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# Impact of coupling thermal and electrical carriers on the optimal management of a multi-energy network

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**Abstract**—Multi-energy networks are becoming a leading research subject in the last years, particularly, with the accelerating emergence of renewable resources into the energetic system. Decoupling this problem into several single-vector networks results in a sub-optimal solution. However, this approach comes up against a great technological complexity, from the design of each of the components necessary for such a hybrid network to their modeling and the global management of the whole. In this work, we propose coupled electrical and thermal networks, with an energy hub integrating electrochemical and thermal storage systems, and conversion systems: Heat To Power and Power To Heat. To achieve this, a modeling of the different physical subsystems and a management of the whole system using Model Predictive Control (MPC) are investigated. Finally, a comparison of the two configurations without and with coupling is conducted to evaluate the impact of such a multi-energy network.

**Keywords**—Multi-Energy networks, Power storage, Thermal storage, Heat To Power, Power To Heat, Model Predictive Control, Optimization, Energy systems modeling.

## NOMENCLATURE

$\alpha$	Weight of Deviation Cost
$\beta$	Weight of Losses Cost
$\Delta t$	Time Step
$\delta$	Weight of Aging Cost
$\eta$	Efficiency
$\gamma$	Weight of Shedding Cost
$\overline{P}^{rated}$	Maximum Charging Power
$\overline{P}_{H2P}$	H2P Nominal Power
$\overline{P}_{P2H}$	P2H Nominal Power
$\overline{P}^{rated}_{elec}$	Maximum Discharging Power
$elec$	Electrical Parameters
$heat$	Heat Parameters
$residual-heat$	Heat Output from ORC System
$C_{aging}$	Materials Aging Cost
$C_{del}$	Power Shedding Cost
$C_{dev}$	Deviation Cost
$C_{losses}$	Cost of Energy Losses

$C_{tot}$	Total Operating Cost
$E^{rated}$	Storage Installed Capacity
$E_{elec}$	Power Storage Energy Level
$E_{sto}$	Storage State of Energy
$E_{th}$	Thermal Storage Energy Level
$n_w$	Sliding Window Size
$P_{del}$	Shedding Power
$P_{dev}$	Deviated Power
$P_{loss}$	Loss Power
$P_{sto}$	Storage Power Command
ADMM	Alternating Direction Method of Multipliers
CHP	Combined Heat and Power plants
H2P	Heat To Power System (ORC)
MPC	Model Predictive Control
ORC	Organic Rankine Cycle
P2H	Power To Heat System (Electrical Resistance)
SLSQP	Sequential Least Squares Programming

## I. INTRODUCTION

The energy needs of both private and industrial consumers are fundamentally multimodal. Several forms of energy are required depending on the use: domestic heating, mobility, electrical appliances, industrial processes... Moreover, conversion devices, in production and in consumption, allow transitions from one form to another. Achieving the best energy supply system therefore requires considering the problem in a multi-modal approach. To accomplish such multi-energy network, concept design, modeling and management of each component need to be considered [1].

In heat networks, the use of variable heat resources requires specific components in order to gain in flexibility, such as in concentrated solar power plants [2]. Thus, it is not necessary to convert heat into electricity instantaneously. Indeed, a decoupling between the capture of the primary energy source and the power production can be achieved via a thermal storage [3]. Today several thermal storage types exist, including thermocline storage system



Fig. 1. First industrial scale EcoStock® of 4MWh<sub>th</sub> at 600 °C developed by ETC.

which can be of a great value (figure 1). In addition, the use of heat sources also requires converters capable of transforming thermal energy into electricity - and vice versa. Solutions such as Organic Ranking Cycles (ORC), gas turbines or Stirling engines are widely used in industry today for this purpose.

Symmetrically, electrical networks have the same need for flexibility in order to satisfy consumption and guarantee the permanent balance of the grid. In particular, variable renewable energy sources such as photovoltaic or wind power have the complexity of being intermittent, hardly controllable and predictable. One way to reduce the impact of these limitations is to have sufficient degrees of flexibility such as electrochemical storage or production clipping and consumption shaving. These degrees of freedom combined with an optimal and predictive management of power flows allow better sizing of generation and storage capacities [4].

The objective of this study is to compare and evaluate the management performance of coupled and uncoupled networks. To do this, a case study of multi-energy network, coupling heat and electricity sources and loads, will be used (figure 2). Following sections will discuss physical components models, mathematical formulation of the problem and the resolution method for an optimal management. In addition, an optimal management of multi-energy network will be analyzed. Finally, the comparison between coupled and uncoupled networks will be evaluated on the basis of the total management cost for various thermal and power storage installed capacities.

## II. STATE OF THE ART

Models of thermal and electrical storage are numerous in the literature. [5] and [6] have proposed different levels of modeling for the dynamics and aging of electric battery. The paper [7] discusses four models of increasing

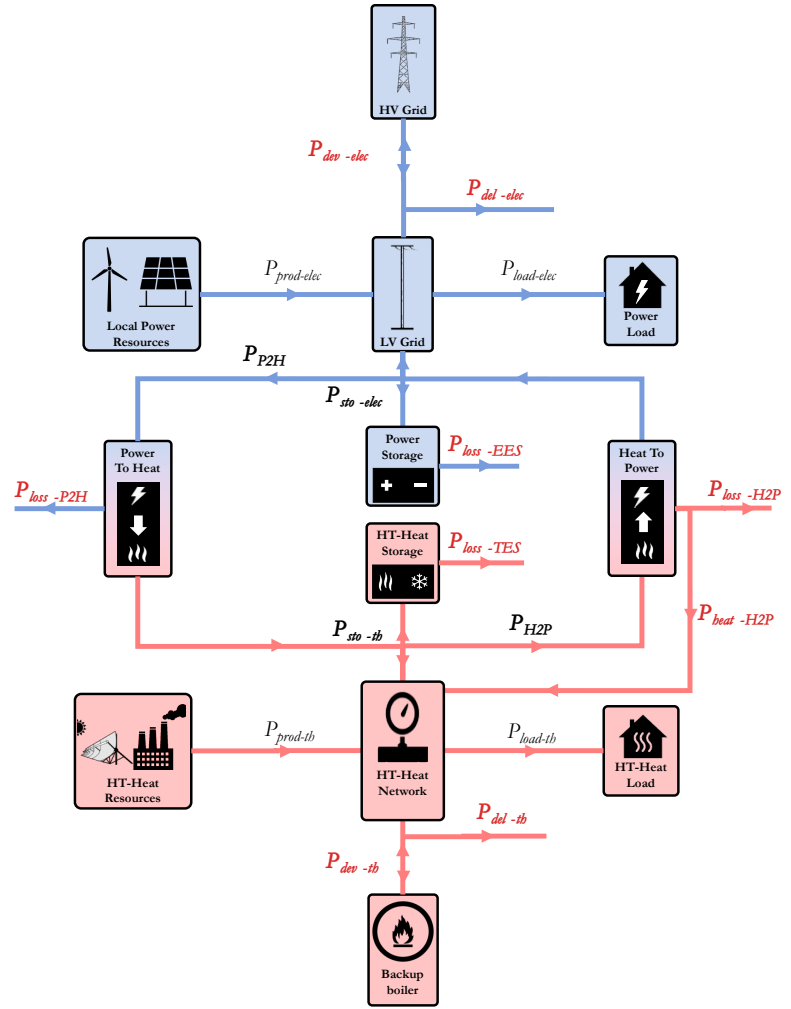


Fig. 2. Multi-energy network concept coupling heat and electricity with storage and conversion systems

level of accuracy to represent the dynamics of thermal storage. Conclusions show that simple models for storage optimization is capable of reaching suitable management strategy on system scale.

Several research works deal with the coupling of heat and electrical networks using Combined Heat and Power units (CHP) [8]. Generally, distribution and conversion systems modeling is simplified in order to solve a global optimization problem with reasonable calculation time and with linear approaches. [9] suggests that district heating network losses should be taken into account when designing decentralized energy supply technologies at small district level. In this case, authors assume 15% of losses for small heating networks. However, for large heating networks and other technologies such as power grids, losses are neglected.

[10] and [11] propose Alternating Direction Method of Multipliers (ADMM) to deal with an energy hub management scheduling. Multiple scenarios are studied with and without storage systems, however design of bat-

teries is always fixed. [12] solves a multi-period planning problem for multi-energy microgrids under uncertainties, to do so, a MILP formulation is used. In addition, other optimization approaches such robust optimization can be applied on energy hub management problems [13].

Few works in literature deal with the design of storage systems in coupled heat and electrical networks [14]. [15] and [16] suggest new energy hub design to store electricity massively. Authors use combined steam, Organic Rankine Cycles and gas turbines to convert previously stored energy into electricity during demand peak periods. Several high temperature thermal storage designs are used to store windfarm produced electricity. Here, particle swarm optimization approach is used to deliver optimal management strategy. Results show high electrical and heat delivery efficiency of such design where profitable business cases are accessible.

This review of state of the art shows that simple models are, in most cases, used to optimize physical components management. Most of found studies explore energy hubs with focus on electrical network and CHP plants. Furthermore, articles mainly study energy hub as either a planning or design problem without focusing on the interaction between design and management. It is then necessary to study the impact of storage and conversion systems designs on the management performance of heat and electrical networks. Therefore, the purpose of this contribution is to evaluate such interaction to get closer to co-optimized multi-energy networks.

### III. MODELING OF STORAGE AND CONVERSION SYSTEMS

#### A. Storage systems

In this work, both storage systems are supposed perfect storage without loss. For the thermal storage, model supposes perfect battery with loss  $P_{loss-TEs}$  when battery is overloaded [7]. The dynamics of the system according to this model is expressed as follows :

$$E_{sto}(t + \Delta t) = E_{sto}(t) + P_{sto}(t) \cdot \Delta t \quad (1)$$

$E_{sto}$  is the storage state of energy,  $P_{sto}$  is the storage command (charge for positive values and discharge for the negative ones).  $\Delta t$  is the time step of the investigated problem.

Batteries aging is simply modeled as the sum of the exchanged energies over studied period:

$$C_{aging}^{storage}(t) = |P_{sto}(t)| \quad (2)$$

#### B. Conversion systems

As explained in section I, the Power To Heat system is composed of electric resistances that heat air to high temperature (600 °C). Modeling this system and it's aging can be quite simple and can be expressed as follows:

$$\begin{aligned} P_{P2H}^{heat} &= P_{P2H}^{elec} \cdot \eta_{P2H} \\ P_{loss-P2H} &= P_{P2H}^{elec} \times (1 - \eta_{P2H}) \\ C_{aging}^{P2H}(t) &= P_{P2H}^{elec}(t) \end{aligned} \quad (3)$$

$\eta_{P2H}$  is a constant efficiency that takes into account the heat loss when converting electricity into heat by joule effect (here  $\eta_{P2H} = 0.95$ ).

For the Heat To Power part, an ORC system is selected and modeled based on real data from a French ORC technology manufacturer. Power and residual heat output from such a system depends on the thermal power input as shown below :

$$\begin{aligned} P_{H2P}^{elec} &= P_{H2P}^{heat} \cdot \eta_{H2P}^{elec}(P_{H2P}^{heat}) \\ P_{H2P}^{residual-heat} &= P_{H2P}^{heat} \cdot \eta_{H2P}^{heat}(P_{H2P}^{heat}) \\ P_{loss-H2P} &= P_{H2P}^{heat} \times (1 - \eta_{H2P}^{elec} - \eta_{H2P}^{heat}) \\ C_{aging}^{H2P}(t) &= P_{H2P}^{heat}(t) \end{aligned} \quad (4)$$

Where  $P_{H2P}^{heat}$  is the thermal input of ORC,  $P_{H2P}^{elec}$  is the electrical output and  $P_{H2P}^{residual-heat}$  is the heat residual output from the system that can still be exploited for heating. In this paper,  $\eta_{H2P}^{elec}$  varies between 0 and 0.20, for 0 and the nominal power input of the ORC system respectively. Throughout this work the temperature of the heat network is supposed to be constant and at high temperature. To simplify, the networks are assumed to be perfect and lossless in this work, as their modeling can be very sophisticated.

### IV. DESCRIPTION OF CASE STUDY AND OPTIMAL MANAGEMENT

The case study used for optimization and simulation work is presented in figure 2. Both electrical and thermal sources and loads are time-varying. The control to be optimized is the command of electrical  $P_{sto-elec}$  and thermal storage  $P_{sto-th}$  as well as conversion ( $P_{P2H}$  and  $P_{H2P}$  for P2H electrical and H2P thermal inputs respectively) and two shedding systems  $P_{del}$ . The main objective here is to minimize the deviation on electric  $P_{dev-elec}$  and heat networks  $P_{dev-th}$ . In other words, the call on the auxiliary boiler and the main grid in case of overconsumption, and the loss of profit in case of overproduction  $C_{dev}$  is to be avoided. Moreover, losses related to storage and conversion systems  $C_{losses}$  should

be minimized along with power shedding  $C_{del}$  and physical components aging  $C_{aging}$  as described below :

$$\min \sum_{t=0}^{n_w} \alpha \times C_{dev}(t) + \beta \times C_{losses}(t) + \gamma \times C_{del}(t) + \delta \times C_{aging}(t)$$

s.t.

$$\begin{aligned} \frac{P_{th}^{rated}}{t} &\leq P_{sto-th}(t) \leq \overline{P_{th}^{rated}} \\ \frac{P_{elec}^{rated}}{t} &\leq P_{sto-elec}(t) \leq \overline{P_{elec}^{rated}} \\ 0 &\leq E_{th}(t) \leq \infty, \quad 0 \leq E_{elec}(t) \leq E_{elec}^{rated} \\ 0 &\leq P_{P2H}^{elec}(t) \leq \overline{P_{P2H}}, \quad 0 \leq P_{H2P}^{heat}(t) \leq \overline{P_{H2P}} \\ 0 &\leq P_{del}^{elec}(t) \leq \overline{P_{del}^{elec}}, \quad 0 \leq P_{del}^{heat}(t) \leq \overline{P_{del}^{heat}} \end{aligned}$$

with

$$\begin{aligned} C_{dev} &= P_{dev-elec}^2 + P_{dev-th}^2 \\ C_{losses} &= P_{loss-EES}^2 + P_{loss-TEs}^2 + P_{loss-P2H}^2 \\ &+ P_{loss-H2P}^2 \\ C_{del} &= P_{del-elec}^2 + P_{del-th}^2 \\ C_{aging} &= |P_{sto-elec}| + |P_{sto-th}| + P_{P2H}^{elec} + P_{H2P}^{heat} \end{aligned} \quad (5)$$

### Electrical network energy balance

$$\begin{aligned} P_{mis-elec} &= P_{prod-elec} - P_{load-elec} \\ P_{dev-elec} &= P_{mis-elec} - P_{sto-elec} - P_{P2H}^{elec} \\ &+ P_{H2P}^{heat} \times \eta_{H2P}^{elec} - P_{del-elec} \end{aligned}$$

### Heat network energy balance

$$\begin{aligned} P_{mis-th} &= P_{prod-th} - P_{load-th} \\ P_{dev-th} &= P_{mis-th} - P_{sto-th} - P_{H2P}^{heat} \\ &+ P_{H2P}^{heat} \times \eta_{H2P}^{heat} + P_{P2H}^{elec} \times \eta_{P2H} - P_{del-th} \end{aligned}$$

$P_{mis-th}$  and  $P_{mis-elec}$  represent the initial deviation on both thermal and electrical network.  $P_{dev-th}$  and  $P_{dev-elec}$  are the resulted deviation after adding physical components such as storage, conversion and shedding systems. Here  $E_{th}$  and  $E_{elec}$  stand for thermal and power storage states of Energy, and  $E_{elec}^{rated}$  for Electrical battery capacity.  $\overline{P_{P2H}}$  and  $\overline{P_{H2P}}$  are the nominal power of P2H and H2P systems.  $\overline{P_{del}^{elec}}$  and  $\overline{P_{del}^{heat}}$  are the maximum power of electrical and thermal shedding systems.  $\frac{P_{th}^{rated}}{t}$ ,  $\frac{P_{elec}^{rated}}{t}$  and  $\frac{P_{del}^{rated}}{t}$  are thermal and electrical maximum charging and discharging inputs.

Here  $\alpha, \beta, \gamma, \delta$  represents the weighting of different terms of the cost function to be minimized. The heat and electrical networks are supposed to be perfect without losses. All long the heat carrier, air flow is supposed to be on high temperature (600 °C).

In this case study, the thermal and electrical load are based on time-series found in [17] and [18], representing hourly load profiles measures and models. The electrical production profile is based on wind farm real measurements of 10 mins time step [19]. The waste heat time-series is real measurements from french ceramics factory. This series measures the heat output from a gas industrial furnace used for cooking of materials.

As shown in figure 3, all datasets are being normalized and manipulated to construct the case study composed of a residential area consuming 20 GWh/year (50% of the whole consumption are for space heating and domestic hot water needs [20]). This residential area is connected to a wind farm of 5 wind turbines of 2 MW, producing a total of 15 GWh/year. Finally, an industrial rejecting 15 GWh/year of waste heat is supposed to be nearby and connected to the district heating network.

The problem is solved numerically using MPC [21] and SLSQP optimization method from SciPy Python-based library. The time horizon  $N$  of the resolution is 8760 h. At each time step (here 1 h), the formulated optimization problem (eq. 5) is solved on a sliding window of size  $n_w$ . Only the first sample of the output sequence is implemented for simulation, subsequently the sliding window is shifted of 1 h. At the next time step, the new state of the system is estimated by the selected model simulation, and a new optimization problem is solved using this new information. All along this work, the studied problem is assumed to be deterministic.

Examples of obtained management for uncoupled and coupled networks, with 9 MWh of thermal storage and 3 MWh of electrical storage, are illustrated in figure 4 and 5. It represents hourly energy fluxes evolution over a sample of 10 days with a P2H and H2P of 5 MW.

Deviations before and after adding investigated components are massively decreased, due to the flexibility from installed storage capacities and over production shedding. Moreover, the impact of coupling thermal and electrical networks is noticed on the deviation of figure 5. Additionally, storage systems operating rate is increased by coupling both networks. In fact, conversion systems allow to put both storage systems at the service of a network at the time of consumption or production peaks. In coupled networks, lower operating rate of shedding systems is being noticed.

## V. DESIGN RESULTS AND ANALYSIS

The goal of this section is to determine suitable sliding window size for the optimization process. Furthermore, results for four physical configurations, using

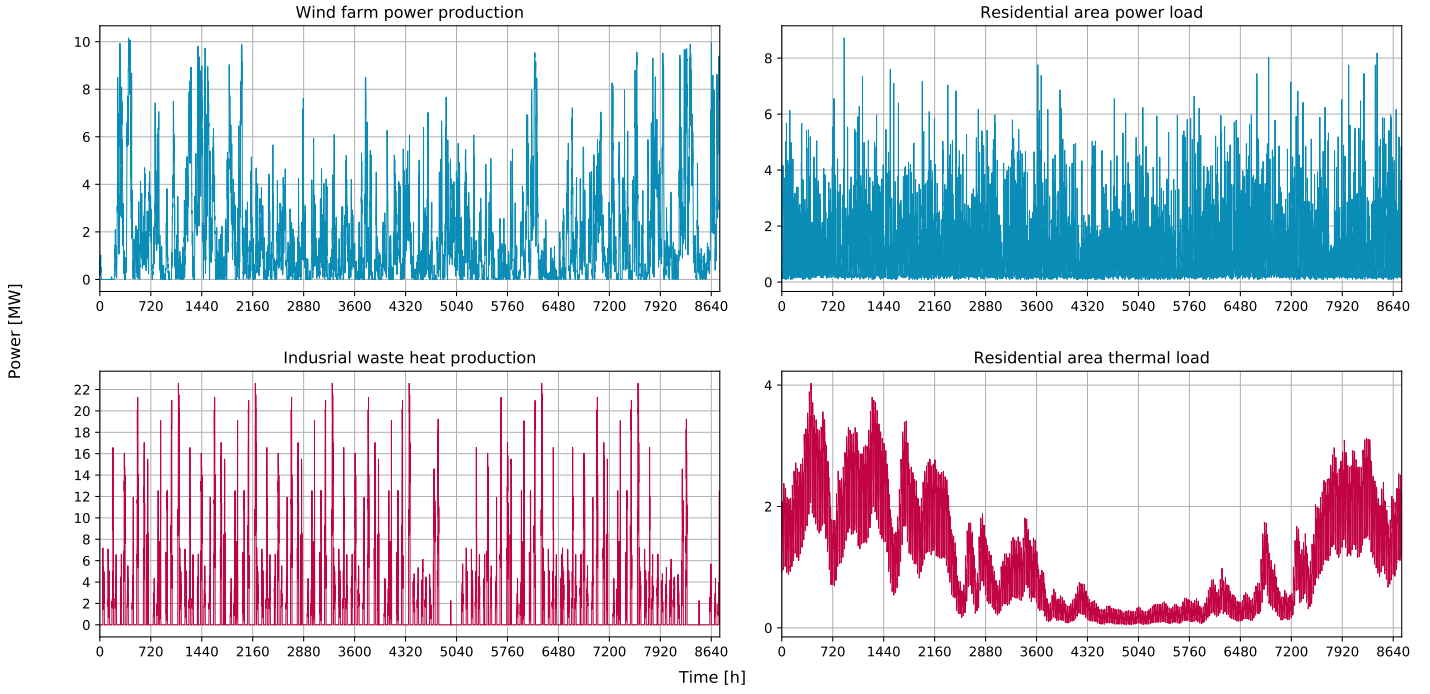


Fig. 3. Case study datasets over a year. Blue plots corresponds to windfarm production of five wind turbines of 2 MW, and electrical load of the studied residential area. Red plots represent industry waste heat release and thermal load of residential area

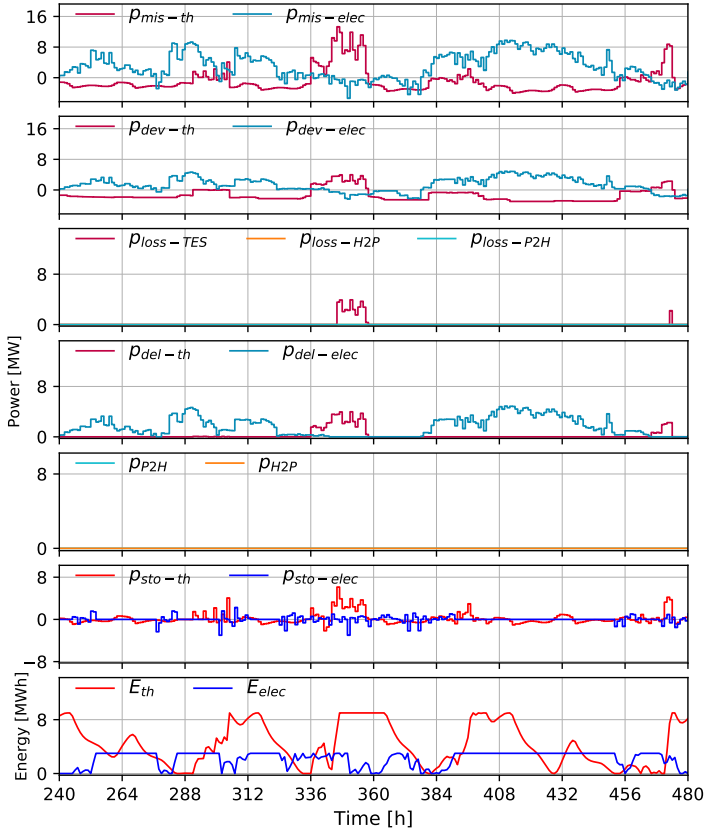


Fig. 4. Simulated optimal management of uncoupled networks over 240 h. 9 MWh of thermal storage, 3 MWh of electrical storage are installed without P2H and H2P conversion systems.  $\alpha, \beta, \gamma, \delta = 1, 1, 1, 0.1$ . (see eq. 5)

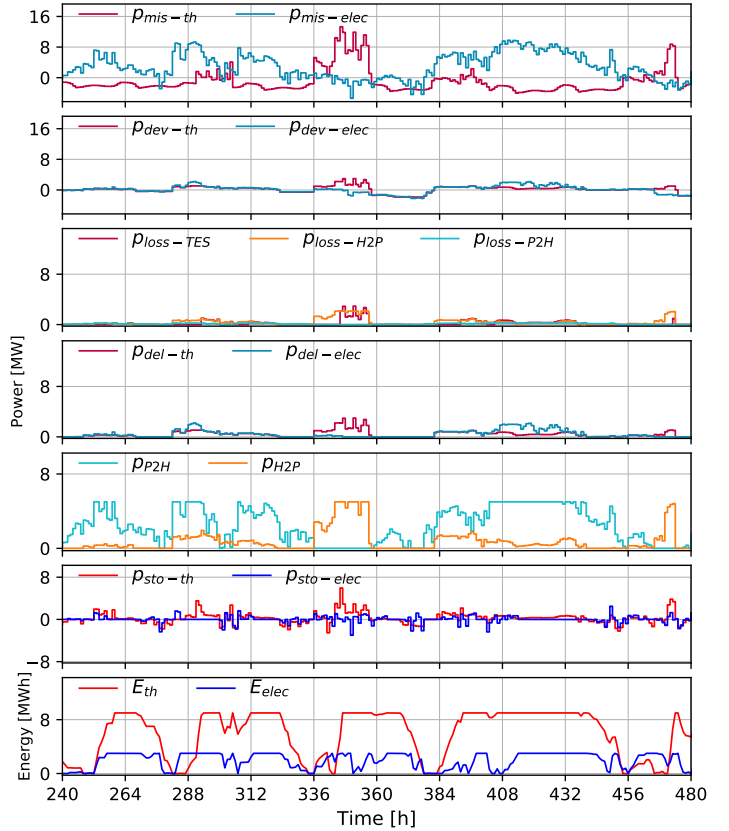


Fig. 5. Simulated optimal management of coupled networks over 240 h. 9 MWh of thermal storage, 3 MWh of electrical storage and 5 MW of P2H and H2P conversion systems are installed.  $\alpha, \beta, \gamma, \delta = 1, 1, 1, 0.1$ . (see eq. 5)



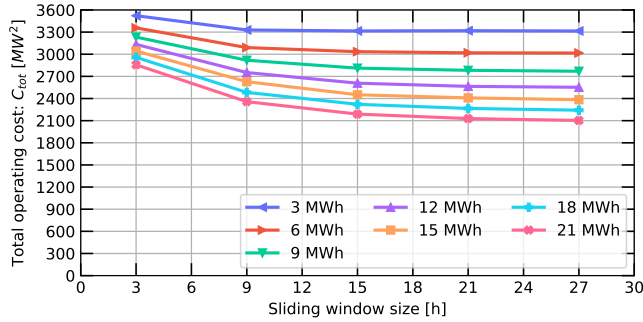


Fig. 6. Evolution of total operating cost over 720 h according to increasing sliding window size  $n_w$ . Legends stand for different thermal and electrical storage designs (for example, green legend stands for 9 MWh of thermal and 9 MWh of electrical storage.)

the case study datasets, will be presented : without load shedding and conversion systems, with load shedding and without conversion system, and finally with load shedding and conversion systems of 5 and 15 MW of installed nominal power. Whole configurations will be using different thermal and electrical storage capacities. The initial case for comparison excludes storage, conversion and load shedding systems. Thereafter, electrical and thermal batteries capacities are being varied between 0 and 21 MWh with 3 MWh step. P2H and H2P systems are of 0, 5 and 15 MW of nominal power. Along this work, shedding systems are of 10 MW of maximum power for each network. In addition, cost function evolution as function of the four configurations and storage capacities will be visualized and commented. Finally a summary table will be presented to compare the various designs.

#### A. Identification of sliding window size

For this part, MPC problem is solved on 720 h with increasing sliding window size, and for each storage system capacity. For each design, total operating cost decrease with increasing sliding window size until reaching an asymptote as illustrated in figure 6. Convergence condition is then applied on the total cost to determine the smallest window size that satisfies the chosen condition. Figure 7 shows sliding window size for each design with a variation on the total cost  $C_{tot} < 2\%$ .

Regarding investigated storage capacities, sliding window size converges rapidly for small storage designs. On the other hand, for large storage capacities, the window size needs to be increased to anticipate more future events. Based on showed results, sliding window size will be set at 24 h for the rest of this study. Irregularities in figure 7 are caused by the weak number of tested sliding window sizes to avoid long calculation time.

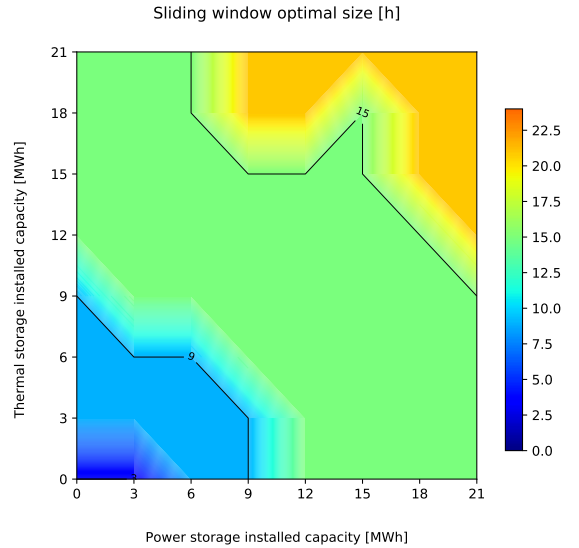


Fig. 7. Evolution of the sliding window size for different thermal and electrical storage designs

#### B. Optimization results and analysis

Figure 8 describes the evolution of the total operating cost normalized by the initial configuration cost (uncoupled network excluding storage and shedding systems). Four subplots are drawn for uncoupled networks without and with shedding systems, and two coupled networks with different conversion systems designs including shedding systems. Axes  $x$  and  $y$  represent the installed capacity of electrical and thermal batteries respectively.

Total cost for uncoupled networks decrease slowly with increasing power storage capacity and faster with increasing thermal storage capacity. This is explained by more important peaks of waste heat release compared to windfarm production peaks in the studied datasets. Moreover, the thermal storage operates in an open physical loop, and so that it is able to evacuate overproduction during charging phase. In this case, storage along with shedding systems allows to reduce the total cost by 70% for the largest investigated capacities (here 21 MWh per storage system). It is to be noticed that decrease in cost function seems to reach a limit for large storage capacities, therefore it is of interest to couple networks.

The impact of coupling heat and electrical networks is this case study is demonstrated on the two lower plots of figure 8. For largest batteries and with 5 MW of P2H and H2P systems, cost function is reduced by 84%. In case of batteries absence, coupling along shedding systems decrease the operating cost by 70%, which is of same order as large capacity batteries impact. In fact, for a total normalized cost of 30%, this is reachable by 21 MWh

of thermal and 21 MWh of power storage in case of uncoupled networks. On the other hand, the same cost can be achieved with P2H and H2P of 5 MW installed power and small storage systems. In this situation the needed storage capacity is almost divided by a factor of 10. Finally, in this study case and for coupled networks, both batteries seem to have similar impact on the total cost function. This suggests that part of electric batteries can be substituted by thermal storage in case of coupling.

Table I summarizes normalized total cost, normalized total deviation and self-consumption for eight relevant designs. Up to 76 % of total consumption can be satisfied, using local resources, with 21 MWh of each thermal and power storage and 5 MW of P2H and H2P nominal power facility. According to results, increasing the conversion systems nominal power do not always results in higher self-sufficiency.

## VI. CONCLUSIONS AND PERSPECTIVES

Multi-energy networks are becoming a leading research subject in the last years, particularly, with the accelerating emergence of renewable resources into the energetic system. Many works have been conducted and showed the benefits of coupling energy carriers but more investigations on concept, modeling, design and management are to be conducted.

In this work, we proposed a concept of power and heat networks coupling. Simple models are being implemented for simulation and optimization of such concept with MPC algorithm. Real datasets have been used to conduct a realistic case study including a residential area, a windfarm and an industry releasing waste heat and connected to a district heating network.

Investigation on the optimal sliding window size for the optimization process has determined it to be of a day. Optimal management results for uncoupled and coupled networks with various thermal and power storage designs have been analyzed. Results show a complementarity between both carriers and higher flexibility due to shared storage facilities when coupled. Moreover, it is suggested that part of electrical batteries is possibly substituted by thermal storage in case of coupled networks. Finally, conversion systems of appropriate size can decrease massively the needed storage capacity.

Nevertheless, this work has several limitations such as the assumption of perfect networks, the homogeneous temperature along the heat network and the simplified models used for simulation and optimization of storage and conversion systems. More studies need to be conducted on the impact of the system modeling, particularly

for the H2P system and the heat network.

In addition, this work needs to be conducted on different datasets corresponding to different profiles of thermal and power production inputs. Conclusions can be sensitive to the nature of locally available resources. It is to be mentioned that the studied cost function terms are weighted using  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$  which took fixed values along this study. It is therefore essential to conduct a sensibility study on impact of those parameters on the global management performance.

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## Total normalized operating cost over a year [ $MW^2/MW^2$ ]

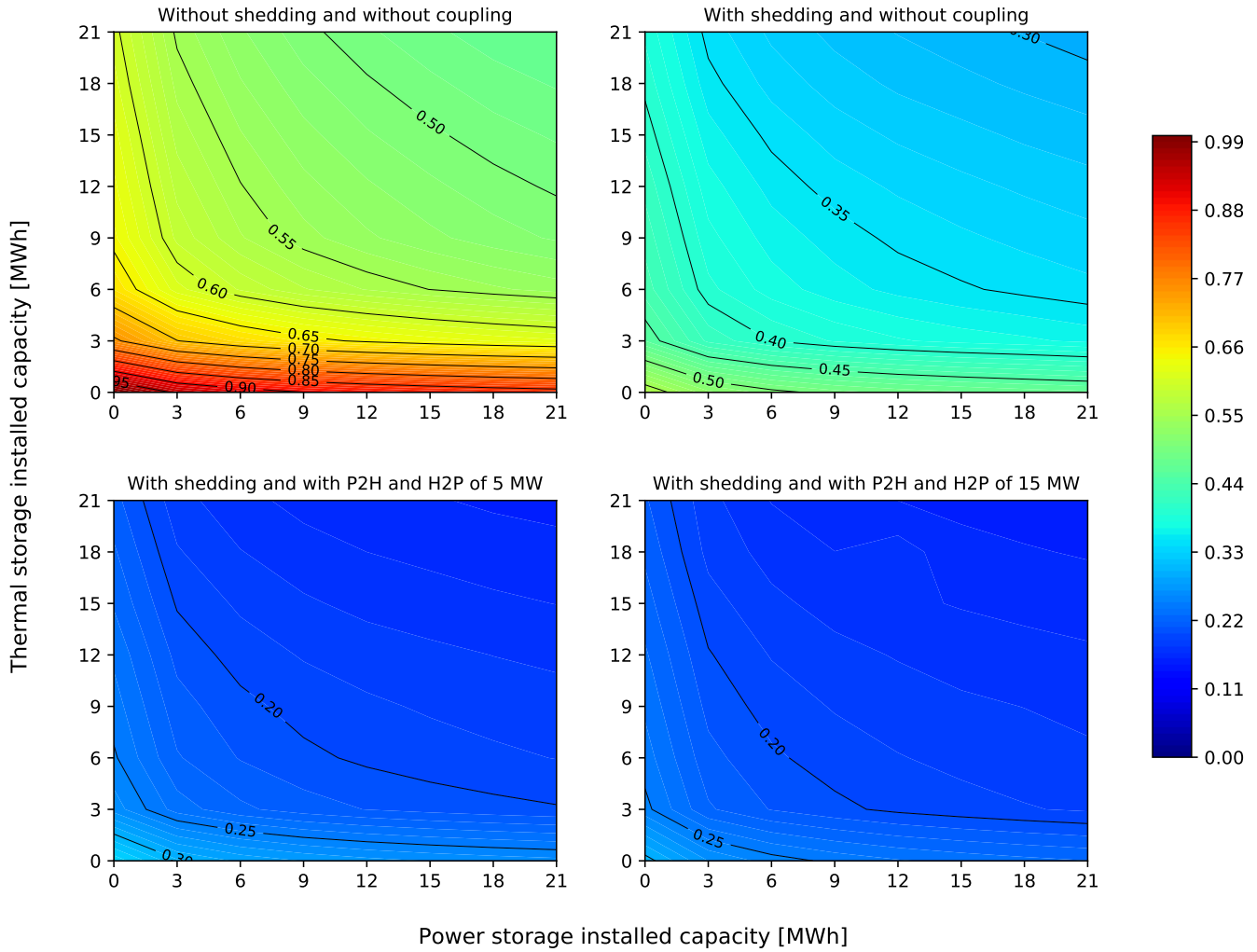


Fig. 8. Evolution of total normalized operating cost over a year according to various physical configurations and storage designs

TABLE I. SUMMARY TABLE RESUMING NORMALIZED COST, DEVIATION AND SELF-CONSUMPTION FOR MAIN INVESTIGATED CONFIGURATIONS (FOR  $\alpha = 1.0$ ,  $\beta = 1.0$ ,  $\gamma = 1.0$ ,  $\delta = 0.1$ )

Case n <sup>o</sup>	Shedding	Storage capacities [MWh]	P2H & H2P nominal power [MW]	Normalized total cost [%]	Normalized total deviation [%]	Self-consumption [%]
1	no	0	0	100	100	40
2	no	21	0	47	63	62
3	yes	0	0	56	67	40
4	yes	21	0	30	45	62
5	yes	0	5	33	47	56
6	yes	21	5	16	28	76
7	yes	0	15	30	45	56
8	yes	21	15	15	29	76

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