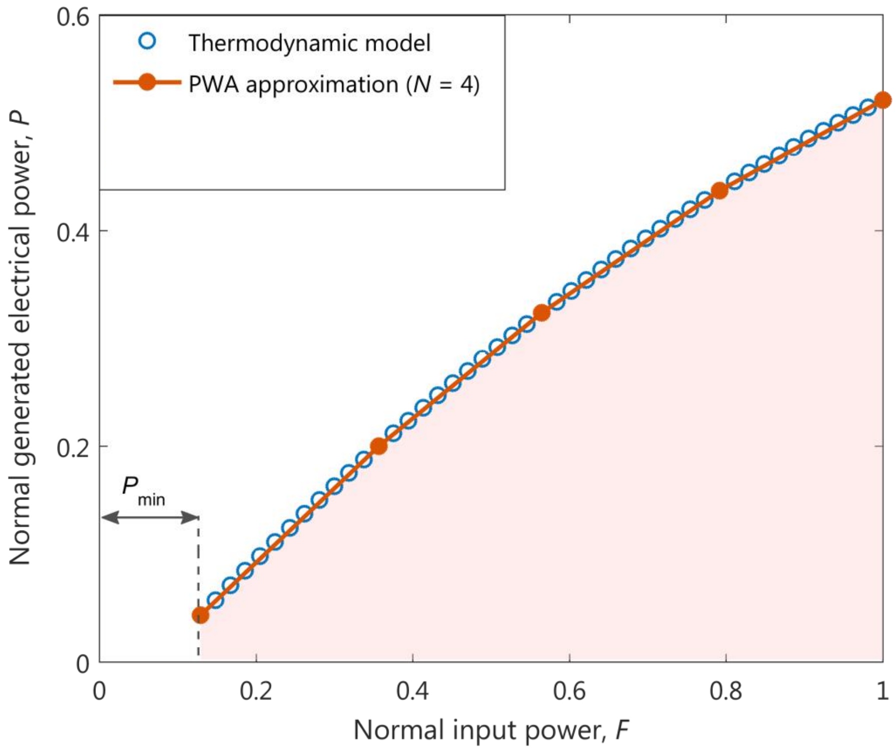
- We studied the optimal design of integrated MES including:
  - Detailed description of electrochemical conversion technologies. Reduced order models were derived from first-principle models of fuel cells and electrolyzers and included within an optimization framework
  - Seasonal operation cycles for the storage technologies. Two MILP approaches, based on design days, were proposed to enable the optimal design of complex MES including seasonal storage with limited computational complexity
- The optimal behavior of the system was investigated in terms of total annual cost and CO_2 emissions
- Seasonal operation cycles become convenient at low CO_2 emissions and are performed through power-to-gas technology, where hydrogen is generated through the excess of renewable energy

BACKUP SLIDES

Work in progress: tool development



Linear approximation: conversion performance



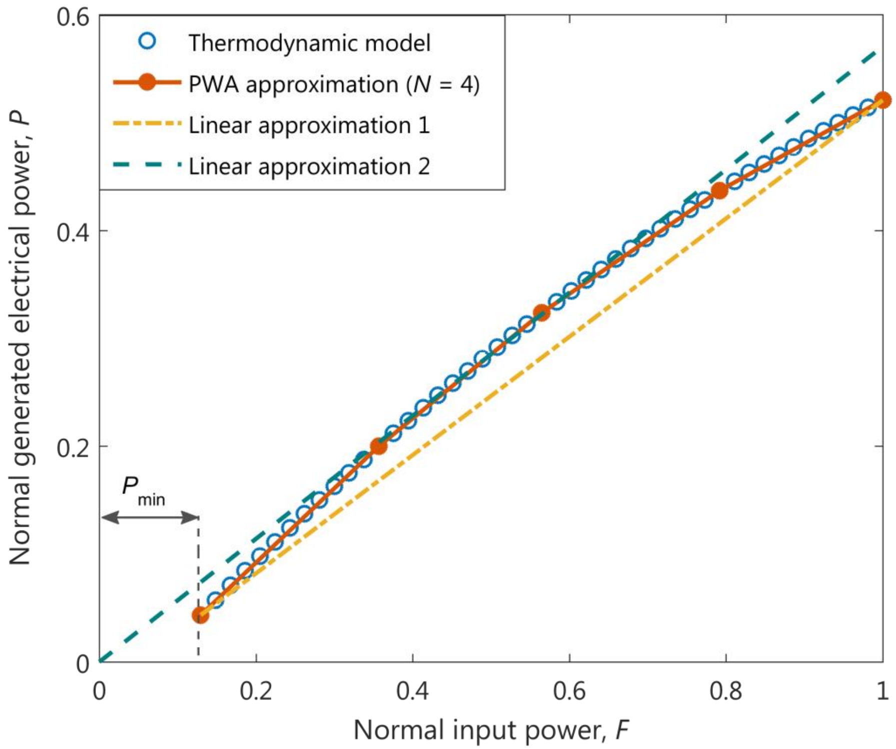
Piecewise affine (PWA) approximation

$$P \leq \alpha_i F + \beta_i S + \gamma_i,$$

$$\forall i = 1, \dots, N$$

- Steady-state behavior of conversion performance
- Conversion performance at a reference temperature (neglecting temperature dependency at design phase)
- The thermodynamic model needs to be linearized to be used in an optimization framework

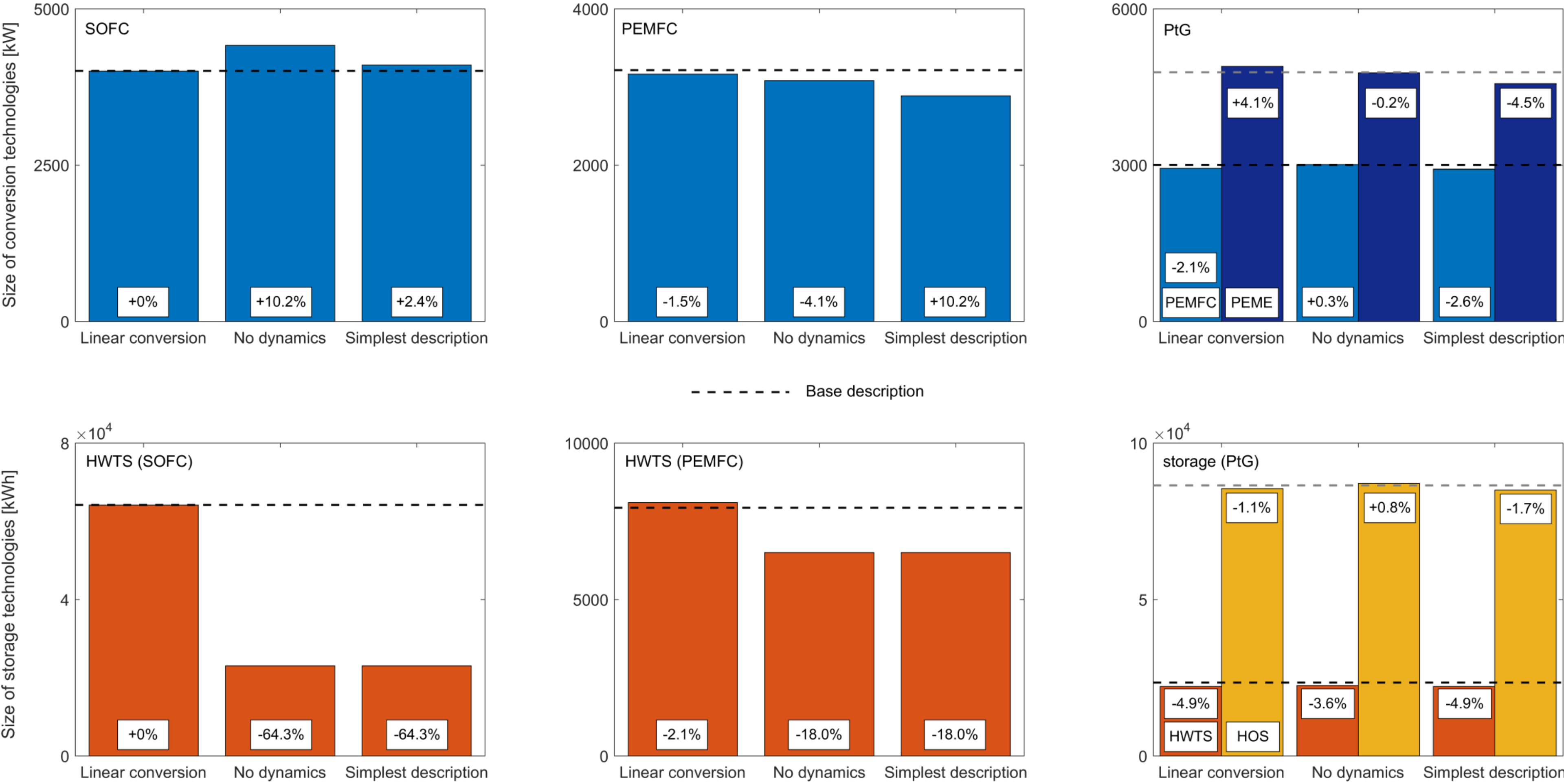
Linear approximation: conversion performance



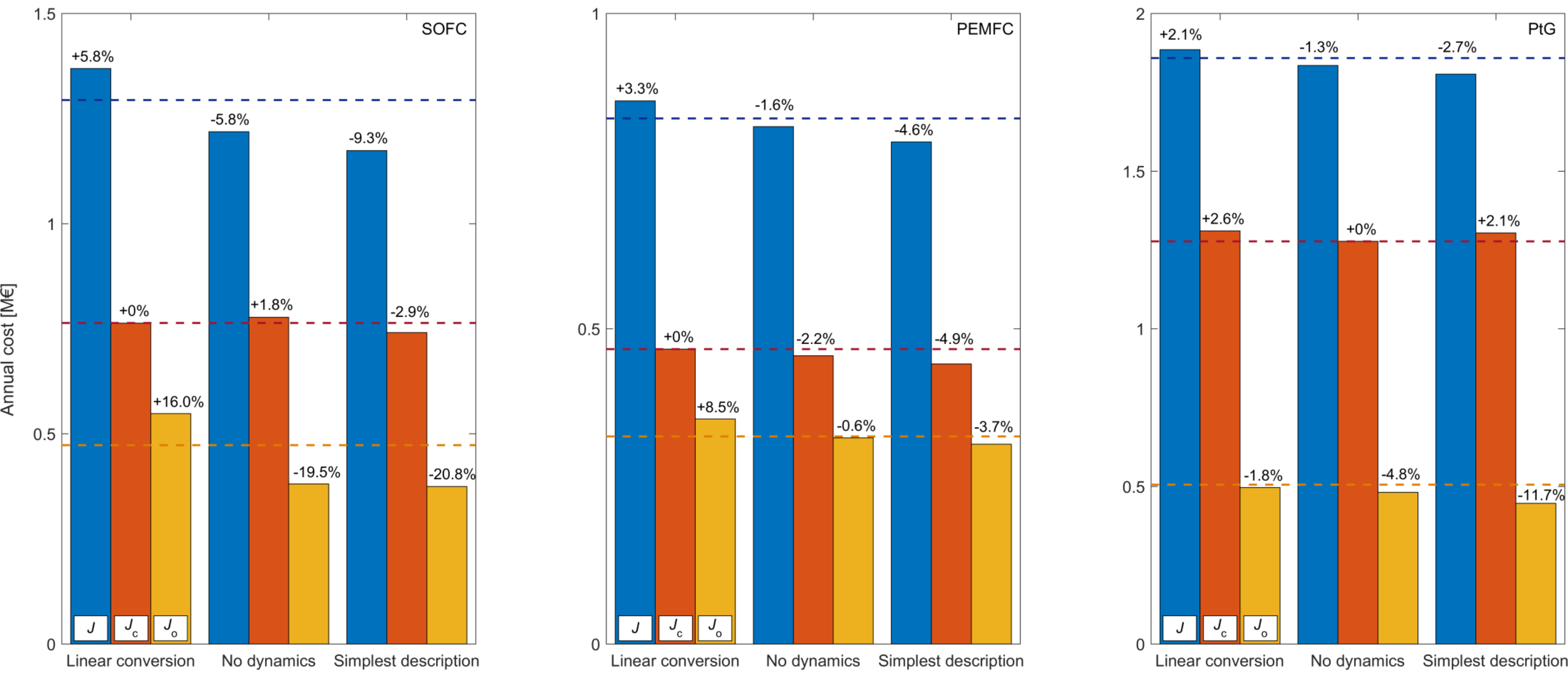
- Steady-state behavior of conversion performance
- Conversion performance at a reference temperature (neglecting temperature dependency at design phase)
- The thermodynamic model needs to be linearized to be used in an optimization framework

Piecewise affine (PWA) approximation	Linear approximation 1	Linear approximation 2
$P \leq \alpha_i F + \beta_i S + \gamma_i, \quad \forall i = 1, \ldots, N$	$P = \alpha F + \beta S + \gamma$	$P = \alpha F$

Impact of modeling approximations: size



Impact of modeling approximations: cost



Modeling the time horizon: novel methods

$$E_t = (\lambda E_{t-1} + \eta P_t)\Delta t \, , \forall t = \{1, \dots, 8760\}$$

$$\boxed{\boldsymbol{E_0 = E_{8760}}}$$

Methods	Traditional method (M0): • Typical demand profiles • **Daily periodicity constraint** • Same stored energy for each design day • Unit commitment through design days
Description	Definition of *D* design days which are considered independently. $E_{d,k} = \left(\lambda E_{d,k-1} + \eta P_{d,k}\right)\Delta k \, , \forall d, k$ $\boxed{\boldsymbol{E_{d,0} = E_{d,K} \, , \forall d, k}}$ $d = \{1, \dots, D\}$ is the *d*-th design day $k = \{1, \dots, K\}$ is the *k*-th daily time step

Modeling the time horizon: novel methods

$$E_t = (\lambda E_{t-1} + \eta P_t)\Delta t \,, \forall t = \{1, \dots, 8760\}$$
$$\boxed{\boldsymbol{E_0 = E_{8760}}}$$

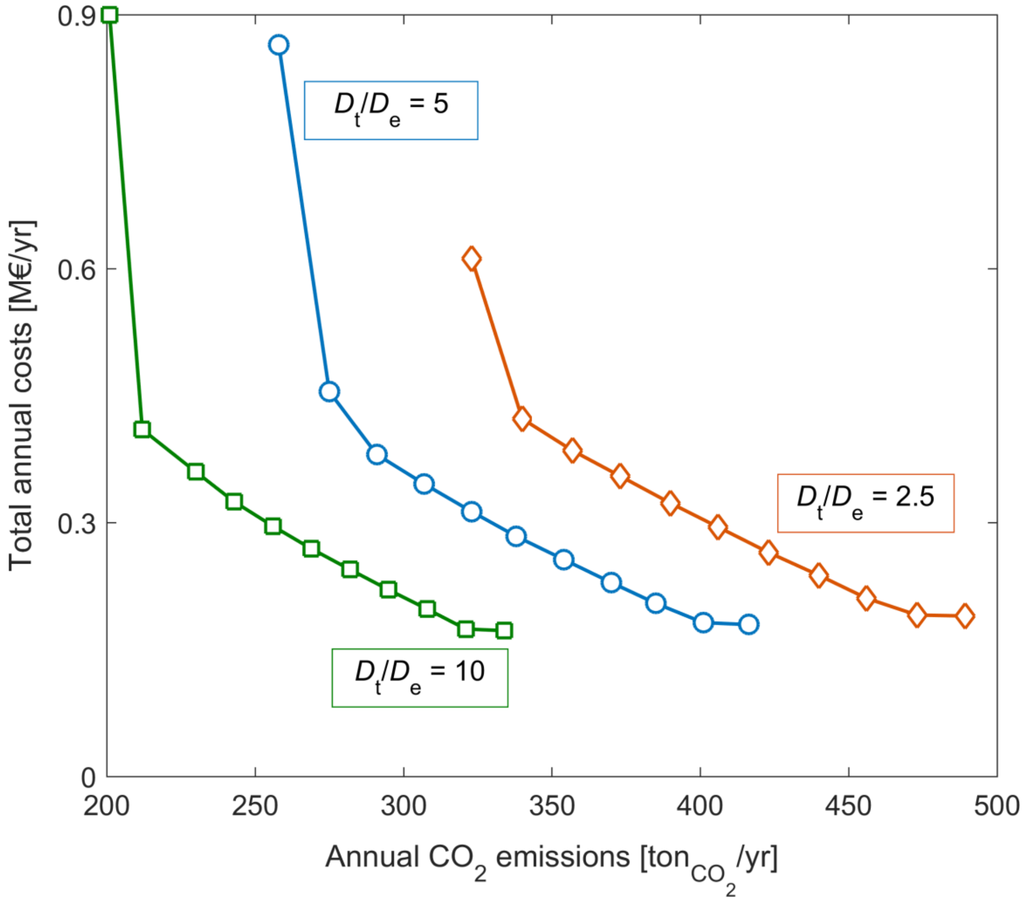
	Traditional method (M0):	Method 1 (M1):
Methods	• Typical demand profiles • **Daily periodicity constraint** • Same stored energy for each design day • Unit commitment through design days	• Typical demand profiles • **Yearly periodicity constraint** • **Free stored energy** • Unit commitment through design days
Description	Definition of D design days which are considered independently. $E_{d,k} = \left(\lambda E_{d,k-1} + \eta P_{d,k}\right)\Delta k \,, \forall d, k$ $\boldsymbol{E_{d,0} = E_{d,K} \,, \forall d, k}$ $d = \{1, \dots, D\}$ is the d-th design day $k = \{1, \dots, K\}$ is the k-th daily time step	**Sequence of design days σ.** $\boldsymbol{E_{y,k} = \left(\lambda E_{y,k-1} + \eta P_{\sigma(y),k}\right)\Delta k \,, \forall y, k}$ $\boldsymbol{E_{y,1} = \left(\lambda E_{y-1,K} + \eta P_{\sigma(y),1}\right)\Delta k \,, \forall y}$ $\boldsymbol{E_{0,K} = E_{Y,K}}$ $\sigma(y) \leq D, \forall y$ $y = \{1, \dots, Y\}$ is the y-th day of the year

Modeling the time horizon: novel methods

$$E_t = (\lambda E_{t-1} + \eta P_t)\Delta t \,, \forall t = \{1, \dots, 8760\}$$
$$\boxed{\boldsymbol{E_0 = E_{8760}}}$$

	Traditional method (M0):	Method 1 (M1):	Method 2 (M2):
Methods	• Typical demand profiles • **Daily periodicity constraint** • Same stored energy for each design day • Unit commitment through design days	• Typical demand profiles • **Yearly periodicity constraint** • **Free stored energy** • Unit commitment through design days	• **Detailed demand profiles** • Yearly periodicity constraint • **Free stored energy variation** • **Unit commitment through design days for some technologies**
Description	Definition of D design days which are considered independently. $E_{d,k} = (\lambda E_{d,k-1} + \eta P_{d,k})\Delta k \,, \forall d, k$ $\boldsymbol{E_{d,0} = E_{d,K} \,, \forall d, k}$ $d = \{1, \dots, D\}$ is the d-th design day $k = \{1, \dots, K\}$ is the k-th daily time step	**Sequence of design days σ.** $\boldsymbol{E_{y,k} = (\lambda E_{y,k-1} + \eta P_{\sigma(y),k})\Delta k \,, \forall y, k}$ $\boldsymbol{E_{y,1} = (\lambda E_{y-1,K} + \eta P_{\sigma(y),1})\Delta k \,, \forall y}$ $\boldsymbol{E_{0,K} = E_{Y,K}}$ $\sigma(y) \leq D, \forall y$ $y = \{1, \dots, Y\}$ is the y-th day of the year	**Distinction between different decision variables.** $\boldsymbol{E_{y,k} = (\lambda E_{y,k-1} + \eta P_{y,k})\Delta k \,, \forall y, k}$ $\boldsymbol{E_{y,1} = (\lambda E_{y-1,K} + \eta P_{y,1})\Delta k \,, \forall y}$ $E_{0,K} = E_{Y,K}$

Sensitivity of Pareto fronts: user demand



Sensitivity analysis on ratio between thermal and electrical demands:

- The level of minimum emissions depends on the ratio between thermal and electrical demand
- Due to the possibility of efficiently converting electricity into heat (heat pumps), lower emissions can be achieved for high thermal-to-electrical demand ratio.

Sensitivity of Pareto fronts: user demand