POLITECNICO MILANO 1863

Towards the optimal design and operation of Aggregated Energy Systems

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Carnegie Mellon University

The Department of Energy @ Politecnico, divisions & our group

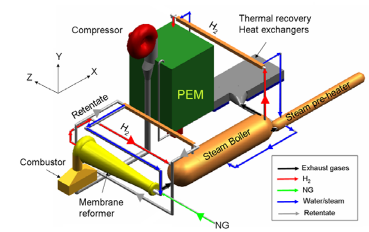
The Department of Energy at Politecnico joins researchers originally belonging to 5 divisions.
It has ~130 permanent researchers and professors

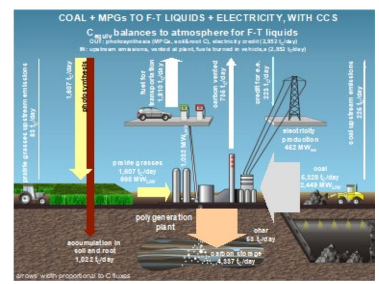
1. Chemical Technologies and Processes and NanoTechnologies Division
2. Electrical Division
3. Nuclear Engineering Division
4. Thermal Engineering & Environmental Technologies Division
5. Fluid Dynamic Machines, Propulsion & Energy Systems Division
   - Fluid-dynamics of turbomachines
   - Internal combustion engines
   - Propulsion and combustion
   - *Group of Energy COnversion Systems (GECOS):*

GeCOS
Group of Energy COnversion Systems

MAIN RESEARCH AREAS

1. **CARBON CAPTURE TECHNOLOGIES**
2. **RENEWABLE ENERGY SOURCES AND WASTE-TO-ENERGY**
3. **ENERGY STORAGE, HYDROGEN AND FUEL CELLS**
4. **ORC, S-CO2 AND ADVANCED POWER CYCLES**
5. **MICRO-GRIDS AND MULTI-ENERGY SYSTEMS**
6. **SYSTEM MODELLING AND OPTIMIZATION**
   - a) Process optimization
   - b) Heat integration and heat recovery cycles
   - c) Aggregated Energy Systems:
     - Virtual Power Plants
     - Multi-Energy Systems
     - Energy Districts
     - Microgrids





Virtual Power Plants

A **virtual power plant** (**VPP**) is a cloud-based power plant that aggregates several energy systems with different primary energy sources and different features as well as energy storage systems.

On the electricity market it is seen as a single (aggregated) power plant. Its primary purpose is to generate and sell electricity and services to the electric grid.

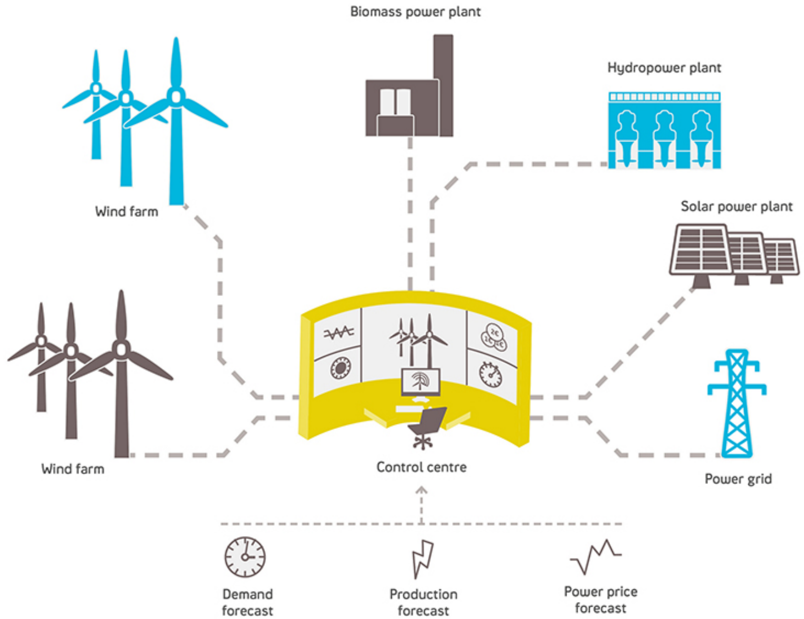


Figure Source: https://www.solarpowerworldonline.com/

VIRTUAL POWER PLANTS

Advantages of VPPs compared to stand-alone units:

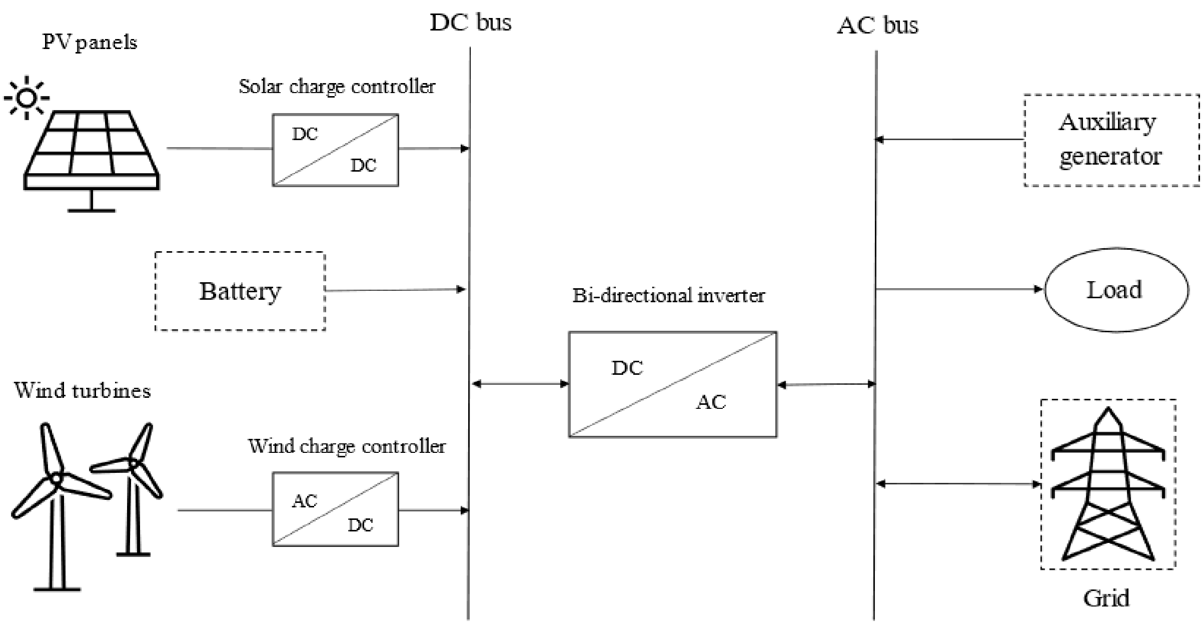
(The centralized control system allows to:)

- exploiting the synergies between the different energy technologies/storages to maximize the part-load efficiency (i.e., using more efficient units for each load, compensate solar with wind, etc).
- Adjusting loads and storage management to decrease fluctuations of power supplied to the electric grid (compared to stand-alone solar/wind plants) and participate to the day-ahead market (advantage for the control of the grid)
- Higher operational flexibility in increasing/decreasing the load on short notice (via the optimized management of storage systems, and/or use of quick-start units like GTs or dispatchable loads for demand side management sites).
- Providing ancillary services to the electric grid (frequency regulation, load balancing/following, spinning and non-spinning reserve in case of failure)

Disadvantages:

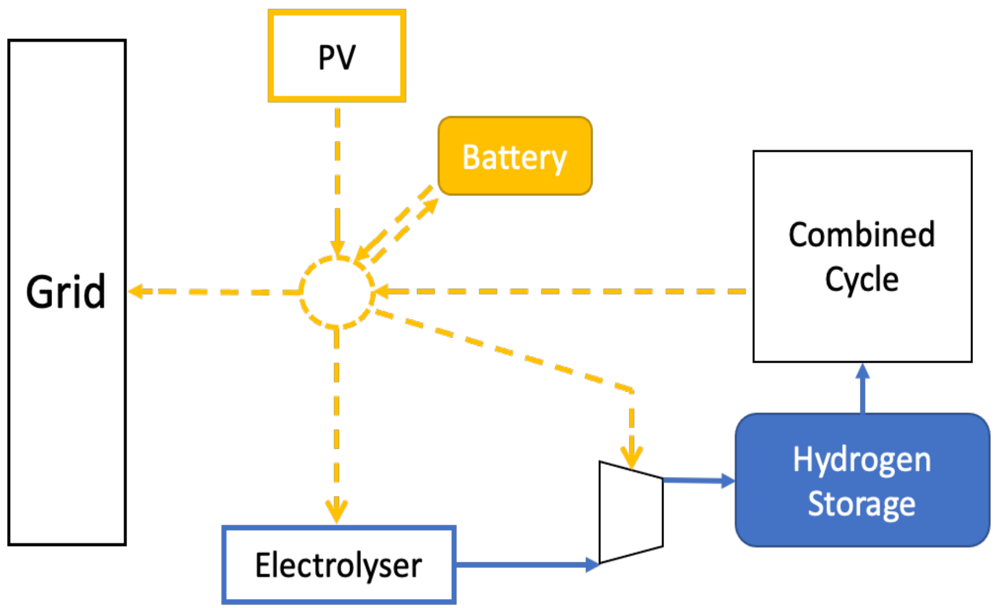
- the complexity requires advanced optimization techniques for the design and operational planning (unit commitment + economic dispatch) + control.

VPP EXAMPLES



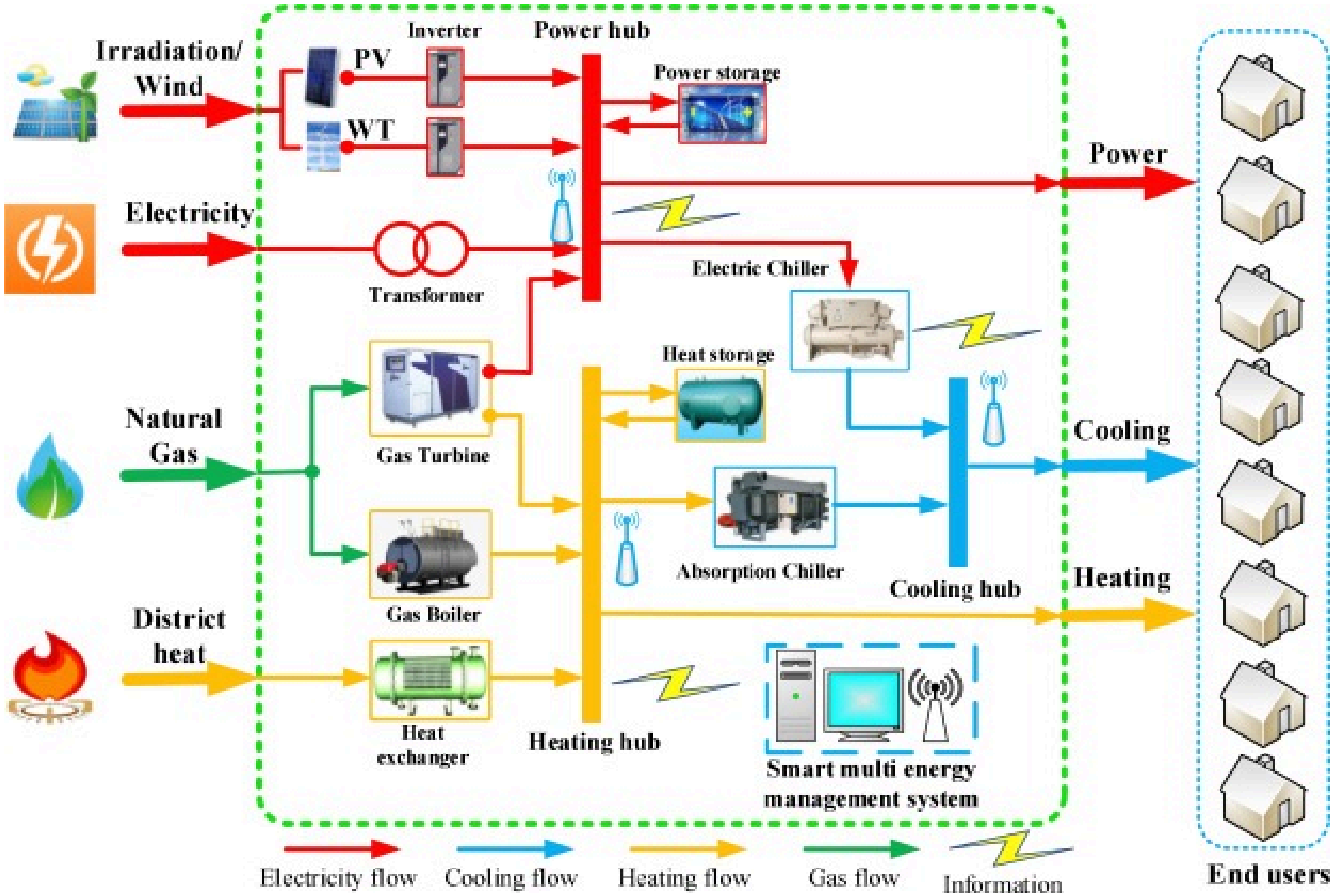
VPP EXAMPLES

- GT + Battery («peaker»)
- NGCC + Battery (faster ramping)
- NGCC + PV + Battery
- NGCC + PV + Electrolyzer + H2 storage + H2 export



MULTI-ENERGY SYSTEMS

- Multiple primary energy sources
- Multiple energy vectors as output (e.g., electricity, heating, cooling, hydrogen)



https://www.sciencedirect.com/science/article/abs/pii/S0360544218312635

MULTI-ENERGY SYSTEMS

Advantages of MES compared to stand-alone units:

- exploiting the synergies between the different energy technologies/storages to maximize the part-load efficiency (i.e., using more efficient units for each load)
- Storing energy (heat/electricity) to increase the share of intermittent renewables sources while preserving good reliability
- Using cheapest primary energy source depending on the hourly profiles and renewable production
- Optimizing management of storage systems to operate CHP units (specially 1 d.o.f. units, see later) with high efficiency and/or lower costs of power exchanges with grid.
- Sizing the units not for the peak demand thanks to the possibility of exploiting the aid of energy storage systems to meet the peak demand.
- Using high efficiency technologies (e.g., high temp. fuel cells) with limited operational flexibility (start-up, shut-down times/costs)

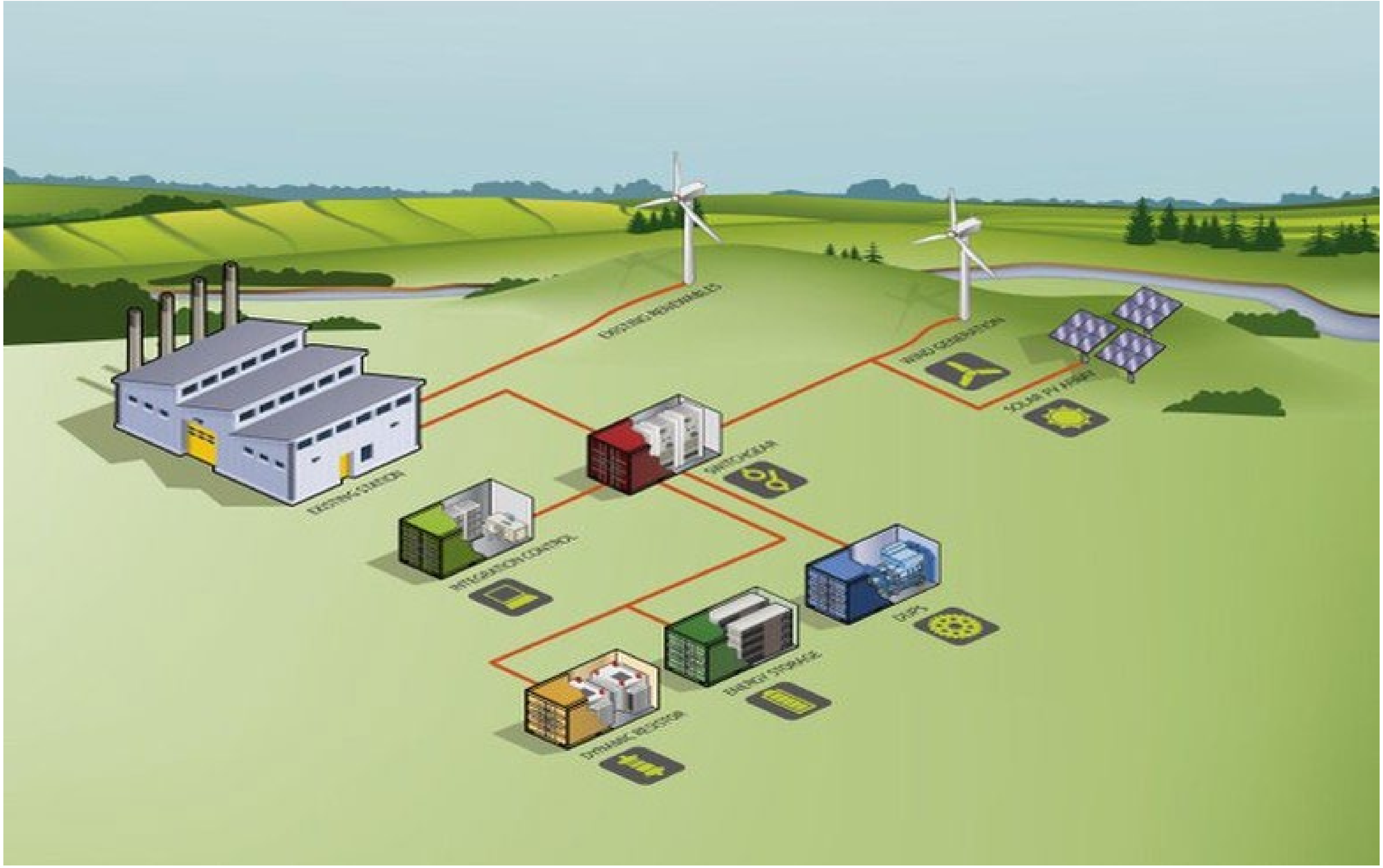
Disadvantages:

The complexity requires advanced optimization techniques for the design and operational planning (unit commitment + economic dispatch) + control.

MICROGRIDS FOR ISLANDS AND REMOTE/RURAL SITES

https://share.america.gov/alcatraz-one-of-the-largest-microgrids-in-u-s/

MICROGRIDS FOR ISLANDS AND REMOTE/RURAL SITES



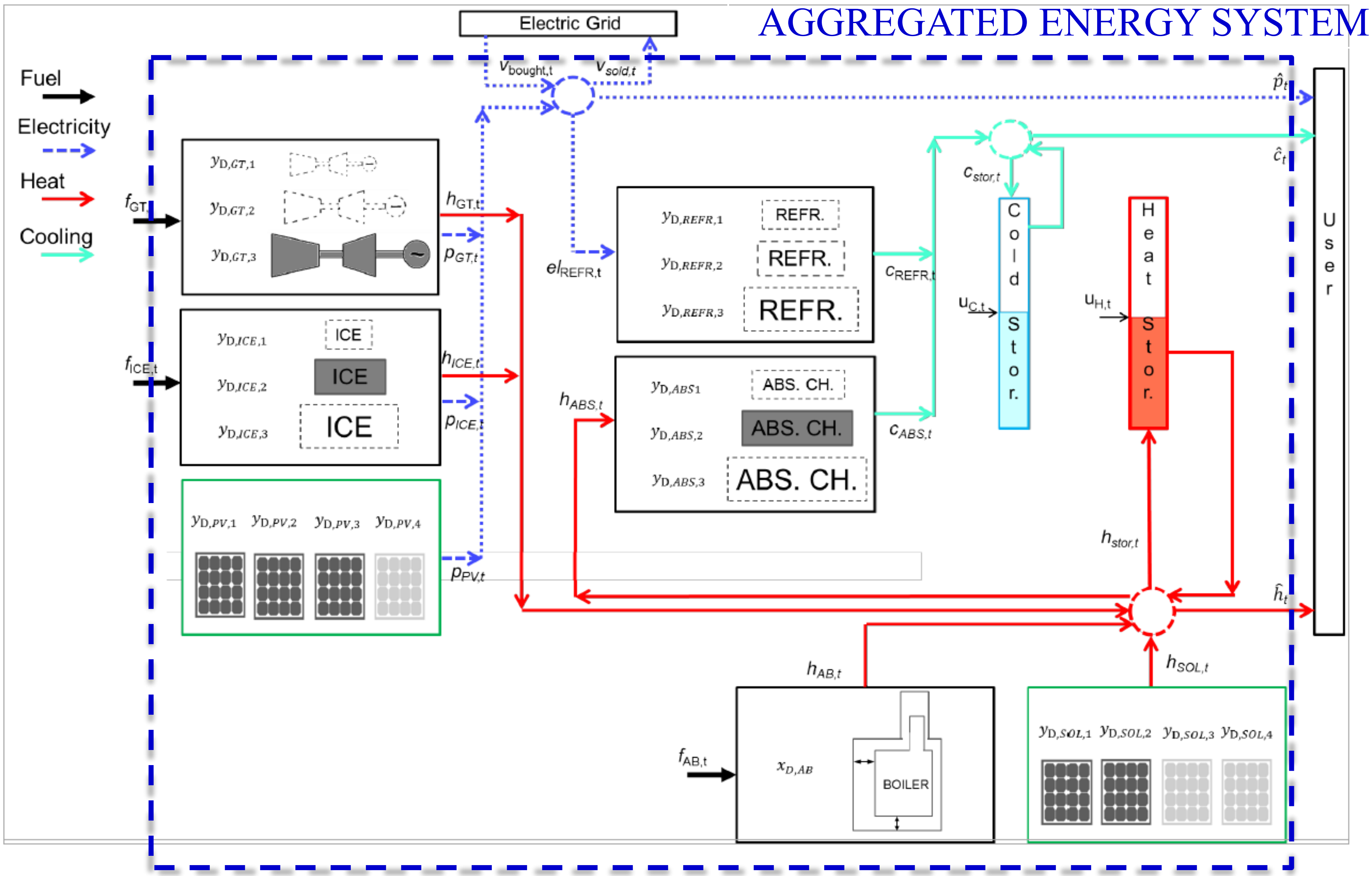
https://renewablesnow.com/news/frances-eps-provides-storage-for-flinders-island-microgrid-558389/

OPTIMIZATION OF AGGREGATED ENERGY SYSTEMS (MES, VPP, PED, ETC)

Types of optimization problems associated to aggregated energy systems:

1. Design/retrofit of the system («investment planning»)
2. Long-term operation planning accounting for yearly constraints (incentives, yearly limits on emissions, and/or seasonal storage systems)
3. 24h-ahead scheduling (unit commitment)
4. Intraday dispatch optimization (e.g., 15 min basis)
5. Optimal control (e.g., < 1 min basis)

OPTIMIZATION OF AGGREGATED ENERGY SYSTEMS



Given:

- Forecast of Electricity demand profile
- Forecast of heating and cooling demand profile
- Forecast of production from renewables
- Forecast of time-dependent price of electricity (sold and purchased)
- Performance maps of the installed units
- Operational limitations (start-up rate, ramp-up, etc) of units
- Efficiency and Maximum capacity of storage systems

Objective: minimize the Daily/Weekly Operating Cost

$$\sum_{t=1}^{24\cdot 7} C_{\mathrm{Fuel,tot,t}} + \sum_{t=1}^{24\cdot 7} C_{O\&M,tot,t} + \sum_{t=1}^{24\cdot 7} C_{start-up,tot,t} \mp \sum_{t=1}^{24\cdot 7} El_{tot,t}$$

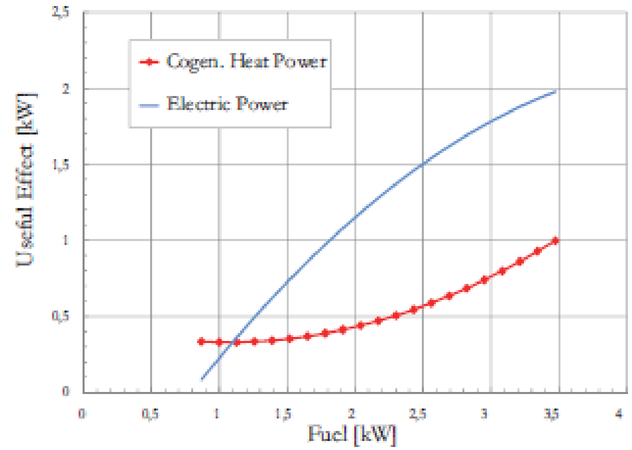
Indep. variables: on/off of units, load of units, storage level in each time period *t*

Assumption: All thermal generators are connected in parallel and provide hot water / steam at similar temperatures

Assumption: All thermal generators are connected in parallel and provide hot water / steam at similar temperatures

Constraints:

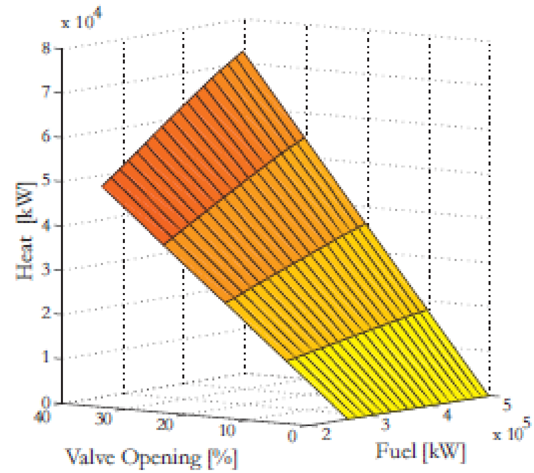
- Electric energy balance constraint ∀ *t* (linear)
- Heating energy balance constraint ∀ *t* (linear)
- Cooling energy balance constraint ∀ *t* (linear)
- Start-up constraints ∀ *t*, ∀ unit (linear)
- Ramp-up constraints ∀ *t*, ∀ unit (linear)
- Performance maps of units ∀ *t*, ∀ unit *i* (nonconvex)



⇓

Nonconvex MINLP

Available MINLP optimizers cannot find the optimal solution for problems with more than 2-3 units



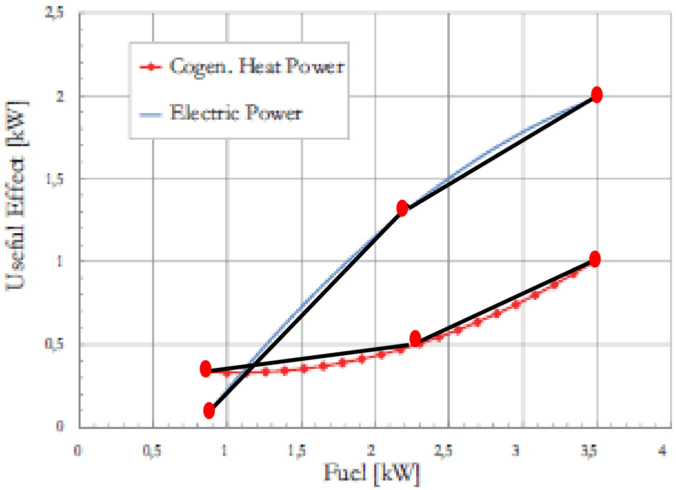
Amaldi et al., 2017. *Short-term planning of cogeneration energy systems via MINLP*, in SIAM book: "Advances and Trends in Optimization with Engineering Applications".

MILP WITH PWL APPROXIMATION OF MAPS

Basic idea: conversion into MILP via linearization of the performance maps

Advantages of MILP formulations:
- Guarantee on the global optimality of the solution
- Super-efficient commercial MILP solvers (e.g., CPLEX, Gurobi)

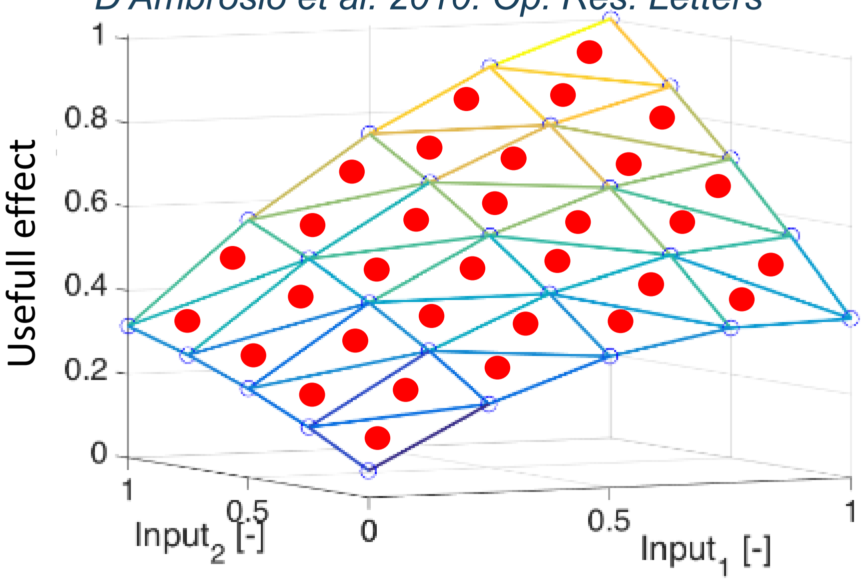
1-D PWL approximation



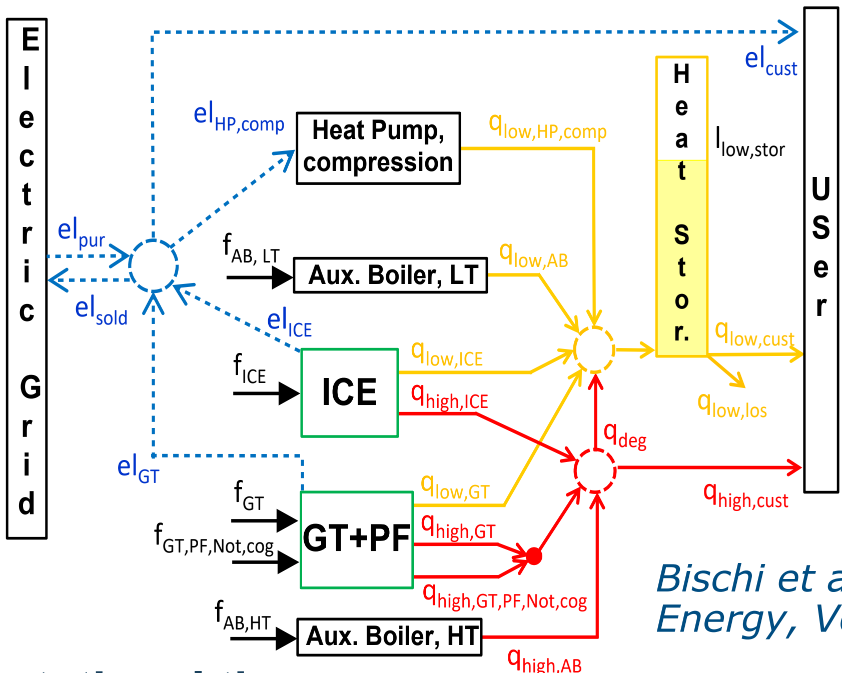
Bischi et al. 2014. Energy, Vol. 74

2-D PWL approximation with the «triangular method»

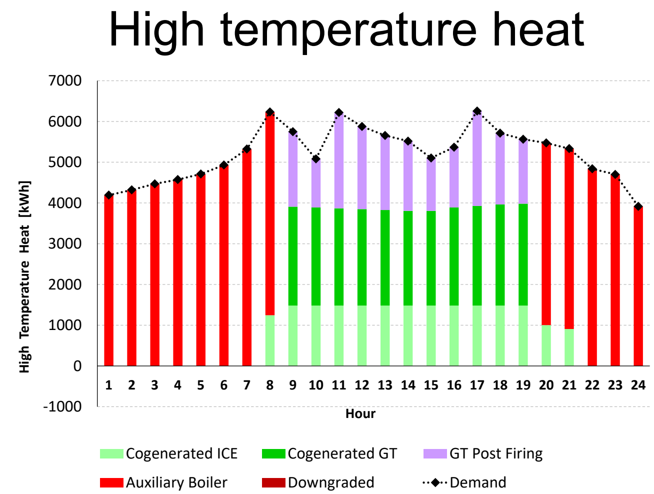
D'Ambrosio et al. 2010. Op. Res. Letters

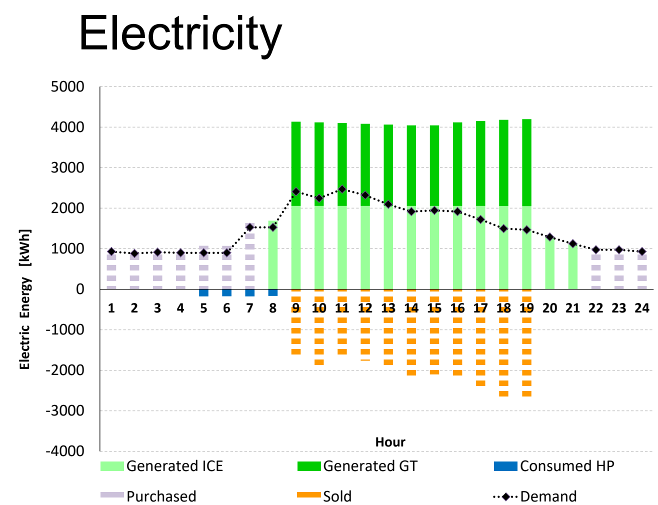


MILP PWL FOR DAILY AND WEEKLY PROBLEMS



Bischi et al. 2014. Energy, Vol. 74





Computational time:

1 day operation: < 1 sec

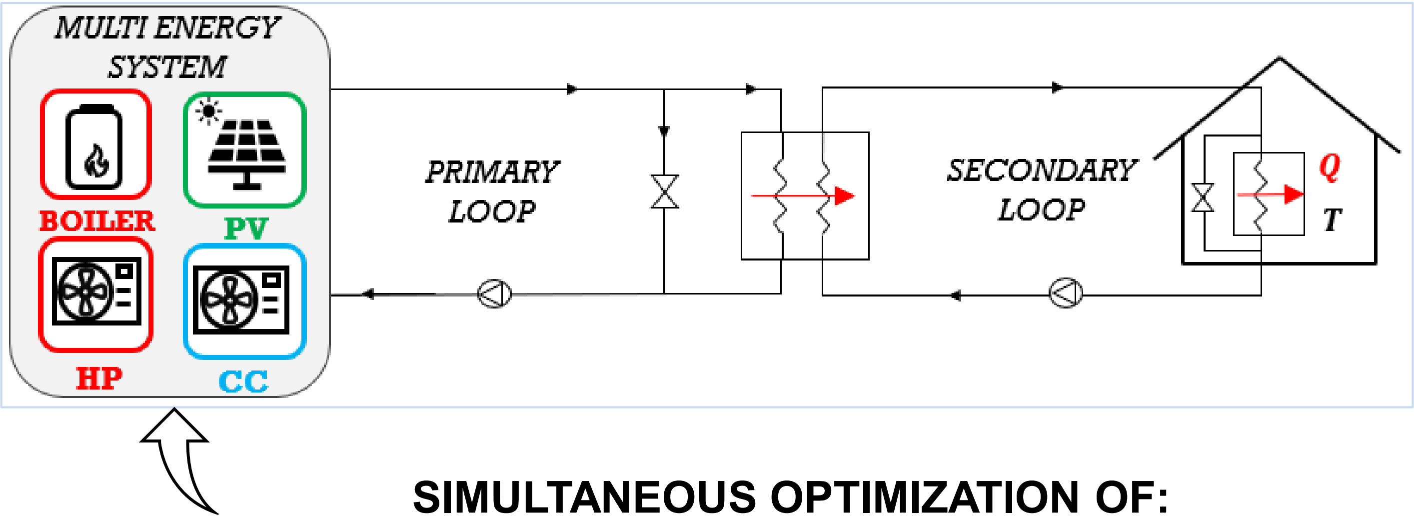
1 week operation: < 10 sec

Up to 18% primary energy saving compared to usual operation strategies!

MILP model implemented within the Energy Management Strategy (EMS) of several microgrids and MESs

CO-OPTIMIZATION OF THERMAL COMFORT AND MES OPERATION

Optimal operation of a MES providing **heat**, **cooling** and **electricity** to a university campus, served by a district heating network (DHN)



SIMULTANEOUS OPTIMIZATION OF:

UNIT COMMITMENT AND ECONOMIC DISPATCH + WATER DELIVERY/RETURN TEMPERATURES OF THE DHN/DCN + INTERNAL BUILDING TEMPERATURES

Considering thermal comfort requirements of users in each building during the occupancy hours.

Ghilardi, Castelli, Moretti, Morini, Martelli, Co-optimization of multi-energy system operation, district heating/cooling network and thermal comfort management for buildings, Applied Energy, Volume 302, 2021, 117480

GENERATING UNITS:

- Linearized **part load performance** of the generators
- **Air temperature effect** on the COP of heat pumps and chillers

BUILDINGS

Each building may have a different internal temperature T_i

$$C\frac{dT}{dt} = (UA + mc_p)\cdot(T_{ext} - T_i) + mc_{p,UTA}\cdot(T_{UTA} - T_i) + Q_{in}$$

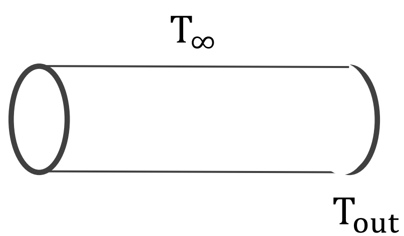
ODE is discretized over time (15 minutes) using finite differences. Error in temperature estimate < 0.1 °C.

DISTRICT HEATING NETWORK

Assumptions: Radial topology with primary/secondary loop for each building, constant mass flow rates

- **Delay in heat propagation** within the pipes

$$T_{out}(t) = T_\infty + (T_{in}(t-\Delta t) - T_\infty)\cdot\left(1 - \frac{4\cdot k_p}{D_p\cdot c_w\cdot \rho_w}\cdot\Delta t\right)$$



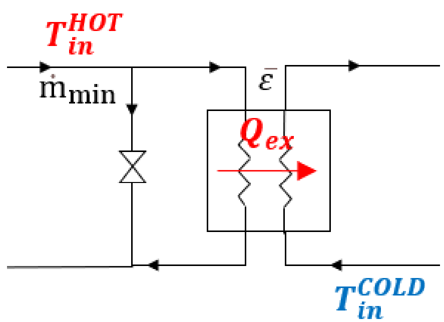
Δt time delay

k_p, D_p pipe parameters

(1D flow, no axial conduction, neglected pipes heat capacity)

- **Upper bound on heat transfer** in HEx

$$Q_{ex} \le \bar{\varepsilon}\cdot c_w\cdot \dot{m}_{min}\cdot\left(T_{IN}^{HOT} - T_{IN}^{COLD}\right)$$



(Minimum thermal capacity always on the same side)

Methodology: Large scale MILP

Objective function: Minimize the total operating cost for the planning horizon

Key Variables:

- On/off (binary) and loads of each generator
- Internal temperature of each building in each time step
- Water delivery and return temperatures of the DHN

Key Constraints (for each time step):

- Linearized performance maps of generators
- Discretized differential equation of each building
- DHN Pipe delay equation
- Heat transfer across each primary-secondary heat exchanger of the DHN
- Ramping limitations on generators
- Maximum allowed temperature ramps in buildings recommended by ASHRAE
- Internal building temperature within comfort range during occupancy hours (e.g., 20-22 °C in winter, 25-27°C in summer)

THERMAL COMFORT MANAGEMENT CONSTRAINTS

Planning horizon: 1 week to exploit thermal capacity of buildings

Time step: 7-15 minutes, depending on the lenght of the DHN.

Computational time depends on the number of buildings and number of time steps

Campus of university of Parma

- 12 buildings with diverse thermal properties
- Radially arranged (primary/secondary loop)
- Occupancy in working hours (Mon-Fri 8 am-6 pm)

- 3 weeks of the year
- 2 MES configurations:
  Design 1: boiler + compression chiller (CC)
  Design 2: HP + auxiliary boiler + Chiller + PV panels

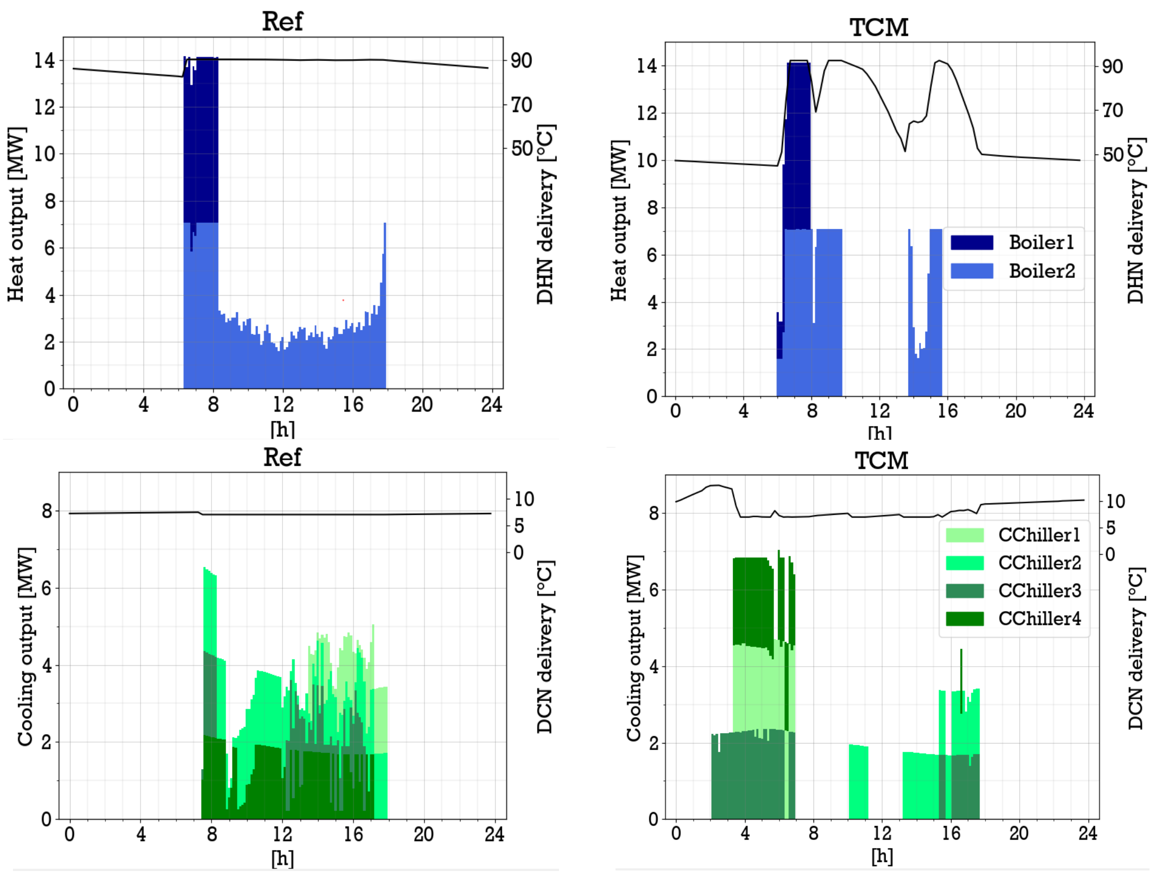
	Buildings temperature	DHN delivery temperature
Ref	FIXED	FIXED (Function of air temperature)
TCM	OPTIMIZED (±2°C wrt set-point when open to public, no temperature constraints when closed)	OPTIMIZED (≤90°C heating; ≥ 7°C cooling)

THERMAL COMFORT CONSTRAINTS

Solver: Gurobi
Problem dimensions (1 week, 7.5 min time steps): 6725 binary, 250160 continuous variables, 384000 constraints
Computational time: 5 hours, gap 0.5% (20 min if considering 12 buildings and 3 days, < 1 min for 7 days and 1 building)

Main results:

1) TCM reduces energy demand of buildings thanks to the flexibility allowed by the comfort interval
2) TCM is essentially a Thermal Demand-side management tool
3) TCM exploits buildings' thermal inertia as a HEAT STORAGE system

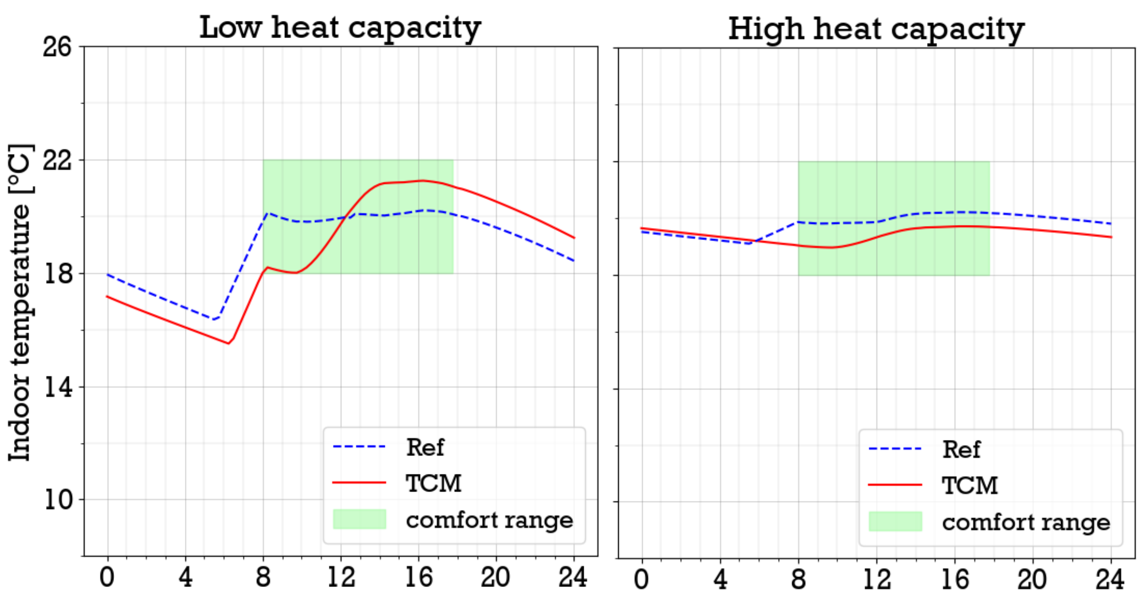


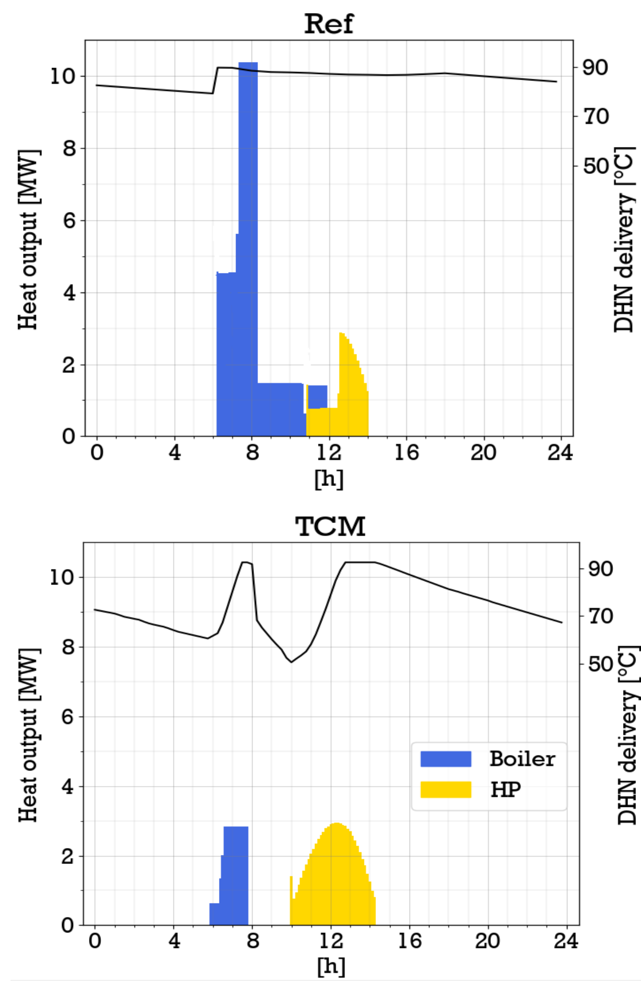
Less part load operation
→ average η boiler from 88% to 92%
→ 14% savings in winter

Chillers start-up in advance
→ Average COP from 3.7 to 4.2
→ Buy cheaper electricity
→ 26% savings in summer

Case Study

- Different profiles depending on buildings' properties





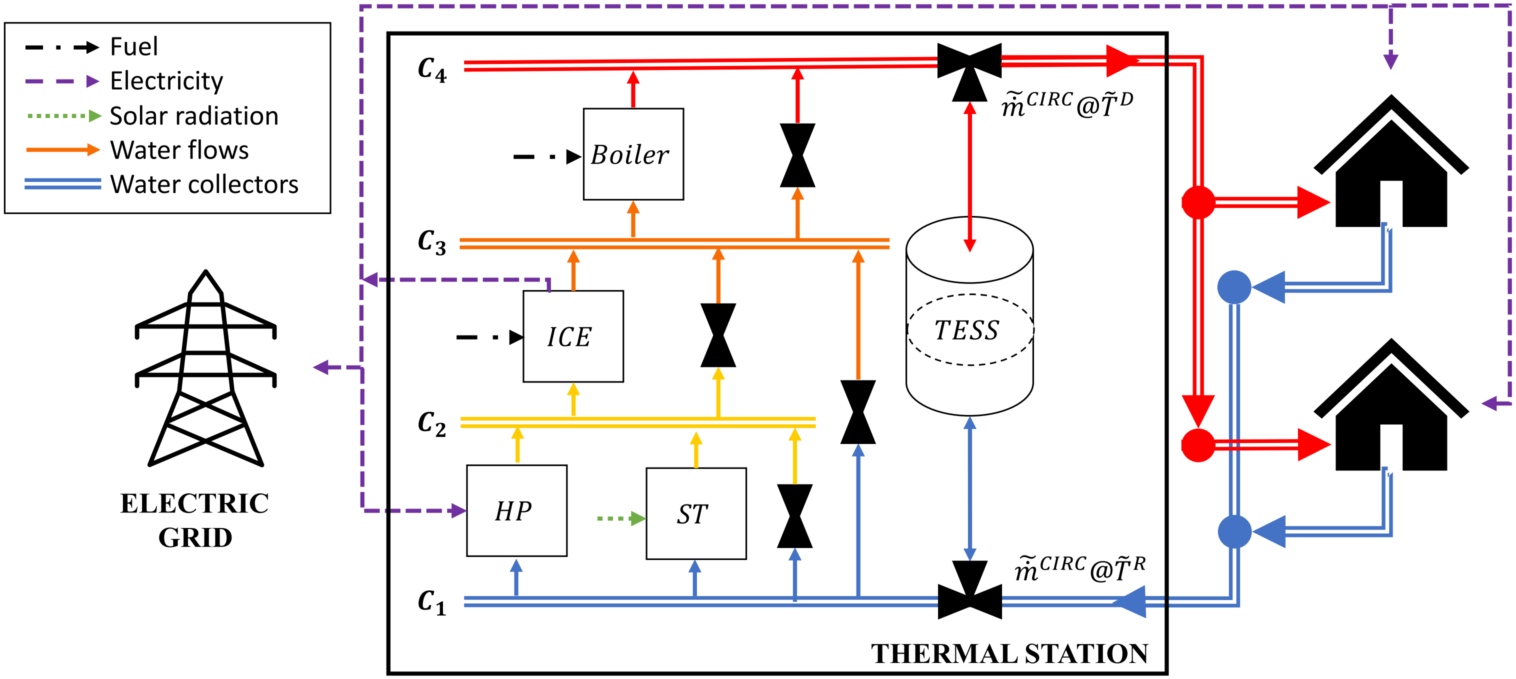
Notes

→ Optimal temperature profiles depend on the building time constant (heat capacity/dispersion coeff.)

→ TCM allows saving fuel by reducing the morning peaksof the boiler and using the HP during sunny hours (PV panels)

→ 22% savings in spring, 3% in winter, 8% in summer

Impact of Series/Parallel Connections and Headers topology



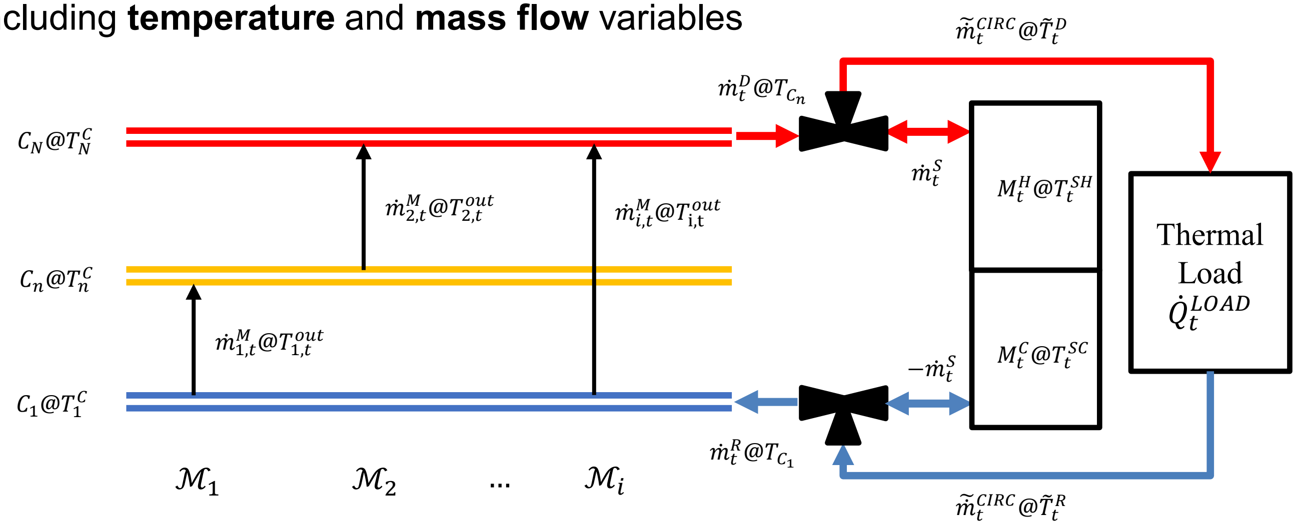
i. Thermal generators may have different heat generation temperatures
   → series / parallel arrangement

ii. Direct stratified thermal storages are normally employed
   → interaction with variable delivery/return temperature

iii. Non-isothermal mixing occurs in the headers

Current MILP models consider only Energy-flows neglecting the impact of **system topology and water temperatures**

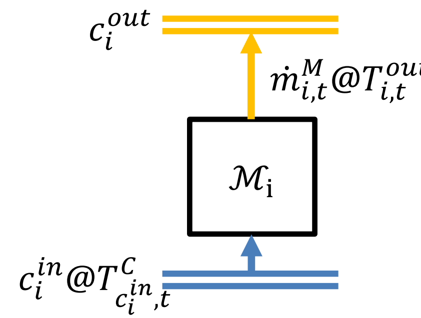
- To account for the heat network topology it is necessary to extend the *energy-flow* formulation of the scheduling problem, including **temperature** and **mass flow** variables



- **Heat and mass balances** must be enforced on all thermal units (generators and storages) and on the water collectors

- The product of mass flow and temperature variables makes the problem a **Mixed Integer Non-Linear Problem** (MINLP)

GENERATORS



- Thermal energy balance:

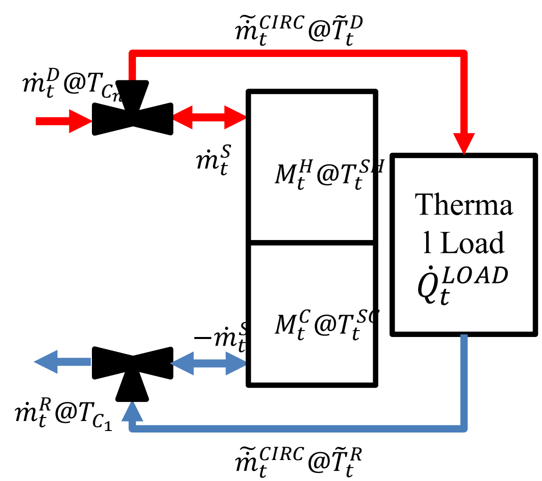
$$p_{i,th,t} = \dot{m}_{i,t}^{M}\left(T_{i,t}^{out} - T_{c_i^{in},t}^{C}\right) \qquad \forall i \in \boldsymbol{\mathcal{M}_{th}}, t \in \boldsymbol{\mathcal{T}}$$

- Operating temperature range:

$$\underline{\tilde{T}_i^{out}} \le T_{i,t}^{out} \le \overline{\tilde{T}_i^{out}}$$

$$\underline{\tilde{T}_i^{in}} - (1 - z_{i,t})\tilde{T}^M \le T_{c_i^{in},t}^{C} \le \overline{\tilde{T}_i^{in}} + (1 - z_{i,t})\tilde{T}^M$$

THERMAL STORAGE



- Mass balance:

$$M_{t+1}^{H} = M_t^{H} - \dot{m}_t^{S}\widetilde{\Delta t}$$

$$M_{t+1}^{C} = M_t^{C} + \dot{m}_t^{S}\widetilde{\Delta t}$$

- Thermal energy balance (non-isothermal mixing):

$$M_{t+1}^{H}T_{t+1}^{SH} = M_t^{H}T_t^{SH} - (\dot{m}_t^{S,out}T_t^{SH} - \dot{m}_t^{S,in}\tilde{T}_t^{D})\widetilde{\Delta t}$$

$$M_{t+1}^{C}T_{t+1}^{SC} = M_t^{C}T_t^{SC} - (\dot{m}_t^{S,in}T_t^{SC} - \dot{m}_t^{S,out}\tilde{T}_t^{R})\widetilde{\Delta t}$$

- Net power contribution:

$$p_t^{S} = \dot{m}_t^{S,out}(T_t^{SH} - \tilde{T}_t^{R}) - \dot{m}_t^{S,in}(\tilde{T}_t^{D} - T_t^{SC})$$

WATER COLLECTORS

- Energy balance (non-isothermal mixing)

$$\begin{cases} \left(\tilde{\dot{m}}_t^{DHN} - \dot{m}_t^{S,out}\right)\tilde{T}_t^R + \dot{m}_t^{S,in} T_t^{SC} = \left(\sum_{i \in \mathcal{M}_c^{with}} \dot{m}_{i,t}^M + \sum_{k \in \mathcal{C}} \dot{m}_{c,k,t}^{BP}\right) T_c^C & c = c_1, \forall t \in \mathcal{T} \\ \sum_{i \in \mathcal{M}_c^{del}} \dot{m}_{i,t}^M T_{i,t}^{out} + \sum_{k \in \mathcal{C}} \dot{m}_{k,c,t}^{BP} T_k^C = \left(\sum_{i \in \mathcal{M}_c^{with}} \dot{m}_{i,t}^M + \sum_{k \in \mathcal{C}} \dot{m}_{c,k,t}^{BP}\right) T_c^C & \forall c \in \mathcal{C}/[c_1, c_N], t \in \mathcal{T} \\ \sum_{i \in \mathcal{M}_c^{del}} \dot{m}_{i,t}^M T_{i,t}^{out} + \sum_{k \in \mathcal{C}} \dot{m}_{k,c,t}^{BP} T_k^C + \dot{m}_t^{S,out} T_t^{SH} = \left(\tilde{\dot{m}}_t^{DHN} + \dot{m}_t^{S,in}\right)\tilde{T}_t^D & c = c_N, \forall t \in \mathcal{T} \end{cases}$$

- Mass balance:

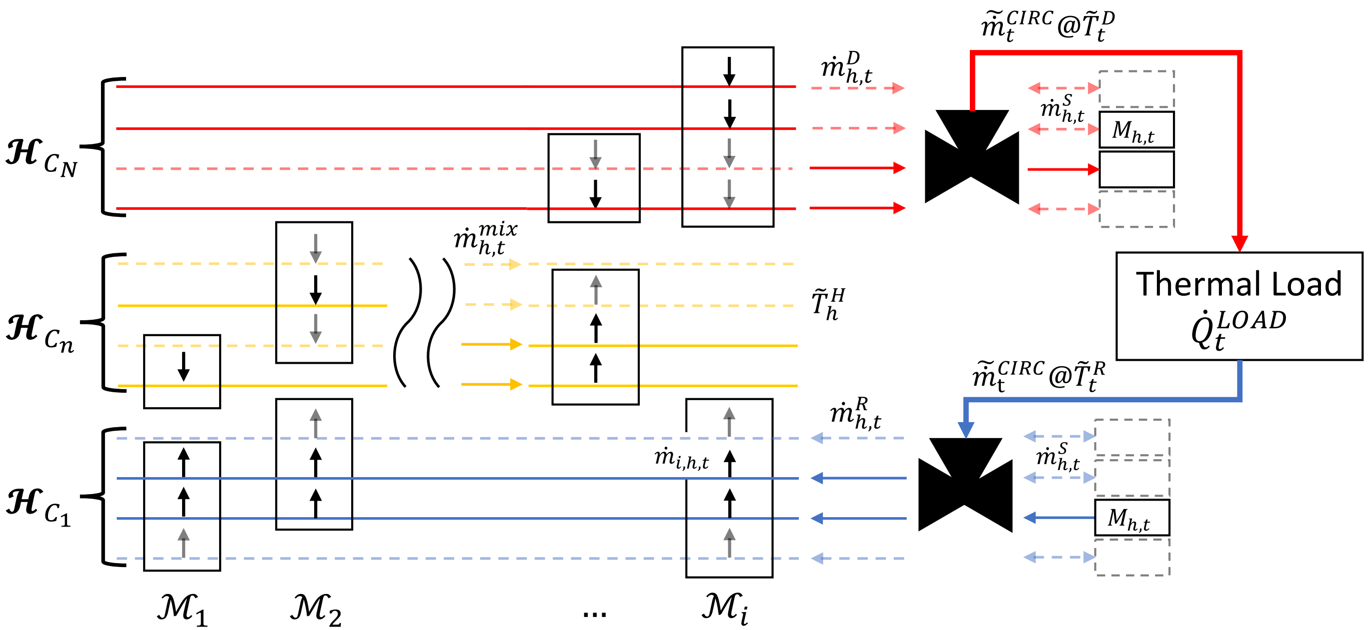
$$\begin{cases} \tilde{\dot{m}}_t^{DHN} + \dot{m}_t^{S,in} - \dot{m}_t^{S,out} = \sum_{i \in \mathcal{M}_c^{with}} \dot{m}_{i,t}^M + \sum_{k \in \mathcal{C}} \dot{m}_{c,k,t}^{BP} & c = c_1, \forall t \in \mathcal{T} \\ \sum_{i \in \mathcal{M}_c^{del}} \dot{m}_{i,t}^M + \sum_{k \in \mathcal{C}} \dot{m}_{k,c,t}^{BP} = \sum_{i \in \mathcal{M}_c^{with}} \dot{m}_{i,t}^M + \sum_{k \in \mathcal{C}} \dot{m}_{c,k,t}^{BP} & \forall c \in \mathcal{C}/[c_1, c_N], t \in \mathcal{T} \\ \sum_{i \in \mathcal{M}_c^{del}} \dot{m}_{i,t}^M + \sum_{k \in \mathcal{C}} \dot{m}_{k,c,t}^{BP} + \dot{m}_t^{S,out} - \dot{m}_t^{S,in} = \tilde{\dot{m}}_t^{DHN} & c = c_N, \forall t \in \mathcal{T} \end{cases}$$

- The MINLP formulation is non-convex due to the bilinear products between mass flow and temperature

  → very difficult to find global optimum, especially for MES with complex unit commitment problems (many binary variables)

- We propose a linearized formulation based on the definition of **discrete constant temperature levels** ("virtual headers")

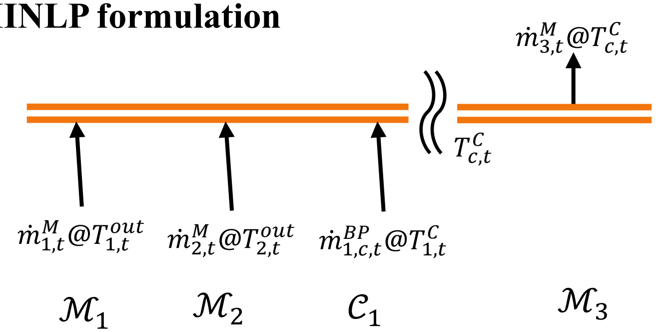
  ➢ Each header is represented as a set of multiple virtual headers wit fixed temperatures



➢ Water flows are represented as the combination of multiple virtual flows at constant temperatures

➢ Generators withdraw and deliver water on the virtual headers within their inlet/outlet operating temperature range

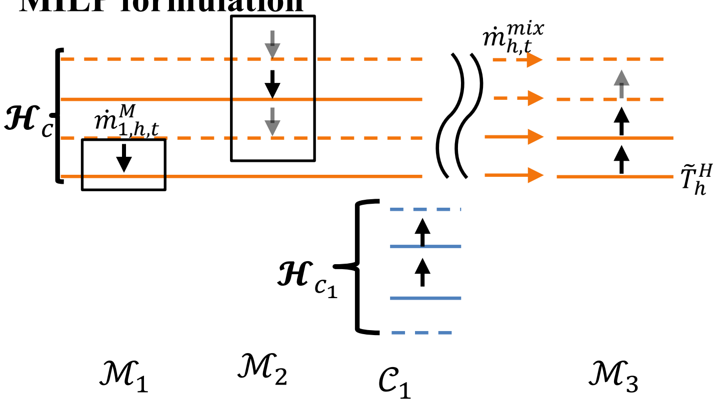
MINLP formulation



$$\sum_{i\in\mathcal{M}_c^{del}} \dot m^M_{i,t} T^{out}_{i,t} + \sum_{k\in\mathcal{C}} \dot m^{BP}_{k,c,t} T^C_{k,t} = \left(\sum_{i\in\mathcal{M}_c^{with}} \dot m^M_{i,t} + \sum_{k\in\mathcal{C}} \dot m^{BP}_{c,k,t}\right) T^C_{c,t}$$

$$\sum_{i\in\mathcal{M}_c^{del}} \dot m^M_{i,t} + \sum_{k\in\mathcal{C}} \dot m^{BP}_{k,c,t} = \sum_{i\in\mathcal{M}_c^{with}} \dot m^M_{i,t} + \sum_{k\in\mathcal{C}} \dot m^{BP}_{c,k,t} \qquad \forall c\in\mathcal{C}, t\in\mathcal{T}$$

MILP formulation



SOS_2 on $h\in\mathcal{H}_c, \forall t$

$$\sum_{i\in\mathcal{M}_c^{del}} \sum_{h\in\mathcal{H}_c} \dot m^M_{i,h,t} \tilde T^H_h + \sum_{k\in\mathcal{C}} \sum_{h\in\mathcal{H}_k} \dot m^{BP}_{h,c,t} \tilde T^H_h = \sum_{h\in\mathcal{H}_c} \dot m^{mix}_{h,t} \tilde T^H_h \qquad \forall c\in\mathcal{C}, t\in\mathcal{T}$$

$$\dot m^{mix}_{h,t} = -\sum_{i\in\mathcal{M}_h^{with}} \dot m^M_{i,h,t} + \sum_{c\in\mathcal{C}} \dot m^{BP}_{h,c,t} \qquad \forall c\in\mathcal{C}, h\in\mathcal{H}_c, t\in\mathcal{T}$$

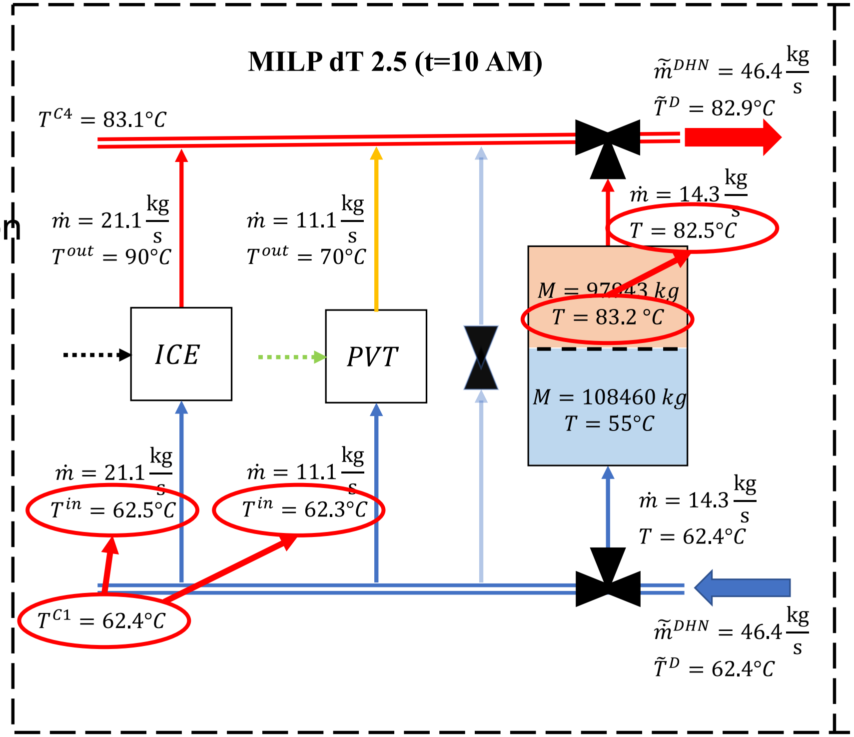
- SOS2 constraint allows determining in which temperature interval (between those of the virtual headers) results the mixed water stream.

- The temperature discretization introduces a **«demixing» effect**

local possible violations of second law of thermodynamics (due to the temperature discretization and SOS2)

It underestimates costs (LB)

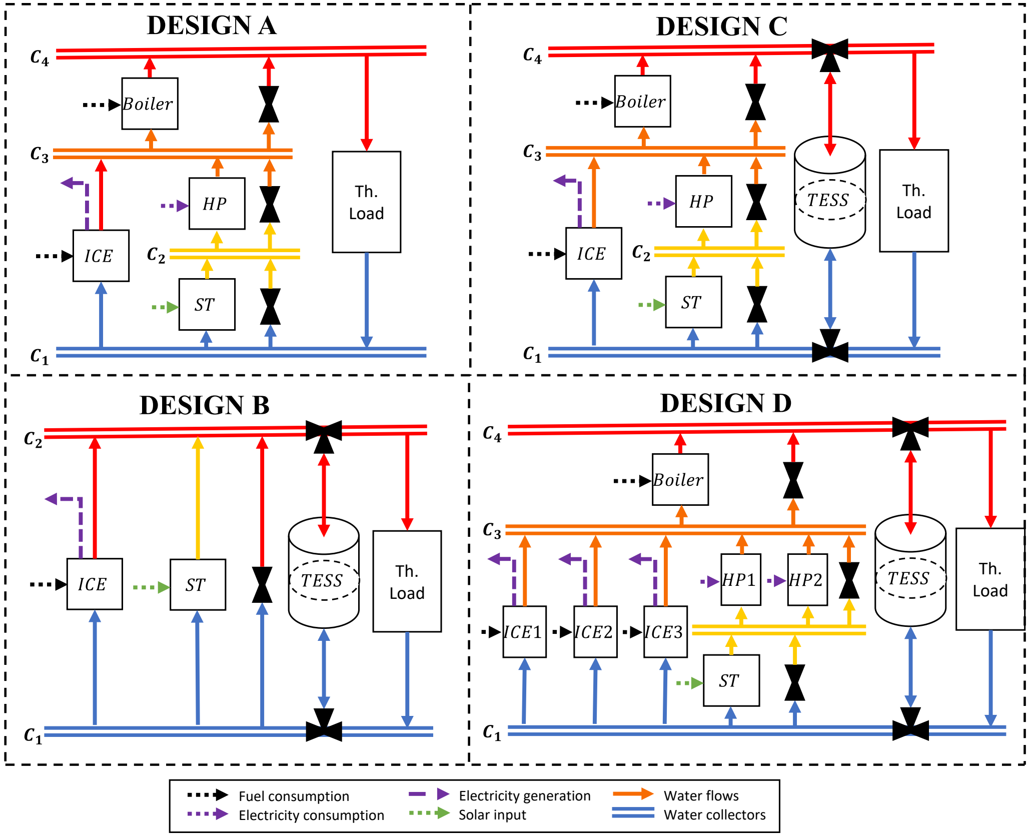
- Its impact can be contained by reducing the temperature difference between adjacent temperature levels (e.g., 1 °C)
- In the proximity of relevant temperature thresholds temperature levels resolution can be refined



- Load and delivery/return temperature profiles measured in the Politecnico di Milano CHP power station

- Four system architectures, associated to different degrees of complexity of the scheduling problem, are evaluated

- Three alternative formulations are compared:
  - ➢ Classic **MILP *energy-flow*** formulation
  - ➢ **MINLP *water-flow*** formulation
  - ➢ **MILP *water-flow*** formulation (with different temperature resolutions ΔT)



KEY FINDINGS: NUMERICAL EFFECTIVENESS OF LINEARIZED WATER-FLOW MODEL

Practical feasibility and «real operating costs» of MILP solutions is tested imposing the scheduling in the MINLP formulation and solving the NLP subproblem.

- The *energy-flow* MILP formulation does not find practically feasible scheduling plans
- The MILP *water-flow* model needs a temperture resolution of < 2.5 °C to find practically feasible solutions
- In most MINLP runs (7/10), no feasible solution is found → careful initialization required
- The *water-flow* MILP formulation is more reliable and finds better or equal solutions within the computational time limit (1 hour)

DESIGN A	3 UNITS	MILP Energy-flow	MILP ΔT 5	MILP ΔT 2.5	MILP ΔT 1	MINLP (best run)
Best solution found	**OF [€]**	**4528**	**5051**	**5072**	**5102**	**5109**
	Sol Time [s]	0.4	1.2	1.6	3.9	260
	Gap [%]	0.00%	0.00%	0.00%	0.00%	1.83%
	NLP OF [€]	**unfeas.**	**unfeas.**	**5126**	**5109**	**5109**
Thermal Energy Production Summary [kWh]	ICE	28340	30993	30554	30740	30923
	Boiler	382	4694	4879	5141	5188
	HP	16104	13688	13465	13859	13802
	PVT	8926	4376	4853	4012	3840
Operating Hours [h]	ICE	24	24	24	24	24
	Boiler	1	11	11	12	12
	HP	19	21	21	22	22

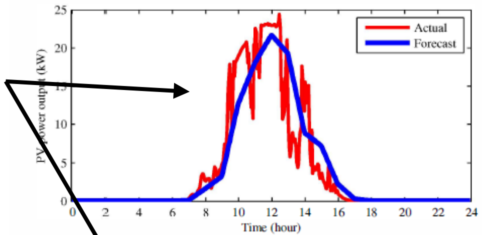
DESIGN B	2 UNITS + TES	MILP Energy-flow	MILP ΔT 5	MILP ΔT 2.5	MILP ΔT 1	MINLP (best run)
Best solution found	**OF [€]**	**5147**	**5903**	**5944**	**5961**	**5960**
	Sol. Time	0.5	25.7	261.3	1800.0	1800.0
	Gap [%]	0.00%	0.07%	0.10%	2.11%	5.85%
	NLP OF [€]	**unfeas.**	**unfeas.**	**5960**	**5960**	**5960**
Thermal Energy Production Summary [kWh]	ICE	38936	49494	50051	50294	50266
	PVT	14863	5458	4777	4553	4386
TESS throughput [kWh]		8119	5700	5511	5598	5436
Net energy export to grid [kWh]		15015	26717	27338	27610	27579
Operating Hours [h]	ICE	23	24	24	24	24

DESIGN D		MILP Energy-flow	MILP ΔT 5	MILP ΔT 2.5	MILP ΔT 1	MINLP (best run)
First incumbent 1% from final incumbent	OF [€]	-	5495	5537	5688	6028
	Time to find [s]	-	545	310	2033	2145
	Gap [%]	-	2.8%	4.4%	6.3%	15.2%
Best solution found	**OF [€]**	**5103**	**5443**	**5498**	**5658**	**5828**
	Sol. Time [s]	2.3	3120.7	3600	3600	3600
	Gap [%]	0.0%	0.01%	2.61%	5.58%	12.3%
	MINLP OF [€]	**unfeas.**	**unfeas.**	**5499**	**5613**	**5828**

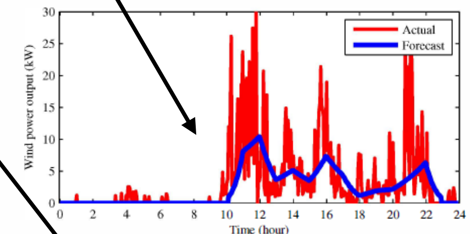
OPTIMAL OPERATION OF AGGREGATED ENERGY SYSTEMS UNDER FORECAST UNCERTAINTY

Given:

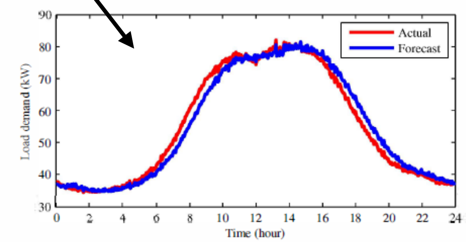
- Forecast of power production from renewables and its uncertainty
- Forecast of energy demand profiles and its uncertainty
- Forecast of electricity prices and its uncertainty
- Performance maps of the installed units
- Operational limitations (start-up rate, ramp-up, etc) of units
- Efficiency and Maximum capacity of storage systems



(a) PV power output.



(b) Wind power output.



(c) Local user demand.

Determine:

Day-ahead UC and EC: on/off of units, load of units, storage manag.

Minimizing the expected daily operating cost considering the possible future "scenarios"

Constraints: meet energy demands, technical limitations of units, performance maps, etc in all the considered future scenarios

Robust Optimization approach:

(+) It guarantees that the users' demand is always satisfied (no outages/black-out).

(+) Prob. Distribution of the uncertain factors not required

(+/-) Need of defining a-priori "recourse laws" (not fully flexible BUT useful for real-time operation)

(-) Excessively conservative (suboptimal) solutions

(-) Correlation between uncertain factors not considered

Recommended for MES systems with high reliability requirements (e.g., serving hospitals) and off-grid microgrids (due to the black-out risks).

Stochastic Optimization Approach:

(+) It targets that the minimization of the expected cost in the set of possible future scenarios

(+) scenarios can keep correlation between uncertain factors

(-) No "recourse laws" are provided

(-) Prob. Distribution of the uncertain factors not required Recommended for CHP systems with high reliability requirements and microgrids.

(-) Operating feasibility in the worst possible case may not be guaranteed.

Ideally suited for maximizing the profit of Virtual Power Plants providing balancing/ancillary services to the electric grid. → Ongoing work (Alessandro's PhD thesis)

Piece-Wise Affine Adjustable Robust Optimization

Adjustable robust formulation of the “energy-flow” MILP model:

$$\min_{\boldsymbol{x}_\delta}\left\{\mathbb{E}[\tilde{\boldsymbol{c}}^{\mathrm{T}}\boldsymbol{x}_\delta] \,:\, \forall\tilde{\boldsymbol{\delta}} \in \mathcal{U}\;\; \tilde{A}^e\boldsymbol{x}_\delta = \tilde{\boldsymbol{b}}_\delta^e \wedge \tilde{A}^i\boldsymbol{x}_\delta \leq \tilde{\boldsymbol{b}}_\delta^i\right\}$$

$$\boldsymbol{x}_\delta = \begin{bmatrix}\boldsymbol{x} \\ \Delta\boldsymbol{x}_\delta\end{bmatrix}$$

“Here and now” decisions = day-ahead committment

“Recourse” decisions = real-time corrections

Uncertainty set is defined by:
- Bounds for instantaneous power deviation
- Bounds on total error over a given time window (budget of uncertainty)

«Polyhedral» uncertainty set:

$$\mathcal{U} = \{\boldsymbol{\delta} \mid \underline{\delta_t} \leq \delta_t \leq \overline{\delta_t}, \|\boldsymbol{\delta}\|_1 \leq \Gamma\} \equiv \{\boldsymbol{\delta} \mid L\boldsymbol{\delta} \leq \boldsymbol{l}\}$$

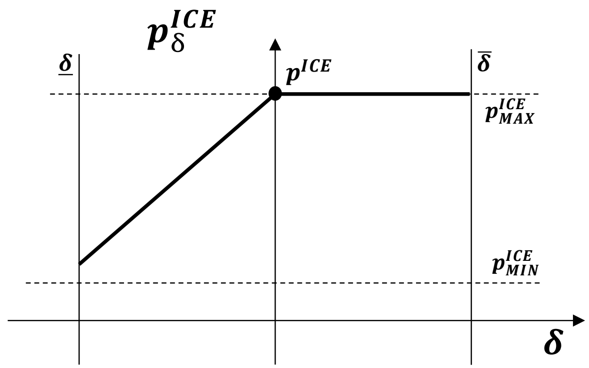
Bounds and budget determined by statistical analysis of prod. and demand forescast errors (99.5° percentile)

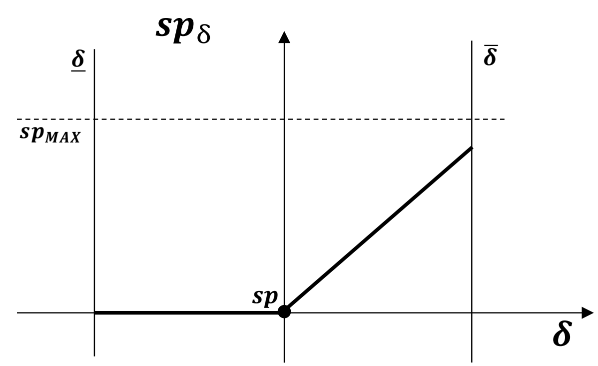
Moretti, Martelli, Manzolini, 2020. An efficient robust optimization model for the unit commitment and dispatch of multi-energy systems and microgrids, Applied Energy, vol. 258.

AFFINE ADJUSTABLE ROBUST OPTIMIZATION

Piece-Wise Linear recourse:

$$\Delta \boldsymbol{x}_\delta = Y^+ \widetilde{\boldsymbol{\delta}}^+ - Y^- \widetilde{\boldsymbol{\delta}}^- = \begin{bmatrix} Y^+ & 0 \\ 0 & Y^- \end{bmatrix} \begin{bmatrix} \widetilde{\boldsymbol{\delta}}^+ \\ \widetilde{\boldsymbol{\delta}}^- \end{bmatrix}$$





Semi-infinite program

$$\min_{\boldsymbol{x},Y} \tilde{\boldsymbol{c}} \begin{bmatrix} \boldsymbol{x} \\ Y\hat{\mathbb{E}}[\widetilde{\boldsymbol{\delta}}] \end{bmatrix}$$

$$s.t.\ \left(\widetilde{W}^e Y - \widetilde{H}^e\right)\widetilde{\boldsymbol{\delta}} = \widetilde{\boldsymbol{h}}^e - \widetilde{T}^e \boldsymbol{x} \quad \forall \boldsymbol{\delta} \in \mathcal{U}$$

$$\widetilde{T}^e \boldsymbol{x} = \widetilde{\boldsymbol{h}}^e$$

$$\widetilde{W}^e Y = \widetilde{H}^e$$

$$\max_{\boldsymbol{\delta}\in\mathcal{U}} \left[\left(\widetilde{W}^i Y - \widetilde{H}^i\right)\widetilde{\boldsymbol{\delta}}\right] \le \widetilde{\boldsymbol{h}}^i - \widetilde{T}^i \boldsymbol{x}$$

It is a linear program with respect to $\widetilde{\boldsymbol{\delta}}$

LP duality allows reformulation

Tractable robust counterpart

$$\min_{\boldsymbol{x},Y,\Lambda} \tilde{\boldsymbol{c}} \begin{bmatrix} \boldsymbol{x} \\ Y\widehat{\mathbb{E}}[\tilde{\boldsymbol{\delta}}] \end{bmatrix}$$

$$\tilde{T}^e \boldsymbol{x} = \tilde{\boldsymbol{h}}^e$$

$$\widetilde{W}^e Y = \widetilde{H}^e$$

$$\tilde{\boldsymbol{l}} \Lambda_j \leq \tilde{\boldsymbol{h}}^{\boldsymbol{i}} - \tilde{T}^i \boldsymbol{x}$$

$$\tilde{L}^T \Lambda_j \geq \widetilde{W}_j^i Y - \widetilde{H}_j^i$$

$$\Lambda \geq 0$$

Large scale MILP, tractable for commercial solvers if *number of time steps* < 100

Reductions in computational time achievable with:

1) *Aggregating uncertain factors of energy demand and renewable production*
2) *«Partial-past recourse» laws*: correction law depends only on a few past realizations of the uncertain factors.

Moretti, Martelli, Manzolini, 2020. An efficient robust optimization model for the unit commitment and dispatch of multi-energy systems and microgrids, Applied Energy, vol. 258.

AARO TEST CASES

Test Case	Energy Provided			Uncertainty Factors
	Energy	Peak Power [MW_p]	Daily Demand [MWh/day]	
Off-grid Micro-Grid	Electricity	1.1	14.2	Electric Demand, PV production
On-grid Hospital	Electricity	1.9	35.3	Electric demand, Thermal demand, PV production
	Heat	4.6	83	
On-grid Campus	Electricity	3.7	28.9	Electric demand, Thermal demand, PV production
	Heat	10.3	66.4	

	Microgrid	Hospital							Campus		
CONFIGURATION UNITSS	A	A	B	C	D	E	F	G	A	B	C
Diesel generator [kW_{el}]	2 x 550	-	-	-	-	-	-	-	-	-	-
CHP engine [kW_{el} / kW_{th}]	-	1 x 1900 / 1770	1 x 1900 / 1770	2 x 1000 / 1040	2 x 1000 / 1040	-	1 x 1050 / 1080	-	1 x 960 / 1000	-	1 x 2050 / 1900
Natural gas Boiler [kW_{th}]	-	3 x 1700	3 x 1700	2 x 1270	2 x 1270	-	-	-	1 x 3960	1 x 4170	1 x 5900
PV field [kW_{el}]	1 x 1440	-	-	-	1 x 1000	1 x 1000	1 x 2000	1 x 1500	1 x 3150	1 x 3150	-
Heat Pump [kW_{th}]	-	-	1 x 2070	1 x 2070	1 x 2070	2 x 1050	3 x 2070	-	1 x 1670	-	1 x 1550
ORC CHP unit [kW_{el} / kW_{th}]	-	-	-	-	-	1 x 1000 / 4830	-	1 x 1000 / 4830	2 x 60 / 350	1 x 515 / 2570	-
Biomass Boiler [kW_{th}]	-	-	-	-	-	1 x 1680	-	1 x 1680	-	-	-
Thermal Storage [kWh_{th}]	-	1 x 1274	1 x 1274	1 x 1274	1 x 10000	1 x 10000	1 x 10000	1 x 10000	1 x 21140	1 x 28400	1 x 4626
Lithium-Ion Battery [kWh_{el}]	1 x 3600	-	-	-	-	-	-	-	-	-	-

Moretti, Martelli, Manzolini, 2020. An efficient robust optimization model for the unit commitment and dispatch of multi-energy systems and microgrids, Applied Energy, vol. 258.

AARO vs. Reserve Constraints + Heuristic corrections

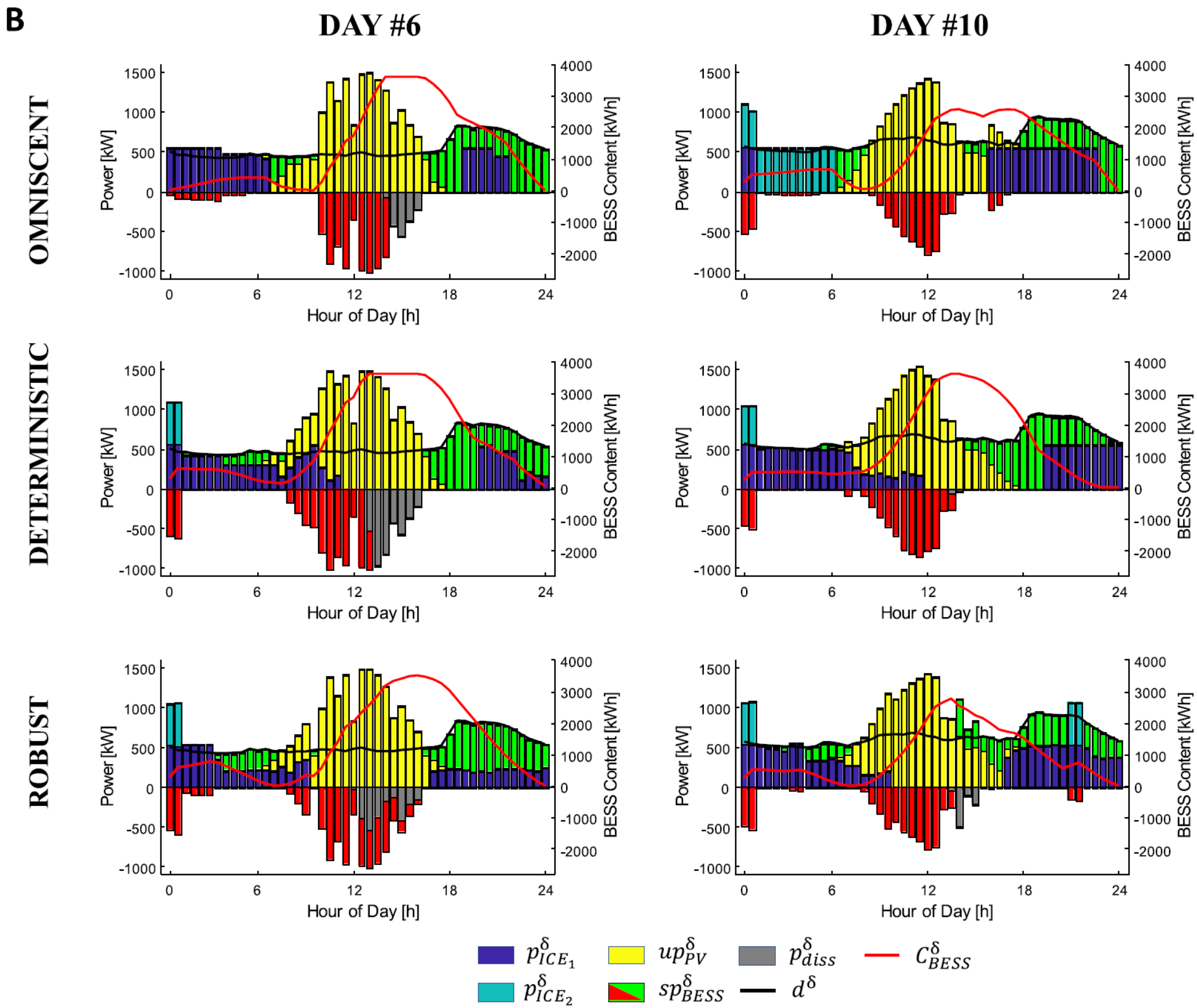
Name	R0	R1	R2	R3
Extended Uncertainty Characterization (Section 6.2)		✓	✓	✓
Uncertain Net Demand (Section 6.3)			✓	✓
Partial-past recourse (Section 6.1)				✓

El. Demand – Production from PV panels

Data-driven ad hoc linear constraints to limit the uncertainty set (intraday budgets + ramp limits in forecast error)

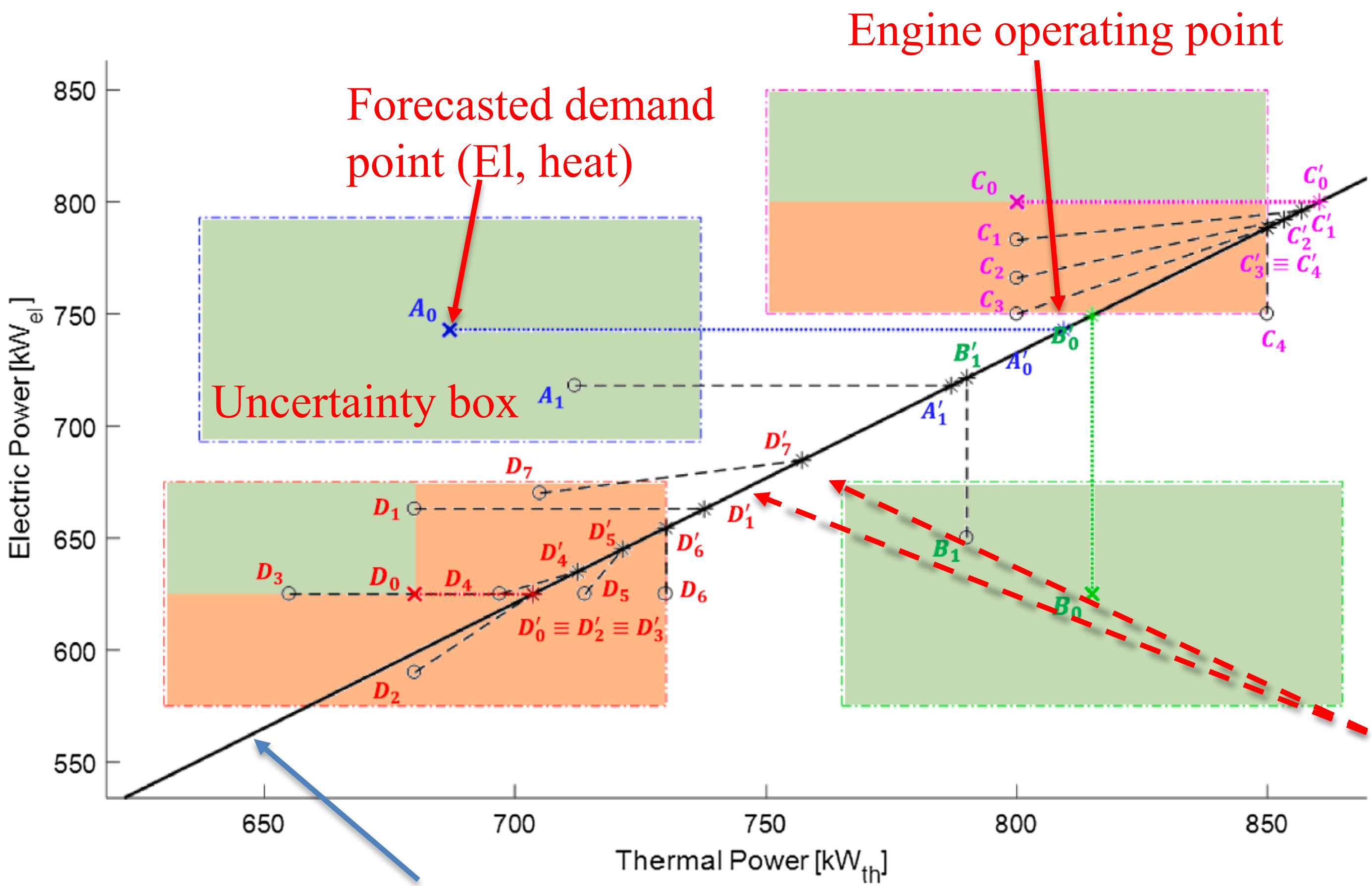
Off-grid microgrid		Expected Total Diesel Consumption [L]	Actual Total Diesel Consumption [L]	GAP (increase wrt LB) [%]	Service Interruptions: Total Unserved Energy [kWh]	Service Interruptions: Service Reliability [%]	Avg. Sol. Time
OMNISCIENT (lower bound)		12605	14020 (LB)	-	0	100	6.4
MILP with Reserve + heuristic correct.	No reserve	12609	12772*	-8.9%*	5000	88.5	7.6
	T^{res}= 1h	13672	14634*	4%*	1568	96.4	6.8
	T^{res}= 2h	14291	15624*	11%*	670	98.5	6.5
	T^{res}= 3h	15010	16573*	18%*	53	99.5	6.3
ROBUST + Affine correction	R0	13838	16515	18%	0	100	406
	R1	13597	15943	14%	0	100	778
	R2	13618	16097	15%	0	100	175
	R3	13710	16191	16%	0	100	48

AARO vs. Reserve Constraints + Heuristic corrections



AARO LIMIT 1: OVER-CORRECTION OF CHP UNITS

Green region around point A_0: Any possible uncertain deviation in heat demand is automatically satisfied by the excess heat produced by the engine → the heat demand recourse coefficients are zero (not necesary)



Engine operating map (linear approximation)

Red region around D_0 :
D_0: forecasted demand
D_7: realization demand

Recourse coefficients for both demands (heat and electricity) are non-zero, determined to compensate variations of only electricity or only heat demand.
If both demand variations are positive, engine load is overcorrected (engine operating in D'_7)

AARO limit 2: Quick Ramp Units

Microgrids and MESs feature mainly quick-start units such as:

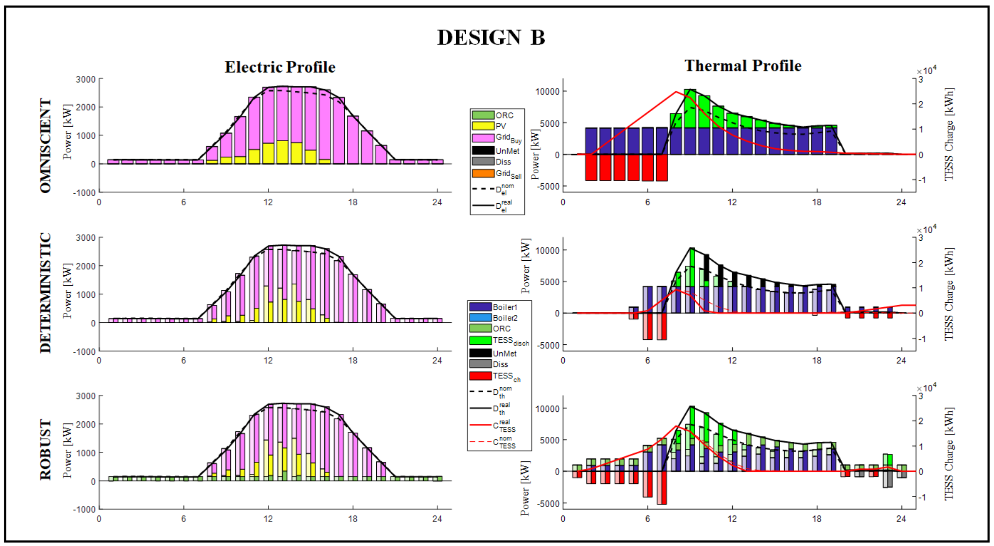
- Boilers
- Internal combustion engines
- Gas turbines
- Heat pumps

For these units, on/off (binary) recourse decisions should be included.

Unfortunately the available approaches (e.g., Bertsimas's binary decision rules + cutting plane algorithm of Blankenship and Falk) are computationally intensive and not easily scalable to industrial scale problems with > 2 units and 24 or more time steps.

AARO VS. RESERVE CONSTRAINTS + HEURISTIC CORRECTIONS

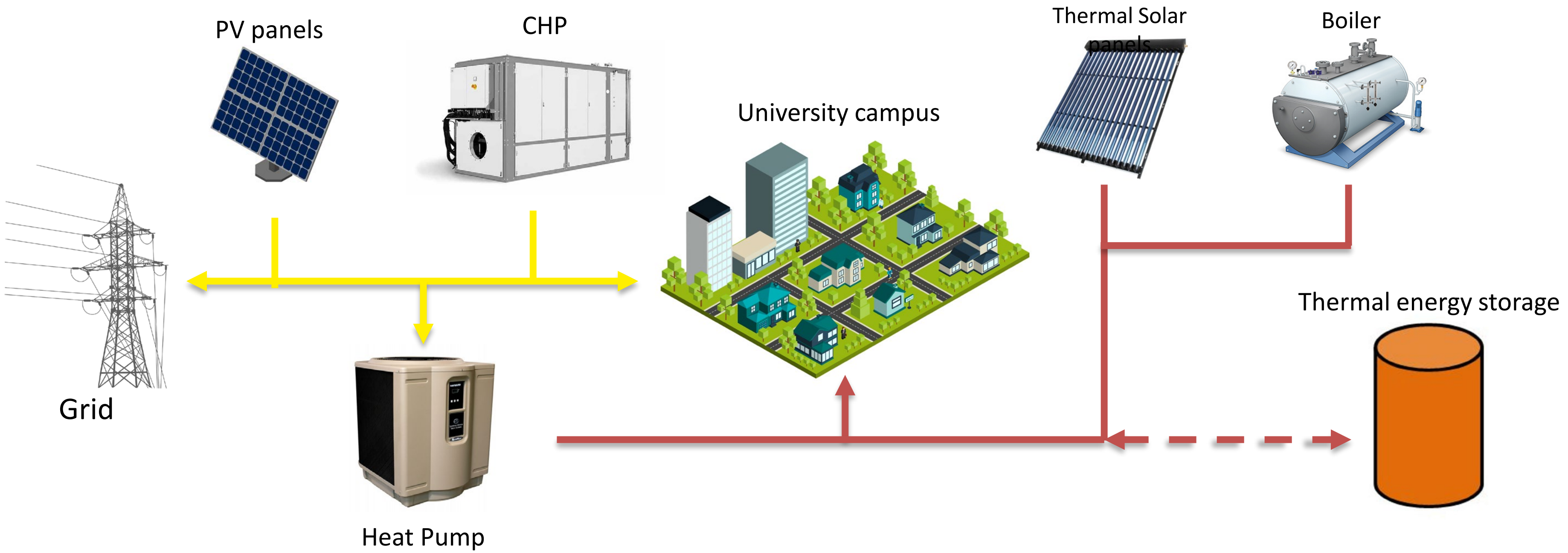
CAMPUS						
Design	Simulation Mode	Expected Operating Cost [€]	Actual Operating Cost [€]	GAP [%]	Unserved Thermal Energy[kWh]	Service Reliability [%]
CA	OMNISCENT	20160		0	100%	
	DETERMINISTIC	17205	21855	8.4%	0	100%
	ROBUST	17490	20955	4.0%	0	100%
CB	OMNISCENT	33210			100%	
	DETERMINISTIC	30285	33345*	0.4%*	1970	94.6%
	ROBUST	31755	34695	4.5%	0	100%
CC	OMNISCENT	32925			100%	
	DETERMINISTIC	31485	34740	5.5%	0	100%
	ROBUST	31710	33525	1.8%	0	100%



Conclusions on AARO:

1. AARO leads to higher reliability for same op. cost or lower op. cost for same reliability
2. Piecewise affine recourse laws, although limited, better than det. MILP + heuristics corrections for real-time operation
3. Computational time can be effectively limited with the partial-past approach
4. Binary decision rules may futher improve solutions

Long-Term Operational Planning



Optimal daily operation while considering yearly behavior

- To get ”white certificate” incentives, CHP yearly constraints must be met:
  - Constraint on minimum yearly Primary Energy Saving index
  - Incentive value depends also on the yearly First Law Efficiency
- Some MESs have a maximum allowed yearly electricity net export
- Seasonal Storage energy systems (e.g. Hydrogen, Underground Thermal Storage, CAES) might be used

Problem statement

Given:

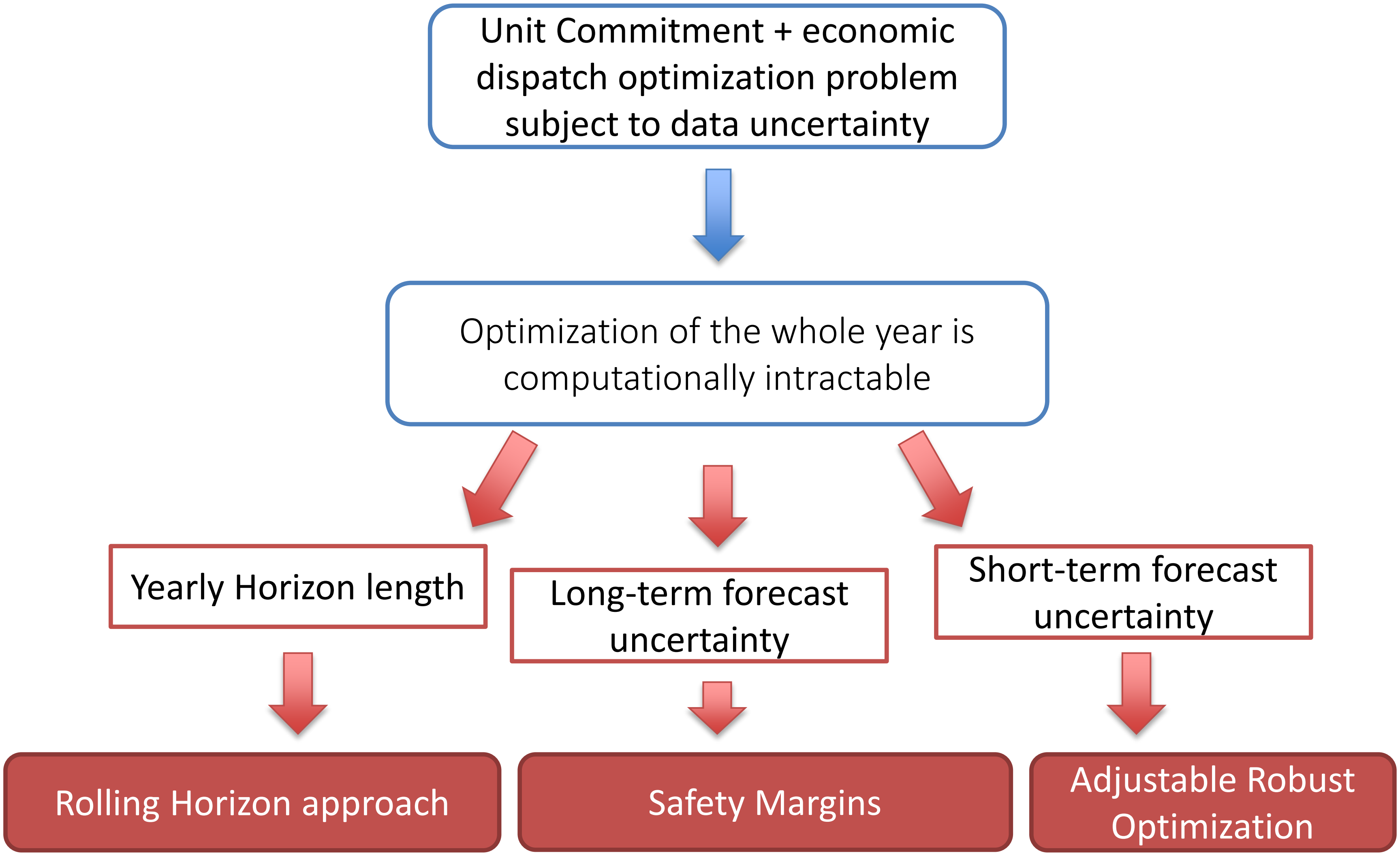
- Units and energy storage performance data and maps
- Forecast of energy demands and solar production
- Forecast of fuel and electricity price profiles
- Forecast uncertainty

Determine the optimal robust operation schedule which minimize the sum of:

- Machines fuel consumption cost
- O&M costs
- Electricity revenues/purchase cost
- Yearly incentives for CHP units

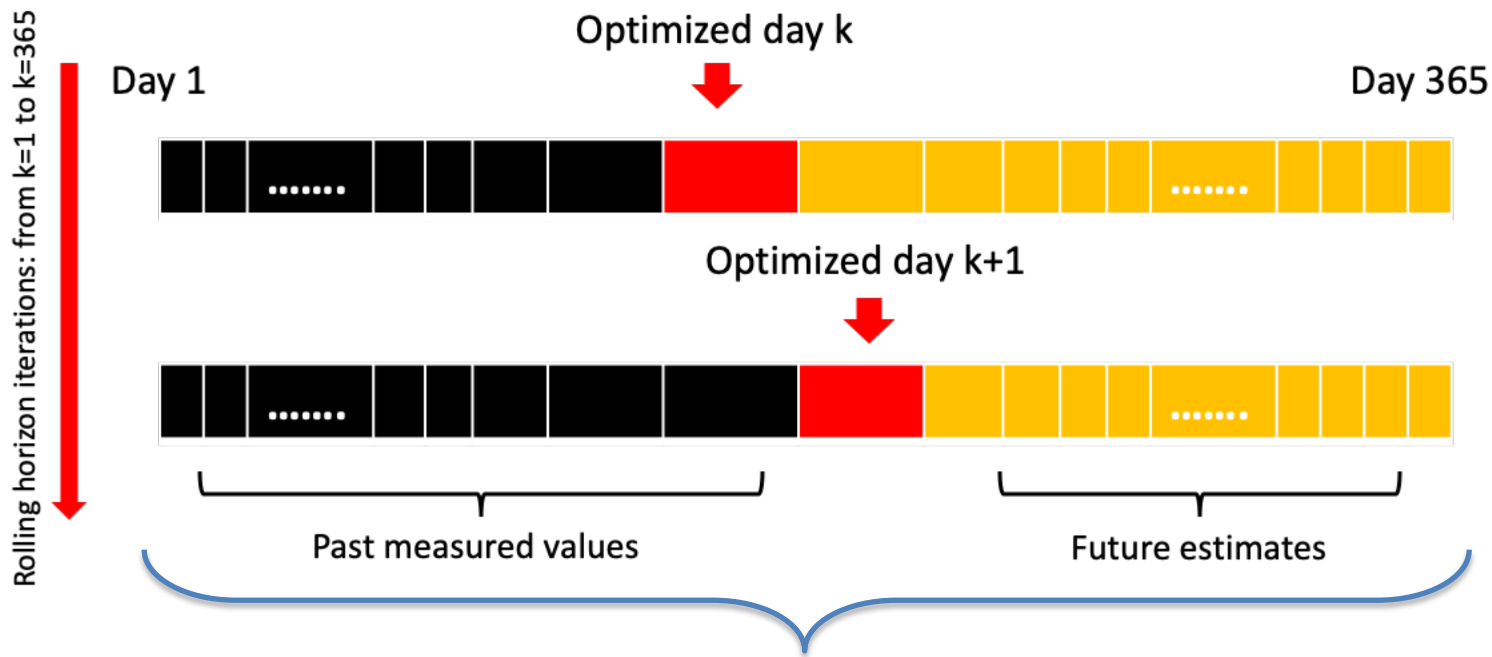
Subject to the following constraints:

- Operational/commitment constraints on units and storage systems
- **Yearly incentive constraints on CHP units** (minimum required efficiency index)
- **Maximum allowed yearly electricity net export**
- **(optionally) operational limits on the seasonal storage system (max charge/discharge rate, max/min charge levels, target charge level at end of year)**



Castelli, A.F., Moretti, L., Manzolini, G., Martelli, E. A Robust Rolling-Horizon Algorithm for the Optimal Operation of Multi-energy Systems with Yearly Constraints and Seasonal Storage. (2020) Computer Aided Chemical Engineering, 48

ROLLING HORIZON APPROACH



MILP model features

Optimization Variables:

- Operation variables of day k
  - Machines
  - Storage
  - Grid Exchange
  - Etc.

Constraints:

- Operational constraints of day k
- Minimum storage set-point level at the end of day k
- Yearly basis constraints for CHP unit

Short and Long-term Forecasts

SHORT TERM (24h AHEAD)

Heat and Electricity demand forecasts → Persistence Method

- Forecast of day d is real profile of day d-1
- Forecasts of Saturdays and Sundays are real profile of previous Saturday and Sunday

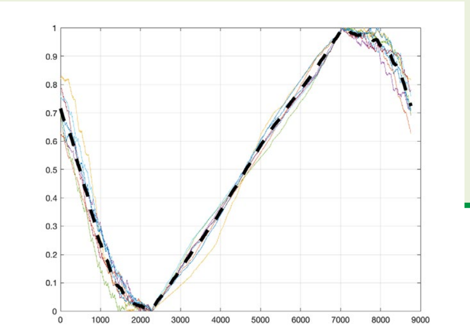
PV and Thermal Solar production forecasts → Artificial Neural Network (Ogliara et al., 2017, Renewable energy)

LONG TERM (TILL END OF THE YEAR)

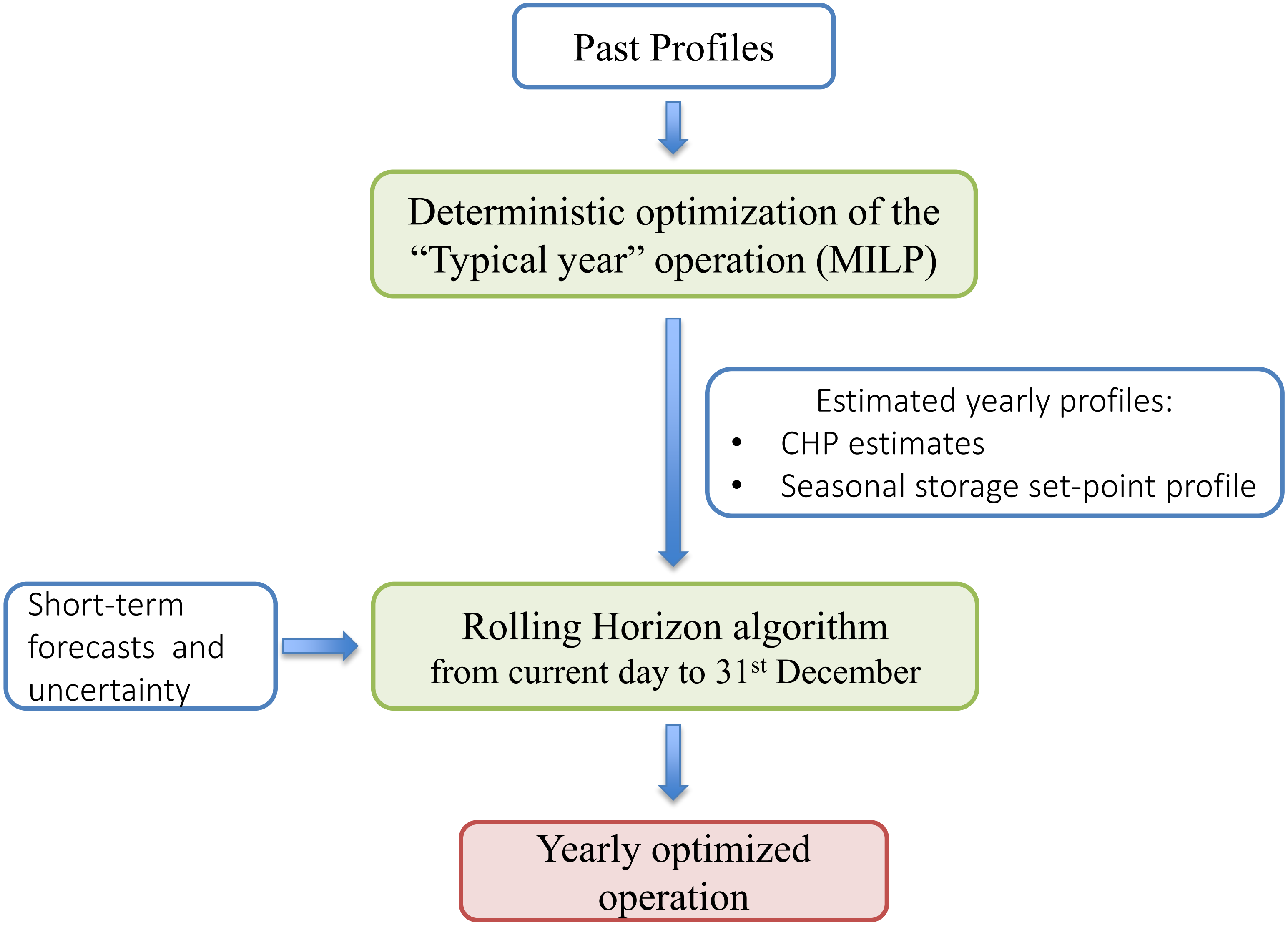
CHP Fuel, Electricity and Heat estimates

SOC of seasonal storage at the end of each day

→ Optimization of representative typical year (made of 24 typical days)



METHODOLOGY FLOW CHART



HANDLING UNCERTAINTY

SHORT TERM

Uncertainty factors:

- Electricity demand
- Heating demand
- PV electricity production
- Thermal Solar heating production

Robust optimization model with affine recourse:

- Recourse just on short term uncertainty
- Provides a solution feasible for each possible scenario considered
- Provides robust strategy for online control

LONG TERM

Uncertainty related to forecasts of :

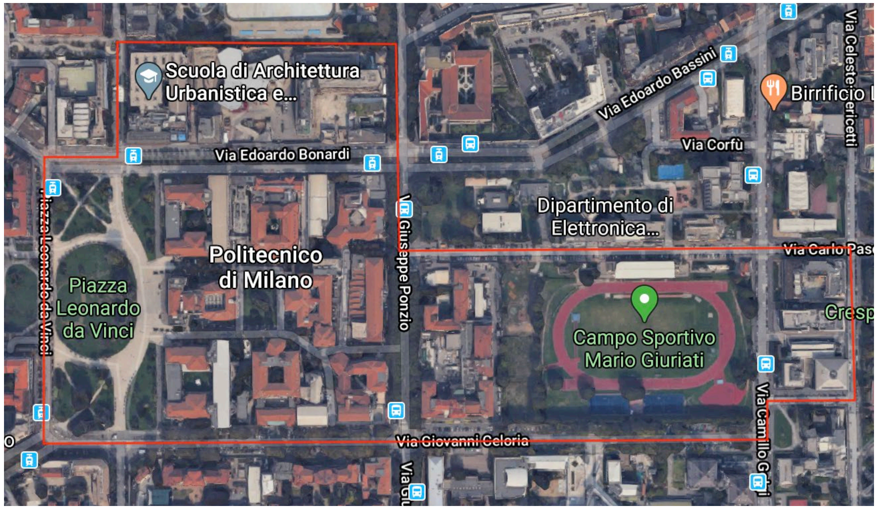
- Renewable energy production
- Heating demand
- Electricity demand

affecting CHP fuel consumption and seasonal storage management

Safety margins:

- Margin profile is tunable (high in the beginning of the summer, lower towards the end of the year)
- Margin value can be adapted “online” (based on measured performance in past days)
- Penalty proportional to violation of safety margins

CASE STUDIES – 2018 DEMAND PROFILES



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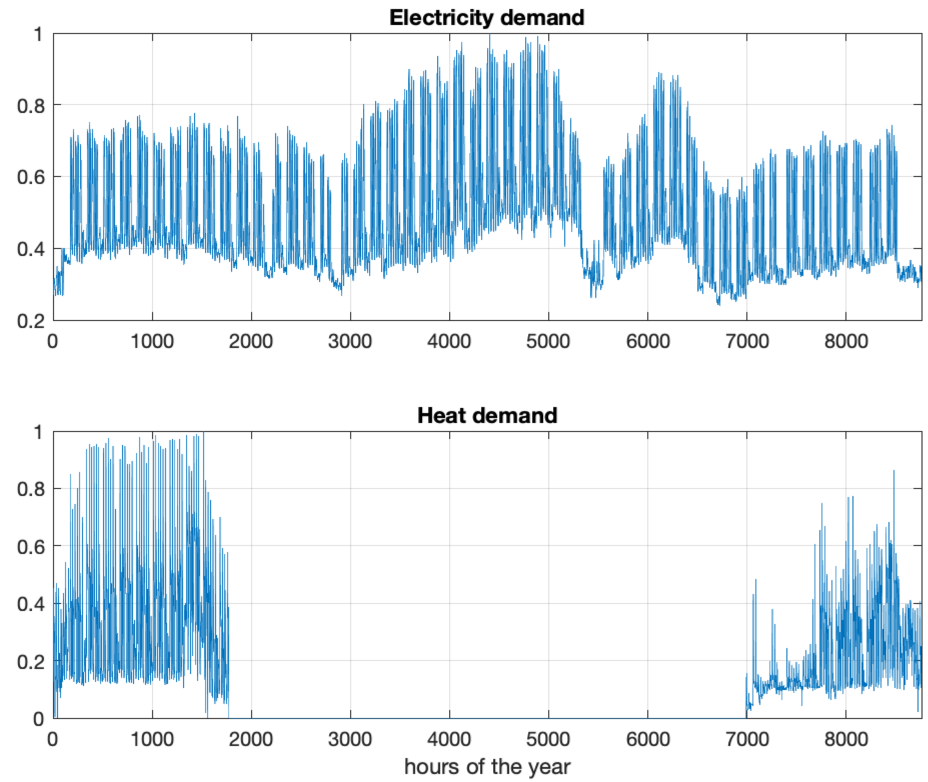


	Past 10 years			Test year (2018)
	Average (10 years)	Max	Min	Yearly average
Temperature [°C]	13.8	14.91	10.92	15.08
Irradiance [kW/m^2]	299.52	286.14	326.43	325.6

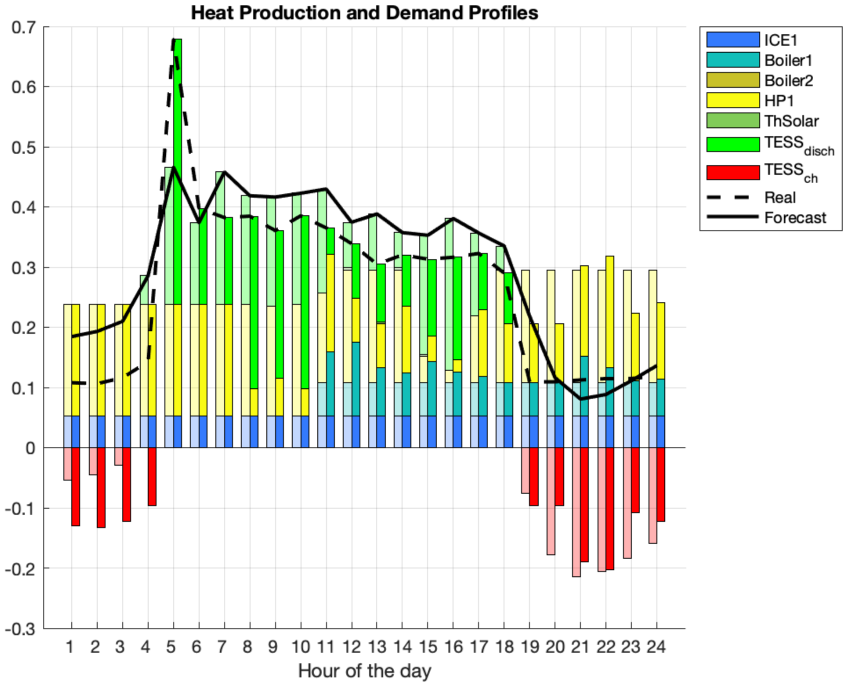
CASE STUDIES – MES DESIGNS

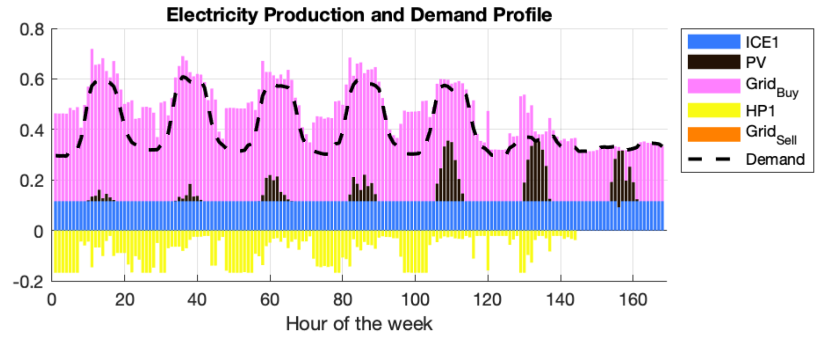
CASE 1 = conventional design with large CHP engine
CASE 2 = fully renewable with seasonal storage assisted by a back-up boiler
CASE 3 = hybrid design with CHP + renewable with seasonal storage

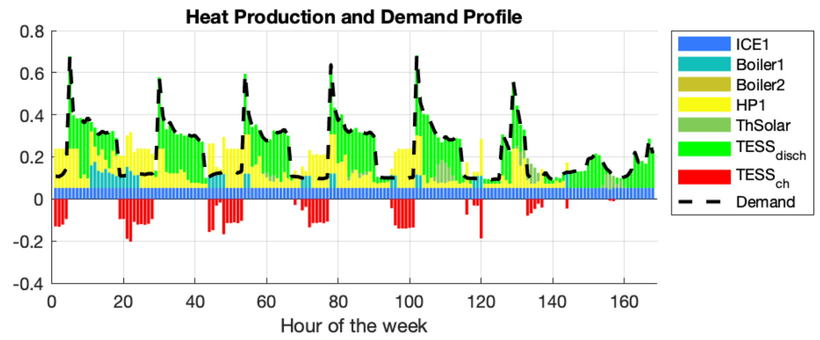
UNIT	CASE 1		CASE 2	CASE 3	
CHP ICE	El: 2.9 MW	Q: 2.6 MW	-	El: 344 kW	Q: 497 kW
Boiler 1	Q: 2.4 MW		Q: 3.5 MW	Q: 2.4 MW	
Boiler 2	Q: 2.4 MW		-	Q: 2.4 MW	
Heat Pump	Q: 1.7 MW		Q: 3.5 MW	Q: 1.7 MW	
Storage	**Max Capacity**				
TESS	5 MWh (non-Seasonal)		7.2 GWh (Seasonal)	1.8 GWh (Seasonal)	
Non-dispatchable	**Installed power**				
PV panels	-		4.5 MW	1 MW	
Thermal Solar panels	-		5.9 MW	1.6 MW	

RESULTS

	CASE 1	CASE 2	CASE 3
Average run time per day	3 min	35 sec	3 sec







- Nominal solution (based on forecast values) are the small half-columns on the left.
- Affine decision rules (recourse laws) adopted for real-time operation of the MES

BENCHMARK OPTIMIZATION APPROACHES

Different approaches compared

Whole year deterministic MILP
("det wholeyear")

→ Lower Bound of the yearly operating cost

Rolling Horizon with deterministic short-term MILP with safety margins (certain input data)
("det RH")

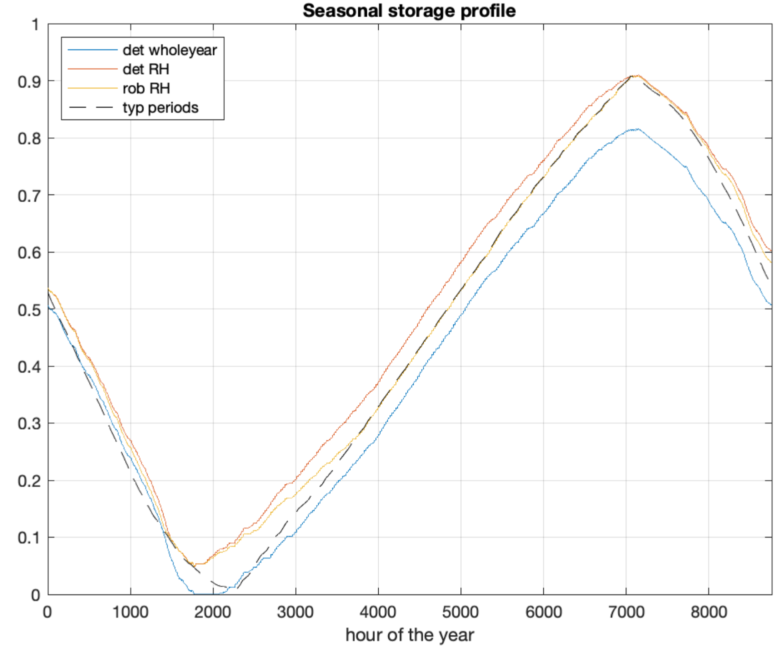
→ Benchmark to assess cost penalty of short-term robustness on daily planning solutions

Rolling Horizon with robust short-term MILP with safety margins (short-term forecasts of demands)
("rob RH")

→ Piecewise affine recourse rules used for real-time operation

RESULTS – CASE 2: SEASONAL STORAGE

Case 2: HP + BOILER + LARGE SOLAR



1) Typical year TESS setpoint agrees well with ”det wholeyear”

2) RH algorithms stay above the desired set points with minor differences

3) Deterministic RH is closer to the desired set point

Yearly cost increase and CB variation with respect to benchmark case "LB" (whole year deterministic)

	YEARLY OPERATING COST		CB incentives	
	Det RH vs LB	Rob RH vs LB	Det RH vs LB	Rob RH vs LB
CASE 1 (CHP only)	+3.19%	+6.13%	-1.67%	-2.11%
CASE 2 (Solar)	+0.59%	+5.23%	n.a.	n.a.
CASE 3 (CHP and Solar)	+0.9%	+1.52%	+5.73%	+6.94%

1) The cost of adding safety margins for long-term operation is acceptable (1-3%)

2) The cost of "short-term robustness" is limited to a few percentage points (2.85% for case 1, 4.61% case 2, 0.62% case 3)

Optimal design of MES and CHP systems

Given:

- A catalogue of possible units (e.g., CHP ICEs, HP GTs, boilers, heat pumps, etc) and the list of available sizes (discrete or continous)
- A catalogue of heat storage systems
- Forecast of future energy demand profiles (whole year) of each building/site
- Forecast of future energy prices and their time profiles of each building/site

Determine:

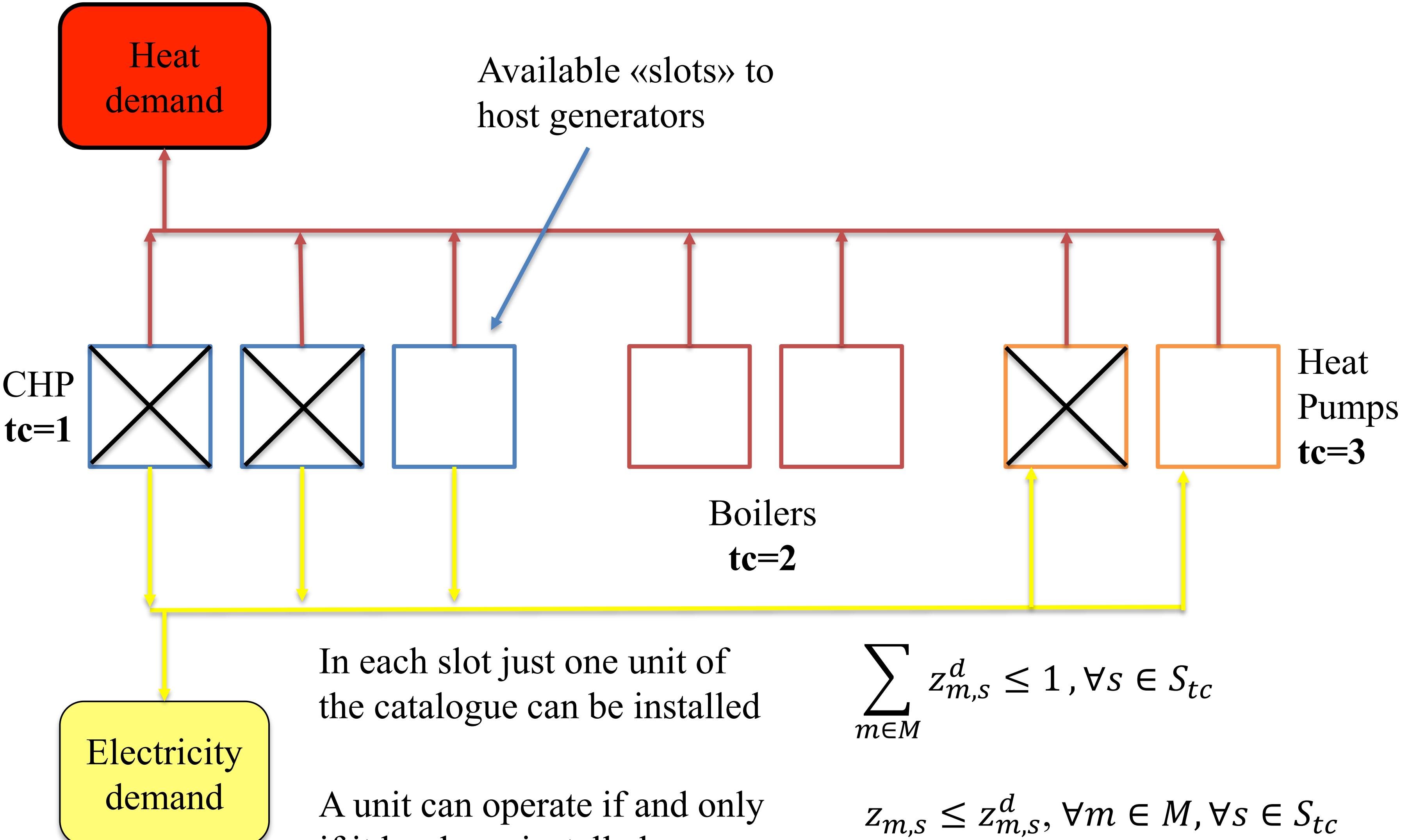
- Which units and heat storage system to install in each district/building
- The sizes of the units and storage systems
- The required energy connections between sites/buildings

Considering:

- Nonlinear size effects on investment costs and efficiency
- On/off and part-load operation of the units

Objectives: Maximize the NPV/Minimize the energy consumption/CO2 emissions

OPTIMAL DESIGN: PROBLEM FORMULATION



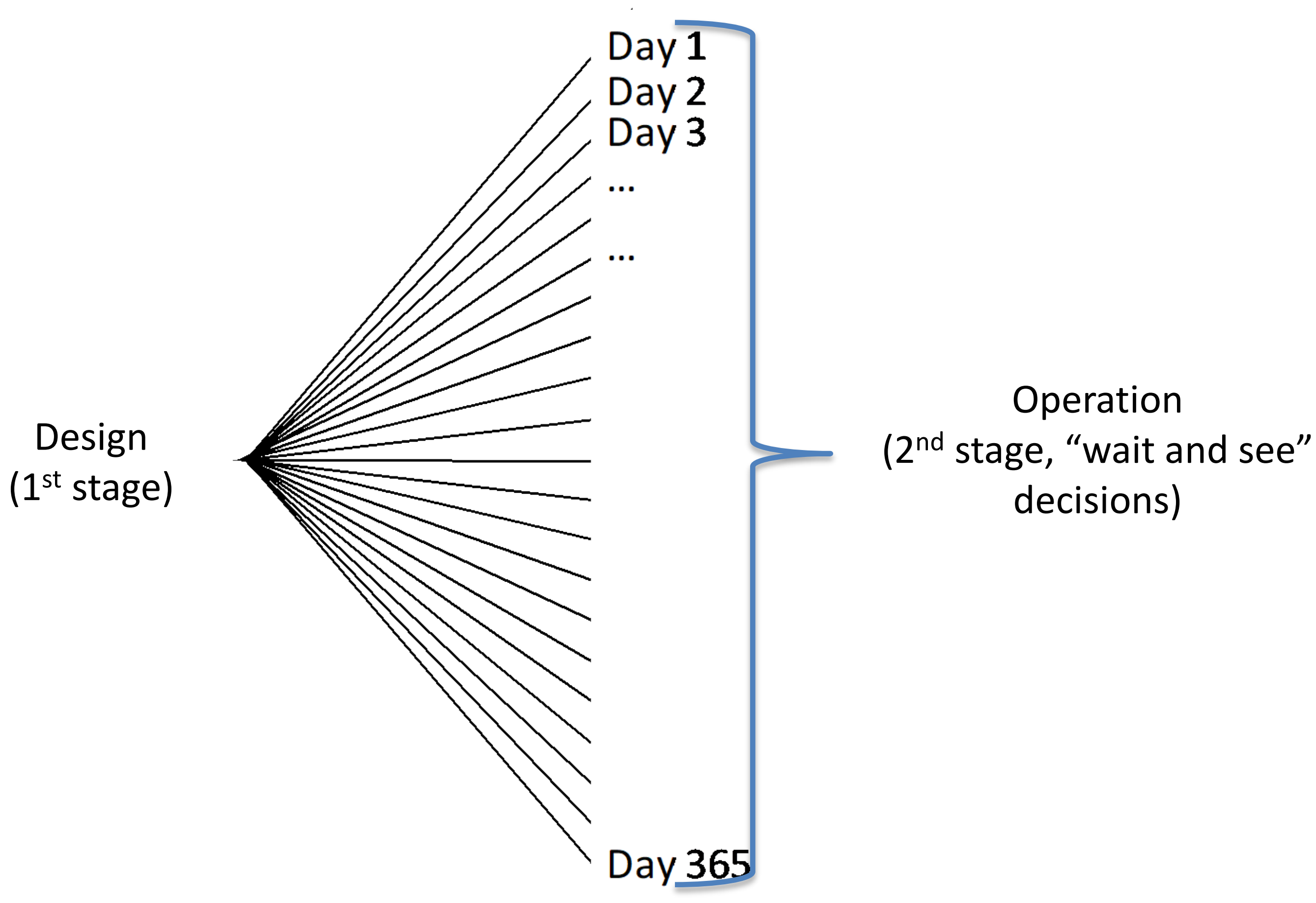
In each slot just one unit of the catalogue can be installed

$$\sum_{m \in M} z^d_{m,s} \leq 1\,, \forall s \in S_{tc}$$

A unit can operate if and only if it has been installed

$$z_{m,s} \leq z^d_{m,s}, \forall m \in M, \forall s \in S_{tc}$$

OPTIMAL DESIGN: EQUIVALENCE TO TWO-STAGE STOCHASTIC PROGRAM



Notes:

- Each day corresponds to a scenario of the stochastic program
- Operation decisions are also binary (binary variables in the second stage)
- Classic Bender's and Lagrangian decompositions (based on dual information) may not lead to a feasible and optimal solution (duality gap)

Design Optimization Approaches

<u>Design-scheduling decompositiom with heuristic design algorithms</u>

(*Elsido et al., 2017. Energy Vol. 121*)

Upper level (evolutionary alg.): optimizes design variables (selection/sizes)

Lower level: MILP scheduling problem

Avantages:

- Size effects accounted for on both performance and costs
- Possibility of considering many operating periods solved in sequence

Disadvantages:

- Slow convergence rate of evolutionary algorithms
- No optimality guarantee

Convergence properties of black-box optimization alg. scaling poorly with the number of variables.
Approach suitable for problems with few units and few design variables

<u>Design + operation MILP</u>

(*Zatti et al, 2017*) (*Gabrielli et al. 2018*)

Units' selection, sizes and operation optimized in a single large scale MILP

Advantages:

- Linear problem (computationally efficient)
- Global optimality guarantee
- Uncertainty can be rigorously handled

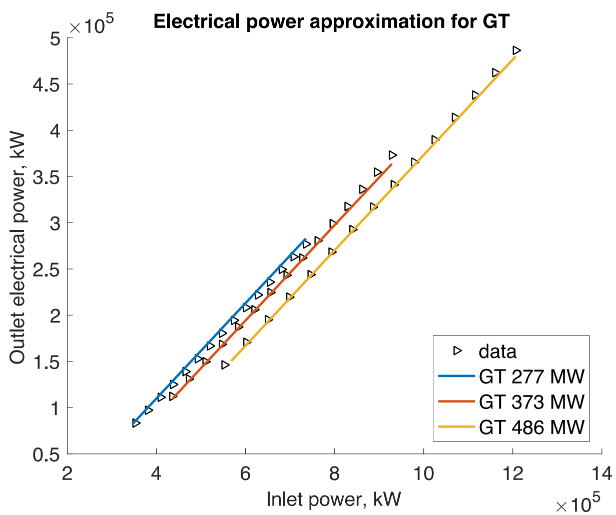
Disadvantages:

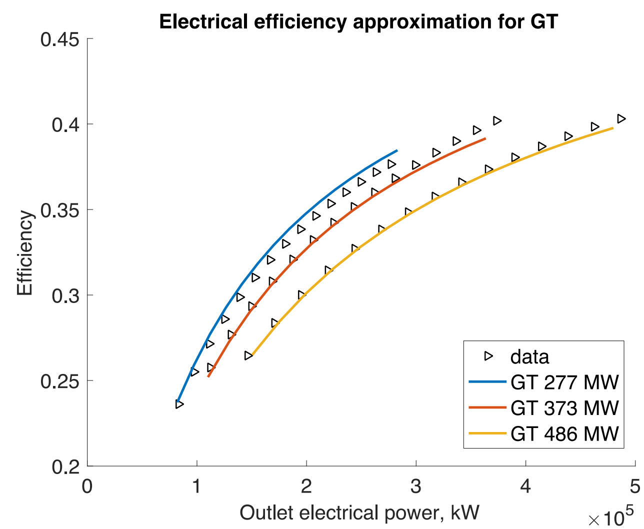
- Size effects on investment costs must be linearized
- Size effects on efficiency must be approximated

DESIGN+OPERATION MILP: LINEARIZATION OF THE SIZE EFFECTS AND PART LOAD PERFORMANCE

The output is a linear function of the input and the size

$$p_t = k^{1P} \cdot in_t + k^{2P} \cdot x + k^{3P}$$ so that $$\eta_{el} = \frac{p}{in} = k^{1P} + k^{2P} \cdot \frac{x}{in} + \frac{k^{3P}}{in}$$





CONVEX HULL FORMULATION

$$k^{IN}_{MIN} \cdot x \le in_t \le k^{IN}_{MAX} \cdot x$$

$$in_t = \sum_i \alpha_{i,t} \cdot k^{IN}_i \cdot x$$

$$\sum_i \alpha_{i,t} = z_t$$

z_t = binary (on/off)

the same holds for the other outputs, e.g. thermal power: $q = k^{1Q} \cdot in + k^{2Q} \cdot x + k^{3Q}$

Zatti et al. 2018. TOWARDS THE OPTIMAL DESIGN AND OPERATION OF MULTI-ENERGY SYSTEMS: THE "EFFICITY" PROJECT. Environmental Engineering and Management Journal, vol. 17

Time periods for the operation optimization

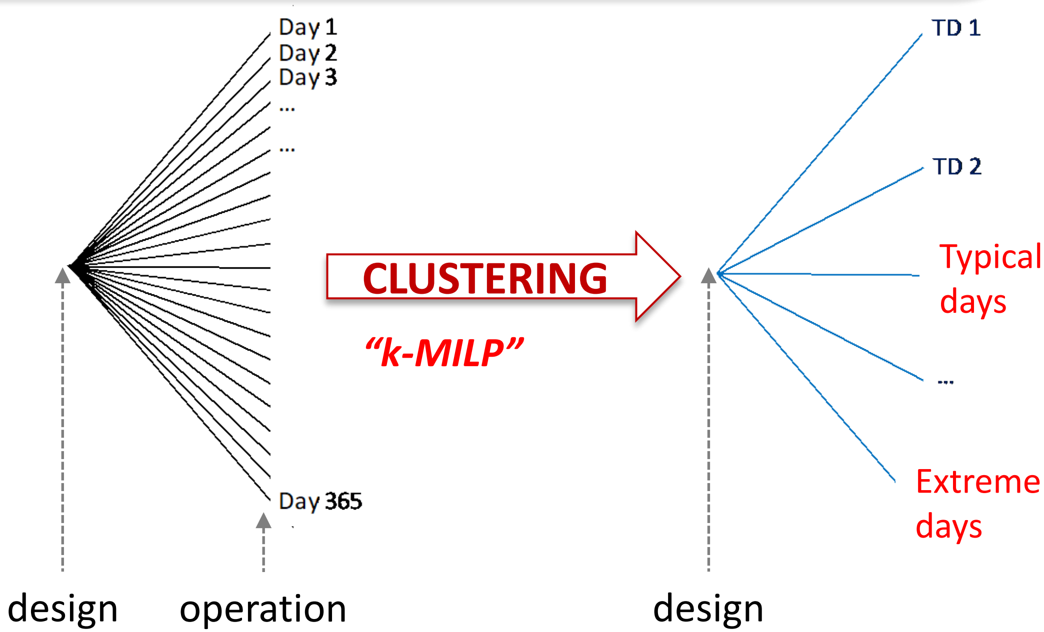
Urban DES have an intrinsic **daily and seasonal periodicity** (energy demands, energy prices, energy storage) → design should be optimized on the basis of the daily operation in 1 year.

1) There is a **binary variable** z_t
   - for each possible unit considered in the design
   - for each time step (hour) considered in the operation

2) In the model there is a number of **inter-temporal constraints** (energy storage).

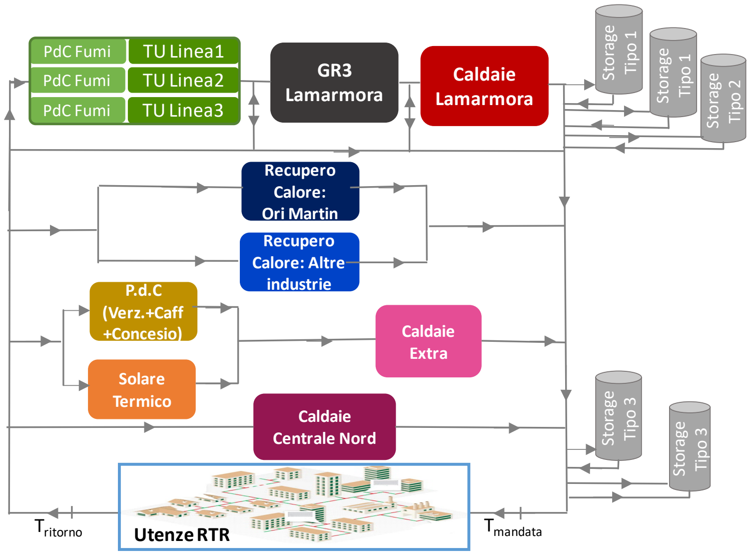
The problem quickly becomes computationally intractable → the design problem is solved considering a set of *n* (<< 365) representative days.

These representative days are determined on the basis of the hourly data of the parameters.

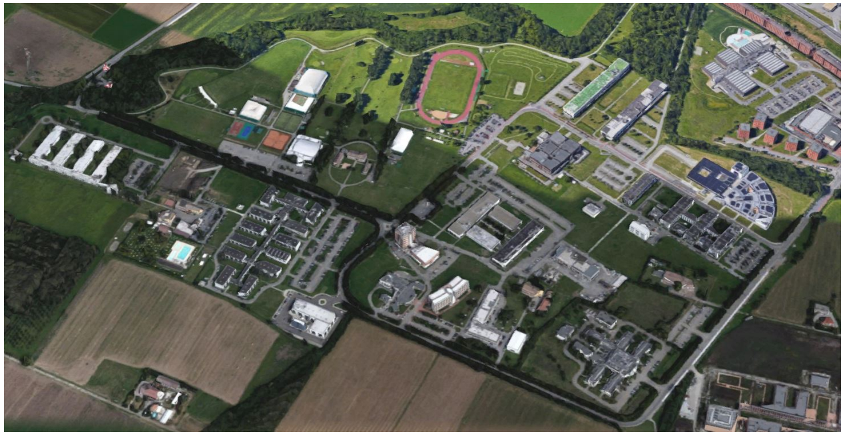


M Zatti, M Gabba, M Freschini, M Rossi, A Gambarotta, M Morini, E. Martelli. 2019. k-MILP: A novel clustering approach to select typical and extreme days for multi-energy systems design optimization. Energy 181, 1051-1063

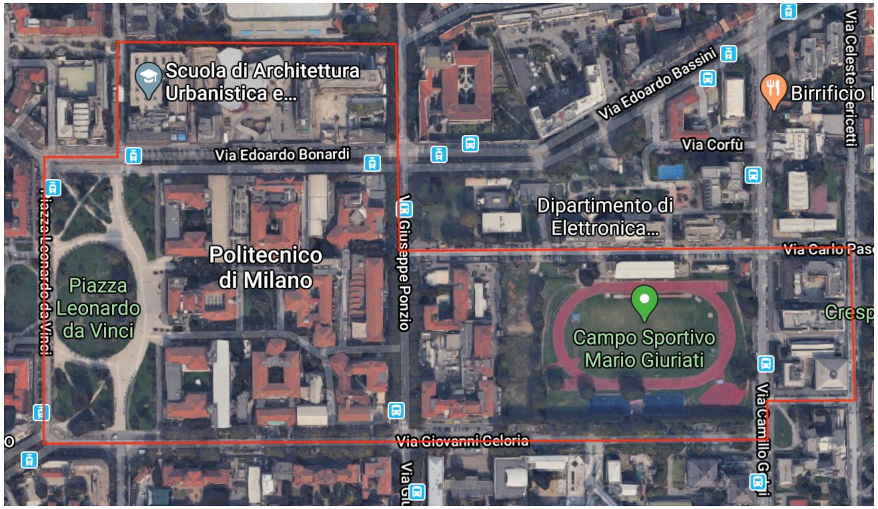
DH network of cities



University of Parma Campus

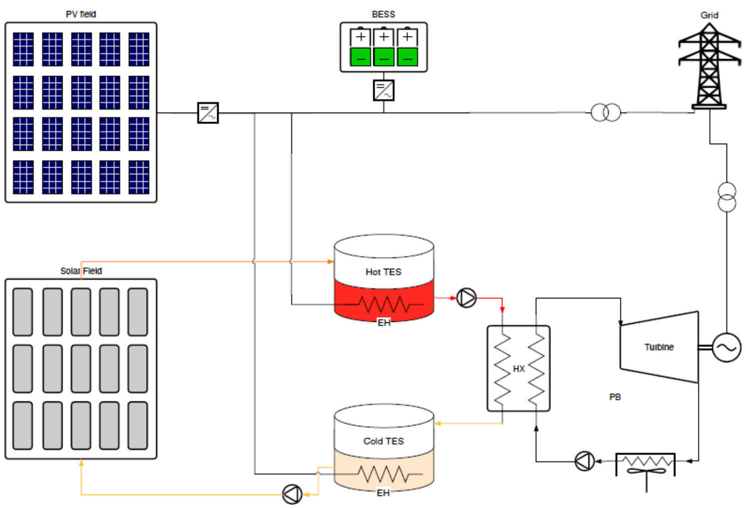


Campus of Politecnico di Milano

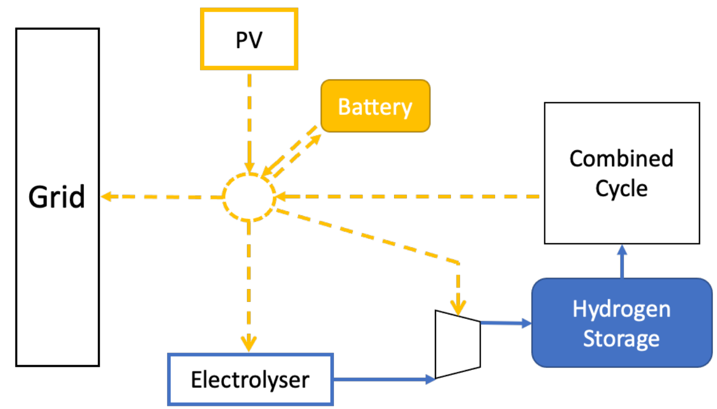


Largest Italian Hospitals

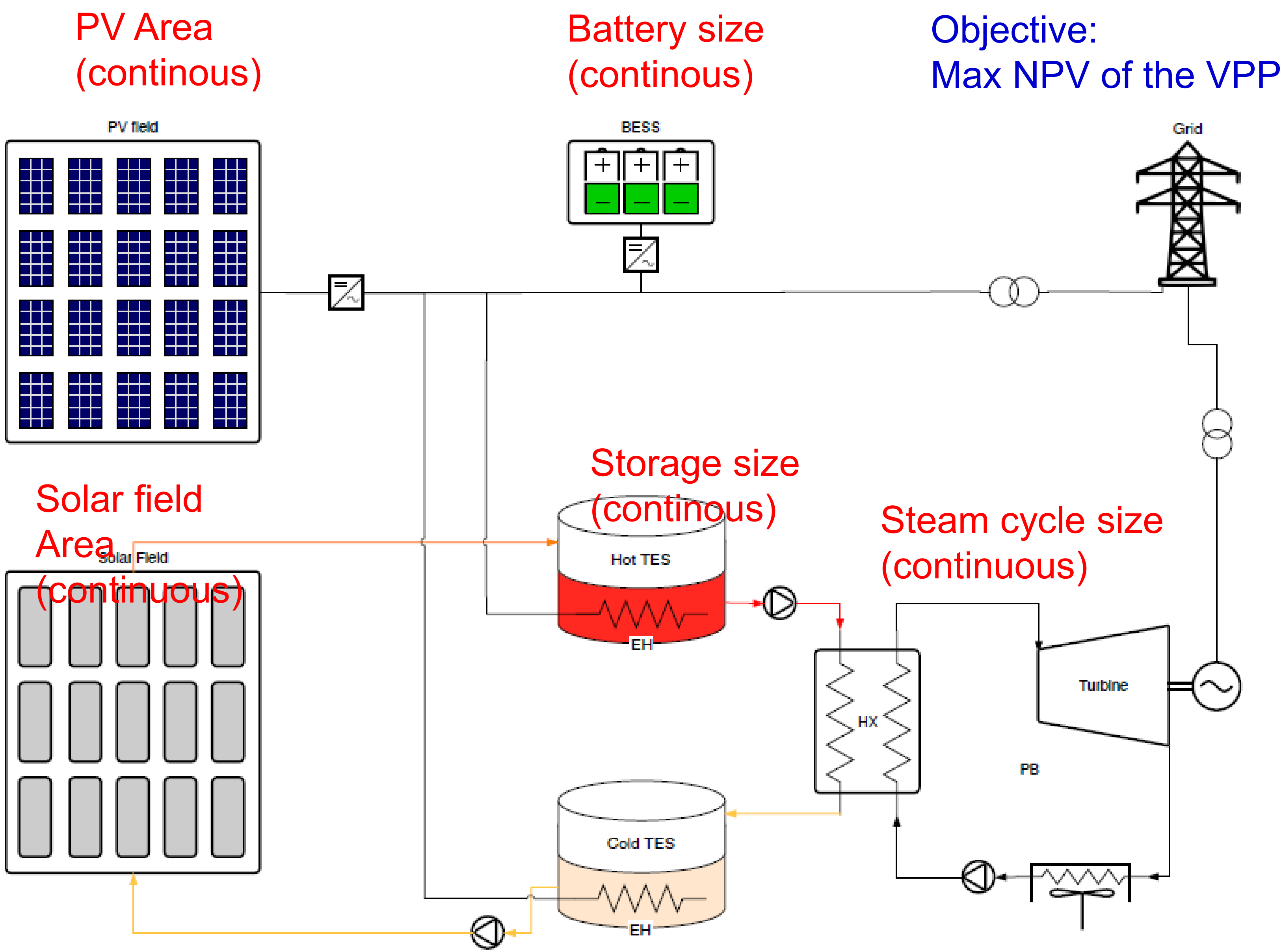
VPP: CSP + PV + battery



VPP: GT + H2 storage + H2 production system + PV + battery



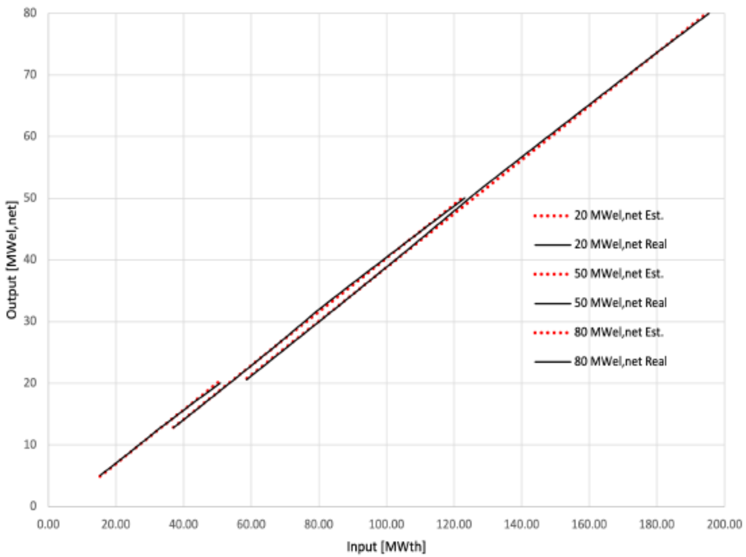
Optimal Design of Hybrid CSP-PV VPP



Optimal Design of Hybrid CSP-PV VPP

Power block linearized model

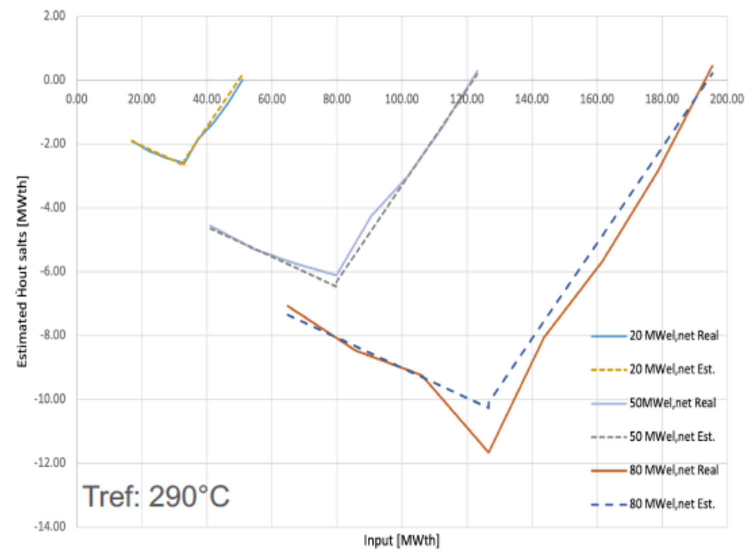
Net electric output



Multiple linear regression

$$P_{el} = K_1 \dot{Q}_{in} + K_2 S + K_3 \ [1]$$

Molten salts enthalpy flow at HX outlet



Piecewise multiple linear regression

$$\dot{H}_{out} = \sum_{j=1,2} (K'_{1,j} \dot{Q}_{in} + K'_{2,j} S_j) \ [1]$$

j depends on the segment selected at time t

The MILP energy-flow model is extended to account for the Molten Salt temperatures and non-isothermal mixing occurring in the storage tanks

Work to be submitted to the ICAE 2021 conference

Optimal Design of Hybrid CSP-PV VPP

- 432 time steps: 6 typical periods of 72 hours (3 consecutive days), hourly resolution
- Linking constraints due to ramping, minimum up and down times, thermal storage and batteries
- 5 main continous complicating variables (continous design variables)

Computational time (using Gurobi): 30 minutes

12 typical periods → computational time becomes 7 hours

12 typical periods + hydrogen seasonal stoarage system → (all typical periods are linked) → intractable as a single MILP

OFF-GRID MICROGRID DESIGN PROBLEM DESCRIPTION

Real case of a smart gas station

- Demand: electricity
- Total number of timesteps: 480 (8 representative hours with timestep length of 1 minute)
- Total number of available units in the catalogue: 15
- Available generator slots: 4
- Possibility to install battery (unit with continuous size)

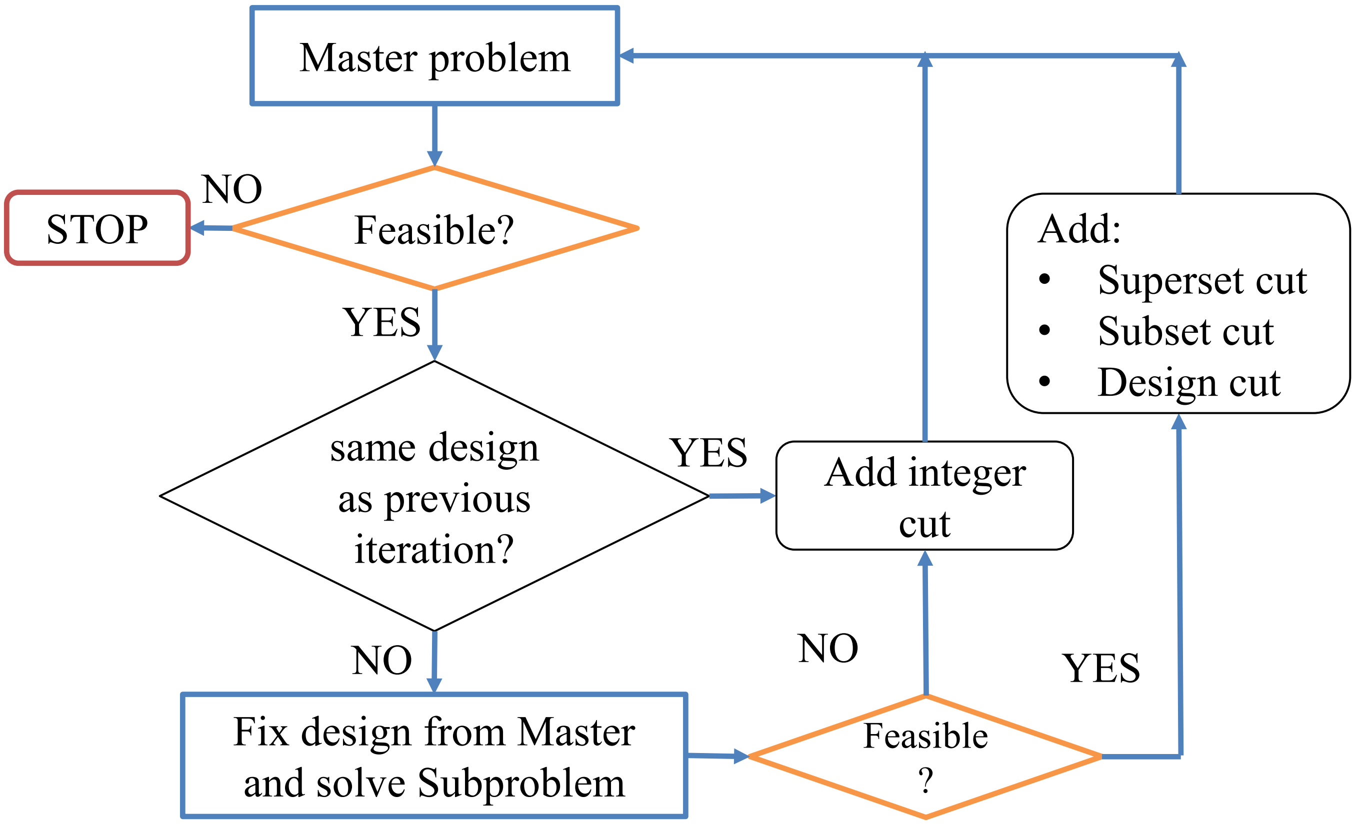
Some remarks:

- Complicating constraints (time linking)
    - Across minutes in each hour: Units minimum up/down time, ramping limits, battery SOC evolution in time
- Many complicating variables (design variables)
- Many symmetries (design and operation) make B&B slow

Using Gurobi (latest version) on multi-core workstation, > 6% gap after 72 hours

Introducing <u>n-1 reliability</u> (i.e., failure scenarios for each generator slot, multiplying by a factor of 4 the time steps) would make the problem computationally intractable.

A modified version of the bi-level decomposition proposed by Iyer and Grossmann (1998) was used to get to the solution.



Master problem: only design binary variables are kept, all other operational binaries are relaxed

Subproblem: design binaries are fixed to the velues found in the Master problems while operational binaries are NOT relaxed (MILP)

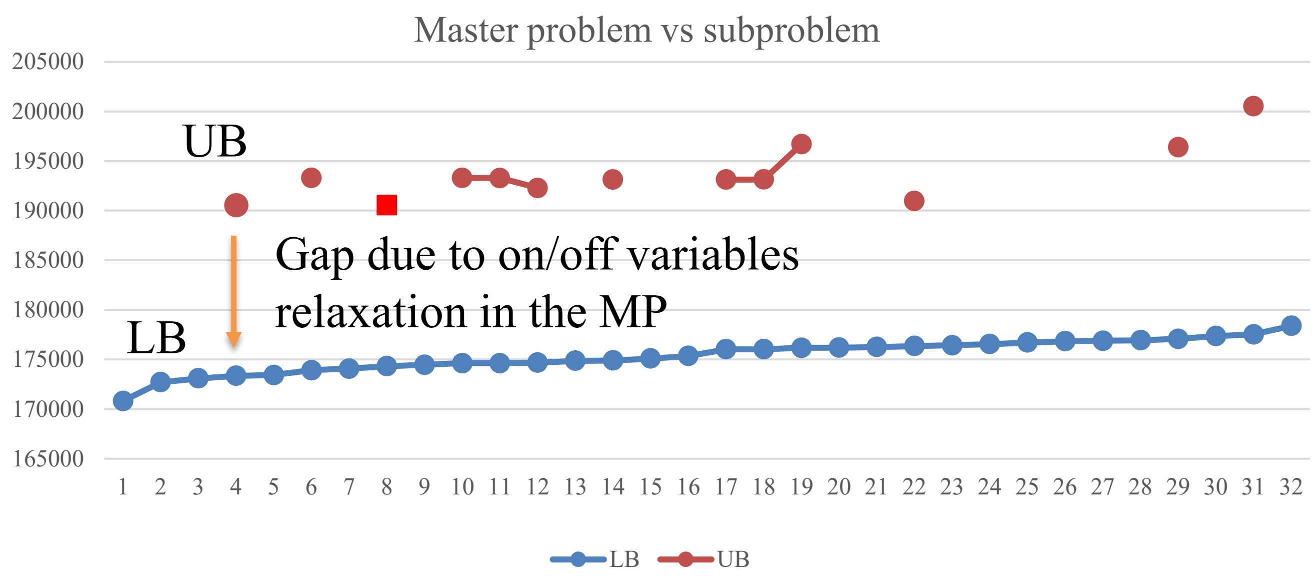
DECOMPOSITION - RESULTS

Problem characteristics:

- 426056 constraints
- 146941 continuous variables
- 145020 binary variables

Solution time:

- No decomposition: stopped after 72 hours (gap 6.2%, UB 195423)
- Decomposition found a better solution in 18 hours (UB 190503)



NOTE:
Although the gap is still quite large and the integer cuts are weak, the decomposition allows finding better solutions than solving the monolithic MINLP.

CONCLUSIONS (1)

1) The deterministic opitmal operation of microgrids, VPPs and most MESs can be formuated as a MILP and solved in few sedonds. It is the state-of-the-art solution in industry.

2) The deterministic operation MILP can be extended to account for:
- Demand-side Thermal management of buindings
- Delivery/return temperature management of the DHN
- Parallel/series connections between thermal generators
- Non-isothermal mixing in water headers
- Long-term constraints as well as seasonal storages

3) Affine Adjustable Robust Optimization (AARO) models can be used for the operation of microgrids and MES operation with good performance if:
- Number of units and time steps are not excessive (< 4 units, < 100 time steps)
- Computational time is reduced using Partial-past recourse laws and aggregating uncertainty factors

For systems with CHP units and quick-start units the solution may be overconserative
→ need of computationally efficient approach to handle binary correction rules

CONCLUSIONS (2)

4) The design opitmization problem must include also the operational problems on a set of typical and extreme periods. It is equivalent to a two-stage stochastic program with binary variables in both stages.

5) Although the design MINLP problem can be linearized into a MILP, the computational time still remains an issue for most industrially relevant problems:

- Problems with rich catalogue of units of discrete sizes (e.g, > 5)
- Problems with continous size units (e.g., storages, steam cycles, etc)
- Problems with seasonal storage systems (e.g., H2 storage)
- Problems requiring hundres operational time steps (e.g., 12 typical days)

→ need of an effective (and possibly rigorous) decomposition approach

Thank you for your attention!

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