Integration of storage and thermal demand response to unlock flexibility in district multi-energy systems

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Abstract. Optimal operation of generation units is crucial when looking for reduction in energy consumption and carbon emissions in multi-energy systems (i.e. multiple generation sources, energy networks and storages). This work proposes an innovative optimization approach that can be applied to energy systems composed by multiple small units for the production and conversion of electricity, heating and cooling. The optimization is conducted acting on the operation of the production units, the capacity and operation of thermal storage units and the application of demand side management to the thermal network. The optimization procedure is based on a two-level approach, combining a genetic algorithm and a linear programming approach and including a physical model of the district heating network. Multiple scenarios corresponding with typical days are considered. An application to a realistic system, which is optimized assuming an economic objective function, is performed. Results show that thermal storage installation can reduce costs of about 1.5%, while its integration with demand-side management leads to a cost reduction up to 4% and allows reducing the storage size.

Keywords: Multi-energy systems; system optimization; district heating; thermal network; thermal storage; demand-side management.

1. INTRODUCTION

District heating and cooling systems are convenient and highly efficient solutions to move towards zero energy cities [1], particularly in areas with high population density. By leveraging low-grade and sustainable energy sources, these systems lead to substantial primary energy reductions for space heating and domestic hot water production resulting in a ground-breaking technology for potential emission reduction [2], [3].

Currently, high-efficiency thermal plants, such as combined heat and power plants (CHP), are typically installed in district heating systems to supply the base load [4]. The peak demand is usually covered adopting other technologies, often heat-only-boilers (HOB). Thus, the occurrence of thermal peaks represents a crucial issue in district heating applications since they lead to an overall reduction of the system efficiency [5]. Moreover, thermal peaks provoke undesirable increases in the mass-flow rates circulating in the network. This compromises the opportunities for the expansion of existing networks that cannot be subjected to high water velocities because of structural constraints [6].

For the above reasons, the identification of different strategies to cut the peaks (and fill the valleys) is attracting ever-growing interest in the recent literature [7]. Among the different possibilities for shaving the peaks, an interesting option consists in the adoption of Thermal Energy Storages (TES) that can be charged when the request is low (e.g. during the night) and discharged when the request is high (e.g. during the start-up transient in the morning, owing to the night attenuation of the heating systems). An analysis of the installation of a large water storage tank in a real district heating system was provided by Verda and Colella [8], who performed a simulation of the Turin district heating network (powered by CHP and HOB) and showed that net primary energy reductions up to 12% can be obtained. Another study, conducted by Gadd and Werner [9], estimated the size of heat storages needed to eliminate daily heat load variations to about 17% of the average daily heat supplied. A different possibility for thermal peak shaving is represented by “virtual storage” [10], which is obtained through modification of the heating load of some of the buildings connected to the district heating network. Thus, “virtual storage” is a Demand-Side Management (DSM) technique that exploits the flexibility and the active role of the consumers in order to tailor the demand to the usability of the production and to increase the overall efficiency of the system [5], [11]. In the last few years, this strategy, which is already widely adopted in the electricity field to improve the electricity network operation [12], is becoming increasingly considered also in district heating applications [13]. Peak reductions up to 35% are reported by different studies involving Demand-Response in real district heating systems [14]–[16]. Also, the two different strategies for peak shaving (i.e. physical thermal storages and demand-side management) can be simultaneously adopted to improve the performances of district heating networks: the effects of TES and DSM are not overlapping, but complementary for the system perspective [17], [18].

Another important aspect that is worth to take into account when dealing with optimization of district heating systems is represented by the increasing evolution towards *smart energy systems* [19]. The future generation of heating networks will be part of an interconnected energy system, including heating, cooling, electricity, and gas grids [20], [21]. This ongoing transition leads to the need to identify the synergies between the different systems: the optimal management of district heating (and, by extension, of each other system) is no more only determined by the system itself, but also by the other energy systems (e.g. electricity and cooling grids) to which it is connected. A great number of papers in the literature deal with these innovative Multi-Energy Systems (MES) [22]–[24], which allow a greater exploitation of renewable energy technologies and waste heat from industrial plants [25], [26] and will increase the already fundamental role of the storages [27].

In this complex context, the development of a comprehensive optimization tool which is able to take into account all the relevant features of MES becomes essential. The optimal plant operation is often not easily predictable due to the large number of variables associated to the multiple layouts, the presence of conversion units and storages, the possibility to perform demand side management, and so on. In the literature, the operation management of multi-energy systems has been performed using different approaches. Specifically, a linear programming (LP) algorithm was chosen by Ren et al. [28] to perform a multi-objective optimization of a distributed energy system. Most of the studies used approaches based on mixed integer linear programming (MILP) to solve multi-energy production optimization. A MILP has been adopted in [29] in order to schedule the operations for heating, cooling and electricity supply in a short-term framework. In [30] the supply of heating, cooling and electricity has been studied taking into account the uncertainly on the load estimation, by using a rolling horizon algorithm. The MILP approach can also be adopted for multi-energy system design, as done in [31]. The adoption of non-linear programming (NLP) or Mixed Integer Non-linear programming (MINLP) is usually reserved for problems highly non-linear, such as [32], [33]. These approaches focus the attention on the best operation of the generation/conversion systems, often combined with thermal storages. Thus, the approach to the optimization used by previous works is mainly based on the supply-side, while the combination of supply-side optimization and demand-side management in the optimization of interconnected multi-energy grids is taken into account by few studies, especially with regard to thermal users flexibility [34], [35], [36]. Moreover, most of these studies do not take into account the thermal dynamics of the district heating network, despite their relevance is confirmed by numerous papers in literature [37],[38].

The aim of this paper is to propose an approach to estimate the benefits of an optimal storage installation and optimal demand-side management in existing multi-energy systems, and their possible combination. Specifically, the goal is to develop a methodology to assess not only which are the more convenient production units to be used to satisfy the heating, cooling, and electricity loads of Multi-Energy Systems, but also:

1. understand whether it is convenient or not to install a physical thermal energy storage within an existing Multi-Energy system in order to shave the peaks and to optimize the production of the whole interconnected system (also the cooling and electricity production, due to the possibility of converting energy from one form to one another);
2. determine the optimal size of the storage to be installed in such system;
3. calculate the impacts of introducing thermal demand-side management in existing Multi-Energy Systems and understand whether demand-side management is useful in combination with thermal storage to shave the peaks and optimize the production.

These objectives are reached by means of a complex optimization tool that optimally selects a) the operation of the generation units b) the optimal size of the thermal storage c) the thermal load shifting of each user (demand response), in order to minimize the energy operation cost in a district Multi-Energy System. An important feature of the tool is that it takes into account the thermal dynamics within the District Heating Network by accurately evaluating the change in the plant heating load due to DSM through a physical simulation of the network.

The structure of the paper is the following: in Section 2, the layout of the multi-energy system is presented to explain the structure of the problem; in Section 3, the optimization approach (including the structure of the algorithm, the optimization variables, the constraints of the problem and the objective function considered in this analysis) is developed; in Section 4, a case-study is introduced; Section 5 discusses the results of different optimizations; finally, Section 6 is devoted to the final considerations and the main conclusions that can be drawn from this work.

2. SYSTEM CONFIGURATION

The problem analyzed in this work deals with small-scale district energy systems, with heating, cooling and electricity loads. The three major interconnected components of such systems are: the production units, the distribution networks, and the customers. In the case considered in this paper, the various buildings are connected to a local production plant

through three distribution networks that provide the required heating, cooling and electricity to the customers: a district heating network, a district cooling network and an electricity network.
The production plant can be composed by multiple technologies. In this work, the followings have been taken into account:

- a combined heat and power plant (CHP);
- a heat-only boiler (HOB)
- a photovoltaic plant (PV);
- an electric heat pump (EHP) for heating and cooling production;
- an absorption refrigeration unit (AR).

The following resources are used to supply the whole system:

- natural gas purchased from the national distribution system;
- electricity purchased from the national grid.

The electricity surplus, if present, may also be sold to the national grid.
A schematic of the production plant is represented in Figure 1. The same approach can be applied to production plants with different types of technologies.
The operation of the system can be optimized considering different objectives. In this case, an economic optimization is proposed. Two opportunities are investigated to improve the performances of the system:

1. the possibility to install a thermal storage tank within the production plant; this unit would be associated to extra investment costs depending on its capacity;
2. the possibility to act on the thermal demand of the customers (demand-side management) during the space-heating season.

Thus, the total yearly cost needs is evaluated in order to perform a comprehensive analysis of the system operation. The cost depends on the difference between the expenses, which are related to the costs for natural gas and electricity and possibly to the installation of the storages, and the revenues, associated with the electricity sold to the electric grid.

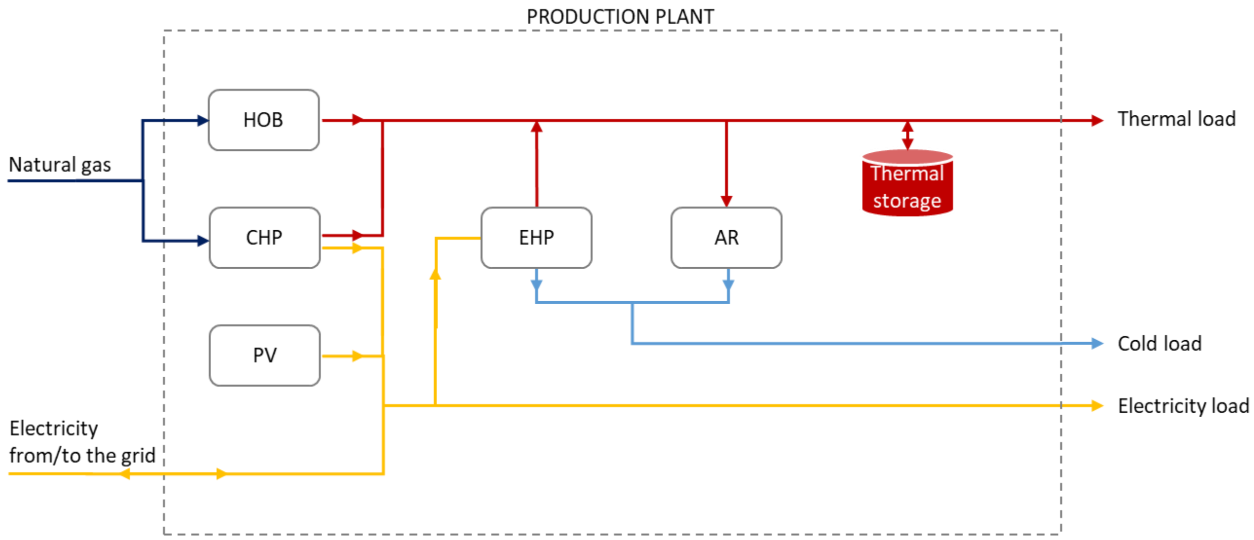

Figure 1. Schematic representation of the production units in the plant (HOB: Heat-Only Boiler; CHP: Combined Heat and Power; PV: Photovoltaic system; EHP: Electric Heat Pump; AR: Absorption Refrigeration unit). Red, light blue and yellow lines represent the heating, cooling and electricity flows. The possible installation of a thermal storage is discussed in the following sections.

3. OPTIMIZATION APPROACH

The goal of the proposed approach is to minimize the yearly operating cost for an existing energy system characterized by various generation/conversion technologies used to supply heating, cooling and electricity to a district energy system. To reach this objective, different strategies are considered in this analysis:

1. the smart management of the production units, i.e. the possibility to identify the most convenient components to be switched on for each time-interval of the four days considered;
2. the possibility of installing a thermal storage unit within the system;
3. the flexibility of the heating load of the customers (Demand-Side Management).

The objective function of the optimization problem is the yearly operation cost, which is given by the sum of the production costs for each of the selected days of the year. The problem can be formulated as follows:

$$\min_{\mathbf{x} \in X}(f_{eco}(\mathbf{x})) \tag{1}$$

where $\mathbf{x}$ is the decision vector and X is the feasible region of the decision vector; f_{eco} is the economic objective function and this is discussed later on in subsection 3.2. The decision variables of the problem include:

- the input production fluxes involved in the different technologies, at each time of the day and for all the days considered in this analysis;
- the capacity of the thermal storage;
- the variables related to thermal Demand-Side Management (i.e. variables associated with the modifications of the heating demand of each customer during the days of the space-heating season).

The whole set of variables is listed and further discussed in subsection 3.1 and subsection 3.2.
Due to the different nature of the phenomena considered in this analysis, the optimization has been structured into two different levels:

- the upper-level optimization is solved by means of a genetic algorithm and allows estimating the best set of heating load shifting (i.e. the demand-side management variables $\mathbf{d}$);
- the lower-level optimization faces the production optimization and uses a deterministic algorithm to find the optimal values of production fluxes and storage capacities (that are grouped in the vector $\mathbf{p}$).

This decomposition allows to better address the peculiarities of each part of the optimization problem. A flow-chart describing the structure of the optimization approach is reported in Figure 2. This approach can be summarized as follows:

a) at each iteration of the genetic algorithm, a new generation of $\mathbf{d}$ (thermal demand-side management variables, including one variable for each building i, for each day j' in the heating season) is considered;
b) the thermal demand-side management variables are used to calculate the evolution of the heating load at plant level for the days with demand-side management; this is done by means of a physical model which allows to simulate the thermo-fluid dynamic behavior of the district heating network;
c) once the heating loads of space-heating season days have been estimated (depending on the given set of demand-side management variables), they are used, along with the heating loads of the days without space-haeating and the cooling and electricity loads (which are calculated before the optimization, since they are not subjected to demand-side management), to establish some constraints on the production plant (i.e. to define the search space for the lower-level optimization variables $\mathbf{p}$);
d) then, the lower-level optimization is carried out to estimate the optimal operation of the generation units and storage system and to evaluate the objective function;
e) if convergence is reached, the solution is obtained and the algorithm stops; otherwise, a new generation is created by the genetic algorithm and the whole procedure is repeated.

The different steps of the algorithm are detailed in the next subsections.

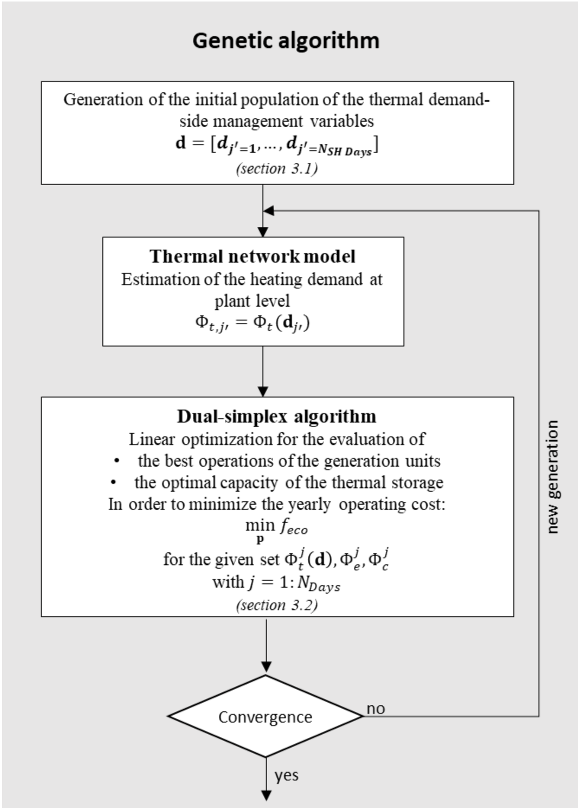

Figure 2 Flowchart of the optimization algorithm

3.1 Demand-side management

In order to evaluate the yearly operation cost, the knowledge of the evolution of the heating, cooling and electricity loads during the different days is required. The heating loads of the days without space-heating, the cooling loads and the electricity loads at plant level can be estimated before the optimization algorithm since they do not depend on the optimization variables. By contrast, the heating loads of the days with space-heating (thus with the possibility to perform demand-side management) are evaluated at each step of the optimization process, since they could be subjected to demand side management during the winter and autumn days (characterized by a significant thermal peak). This allows to properly estimate the loads by considering the dynamics of the network, even when the demand is modified.

Different options are available for the implementation of thermal demand-side management [13]. The choice of the strategy for real applications can be influenced by several drivers, including technical factors and business models used in each different energy system. In the case-study analyzed in this work, the implementation of demand side management is performed by shifting the time the heating systems are switched-on after the night setback; an example of the application of load shifting to the heating demand of a building is provided in Figure 3. In this application, the load shifting can be operated up to 30 minutes in advance. This limitation was introduced to avoid affecting the users' thermal comfort. For technical reasons, anticipations could be operated every 5 minutes (e.g. 5 min, 10 min, 15 min etc. up to 30 min). In a second analysis, the effects of extending the anticipation range up to 60 minutes are also analyzed.

These anticipations represent the optimization variables of the upper-level optimizer, i.e. the demand-side management part. The decision vector $\mathbf{d}$ has so many elements as the number of buildings connected to the district heating network times the number of days with demand-side management.

Each variable d_i is related to the anticipation time $\Delta t_{i,j'}$ of the i-th building during the j'-th heating day according to the following relationship:

$$\Delta t_{i,j'} = 5\ [min] \cdot d_{i,j'}$$

with $i = 1\!:\!N_{buildings}$ and $j' = 1\!:\!N_{SH\ Days}$. $d_{i,j}$ can only assume integer values and is bounded below by 0 (no anticipation, $\Delta t_i = 0\ min$) and above by 6 or 12, depending on the case analyzed (maximum anticipation allowed, $\Delta t_i = 30\ min$ or $\Delta t_i = 60\ min$).

To solve this complex optimization problem, the genetic algorithm implemented within the Global Optimization Toolbox of MATLAB® was adopted.

At each generation of the genetic algorithm, a new population of demand-side variables $\mathbf{d}$ is considered. These variables (that, as previously explained, represent the anticipation of each building during each of the two days with DSM) are used

to correct the new building loads. The new plant loads (the heating loads at plant level during the space-heating days) are then evaluated by means of a physical model of the district heating network. The model is based on the conservation equations of mass, momentum, and energy (which are integrated according to the finite volume method [39]). The interested reader can consult published works [6], [40], [41] for the complete formulation and resolution of the thermo-fluid dynamic problem.
Finally, once the loads at plant level are all known, the lower-level production optimization part was included within each iteration of the upper-level genetic optimizer.

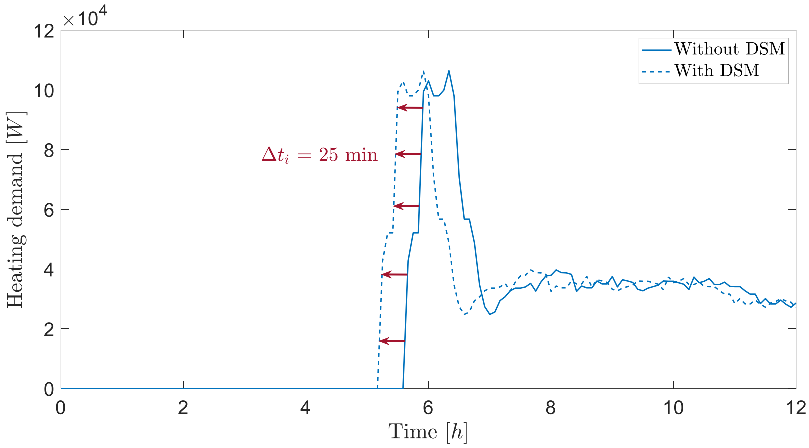

Figure 3. Example of the implementation of demand-side management: heating demand of a building before and after a 25-minutes load shifting.

3.2 Production optimization

At each iteration of the genetic algorithm, once the heating load has been evaluated and all the heating, cooling and electricity loads at plant level are known, it is possible to perform the optimization of a) the production fluxes and b) the size of the thermal storage within the plant. The aim of the lower-level optimizer is to smartly manage, for the different days, the production of the available production units and to understand the optimal size of the thermal storage that can be installed in the system, in order to minimize the yearly operating costs.
The economic objective function considered in this lower-level optimization is the sum of the investment cost for the storage and of the operating costs, given by the sum of the operating costs of all the days in a year:

$$f_{eco} = c_{t,st} C_{t,st} + \sum_{j=1}^{N_{Days}} \sum_{i=1}^{N_{TS}} \left(c_g (\Phi_{g,CHP}^{i,j} + \Phi_{g,HOB}^{i,j}) + c_{e,in}^{i,j} \Phi_{e,in}^{i,j} - c_{e,out}^{i,j} \Phi_{e,out}^{i} \right) \Delta\tau \tag{2}$$

It is important to highlight that the same objective function is adopted for both the optimization steps.
Since the optimization time step is 15 min, the operating cost for each day j is the sum of the costs for each of the 96 time steps of the day.
As concerns the operating costs, the expenses are due to the amount of natural gas consumed by the cogeneration unit and the boiler and to the electricity purchased from the grid, while revenues are available if electricity is sold. The specific cost of the natural gas c_g was considered constant throughout the entire period. Instead, the specific cost of the electricity purchased ($c_{e,in}^{i}$) or sold ($c_{e,out}^{i}$) to the grid depends on the time interval considered: each time interval i can be associated to a different specific cost of the purchased/sold electricity. Due to the fact that the analysis is carried out for a single year, the specific investment costs of the storage $c_{t,st}$ is obtained taking into account their expected life (average values were derived from [42]).
As suggested by Eq. (2), the objective function is linearly dependent on:

- the capacity of the thermal storage to be installed in the system $C_{t,st}$;
- the natural gas required for the operation of the cogeneration unit $\Phi_{g,CHP}^{i,j}$;
- the natural gas required for the operation of the heat-only boiler $\Phi_{g,HOB}^{i,j}$;
- the electric power purchased from the grid $\Phi_{e,in}^{i,j}$;
- the electric power sold to the grid $\Phi_{e,out}^{i,j}$;

These variables represent the independent variables of the lower-level optimization problem, along with the electric power needed by the electric heat pump to produce heat $\Phi_{e,EHP_t}^{i,j}$, the electric power needed by the electric heat pump to produce cooling $\Phi_{e,EHP_c}^{i,j}$, the heat required by the absorption heat pump $\Phi_{t,ARU}^{i,j}$ and the heat absorbed or released by the thermal storage $\Phi_{t,st}^{i,j}$.

Note that the 8 variables associated with energy fluxes must be estimated for each of the 96 time-steps of the day and for each of the N_{Days} days considered in this analysis. This is necessary because of the possible presence of the storage systems, which makes not possible to solve the production optimization independently at each time step. Hence, 768 variables are required for each day; moreover, there is one more variable related with the size of the storage. Therefore, the total number of variables of the lower-level optimization is equal to $(N_{\Phi-var} \cdot N_{TS} \cdot N_{Days} + N_{storage})$.

All the variables are included in the decision vector $\mathbf{p}$. All of them are considered as continuous variables, bounded below by $\mathbf{l_b}$ and above by $\mathbf{u}_{\boldsymbol{b}}$. Except for the storage flows, which assume negative values when the charging process is considered, all the other variables are bounded from below by zero.

The lower-level optimization must satisfy 5 inequality constraints for each time step and for each day. The first three inequality constraints are related to the heating, cooling and electricity balance. For each day $j = 1{:}\, N_{days}$, at each time step $i = 1{:}\, N_{TS}$ and for each energy vector $k = 1{:}\, 3$ (heating, cooling and electricity), the following condition must be satisfied: $production_k^i \geq consumption_k^i$. This means that production must be greater than consumption at any time and for each energy vector. The inequality sign is due to the possibility to dissipate heating, cooling and electricity.

Besides the energy balance, two more inequality constraints for each time step i and for each day j are needed for the solution of the lower-level optimization problem. These constraints are due to the possible presence of the thermal storage system within the production plant. The first constraint is linked with the maximum energy that the storage is able to deliver, which depends on the energy stored in the previous time steps; instead, the latter is related with the maximum energy that the unit can store, depending on its capacity C_t (which is, in this case, an independent variable of the optimization). In this work, the storage was considered as ideal; the thermal losses are not taken into account.

The whole set of inequality constraints is summarized in Table 1. By convention, the heating power of the storage $\Phi_{t,st}^{i,j}$ is negative in the charging phase and positive in the discharging phase; if it is zero, the thermal storage is not used. Moreover, in order to relate the heating, cooling and electricity balances to the independent variables of the optimization problem, it was needed to express the output power of each production/conversion unit as a function of the input power; this was done by introducing proper values of efficiencies and coefficients of performance (COP) of the different components. In the application proposed, these efficiencies could be approximated as constant due to the little variation of the performances of the components.

Table 1. Expressions of the inequality constraints of the production optimization problem.

Inequality constraints
for each time step $\boldsymbol{i = 1{:}\, N_{TS}}$ and for each day $\boldsymbol{j = 1{:}\, N_{days}}$

Heating balance	$\eta_{HOB}\Phi_{g,HOB}^{i,j} + \eta_{CHP_t}\Phi_{g,CHP}^{i,j} + COP_{EHP_t}\Phi_{e,EHP_t}^{i,j} + \Phi_{t,st}^{i,j} \geq \Phi_{t,ARU}^{i,j} + \Phi_{t}^{i,j}$
Cooling balance	$COP_{EHP_c}\Phi_{e,EHP_c}^{i,j} + \eta_{ARU}\Phi_{t,ARU}^{i,j} \geq \Phi_{c}^{i,j}$
Electricity balance	$\eta_{CHP_e}\Phi_{g,CHP}^{i,j} + \Phi_{e,PV}^{i,j} + \eta_{tr}\Phi_{e,in}^{i,j} \geq \Phi_{e,EHP_t}^{i,j} + \Phi_{e,EHP_c}^{i,j} + \Phi_{e}^{i,j} + \dfrac{\Phi_{e,out}^{i,j}}{\eta_{tr}}$
Thermal storage	$\int_0^{t_i} \Phi_{t,st}^{j}(t)dt \leq 0$
Thermal storage capacity	$\left\lvert \int_0^{t_i} \Phi_{t,st}^{j}(t)dt \right\rvert \leq C_t$

Overall, the described formulation of the lower-level optimization turns out to be a Linear Programming problem with $(N_{\Phi-var} \cdot N_{TS} \cdot N_{Days} + N_{storage})$variables and $5 \cdot N_{TS} \cdot N_{Days}$inequality constraints. This linear programming optimization problem is solved (at each iteration of the genetic algorithm) using the dual simplex method, through the MATLAB® Optimization Toolbox function *linprog*.

For different applications, e.g. if the assumption of constant efficiencies cannot be applied, the proposed approach can still be used by slightly modifying the formulation of the lower-level optimization that can be expressed as MILP (if a piecewise linear approximation is used to linearize the performances of the components) or MINLP. This modification would increase the computational cost of the algorithm. To reduce the resolution time, a different option is to use the proposed approach as a preliminary optimization to find the values of the variables that are more computationally intensive (i.e. the variables related to demand-side management and to the storage operation); then, a more detailed optimization (which could include, for example, non-constant efficiencies and/or a greater number of simulation days) can be run to determine with a greater level of accuracy the production energy streams.

4. CASE-STUDY

The optimization approach described in Section 3 is applied to a residential district located in Northern Italy. In this district, the cooling demand occurs only in summer, while the heating demand is present for the whole year: between April and September the heat is just used to produce domestic hot water; between October and March, it is used for both space heating and domestic hot water production.

The customers are connected by means of district heating, cooling and electricity infrastructures to a local production plant (Figure 1) composed by the following units:

- combined heat and power plant (CHP), capacity 4 MW_{gas};
- heat-only boiler (HOB), 4 MW_{gas};
- photovoltaic plant (PV);
- electric heat pump (EHP), 0.5 MW_{el} in heating mode, 0.2 MW_{el} in cooling mode;
- absorption refrigeration unit (AR), 0.6 MW_t.

The annual operation of the multi-energy system is simulated using the energy load evolutions available for four different typical days, one for each season:

a) a winter day (electricity, space heating and domestic hot water);
b) an autumn day (electricity, space heating and domestic hot water);
c) a spring day (electricity and domestic hot water);
d) a summer day (electricity, cooling and domestic hot water).

The selection of four representative days allows reducing the complexity and focusing on the development of the methodology. Using this approximation, the total number of variables is reduced from 10 585 to 116 for the upper-level optimization from 280 321 to 3 073 for the lower-level (-98.9%). Nevertheless, the developed methodology can be applied also to different case-studies involving more simulation days; another option, as previously said, is to use the four typical days to find the values of demand-side management and storage variables and then to perform a further optimization for the production in order to find more accurate values of the energy streams.

In this analysis, the four representative days are selected such that their average air temperature (which is evaluated by means of the database PVGIS [43] for the selected location) is similar to the yearly average temperature over a period of 10 years. The relative error between the two is about 3%, which represents a reasonable trade-off since the proposed approach allows to significantly cut the optimization time. As regards the building demands, the heating load for the winter and autumn days were obtained from experimental measures, while the remaining heating loads and electricity loads were estimated using the software HOMER® and scaled for the system considered. The cooling load is obtained from the difference between the electricity load of the summer day and the average electricity load of the other seasons, since in the original database the cooling load is powered by electricity within the building and not supplied by means of a cooling network.

Because of the significant and sharp thermal peaks that usually affect district heating demands in heating networks during the space-heating season (especially in warmer areas such as the Mediterranean, where the heating devices in the buildings are remarkably attenuated or shut-down during the night), the heating demand is subjected to the application of demand side management as a further technique to shave the peak and to increase the efficiency of the global system (besides the possible installation of storage and the smart integration of the different energy systems). More specifically, the possibility of applying small anticipations to the heating load of the customers of the district heating network (whose main features are reported in Table 2) is discussed in this paper. This is done by performing only sufficiently low modifications such that these not affect the costumers thermal comfort: for this reason, anticipations up to 30 minutes are allowed.

In Figure 4, the heating, cooling and electricity loads for the selected days are presented; the evolution of the heating load reported in the figure is the non-optimized one (without demand side management). It is possible to observe that the electricity load does not considerably vary in the four seasons considered; the electric profile is quite similar and has two peaks during the day. This is due to the fact that cooling in summer is supplied by district cooling. The cooling load occurs only in summer (Day 3). As concerns the heating load, the profiles are significantly different in the various seasons. During winter (Day 1), the heating request for space-heating is quite high. During the autumn season (Day 2), because of the higher external temperatures, the heating demand is lower. Both the heating profiles of Day 1 and Day 2 present a peak request during the morning, that is due to the attenuation or shutdown of the space-heating systems in the buildings during the night. In summer and spring (respectively Day 3 and 4) the heating load just includes the thermal energy required for domestic hot water production. Overall, for each of the days considered there is a different combination of heating, cooling and electricity demand.

Table 2. Main features of the district heating network considered in this work

Specifications of the District Heating Network

Topology	*tree-shaped*
Number of Buildings connected	*58*
Total length of pipelines	*4.5 km*
Minimum pipeline diameter	*2.5 cm*
Maximum pipeline diameter	*25 cm*

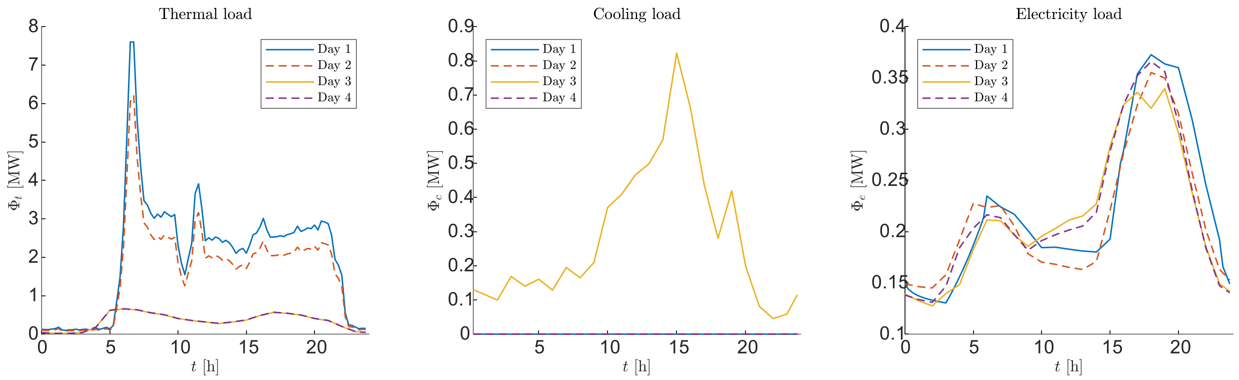

Figure 4. Heating load (without demand response actions), cooling load and electricity load of the district energy system at plant level during four different days (Day 1 = winter, Day 2 = autumn, Day 3 = summer, Day 4 = spring).

5. RESULTS AND DISCUSSION

The economic optimization was applied to the system described in Section 2. The most relevant results are reported and discussed in this section.

5.1 Preliminary analysis I: production optimization without demand-side management and storage

As first analysis, the optimization of the energy fluxes to be managed by each production unit was carried out without considering the storage unit and without the possibility to perform demand-side management. This step was included to create a point of reference in order to better evaluate the advantages provided by the integration of storage and DSM. Due to the absence of demand-response actions, it was possible to use just the lower-level optimization.

This optimization allowed to obtain a yearly cost of 272.6k €.

In this paragraph, just the operations obtained for Day 1 (winter) and Day 3 (summer) are illustrated (respectively in Figure 5 and Figure 6) for example purposes. During the winter day, the heating demand is mainly supplied by the CHP and by the electric heat pump. However, during the peak hours, their capacity is not sufficient to cover the high heat request and the heat-only boiler needs to be switched on. The combined heat and power plant also produces electricity, along with the photovoltaic system (when solar radiation is available). The electricity produced is used to satisfy the electricity demand of the buildings and to be converted into heat by means of the electric heat pump. When the specific cost is high, part of electricity is also sold to the external grid.

Concerning the summer day, the heat consumption is due to: a) the heating load, which is much lower than the previous case since it is only needed to produce domestic hot water, and b) the absorption refrigeration unit. The heat is supplied by means of the combined heat and power plant and through the heat pump which reconverts electricity into heat when the electric load is low. The cooling load is mainly supplied with the electric heat pump. At night and during the cooling peak, the absorption refrigeration unit is also used since heat is available from the CHP production. Finally, electricity is produced with the CHP unit and with the photovoltaic system that during the summer period covers a significant fraction of the electricity demand. The electricity is mainly used to supply the load and to operate the electric heat pump for heat and cooling production. In summer, the sale to the external market is limited to few instants.

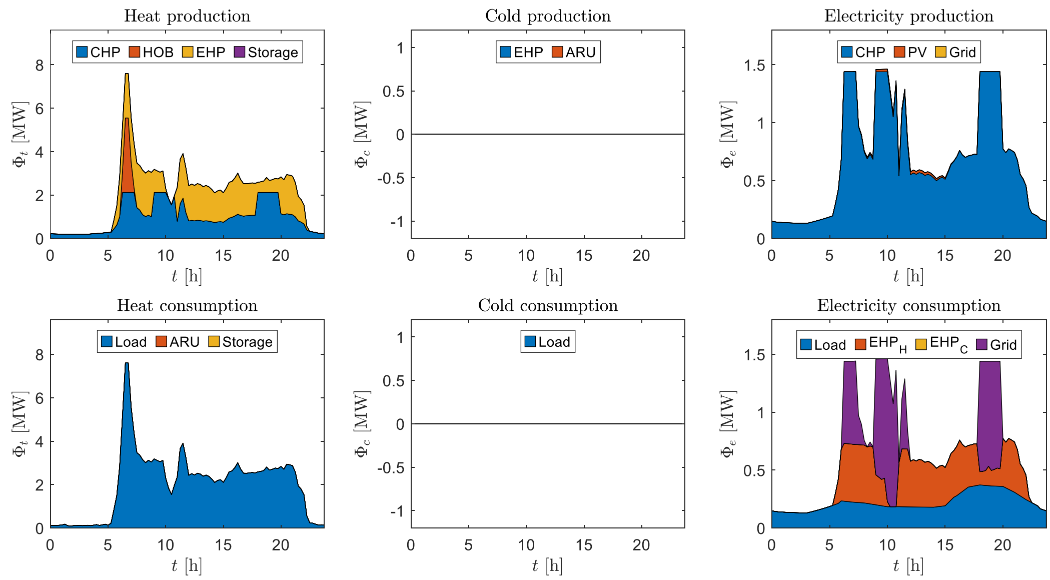

Figure 5. Day 1 (winter): Optimized operation of the production plant resulting from the economic optimization without demand-side management and without storages.

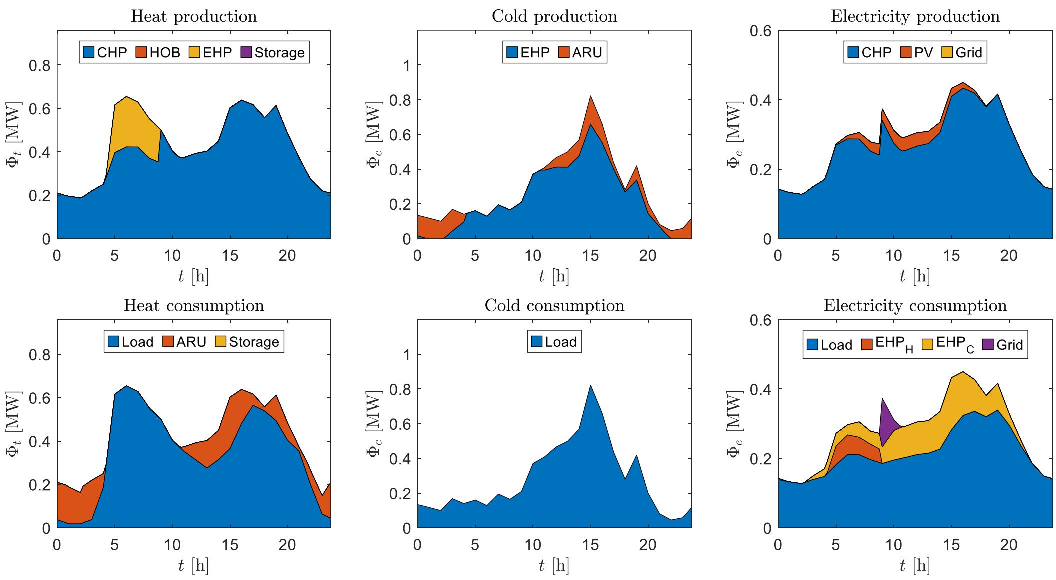

Figure 6. Day 3 (summer): Optimized operation of the production plant resulting from the economic optimization without demand-side management and without storages.

5.2 Preliminary analysis II: production optimization without demand-side management. The effect of the storage

In a second step, the possible installation of a thermal storage is included. The optimization is performed without considering the effects of demand-side management, making it possible to solve the whole problem just by means of the lower-level optimizer.
The configurations obtained for winter (Day 1) and summer (Day 3) are reported in Figure 7 and Figure 8. The main differences with respect to the case without storage are evident observing the heat production and consumption. During the winter, the presence of the thermal storage allows to reduce the heat supplied by the boiler during the peak. The adoption of the thermal storage allows to distribute more uniformly the thermal production, filling the valley and shaving the peaks. The optimal capacity side of the thermal storage is about 790 kWh, therefore a medium size thermal storage.
In this case, the yearly cost turned out to be 268.2k €. This means that a reduction of 1.6% in the yearly cost can be achieved thanks to the introduction of the optimally sized thermal storage.

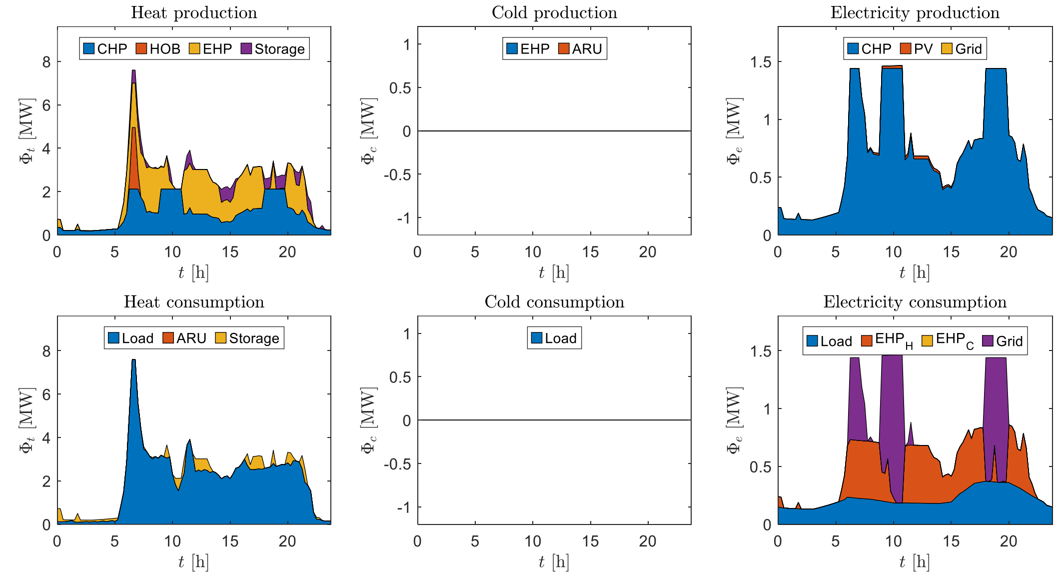

Figure 7. Day 1 (winter): Optimized operation of the production plant resulting from the economic optimization with the possibility to install storages, without demand-side management.

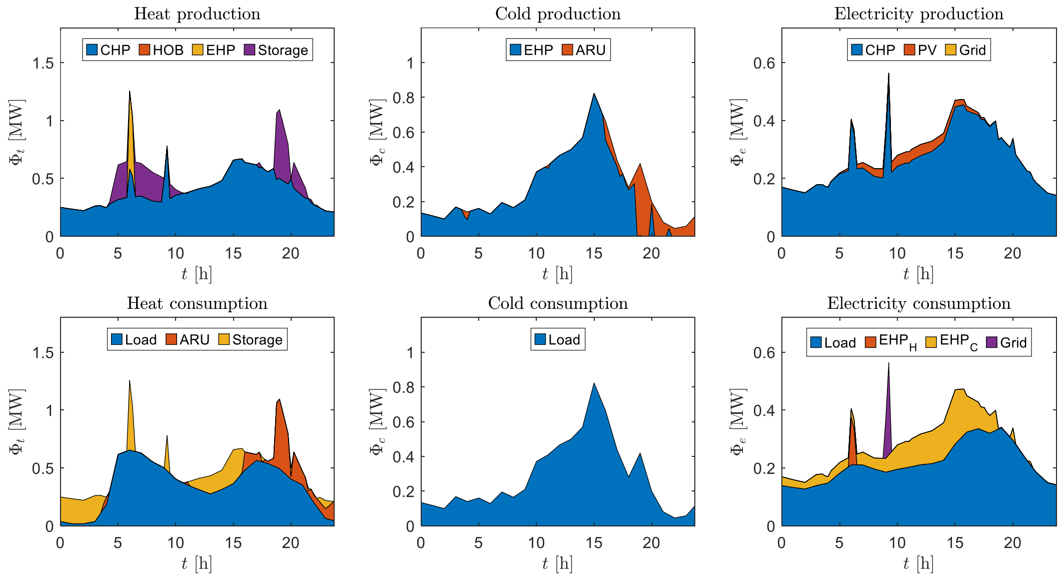

Figure 8. Day 3 (summer): Optimized operation of the production plant resulting from the economic optimization with the possibility to install storages, without demand-side management.

5.3 Demand side-management and production optimization with storages

Finally, the demand side management has been considered along with the possible adoption of the storages. This is done through the use of the whole optimization approach developed in this paper and described in Section 3.

The value of the objective function at each generation of the genetic algorithm is reported in Figure 9. The algorithm converged to the final solution in 256 iterations. The production layout corresponding to this solution is reported for all the different seasons in Figure 10, Figure 11, Figure 12 and Figure 13 (respectively Day 1 = winter, Day 2 = autumn, Day 3 = summer, Day 4 = spring). The most significant aspect of the new configuration can be noticed observing the heating production for Day 1 (winter) and Day 2 (autumn), since demand side management is applied to shift the thermal load used for space heating. Because of the use of demand response, the heating peak of these two days is noticeably smoothed. As a consequence, the use of the heat-only boiler is no more required. This allows a significant cost saving.

Concerning the value of the objective function, the adoption of demand-response actions (in this case, anticipations up to 30 minutes are possible for each building) allows a yearly cost reduction up to 262.3k €. Hence, a reduction in the yearly cost of 3.8% with respect to the case without demand-side management and without storage is possible. The percentage reduction with respect to the optimization with the storage but without demand-side management is around -2.2%: this means that a budget of 5.9 k€/year can be saved by implementing demand side management based on load shifting. This is even more meaningful if one considers that demand-side management is applied only in winter and autumn. Moreover, the size of the thermal storage can be reduced to about 700 kWh through the use of demand-side management.

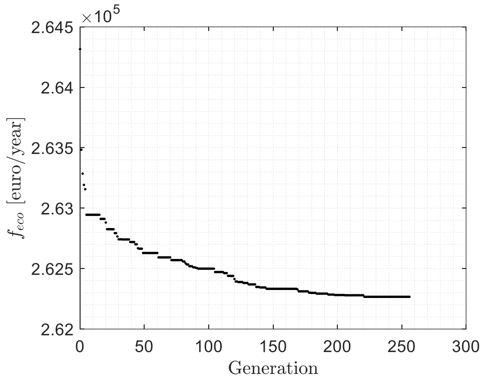

Figure 9. Optimization convergence analysis: value of the objective function at each generation of the genetic algorithm.

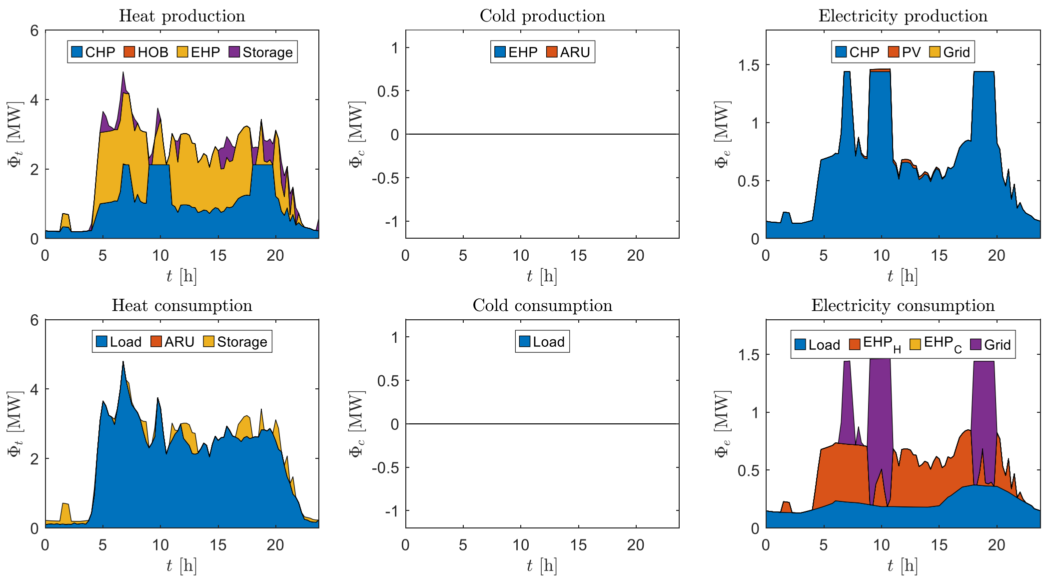

Figure 10. Day 1 (winter): Optimized operation of the production plant resulting from the combined economic optimization of demand and production.

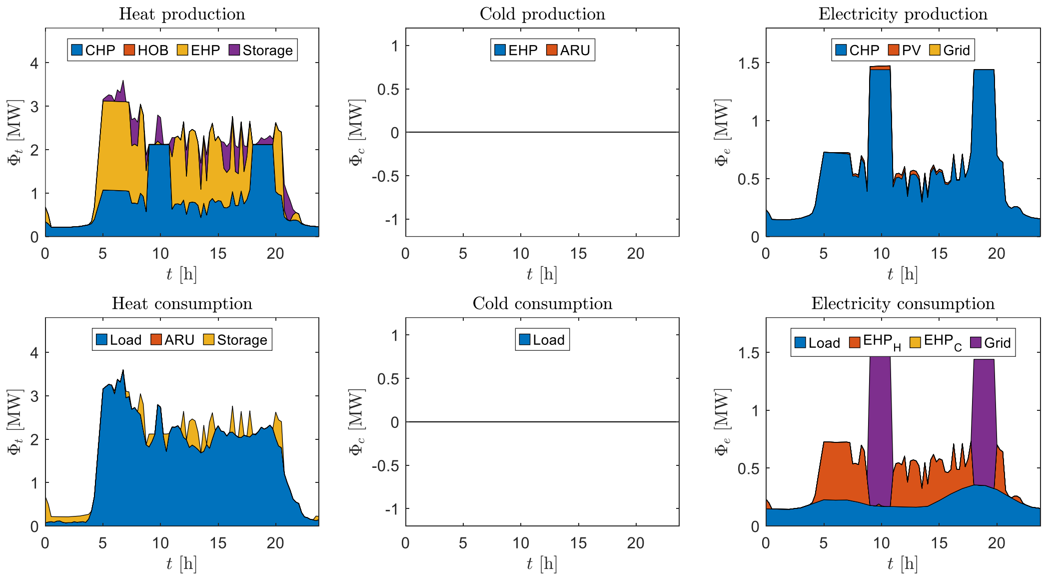

Figure 11. Day 2 (autumn): Optimized operation of the production plant resulting from the combined economic optimization of demand and production.

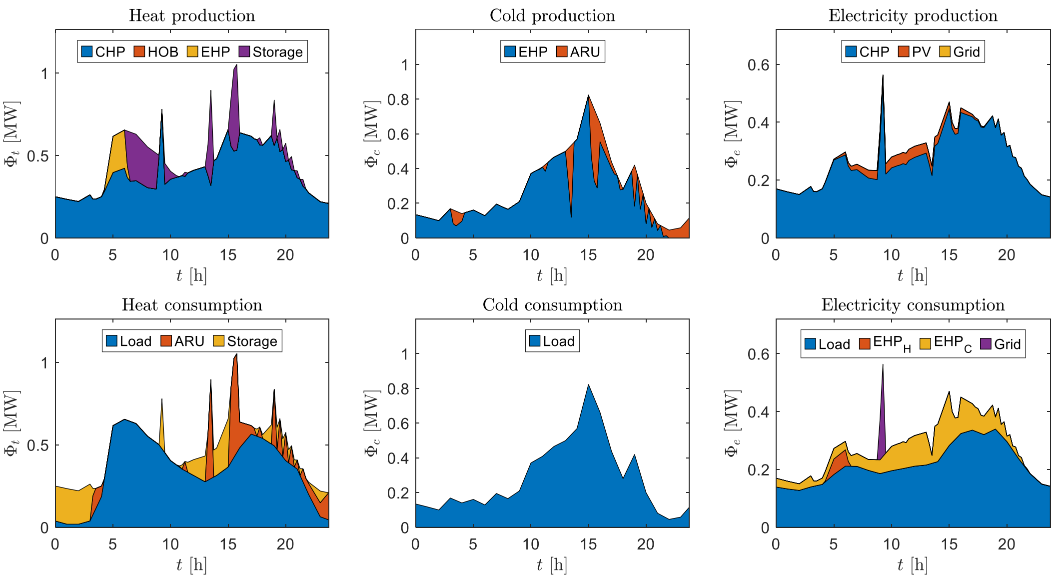

Figure 12. Day 3 (summer): Optimized operation of the production plant resulting from the combined economic optimization of demand and production.

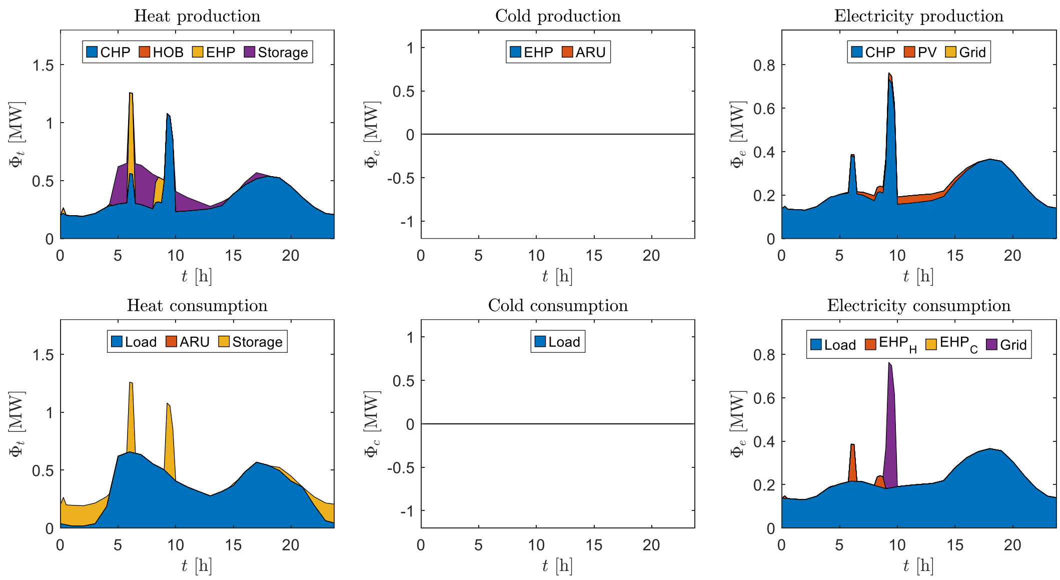

Figure 13. Day 4 (spring): Optimized operation of the production plant resulting from the combined economic optimization of demand and production.

A final test is carried out by enlarging the users' flexibility: load shifting up to 1 hour are allowed (instead of 30 minutes). The modifications of the heating load at the production plant for Day 1 and Day 2 are illustrated in Figure 14. It is possible to notice that significant reductions are possible by setting the maximum allowed anticipation to 30 minutes (in this case the heating peak is reduced of the 36.9% for Day 1 and 42.0% for Day 2). Extending the anticipations to up to 1 hour, the maximum heating load decreases of about 50.5% for Day 1 and 49.5% for the Day 2.
In this case, the combined adoption of storage and demand side management allows achieving a total cost of 261.4 k€ per year. Moreover, the capacity of the storage can be decreased to 685 kWh. In this case, the cost is further reduced of 0.4% with respect to the 30-minutes anticipations case.

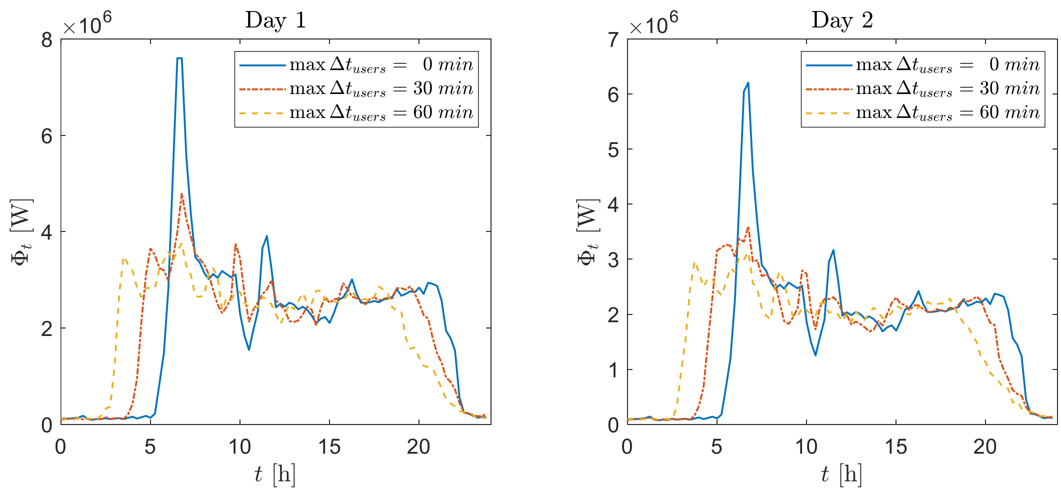

Figure 14. Evolution of the heat load at production plant during the day: comparison of the base-case (without demand side management) with the two optimized configurations obtained with maximum anticipation respectively set to 30 minutes and 1 hour.

Finally, a summary of the results of the different optimizations carried out in this paper is reported in Table 3, where the effects of the adoption of the thermal storage and demand-response are compared to the base case (operations optimized without storage and demand side management). Results show that the installation of an optimally-sized thermal storage (in this case the capacity is of 790 kWh) can contribute to a reduction in the annual operating costs. However, the maximum benefit is obtained with the combined adoption of storage and demand side management: the reduction in the annual operating costs can be increased from 1.6% to 3.8% by introducing flexibilities in the heating load up to 30 minutes in advance; moreover, the optimal capacity of the storage decreases from 790 kWh to 700 kWh. By contrast, the increase of the load shifting range from 30 min to 60 min does not provide further important cost reductions. Therefore, a very good trade-off among cost reduction and thermal comfort can be achieved by applying modifications to the heating demand of the buildings amounting to maximum 30 minutes (in advance) and using a thermal storage with 700 kWh capacity that will cost 746 €/year.

Table 3. Yearly costs resulting from the different economic optimizations.

Case	Optimized thermal storage size	Maximum anticipation allowed	Total cost	Percentage cost reduction (wrt to Case 1)
1	$0\ kWh$	$0\ min$	$272\ 564$ €$/year$	
2	$790\ kWh$	$0\ min$	$268\ 198$ €$/year$	$-1.6\ \%$
3	$700\ kWh$	$30\ min$	$262\ 310$ €$/year$	$-3.8\ \%$
4	$685\ kWh$	$60\ min$	$261\ 376$ €$/year$	$-4.1\ \%$

6. CONCLUSIONS

In this paper, a novel approach for the operational optimization of a complex multi-energy system is presented. The methodology is able to include in the optimization a) the installation of a thermal storage, b) the implementation of demand-response actions, and c) the possible combination of the two strategies.

The best set of heating-load shifting and the optimal capacity of the thermal storage are evaluated by means of a comprehensive optimization tool that takes into account simultaneously a) the effect of demand-response, b) a thermo-fluid dynamic model of the network (to properly relate the heating load at the building to the load of the production plant), and c) the management of the production plant. The operation of the system during a whole year is reproduced by considering four representative days of the year with different combinations of heating, cooling and electricity demands. These days are chosen such that they represent a good approximation of the yearly energy loads, in order to keep the number of optimization variables sufficiently small to avoid the need of too high computational resources and also to simplify the presentation of the procedure.

The optimization is organized in two nested levels: the upper-level uses the genetic algorithm to find the best set of heating-load shifting of the buildings (demand-side management); the lower-level optimization (which is run at each iteration of the genetic algorithm) uses a linear programming algorithm to find the best operation of the production plant, i.e. the optimal capacity of the storage and the production fluxes.

Results show that the installation of a thermal storage brings to a reduction in the yearly cost of 1.6%. If demand-side management is introduced in addition to production optimization, further advantages can be achieved: the combined use of thermal storage and demand-side management (with load shifting up to 30 minutes) allows a yearly cost reduction of about 3.8%, that is 2.2% more with respect to the case in which just the thermal storage is used; moreover, in this case it is possible to reduce the size of the storage, and consequently the installation costs. Despite the decrease in the costs (and in the thermal storage volume) can be enhanced by enlarging the flexibility of the users, more modest reductions are obtained if the anticipation range is further extended: with maximum anticipations allowed up to 1 hour, the cost reduction is of 4.1%.

In conclusion, the case-study presented in this work shows that the installation of storages and the implementation of demand-side management are not alternative options, but they can be simultaneously used and smartly integrated in multi-energy systems, even if they already have an inherent flexibility given by the possibility of converting energy from one form to another. Thus, the methodology developed in this paper is recommended for applications to multi-energy systems in order to determine the best operation of the system without neglecting any of these relevant sources of flexibility; for more accurate results (e.g. if the simulation of the whole year is required), this methodology can be used as a preliminary step to determine the operation of the storage and DSM, and it can be combined with other optimization approaches that are tailored to production optimization only.

NOMENCLATURE

$c_{e,in}$	Specific cost of the electricity purchased [€/kWh]
$c_{e,out}$	Specific cost of the electricity sold [€/kWh]
c_g	Specific cost of the natural gas [€/kWh]

Abbreviations and subscripts

ARU	Absorption refrigeration unit
c	Cooling

$c_{t,st}$	Specific investment cost of the thermal storage [€/kWh]
$C_{t,st}$	Thermal storage capacity [kWh]
COP	Coefficient of performance
d	Demand-side variables vector
$d_{i,j}$	Demand-side variable of the i-th building during the j-th heating day [-]
f_{eco}	Economic objective function [€/year]
$N_{buildings}$	Number of buildings
N_{Days}	Number of days
$N_{SH\ Days}$	Number of days with space heating
$N_{Storage}$	Number of storages
N_{TS}	Number of time steps
$N_{\Phi-var}$	Number of variables associated with energy fluxes
p	Production variables vector
t	Time [s]
$\Delta t_{i,j}$	Anticipation time of the i-th building during the j-th heating day [min]
x	Decision vector
X	Feasible region of the decision vector

Greek letters

η	Efficiency
$\Delta\tau$	Time step
Φ_c	Cooling load at the production plant [W]
Φ_e	Electricity load at the production plant [W]
Φ_{e,EHP_c}	Electricity used to supply the EHP for cooling production [W]
Φ_{e,EHP_t}	Electricity used to supply the EHP for heating production [W]
$\Phi_{e,in}$	Electricity purchased from the grid [W]
$\Phi_{e,in}$	Electricity sold to the grid [W]
$\Phi_{e.PV}$	Electricity provided by the PV [W]
$\Phi_{g,CHP}$	Natural gas used to supply the CHP [W]
$\Phi_{g,HOB}$	Natural gas used to supply the HOB [W]
Φ_t	Heating load at the production plant [W]
$\Phi_{t,ARU}$	Heating used to supply the ARU [W]
$\Phi_{t,st}$	Heating absorbed or released by the storage [W]

CHP	Combined heat and power
e	Electricity
EHP	Electric heat pump
g	Natural gas
HOB	Heat-only boiler
in	Inlet
out	Outlet
PV	Photovoltaic system
st	Storage
t	Thermal/Heating
tr	Transmission

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