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Optimal management with demand response program for a multi-generation energy system

Hilal Bahlawan [a], Giulia Anna Maria Castorino [b,*], Enzo Losi [a], Lucrezia Manservigi [a], Pier Ruggero Spina [a], Mauro Venturini [a]

[a] Dipartimento di Ingegneria, Università degli Studi di Ferrara, via Saragat 1, Ferrara 44122, Italy
[b] Dipartimento di Studi Umanistici, Università degli Studi Di Ferrara, via Paradiso 12, 44121 Ferrara, Italy

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ABSTRACT

The optimal management of a multi-generation energy system is one of the challenges that an ever-growing energy demand requires to deal with. To tackle this urgent issue, this paper presents a methodology to identify the optimal dispatching strategy for a multi-generation energy system. The so-called *time-of-use rate* is one of the main time-based demand response programs which allows shifting the critical loads from a time interval to another (e.g., shifting electricity use to lower-priced hours of a day when demand is lower). Thus, the time-of-use rate is adopted in this paper in order to add flexibility to the management of the multi-generation energy system and thus optimize the interaction between energy production and user demand.

In this paper, the goal is the minimization of primary energy consumption or operating costs. Whatever the considered objective function, the goal can be achieved by simultaneously acting on two levels, i.e., optimization of the demand response program and identification of the most favorable management strategy of the multi-generation energy system. A mixed-integer linear programming algorithm is employed to identify the optimal strategy. The case study considers an entire year of operation with a time step of one hour, by means of a real-world load profile. The proposed methodology allows both saving primary energy (more than 1%) and reducing operating costs (more than 8%). The proposed methodology demonstrates that the implementation of a demand response program within the optimal strategy for energy dispatch allows both saving primary energy and reducing operating costs with respect to the baseline scenario (i.e., no load shifting). The reduction of both primary energy consumption and operational costs is higher in the scenario with higher load shifting (in this paper, 30% of the daily electrical energy peak).

1. Introduction

1.1. Problem statement

Generating clean energy is one of the key targets of the goal of reducing CO2 emissions. Increasing energy production from renewable sources will lead nations to reduce their dependence from fossil fuels and primary energy consumption, as well as environmental impact. Despite the great potential of renewable energy production, its main issue is related to managing daily availability of renewable resources, and therefore their improved integration within a multi-generation energy system (MES) in the context of current energy transition scenario. For this reason, the optimal management of a MES is one of the challenges that an ever-growing energy demand requires to deal with [1]. MES represents an integrated energy system in which electric power, heating, cooling, fuels and transport interact with each other in order to achieve better technical, economic and environmental performance [2].

The increase of electrical, thermal and cooling energy demand clashes with the goal of saving primary energy and reducing greenhouse gas emissions, as targeted by many Countries (e.g., see the European Green Deal). However, in the framework of energy transition, the integration of renewable sources with fossil-fed energy systems is recommended to chase the rapid decarbonization of the energy sector [3]. In fact, despite the rush to more sustainable green technologies, fossil fuels still produce the majority of present energy consumption [4].

A multi-generation energy system represents a viable solution in order to reduce primary energy consumption and greenhouse gas emissions derived from urban energy demand [5,6]. Moreover, MESs have the advantage of meeting several energy demands at the same time,

* Corresponding author.
E-mail address: giuliaannamaria.castorino@unife.it (G.A.M. Castorino).

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Nomenclature

AC	absorption chiller
AE	alkaline electrolyzer
ARR	anaerobic reactor reforming
ASHP	air source heat pump
BCHP	biomass CHP
BES	battery energy storage
CCHP	combined cooling heat and power
CES	cooling energy storage
CHP	combined heat and power
CPP	critical peak pricing
DG	diesel generator
DR	demand response
DRP	demand response program
DSM	demand side management
EC	electric chiller
EV	electric vehicle
FC	fuel cell
GSHP	ground source heat pump
H2S	hydrogen storage
HEP	hybrid energy plant
HP	heat pump
HPDR	hybrid pricing DR
HPT	hydropower turbine
IBDR	incentive base DR
MES	multi-generation energy system
MG	Micro-grid
MGT	micro gas turbine
MILP	mixed-integer linear programming
MINLP	mixed integer non-linear programming
NG	natural gas
NSGA	non-dominated sorting genetic algorithm
OC	operating cost
O&M	operating and maintenance
PEC	primary energy consumption
PV	photovoltaic system
RB	rubbish burning power plant
RHO	Receding Horizon Optimization
RTP	realtime pricing
SoC	state of charge
STES	seasonal TES
TES	thermal energy storage
WT	wind turbine

Symbols

A	area
c	coefficient
COP	coefficient of performance
E	energy
EER	energy efficiency ratio
f	conversion factor
k	time variable
$k_{1,2,3,4}$	coefficient of Eq. (26) and (28)
N	last time-step
P	power
PEC	primary energy consumption
t	time
T	temperature
η	efficiency
λ	penalty temperature coefficient

Subscripts and superscripts

AC	absorption chiller
ASHP	air source heat pump
BES	battery energy storage
BoS	balance of system
c	cell
ch	charging
CHP	combined heat and power plant
cool	cooling
disc	discharging
diss	dissipation
DRP	demand response program
el	electrical
EV	electric vehicle
fuel	fuel
grid	national grid
HP	heat pump
in	entering
k	time variable
load	demand load
M	PV module
nom	nominal
op	optimal
out	outgoing
peak	load peak
PV	photovoltaic system
ref	referred to STP (standard condition)
sent	sent to the grid
taken	taken from the grid
TES	thermal energy storage
t	time
th	thermal
Tot	total

such as electric power, heating, cooling and domestic hot water [7]. The optimization of the energy flows within a MES allows to improve the interaction between the energy system and users [8]. Thus, an optimal management strategy must be identified to minimize primary energy consumption [9], environmental impact [10], as well as costs for the energy consumers.

1.2. Literature review

The literature survey reported in this Section first reviews state-of-the-art studies about the optimal management strategy of multi-energy systems by means of different approaches. Subsequently, the literature review focuses on DRP, which, so far, has been rarely investigated. Such a discussion represents the starting point of the analyses carried out in this paper, as highlighted in Section 1.3.

Roldán-Blay *et al.* [11] proposed an iterative algorithm for optimally managing energy systems with the aim of cost minimization. In that study, eight different scenarios at different conditions of electricity tariffs, availability of renewable source and grid supply were taken into account.

In order to meet heating and cooling demands, Shirazi *et al.* [12] presented the integration of the solar source within an energy system. In that work, the design optimization of solar heating and cooling system (SHC) configuration was addressed by coupling a transient system simulation program (TRNSYS) with a genetic algorithm (GA) developed in MATLAB®.

In order to further investigate the integration of renewables for energy dispatching, Izadi *et al.* [13] employed a TRNSYS for simulating a hybrid renewable energy system (HRES) composed of PV panels, vertical axis wind turbines, and hydrogen storage. In addition, a GA was used to solve the optimization problem and minimize costs, CO2 emissions and losses related to power supply.

With the aim of proving the potential of an integrated energy system, Mayer *et al.* [14] employed an optimization method based on GA including life cycle costs and environmental impacts within the design of a hybrid renewable energy plant.

As shown above, a genetic algorithm is commonly used in the literature to optimize integrated energy systems (e.g., hybrid energy plants optimal sizing [15] or optimal design of a 100 % renewable energy plant [16]). There are indeed many advantages in using metaheuristic algorithms for solving operation management problems since they have proven to be robust and efficient. Despite the several advantages, there are some improvements that should be implemented, as for instance the ones related to premature convergence or setup of start options [17].

For this reason, Bahlawan *et al.* [18] proposed a new approach for both sizing and operation optimization of a hybrid energy plant (HEP) composed of solar thermal collector (STH), photovoltaic panel (PV), combined heat and power (CHP) system, ground source heat pump (GSHP), air source heat pump (ASHP), auxiliary boiler (AB) and hot water storage. Both optimization problems were dealt with by using a dynamic programming (DP) tool, thus demonstrating its superiority with respect to genetic algorithm (GA).

Moghaddas-Tafreshi *et al.* [19] presented an optimization model based on particle swarm optimization (PSO) algorithm to schedule the components of a multiple energy carrier micro-grid by minimizing the operating costs with day-ahead forecasts. A micro-grid, comprising a micro-turbine, a fuel cell, a rubbish-burning power plant, a wind turbine generator system, a boiler, an anaerobic reactor-reformer system, an inverter, a rectifier, and some energy storage units, was simulated by means of the Monte Carlo method.

Among the several optimization techniques, the Mixed Integer Linear Programming (MILP) has been widely employed in the iterative search of minima. This technique is indeed the most efficient method since it guarantees to find the global optimum, though it has the drawback of a longer computational time [20]. Murray *et al.* [21] proposed a model based on MILP algorithm with the aim of assessing the potential of long-term and short-term storage systems in three different scenarios that consider climate change from 2015 to 2030. Nicolosi *et al.* [22] used the MILP algorithm in order to minimize the costs, as well as NOx and CO2 emissions of two different energy systems. The first energy system was composed of four Internal Combustion Generators (ICGs), while the second energy system was composed of three ICGs and a Micro Gas Turbine (MGT). The optimization algorithm was developed by using the PyCharm Integrated Development Environment available in the Python programming language.

With the aim of decreasing primary energy consumption and reducing environmental impact, Manservigi *et al.* [23] simulated the optimal operation strategy for a micro-CHP system, by employing a dynamic programming algorithm (DP). The Investigated micro-CHP system included thermal and electrical energy storage systems with different sizes. DP is widely used as an effective approach to identify energy system optimal operating strategy thanks to its capability to solve non-linear optimization problems. For the purpose of solving the management problem of a complex hybrid energy plant by means of a DP-based approach, Bahlawan *et al.* [24] developed a methodology capable of handling customized energy, economic and hybrid objective functions. Recently, hybrid algorithms have become more attractive for improving the optimization strategy. Their advantage of combining different optimization methods can lead to better solutions and simulation improvements [20,25]. The advantages of using hybrid intelligent algorithms mainly rely on efficient performance, the capacity to solve more complex problems and the higher speed of convergence. On the other side, the main disadvantages are related to the fact that they require more parameters to set and are much harder to code [25]. As an example of application of hybrid algorithms, Bahlawan *et al.* [5] addressed the simultaneous optimization of MES design and operation by employing surrogate modeling optimization (SMO) for MES design and DP for optimizing its operation. Compared to the PSO-DP algorithm, the SMO-DP hybrid algorithm proved to be computationally faster.

In order to add flexibility to aggregate energy system management, a *Demand Response Program* (DRP) has been also investigated in the literature. DRPs enable the demand profile to avoid excessive use of electricity especially during peak hours, hence resulting in an economic advantage for the whole distribution system. DRPs are potentially powerful programs which lead electricity companies and costumers toward the economic and environmental benefits [26]. In this manner, the electricity grid is more stressed when there is high demand for electricity. High demand for electricity requires a higher supply of electricity, which both stresses the grid and results in higher prices for all energy users [27]. *Time of use* (TOU) rate is one of the main time-based DRPs which allow shifting the critical loads from a time interval to another (e.g., by shifting electricity use to lower-priced hours of a day). Shifting some electricity usage to times when both demand and costs are lower allows to lower the bill and support a healthier environment.

X. Wang *et al.* [28] simulated the demand response (DR) of a single-family residential home for four consecutive weekdays in summer, by exploiting the load shifting within one day. Day-ahead and real-time weather forecasting coupled with DRP were applied by using a receding horizon optimization strategy.

Another example of load shifting is provided by Rakipour and Barati [29], who investigated the optimization of energy system operation by employing DRP by means of MILP algorithm. DRP was applied to a summer day, in a tropical region with high cooling demand. The load shifting was able to reduce both the electric power consumption of the energy system and its costs. With the aim of coupling both the design problem and energy demand shifting approach, Y. Zheng *et al.* [30] optimized the design of a biomass-integrated microgrid by employing DRP. In that work, the planning horizon was equal to four hours. Hourly load profiles of both a winter and a summer day were simulated by employing Monte Carlo method using sliding time windows of four hours. The time window was increased by one hour and the process was repeated for a one-day timeframe.

The main feature that should characterize the optimal management strategy of a MES is the capability of meeting the different energy demands. Thus, this topic has been also investigated in the literature in order to provide innovative solutions. Najafi-Ghalelou *et al.* [31] presented a technique targeted at the robust scheduling of a multi-carrier hub energy system for one day. With the aim of minimizing both global costs and CO2 emissions, a model based on time-of-use and real-time-pricing rates of DRPs was developed by means of a robust mixed integer linear programming and solved in the General Algebraic Modeling System platform. In order to cover a longer timeframe, Gazijahani and Saleh [32] considered four different daily load profiles that were used to characterize the typical demand of four seasons. In that study, DRP was coupled with an optimal design of a smart microgrid. Four different daily load profiles were used for each different season to mimic a yearly timeframe.

1.3. Paper's novel contribution

From the literature survey documented and discussed above, it is evident that optimization techniques are necessary to identify the best size combination, optimal scheduling and finely-tuned allocation of power generation of complex energy systems. In fact, Mohseni *et al.* [33] conducted an extensive review about stochastic energy optimization with DR by analyzing 252 publications. The review proved that 87 % of the papers addressed the short-term energy scheduling optimization problem, while 11 % of the analyzed papers presented a multi-objective optimization for energy system scheduling under uncertainty. Only 4 % of examined studies dealt with the optimal trade-offs between minimizing costs and minimizing CO2 emissions. Thus, the literature survey presented in [33] clearly shows that, at present, there is a gap about the investigation of DRPs characterized by long-term optimization strategy. Moreover, several studies that deal with DRP take into account load profiles representative of a short period of time (e.g., a typical day of a season [28,29,34,35]) and replicate the results with the aim of simulating an entire year [32,36,37]. Some authors addressed the problem of optimal allocation of renewable resources by considering DR combined with one energy technology or with the integration of only two different energy conversion systems (e.g., wind turbine [38]; storage and microgrid systems [39]; plug-in-electric vehicles [40]).

The extensive literature survey presented above is summarized in Table A1 in Appendix 1 and is compared to the approach and analyses adopted in this paper, in order to highlight the novel contribution of this study. With the aim of filling the identified research gaps, this paper presents a methodology for the optimized management of a multi-generation energy system by employing the MILP algorithm and exploiting the DRP approach.

Compared to artificial intelligent and hybrid intelligent algorithms, the MILP algorithm is simple to code, easy to implement and has higher precision in the search of global minimum; moreover, it is widely employed for managing the optimal allocation of energy generation or minimizing total costs of system planning (e.g., investment, operation and maintenance costs) [20,25].

In this paper the multi-energy system (MES) consists of photovoltaic system (PV), combined heat and power (CHP) system, air source heat pump (ASHP), absorption chiller (AC), battery energy storage (BES) and thermal energy storage (TES). The sizes of MES components are fixed. Thus, the goal of the optimization process is the identification of the optimal load allocation in order to meet user demand by employing two different objective functions (one at a time). The first objective function is defined with the aim of minimizing primary energy consumption, while the second objective function allows the minimization of the operating costs, by also including the cost of CO2 emissions. It is worth highlighting that an entire year of operation is investigated in this paper.

Thus, the main novel contributions of this paper can be summarized as follows:

- Unlike the studies available in the literature, the MES considered in this paper comprises seven different energy conversion systems, storages and distribution systems including power grid. The integration of both renewable and fossil-fuel sources is considered in order to investigate a feasible and realistic scenario in today's context of the energy transition;
- MES operation is optimized for one year, hour by hour;
- Real-world load profiles over one year are considered, while similar studies available in the literature usually consider daily load profiles [32,34,35,36,37];
- Both load shifting based on demand response and MES management strategy are simultaneously optimized in order to minimize primary energy consumption or operating costs.
- The optimal management strategy is identified, by considering two scenarios which minimize MES primary energy consumption or MES operating costs.

The paper is organized as follows: Section 2 presents the methodology, illustrates the energy plant, the modelling approach, and problem formulation. Section 3 outlines the case of study. Section 4 discusses the results while the last section provides the conclusions.

2. Methodology

In this work, the optimal dispatch strategy for the multi-generation energy system (MES) is identified by considering a timeframe of one year and a time step of one hour. The energy technologies in the MES are modelled by means of power and efficiency curves.

2.1. Grid-connected MES: components and modelling approach

The scheme of the MES considered in this paper is shown in Fig. 1. The MES is composed of a photovoltaic system (PV), a combined heat and power (CHP) system, an air source heat pump (ASHP), an absorption chiller (AC), a battery energy storage (BES) and a thermal energy storage (TES). The heat pump is considered reversible, thus allowing the production of thermal energy in winter and cooling energy in summer. Moreover, it is assumed that electrical energy can be both delivered to and taken from the grid. Finally, it must be highlighted that a fraction of the available electrical energy can be employed to charge electric vehicles (EVs).

The electrical energy produced by the PV system is calculated by means of Eq. (1):

$$E_{PV,el,k} = G_k \cdot A_{PV} \cdot \eta_{PV,k} \cdot \Delta k \tag{1}$$

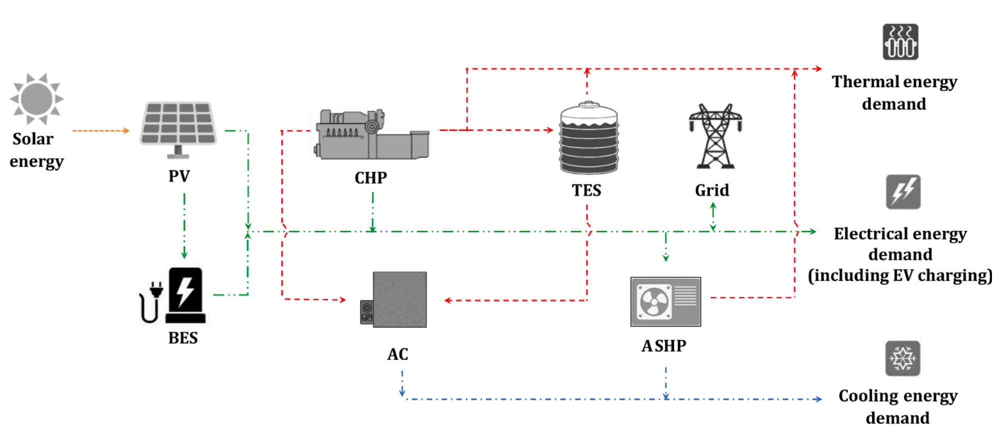

Fig. 1. Multi-generation energy system.

with G representing the solar irradiance expressed in [kW/m^2]. The overall efficiency of the PV system is calculated according to Eq. (2) [41–43]:

$$\eta_{PV,k} = \eta_{BoS} \cdot \eta_{M,ref} \cdot [1 - \lambda \cdot (T_{c,k} - T_{ref})] \tag{2}$$

where η_{BoS} represents the balance of system, $\eta_{M,ref}$ represents the efficiency of the PV module at standard conditions, λ a penalty temperature coefficient, $T_{c,k}$ the effective operating temperature of the cell and T_{ref} the operating temperature of the cell at standard conditions.

The CHP system is based on an internal combustion engine which is fed with natural gas. Equations (3) and (4) express the electrical and thermal energy produced by the CHP system at the k-th time-step, respectively:

$$E_{CHP,el,k} = P_{CHP,el}(T_k) \cdot \Delta k \tag{3}$$

$$E_{CHP,th,k} = P_{CHP,th,nom}(T_k, P_{CHP,el}) \cdot \Delta k \tag{4}$$

As can be noted, the energy produced by the CHP system is corrected according to ambient temperature (T_k) and power de-rating ($P_{CHP,el}$). The CHP system is able to modulate in the range from minimum ($P_{CHP,el,min}$) power to nominal power ($P_{CHP,el,nom}$).

For the ASHP unit, the thermal/cooling energy production and electrical energy consumption are reported in Eq. (5) and Eq. (6), respectively:

$$E_{ASHP,th/cool,k} = \begin{cases} P_{ASHP,th}(T_k) \cdot \Delta k \quad (winter) \\ P_{ASHP,cool}(T_k) \cdot \Delta k (summer) \end{cases} \tag{5}$$

$$\mathrm{E_{ASHP,el,k}} = \begin{cases} \dfrac{\mathrm{E_{ASHP,th}(T_k)}}{\mathrm{COP_{ASHP}(T_k)}} \quad (\text{winter}) \\ \dfrac{\mathrm{E_{ASHP,cool}(T_k)}}{\mathrm{EER_{ASHP}(T_k)}} \quad (\text{summer}) \end{cases} \tag{6}$$

As shown in Eq. (5) and Eq. (6), the produced energy and the efficiency are corrected as a function of the ambient temperature T_k [44].

The AC unit considered in this work is a single-effect lithium-bromide chiller [45]. The produced cooling energy and the thermal energy absorbed by the AC are calculated as shown in Eqs. (7) and (8):

$$E_{AC,cool,k} = P_{AC,cool} \cdot \Delta k \tag{7}$$

$$\mathrm{E_{AC,th,k}} = \frac{\mathrm{E_{AC,cool,k}}}{\mathrm{EER_{AC,K}}} \tag{8}$$

At the beginning of each time step, the thermal energy stored inside the TES is updated according to Eq. (9):

$$E_{TES,th,k} = (1 - d_{diss}) \cdot \left(E_{TES,th,k-1} + E_{TES,th,in,k-1} - E_{TES,th,out,k-1}\right) \tag{9}$$

where $E_{TES,th,in,k-1}$ is the energy recovered from the CHP system, $E_{TES,th,out,k-1}$ is the energy taken from the TES and d_{diss} a coefficient that takes into account the energy released to the environment.

In this work, lithium-ion BESs are employed to store a fraction of the surplus electricity produced by the PV (if required). The stored energy is then used on a short-term basis to meet the electrical energy demand of the user and to charge the EVs. The stored electrical energy inside a BES after one cycle of charging/discharging is expressed as follows:

$$E_{BES,el,k} = E_{BES,el,k-1} + \eta_{BES,ch} \cdot E_{BES,el,in,k-1} - \left(\frac{E_{BES,el,out,k-1}}{\eta_{BES,disc}}\right) \tag{10}$$

where $E_{BES,el,in,k-1}$ is the surplus energy from the PV which is stored in the BES, while $E_{BES,el,out,k-1}$ is the electricity taken to meet the electrical energy demand. Finally, $\eta_{BES,ch}$ and $\eta_{BES,disc}$ are the charging and discharging efficiencies, respectively.

2.2. Problem formulation

In this study, the optimal dispatch strategy is identified by means of MILP formulation and is solved in Matlab® environment by considering a timeframe (N) of one year and a time step of one hour (k). The optimal dispatch of the MES is solved as a single objective optimization problem by considering primary energy consumption (PEC) or operating costs (OC):

$$PEC = min\sum_{k=1}^{N=8760} PEC_{\mathrm{CHP,k}} + PEC_{\mathrm{grid,taken,k}} - PEC_{\mathrm{grid,sent,k}} \tag{11}$$

$$OC = min\sum_{k=1}^{N=8760} OC_{\mathrm{CHP,k}} + OC_{\mathrm{ASHP,k}} + OC_{\mathrm{AC,k}} + OC_{\mathrm{grid,taken,k}} - OC_{\mathrm{grid,sent,k}} \tag{12}$$

The PEC defined in Eq. (11) is the sum of the fuel energy consumed by the CHP system (PEC_{CHP}), the fuel energy related to the electrical energy taken from the grid ($PEC_{grid,taken}$), and the fuel energy related to the electrical energy delivered to the grid ($PEC_{grid,sent}$) [24].

Equation (12) expresses the OC of the MES throughout one year of operation. The term OC_{CHP} stands for the operating costs of the CHP which comprise fuel cost, fixed and variable O&M costs and CO_2 emission costs. The terms OC_{ASHP} and OC_{AC} represent the fixed and variable O&M costs of the ASHP and AC, respectively. The terms $OC_{grid,taken}$ and $OC_{grid,sent}$ represent the cost of electricity of the Italian electricity market and the revenue from selling electricity to the Italian electricity market, respectively.

The objective is thus the minimization of yearly primary energy consumption (Eq. (11)) or yearly operating costs (Eq. (12)). In the following, the constraints of the optimization problem are described. In particular, Eqs. (13) through (16) represent the constraints for electrical energy, electric vehicle charging, thermal energy and cooling energy, respectively.

$$E_{\mathrm{PV,el\to load,k}} + E_{\mathrm{CHP,el,k}} + E_{\mathrm{BES,el\to load,k}} + E_{\mathrm{grid\to load,k}} = E_{\mathrm{load,el,k}} \tag{13}$$

$$E_{\mathrm{BES,el\to EV,k}} + E_{\mathrm{grid\to EV,k}} = E_{\mathrm{EV,el,k}} \tag{14}$$

$$E_{\mathrm{CHP,th\to load,k}} + E_{\mathrm{TES,el\to load,k}} + E_{\mathrm{ASHP,th,k}} = E_{\mathrm{load,th,k}} \tag{15}$$

$$E_{\mathrm{AC,cool,k}} + E_{\mathrm{ASHP,cool,k}} = E_{\mathrm{load,cool,k}} \tag{16}$$

These equations ensure the energy balance at any time step k. In Eq. (13), the sum of the electrical energy produced by the PV, CHP, BES and grid must be equal to user demand. As shown in Eq. (14), the EVs can only be charged by the batteries and the national grid. According to Eq. (15), user thermal energy demand is met by the thermal energy recovered by the CHP, by the TES and the ASHP. Finally, Eq. (16) shows that cooling energy demand is met by the AC and ASHP.

A demand response program (DRP) is usually adopted to reduce energy consumption and/or costs by modifying the load pattern (in this study, the load pattern is the electrical energy demand). Among the different DRPs, the time-of-use (TOU) rate of DRP is adopted in this work [26,31,46]. The TOU program consists of changing the load profile by shifting a certain percentage of the load, for example from peak hours to off-peak hours. Therefore, by including the TOU program, Eq. (13) can be reformulated as in Eq. (17):

$$E_{\mathrm{PV,el\to load,k}} + E_{\mathrm{CHP,el,k}} + E_{\mathrm{BES,el\to load,k}} + E_{\mathrm{grid\to load,k}} = E_{\mathrm{load,el,k}} + E_{\mathrm{DRP,el,k}} \tag{17}$$

In this manner, the electrical load becomes the base load ($E_{load,el}$)

Table 1
Decision variables.

	Decision variable	Type
PV	$E_{PV,el\to load}$	continuous
	$E_{PV,el\to BES}$	continuous
	$E_{PV,el\to grid}$	continuous
CHP	$E_{CHP,el}$	continuous
	$E_{CHP,th\to load}$	continuous
	$E_{CHP,th\to TES}$	continuous
	$E_{CHP,th\to AC}$	continuous
	isON	binary
	start	binary
ASHP	$E_{ASHP,th}$	continuous
	$E_{ASHP,cool}$	continuous
	isHeating	binary
AC	$E_{AC,cool}$	continuous
TES	$E_{TES,th\to load}$	continuous
	$E_{TES,th\to AC}$	continuous
	SoC_{TES}	continuous
BES	$E_{BES,el\to load}$	continuous
	$E_{BES,el\to EV}$	continuous
	SoC_{BES}	continuous
Grid	$E_{grid\to load}$	continuous
	$E_{grid\to EV}$	continuous
DRP	$E_{DRP,el}$	continuous

adjusted by means of a variable load ($E_{DRP,el}$). As reported in Eq. (18), the term $E_{DRP,el}$ represents the amount of load increase/decrease (in fact, it can be either positive or negative) that is obviously lower than the daily peak.

$$-DRP_{max} \bullet E_{load,el,peak,day} \leq E_{DRP,el,k} \leq DRP_{max} \bullet E_{load,el,peak,day} \tag{18}$$

As expressed in Eq. (19), the balance of $E_{DRP,el}$ over one day must be null, since the DRP mechanism just consists of shifting the load within one day (namely, daily shifting).

$$\sum_{day} E_{DRP,el,k} = 0 \tag{19}$$

In summary, Eqs. (17), (18) and (19) represent the mathematical model adopted in this paper to reproduce the proposed demand response program.

More constraints have to be imposed according to Eqs. (20), (21) and (22). The left hand-side of Eq. (20) ensures that the energy produced by the PV and split over the load, the BES and the grid cannot be higher than PV total production. Equation (21) limits the energy sent to the BES, while Eq. (22) limits the energy sent to the grid.

$$E_{PV,el\to load,k} + E_{PV,el\to BES,k} + E_{PV,el\to grid,k} \leq E_{PV,el,k} \tag{20}$$

$$E_{PV,el\to BES,k} \bullet \Delta k \leq E_{BES,el,max} \tag{21}$$

$$E_{el,PV\to grid,t} \leq E_{el,PV,tot,t} \tag{22}$$

The operating status of the CHP is tracked by the binary variable *isON*; Eqs. (23) and (24) relate the operating status of the CHP system to its power production. In fact, when the CHP is switched on (*isON* = 1), its energy production must be within its operating range, i.e. between $E_{CHP,el,min,k}$ and $E_{CHP,el,max,k}$.

The constraint in Eq. (25) relates the operating status of the CHP system to startup (*start*), i.e., start = 1 when the CHP system passes from "off" to "on". The thermal energy production of the CHP system is also related to the operating status of the CHP system and its electrical energy production at the k-th time step as expressed in Eq. (26). Moreover, Eq. (27) ensures that the thermal energy produced by the CHP system

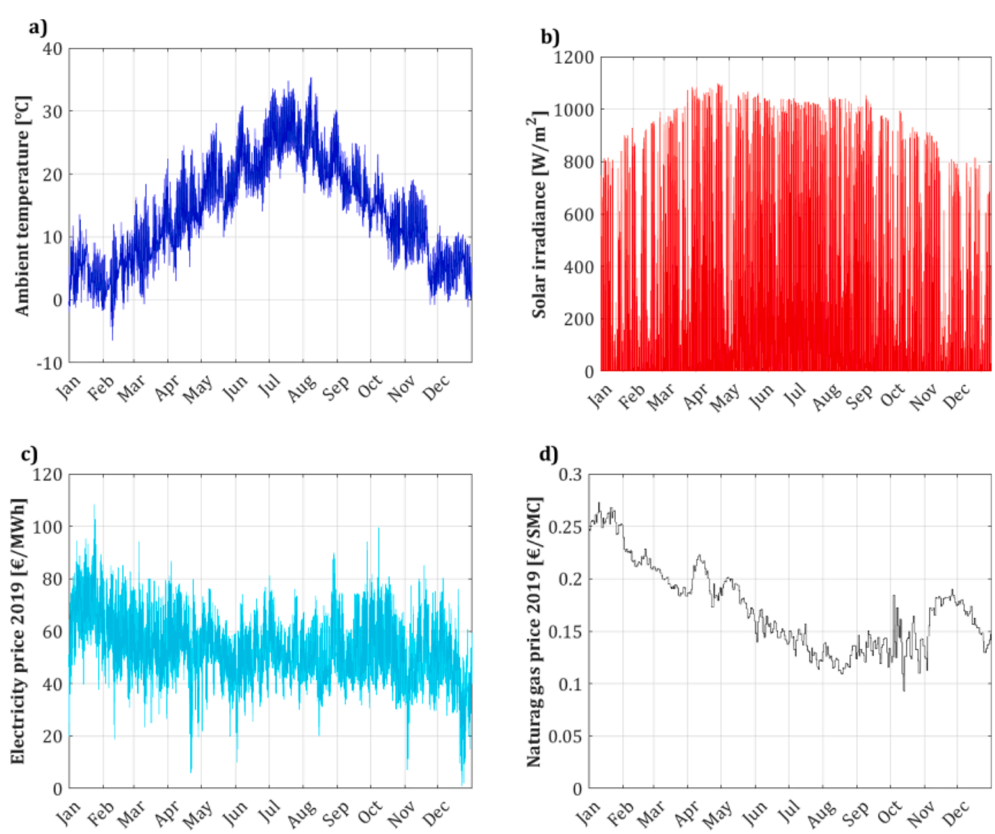

Fig. 2. Ambient temperature (a), solar irradiance (b), electricity price (c) and natural gas price (d).

and split over the load, the AC and the TES is not higher than the total thermal energy. Finally, Eq. (28) defines CHP primary energy consumption as a function of the operating status, energy production, and startup. The term $PEC_{\mathrm{CHP,startup}}$ is defined equal to the fuel consumption required to run the CHP system for five minutes at nominal conditions [18,24].

$$E_{\mathrm{CHP,el,k}} \leq isON_{\mathrm{k}} \bullet E_{\mathrm{CHP,el,max,k}} \tag{23}$$

$$E_{\mathrm{CHP,el,k}} \geq isON_{\mathrm{k}} \bullet E_{\mathrm{CHP,el,min,k}} \tag{24}$$

$$isON_{\mathrm{k}} - isON_{\mathrm{k-1}} \leq start_{\mathrm{k}} \tag{25}$$

$$E_{\mathrm{CHP,th,k}} = k_1 \bullet isON_{\mathrm{k}} + k_2 \bullet E_{\mathrm{CHP,el,k}} \tag{26}$$

$$E_{\mathrm{CHP,th\to load,k}} + E_{\mathrm{CHP,th\to AC,k}} + E_{\mathrm{CHP,th\to TES,k}} \leq E_{\mathrm{CHP,th,k}} \tag{27}$$

$$PEC_{\mathrm{CHP,k}} = k_3 \bullet isON_{\mathrm{k}} + k_4 \bullet E_{\mathrm{CHP,el,k}} + start_{\mathrm{k}} \bullet PEC_{\mathrm{CHP,startup}} \tag{28}$$

Equations (29) and (30) ensure that the thermal and cooling energy production of the ASHP are limited by its maximum thermal and cooling energy production, respectively. Moreover, the binary variable *is Heating* defines whether the ASHP is used for heating or cooling.

$$E_{\mathrm{ASHP,th,k}} \leq isHeating_{\mathrm{k}} \bullet E_{\mathrm{ASHP,th,max,k}} \tag{29}$$

$$E_{\mathrm{ASHP,cool,k}} \leq (1 - isHeating_{\mathrm{k}}) \bullet E_{\mathrm{ASHP,cool,max,k}} \tag{30}$$

Equation (31) relates TES state of charge to the thermal energy taken from the CHP system and the energy used to meet the user thermal energy demand and to activate the AC.

$$SoC_{TES,k} = SoC_{TES,k-1} + E_{CHP,th\to TES,k-1} \bullet \Delta k - \left(E_{TES,th\to load,k-1} + E_{TES,th\to AC,k-1}\right) \bullet \Delta k \tag{31}$$

Equation (32) expresses BES state of charge by considering the inlet/outlet energy flows, as well as its charging/discharging efficiency.

$$SoC_{BES,k} = SoC_{BES,k-1} + E_{PV,el\to BES,k-1} \bullet \eta_{BES,ch} \bullet \Delta k - \left(\left(E_{BES,el\to load,k-1} + E_{BES,el\to EV,k-1}\right) / \eta_{BES,disc}\right) \bullet \Delta k \tag{32}$$

Equation (33) defines the use of the electrical energy taken from the grid, which can be used to meet user electrical energy demand and/or to charge the EVs.

$$E_{grid\to load,k} + E_{grid\to EV,k} \leq \left(E_{load,el,k} + E_{EV,k}\right) \tag{33}$$

Finally, Table 1 summarizes the decision variables and their types (continuous or binary) for each energy conversion technology included in the MES. It must be highlighted that only the electrical load participates in the demand response program, since the load shifting strategy is referred to the daily peak of electric energy demand. The operation of the other technologies that compose the MES varies accordingly.

3. Case study

The case study considered in this work consists of an office building located in Milan (Italy). Fig. 2a and 2b show the ambient data (ambient temperature and total solar irradiance – one value per hour) of the considered site, calculated by using the Photovoltaic Geographical Information System (PVGIS) [47]. Electricity and natural gas prices are

Table 2
Fixed and operating costs for CHP, ASHP and AC.

Technology	Fixed operating costs [€/(kW·year)]	Variable operating costs [€/kWh]	Reference
CHP	9	0.007	[52,54,55]
ASHP	3	0.0018	[52–54]
AC	2	0.00028	[54,56]

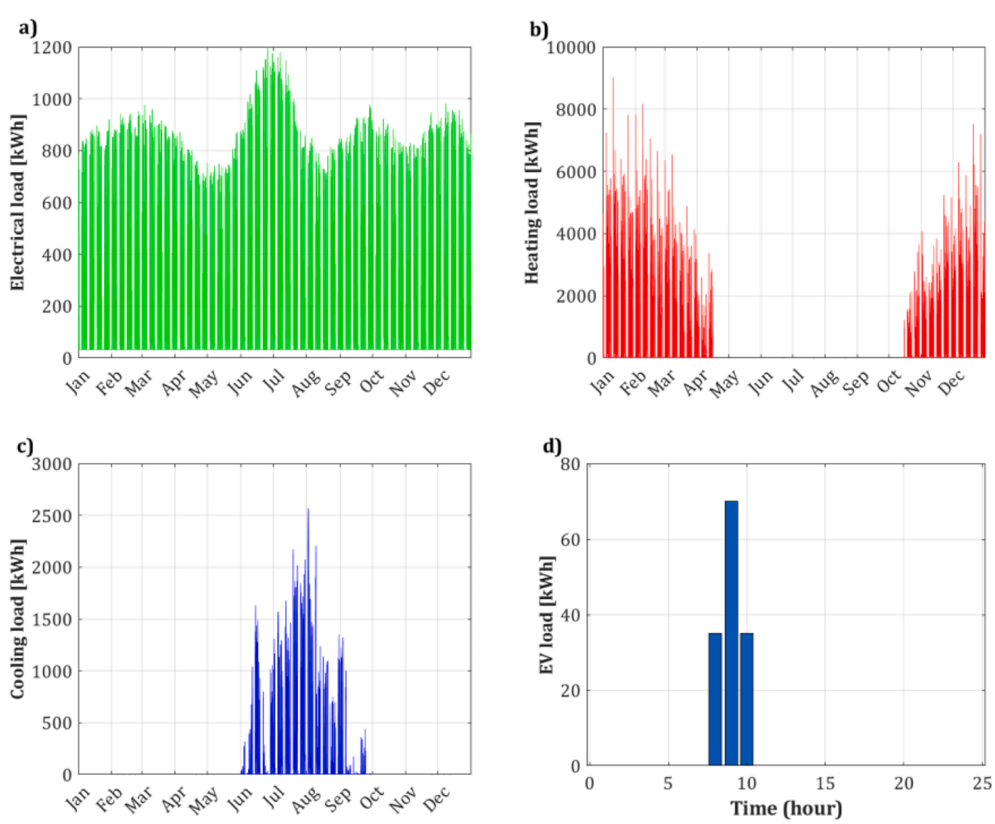

Fig. 3. Electrical (a), heating (b), cooling (c) and EV (d) energy demands.

Table 3
Sizes and nominal performance of MES components [51].

Technology	Size	Value
PV	A_{PV} [m^2]	5510
CHP	$P_{el,CHP,nom}$ [kW$_e$]	238
	$\eta_{el,CHP,nom}$ [–]	0.386
	$P_{th,CHP,nom}$ [kW$_{th}$]	320
	$\eta_{th,CHP,nom}$ [–]	0.513
ASHP	$P_{th,ASHP,nom}$ [kW$_{th}$]	8994
	$COP_{ASHP,nom}$ [–]	3.26
	$P_{cool,ASHP,nom}$ [kW$_c$]	7825
	$EER_{ASHP,nom}$ [–]	2.82
AC	$P_{cool,ABS,nom}$ [kW$_c$]	240
	$EER_{ABS,nom}$ [–]	0.75
TES	$E_{TES,max}$ [kWh]	640
BES	$E_{BES,max}$ [kWh]	270

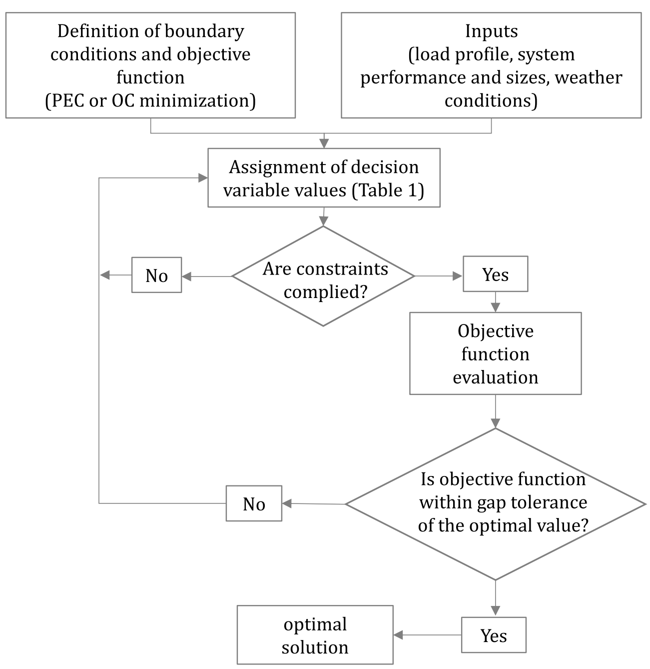

Fig. 4. Flowchart of the proposed optimization approach.

taken from [48] and refer to the year 2019. The electricity price accounts for the real profile of electricity price of the Italian market (Fig. 2c) in the range from 1€/MWh to 108€/MWh, while the cost of natural gas in the same year ranged from 0.10 €/Stdm^3 to 0.28 €/Stdm^3 (Fig. 2d) [49]. This scenario is clearly not affected by the Covid-19 pandemic or energy crisis characterizing the year 2022. The electricity, thermal, cooling and EV energy demand profiles presented in Fig. 3 are derived from real energy consumption data of a tertiary sector user [5]. Electrical energy demand for EV charging covers three hours a day on weekdays, while electrical, thermal and cooling demand cover the whole year. The heating period lasts from 15th October to 15th April, while the cooling period lasts from 15th June to 15th September. In addition, electricity demand peak during the summer is related to air conditioning required by utilities and is typically supplied by electrical chillers.

The cost for CO2 emissions is also considered in this paper and is assumed equal to 22 €/tCO_2 [5]. Such contribution is accounted for in the term OC_{CHP}, according to Eq. (12). An emission factor equal to $1.976{\cdot}10^{-3}$ tCO2/Stdm^3 was considered, by considering the emission factor for power, industry and civil sector reported in [50] for CHP systems fed with natural gas.

Table 2 shows the fixed and variable operating costs of the CHP, ASHP and AC. Instead, the operating costs of PV, TES and BES are assumed null [23].

The sizes of the different MES components are summarized in Table 3. The sizes of the PV, CHP and BES were assumed in agreement with the report [51], with PV panels located on the roof of the building. The ASHP was sized by considering the peak of the thermal demand, the AC was sized according to the nominal thermal power of the CHP system, and the TES was sized in agreement with the CHP system by considering that storage equivalent hours are equal to 2 kWh/kW, as demonstrated in [45]. With regard to the two types of storage systems, it has to be noted that the TES considered in this paper is a hot water thermal storage with a temperature difference between supply and return of 50 °C, while BESs are lithium-ion batteries with total capacity of 270 kWh, according to the report [51].

4. Results and discussion

This section presents the results of dispatch optimization obtained by minimizing primary energy consumption or operating costs. Fig. 4

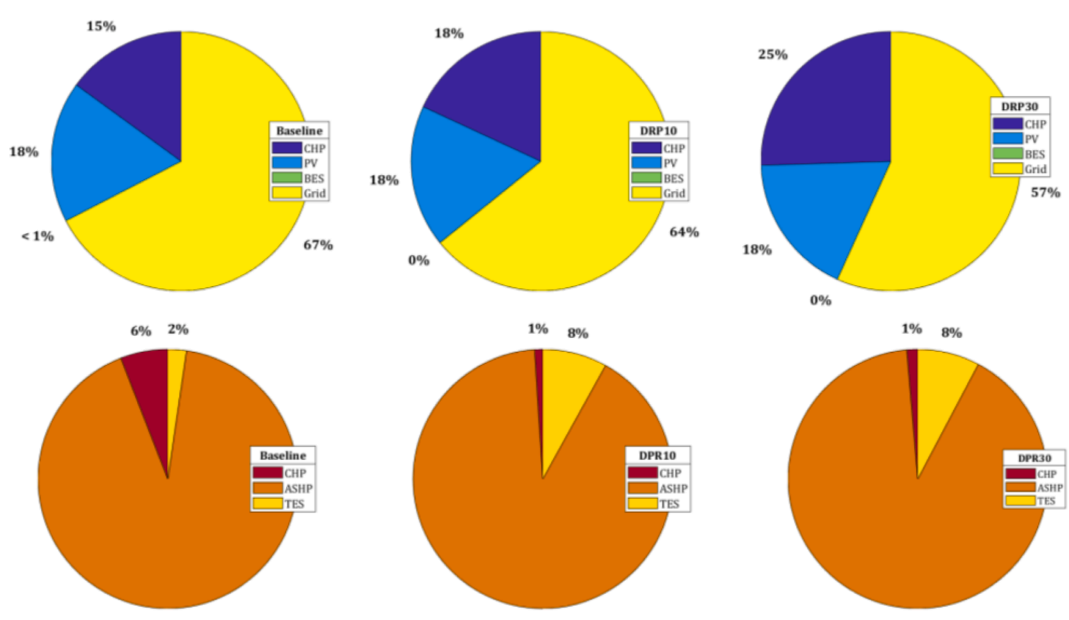

Fig. 5. Production of electrical (a) and thermal energy (b) during one day – minimization of primary energy consumption.

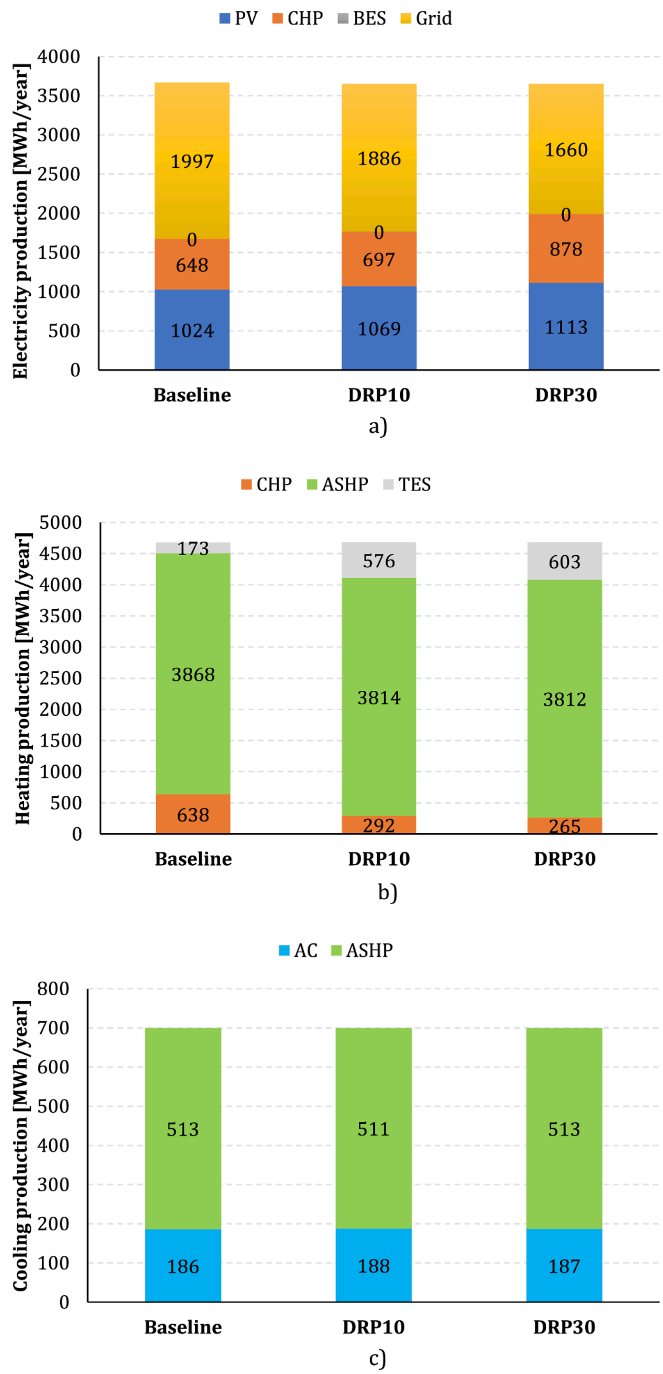

Fig. 6. Production of electricity a), heating b) and cooling energy c) – minimization of primary energy consumption.

shows the flowchart of the proposed optimization approach.

With regard code and software issues, it has to be observed that the MILP algorithm is available in different programming languages and numeric computing environments such as MATLAB®. The MATLAB software employed in this work includes the MILP algorithm and allows its implementation in terms of definition of variables, linear equations, linear constraints and objective function, which is related to the optimization target. For this reason, the coding effort was mainly related to (i) the simulation of the different technologies, (ii) the interaction of the energy fluxes from the different components and (iii) the definition of

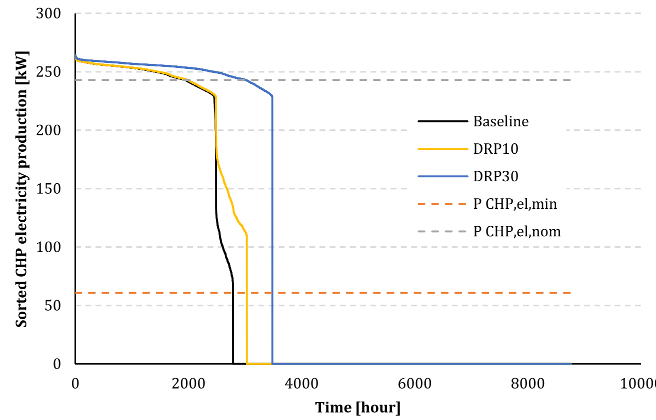

Fig. 7. Electricity duration curve of the CHP system – minimization of primary energy consumption.

the objective function. For the simulations carried out in this paper, the average computational time required to solve the optimization problem was about two hours, by using a computer with an 8 cores 3.60 GHz CPU and 64 GB RAM.

Three scenarios are investigated: (i) the baseline scenario in which the demand is met without load shifting; (ii) the DRP10 scenario in which load shifting is equal to 10 % of the daily electrical energy peak; (iii) the DRP30 scenario in which load shifting is equal to 30 % of the daily electrical energy peak. The value of 10 % represents the average of load shifting referred to daily electrical energy peaks in the TOU program reported in the studies reviewed in [57]. Instead, the 30 % scenario represents a more challenging load shifting strategy. The interaction between all the energy conversion systems within MES is considered in order to meet the energy demand: PV, CHP, BES and grid meet electrical energy demand; CHP, ASHP and TES meet thermal energy demand; AC and ASHP meet cooling energy demand.

4.1. Primary energy consumption

This section presents the results of the simultaneous optimization of both load shifting and MES management by targeting primary energy consumption minimization. The generation mix of electrical and thermal energy for the three scenarios is shown in Fig. 5 for a one-day time frame. The selected day is the one in which the electricity demand peak occurred. This figure shows that, by passing from the baseline scenario to the DRP30 scenario, the share of the CHP passes from 15 % to 25 %, while the share of the grid reduces from 67 % to 57 %. The energy production during one year is depicted in Figs. A1, A2 and A3 in Appendix 2, where the contribution of the different technologies to the electrical and thermal energy demand is shown. Fig. 6 shows the yearly contribution of MES components to the electrical, heating and cooling energy demands for the three considered scenarios. Fig. 6a proves a slight increase of the PV contribution by passing from the baseline to the DRP10 and DRP30 scenario, as well as the contribution of the CHP

Table 4
Primary energy consumption and operating costs – minimization of primary energy consumption.

	Baseline	DRP10	DRP30
PEC [MWh/year]	5401	5361	5330
$(PEC_{Baseline}\text{-}PEC)/\ PEC_{Baseline}$ [%]		0.74	1.32
OC [k€]	357	346	326
$(OC_{Baseline}\text{-}OC)/\ OC_{Baseline}$ [%]		2.93	8.72

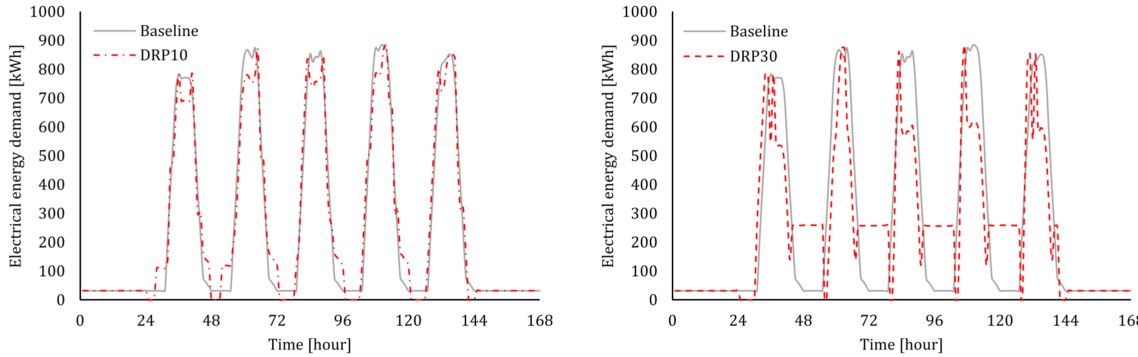

Fig. 8. Load shifting for a week in January – minimization of primary energy consumption.

system. Consequently, the grid contribution decreases by increasing load shifting. Fig. 6a also shows that the BES does not contribute to meet the electrical energy demand, because the dissipations related to BES charging/discharging (expressed by means of Eq. (10)) make their use not convenient in order to minimize PEC. With regard to heating production (in Fig. 6b), in all the scenarios, the ASHP contributes most and almost with the same rate. The thermal energy recovered by the CHP and used to meet the heating energy demand via the TES increases. This highlights the importance of storage technologies in DRPs. Finally, as shown in Fig. 6c, the contribution of ASHP and AC to cooling energy

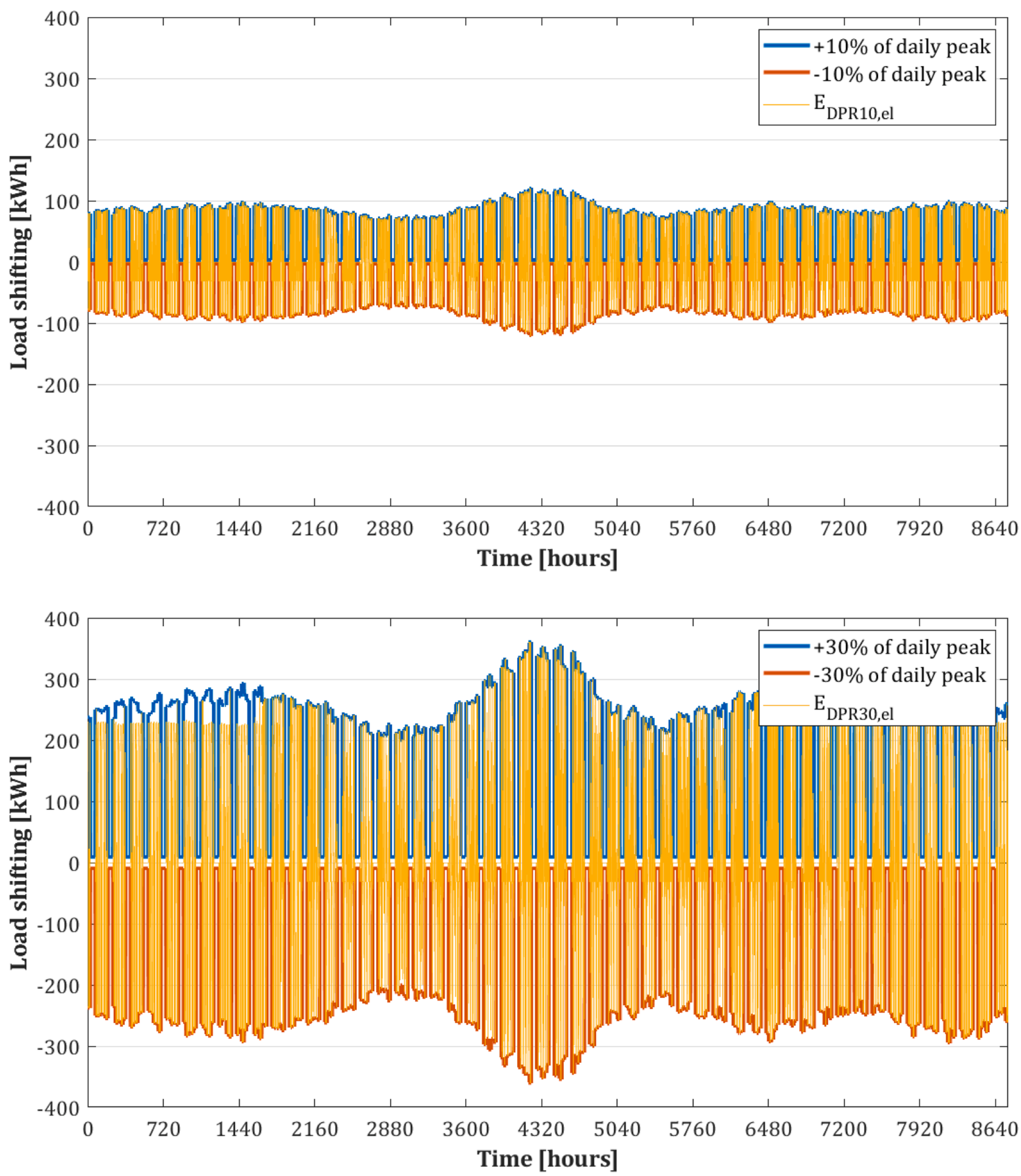

Fig. 9. Load shifting (DRP10 scenario and DPR30 scenario) – minimization of primary energy consumption.

production is not affected by load shifting.

Fig. 7 reports the electricity duration curve of the CHP for the three scenarios. Compared to the baseline scenario, the CHP system works for a longer period (3033 h vs 2788 h) in the DRP10 scenario since, from the standpoint of energy consumption, it is more efficient to meet the electrical energy demand by means of the CHP system instead of taking electricity from the grid (see Fig. 6a). The average CHP efficiency in the baseline and DRP10 scenarios is almost the same and is equal to approximately 88 %. In the DRP30 scenario, the CHP system works longer (3483 h) and the CHP efficiency is about 80 %. However, despite this decrease of efficiency, the number of startups (155) is much lower than in the other scenarios (210 in the baseline scenario; 216 in the DRP10 scenario). Therefore, in the DRP30 scenario PEC is lower since the CHP system more frequently works at nominal conditions and the number of startups is lower. The lower CHP efficiency in the DRP30 scenario is due to the higher unrecovered (and thus unexploited) thermal energy.

Table 4 shows the PEC and OC values for the three scenarios by only considering PEC minimization. As can be noted, the shifting of the electrical energy demand leads to a primary energy saving up to 1.32 %. Moreover, and most noticeably, the optimal dispatch strategy identified with the objective of minimizing primary energy consumption also allows a reduction of operating costs up to 8.72 %.

As an example, Fig. 8 shows the mechanism of load shifting for the DRP10 and DRP30 scenarios for a week in January from Sunday to Saturday. Since the energy demand refers to an office building, energy consumption is minimum on Saturday and Sunday. By increasing load shifting rate, the optimization algorithm correctly shifts the electrical energy demand from peak hours to off-peak hours. Load is shifted from a higher energy rate to lower one, in such a manner to lead users to consume energy during early morning (e.g., from 5 a.m. to 8 a.m.) or during late evening (e.g., from 8p.m. to 12 a.m.). It can be noted that a higher number of hours is affected by load shifting in DRP30 scenarios.

For both scenarios DRP10 and DRP30, Fig. 9 shows the trend of the quantity $E_{DRP,el}$, which represents the amount of load increase/decrease due to load shifting. During the weekends, the electrical load is constant and equal to minimum; thus, load shifting is not exploited. Instead, during the week, load shifting is equal to 10 % of daily peak in DRP10 scenario (i.e., load shifting is fully exploited). In the DRP30 scenario, load shifting is also usually fully exploited, with the exception of approximately 10 % of all weekdays, in which the amount of load shifting ranges from 15 % to 30 %.

4.2. Operating costs

This section presents the results of the simultaneous optimization of both load shifting and MES management by targeting the minimization of operational costs. The generation mix of electrical and thermal energy for the three scenarios is shown in Fig. 10 for a one-day time frame. The selected day is the one in which the electricity demand peak occurred. This figure shows that, by passing from the baseline scenario to the DRP30 scenario, the share of the CHP passes from 15 % to 20 %, while the share of the grid reduces from 67 % to 62 %. The energy production during one year is depicted in Figs. A4, A5 and A6 in Appendix 2, where the contribution of the different technologies to the electrical and thermal energy demand is shown. Fig. 11 shows the yearly contribution of MES components to the electrical, heating and cooling energy for the three scenarios, in the case that operating costs are minimized. Fig. 11a show that grid contribution decreases with the increase of load shifting, i.e., from an economic point of view the electricity taken from the grid is more expensive. A difference with respect to the minimization of primary energy consumption (analyzed in Section 4.1) is that the contribution of BES is not null. A non-negligible amount of electrical energy stored inside the BES meets a small fraction of electrical energy demand. As already observed in Section 4.1, the thermal energy recovered by the CHP system and stored in the TES increases with the increase of load shifting. Therefore, even with the purpose of minimizing costs, storage technologies (BES and TES) are fundamental to optimally manage the MES. Finally, in agreement with the comment made about Fig. 6c, the contribution of ASHP and AC to cooling energy production is not affected by load shifting.

Fig. 12 reports the electricity duration curve of the CHP for the three scenarios. The CHP system works for 3700 h in the baseline scenario, 4372 h in the DRP10 scenario and 3932 h in the DRP30 scenario. It is

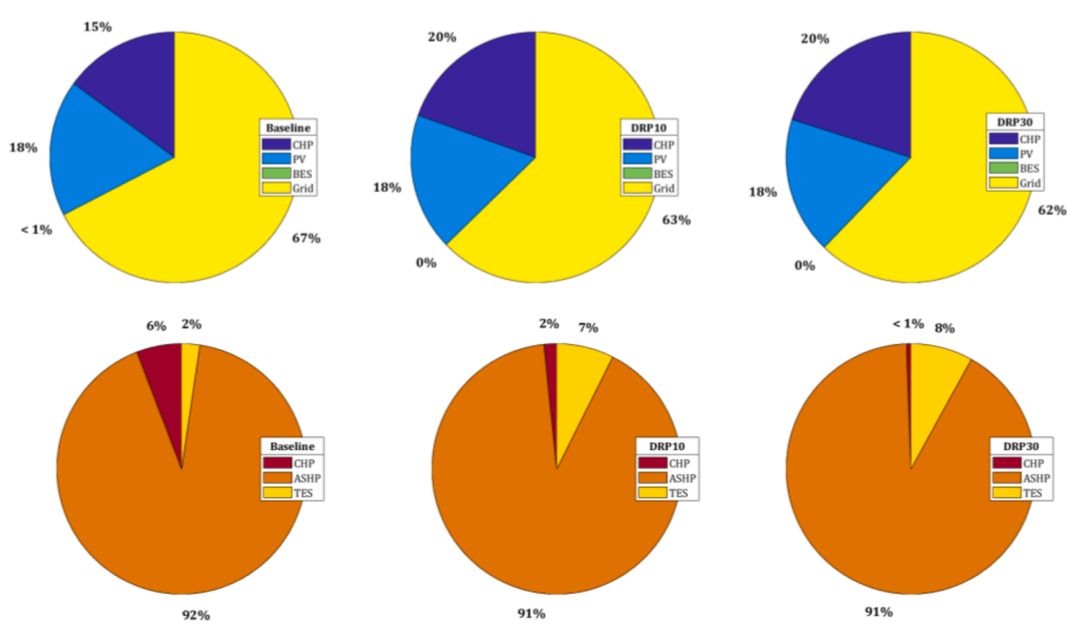

Fig. 10. Production of electrical (a) and thermal energy (b) during one day – minimization of operational costs.

Fig. 11. Production of electricity a), heating b) and cooling energy c) – minimization of operating costs.

evident that, to minimize costs, operating hours are considerably higher than in the case of PEC minimization. In other words, it is more cost-effective to meet the electrical energy demand by means of the CHP system instead of taking electricity from the grid, as shown in Fig. 11a. It can also be seen that the number of operating hours in the DPR10 scenario is higher than in the DPR30 scenario. In fact,

Fig. 12 clearly shows that, in the DPR10 scenario, the CHP system also works at part-load, while in the DPR30 scenario the CHP system almost always work at nominal load.

In the DRP30 scenario, the startups are 341, while they are 380 in the DRP10 scenario and 279 in the baseline scenario. The lower the number of startups, the lower operating and maintenance costs. The CHP efficiency in the baseline scenario is approximately 77 %, while it is approximately 75 % in the other two scenarios. Since in this analysis the objective is cost minimization, CHP efficiency values are lower than the corresponding values obtained by minimizing PEC.

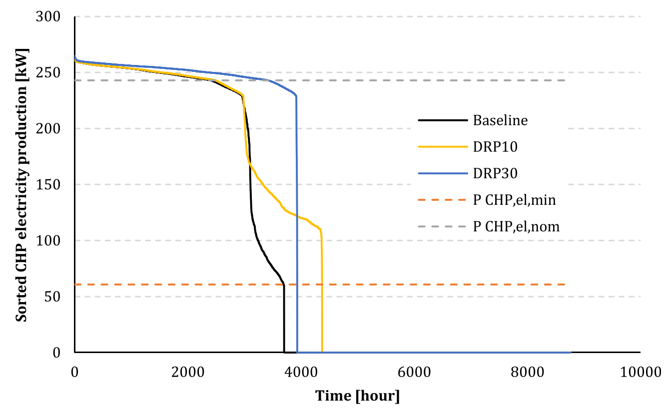

Fig. 12. Electricity duration curve of the CHP system – minimization of operating costs.

Table 5
Primary energy consumption and operating costs – minimization of operating costs.

	Baseline	DRP10	DRP30
PEC [MWh/year]	5480	5463	5388
$(PEC_{Baseline}$-$PEC)/ PEC_{Baseline}$ [%]		0.31	1.67
OC [k€]	336	318	307
$(OC_{Baseline}$-$OC)/ OC_{Baseline}$ [%]		5.19	8.70

Table 5 shows the PEC and OC values for the three scenarios by only considering cost minimization. It should be noted that the values of PEC and OC reported in Table 5 for the baseline scenario differ from the corresponding values reported in Table 4 since, even though the energy demand profiles are the same (see Fig. 3), the MES management strategy identified by the optimization algorithm is different. In this case, the shifting of the electrical energy demand leads to a decrease of operating costs up to 8.70 %. Moreover, load shifting also allows a primary energy saving up to 1.67 %. It should be noted that primary energy saving in the DRP30 scenario is slightly higher than in the case of PEC minimization, while the reduction of operating costs is comparable. This result suggests that the optimization problem should be targeted at minimizing operating costs.

Fig. 13 shows the mechanism of load shifting for DRP10 and DRP30 scenarios for a week in January from Sunday to Saturday. As already observed in Section 4.1, by increasing load shifting rate, the optimization algorithm suggests to shift the electrical energy demand from peak hours to off-peak hours. Even in this case, the optimization strategy indicates that energy consumption has to be shifted from a higher hourly energy rate to a lower one in order to minimize the OC. It results that it is more cost effective to decrease the consumption during day time and increase it during night time (e.g., from 8p.m. to 7 a.m.) in both DRP10 and DRP30 scenarios.

Fig. 14 shows the trend of the quantity $E_{DRP,el}$, which represents the amount of load increase/decrease due to load shifting. During the weekends, the electrical load is constant and equal to minimum; thus, load shifting is not exploited, as already observed in Fig. 9. Instead, during the week, load shifting is equal to 10 % of daily peak in DRP10 scenario (i.e., load shifting is fully exploited). In the DRP30 scenario, load shifting is in practice always fully exploited, with the exception of just 2 % of all weekdays, in which the amount of load shifting ranges from 15 % to 30 %. This means that load shifting is more effective for the minimization of MES operating costs than for PEC minimization.

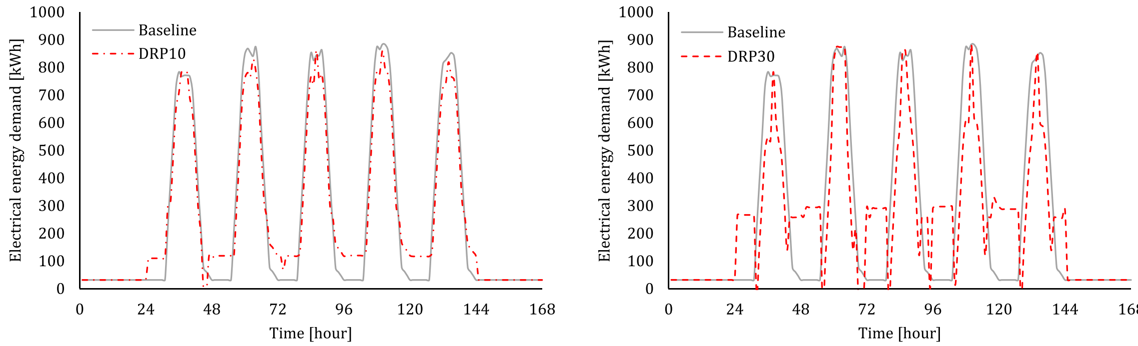

Fig. 13. Load shifting for a week in January – minimization of primary energy consumption.

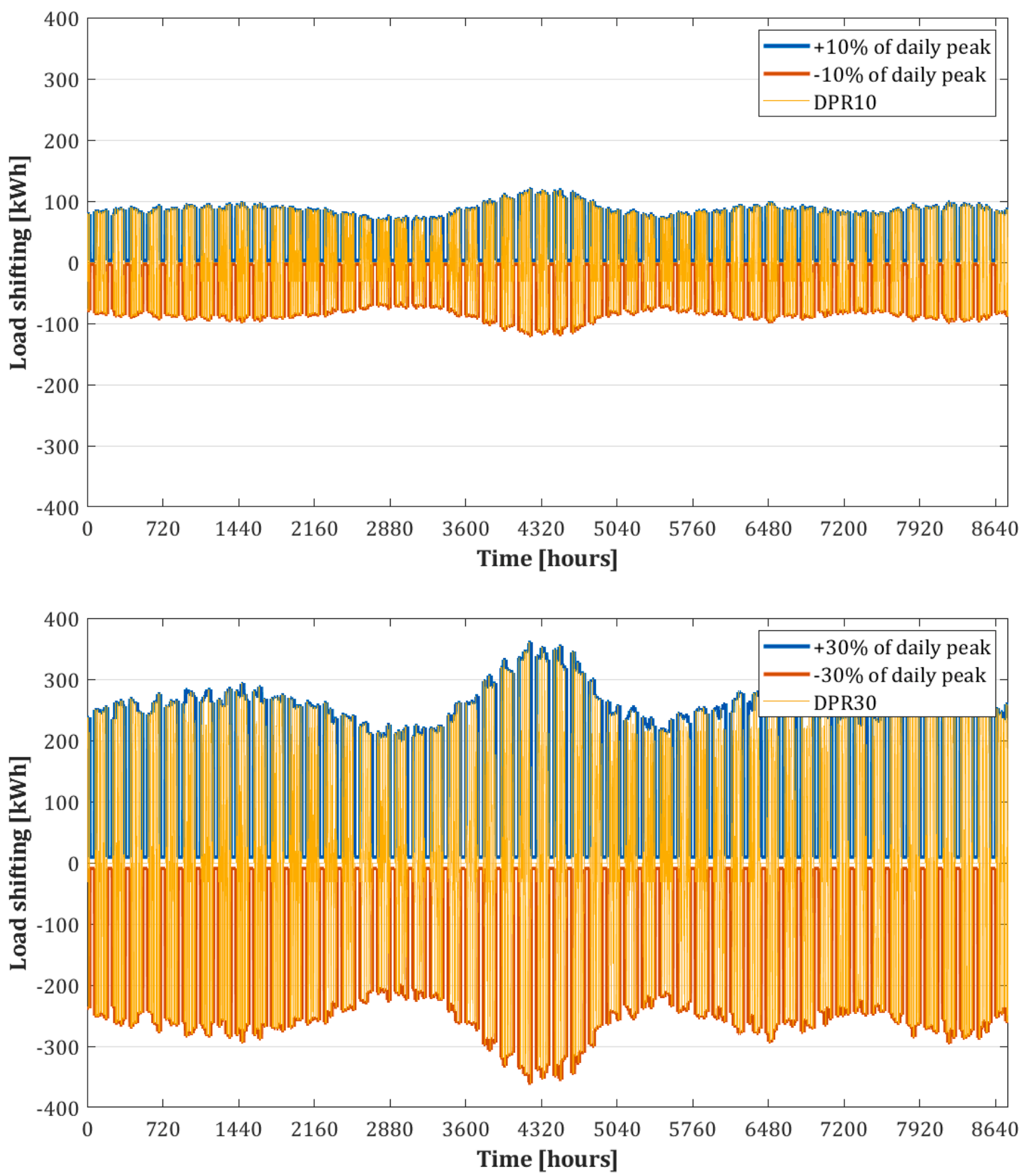

Fig. 14. Load shifting (DRP10 scenario and DPR30 scenario) – minimization of operational costs.

5. Conclusions

In this work, the optimal dispatch problem of a multi-generation energy system was addressed by means of MILP formulation and solved by considering a time horizon of one year and a time step of one hour. The simultaneous optimization of both load shifting based on demand response and MES management strategy was investigated in order to minimize primary energy consumption or operating costs. The case study considered in this work consisted of an office building located in Milan (Italy), characterized by means of electrical, thermal, cooling and electric vehicle energy demand profiles derived from real-world energy consumption data of a tertiary sector user.

The optimal strategy for energy dispatch was identified by considering a single objective optimization problem by minimizing the primary energy consumption or the operating costs. A demand response program was investigated by modifying the electrical load pattern. The time-of-use rate was adopted in order to change the load profile by shifting a fraction of the load within one day while keeping the same amount of daily electrical energy demand. Three different scenarios were investigated: (i) in the baseline scenario, the electrical energy demand was met without load shifting; (ii) in the second scenario, load shifting up to 10 % of the daily electrical energy peak was considered; (iii) in the third scenario, load shifting was increased up to 30 %.

The analyses carried out in this paper demonstrated that the implementation of a demand response program is effective to reduce both primary energy consumption and operating costs. Moreover, as expected, the higher the load shifting, the higher the benefit. However, as expected, there were some differences between the two cases aimed at minimizing primary energy consumption or operational costs. In fact, in the case that the goal is the minimization of primary energy consumption, by passing from the baseline scenario to the DRP30 scenario, the CHP system works longer (3483 h), but with a lower CHP efficiency (80 %), due to the higher unrecovered (and thus unexploited) thermal energy. However, despite this decrease of efficiency, the number of start-ups (155) is much lower than in the other scenarios. Another relevant result is that load shifting is usually fully exploited, with the exception of 10 % of weekdays in the DRP30 scenario. Otherwise, in the case that the goal is the minimization of operational costs, by passing from the baseline scenario to the DRP30 scenario, the CHP system works for 3932 h in the DRP30 scenario, much longer than in the case of minimization of primary energy consumption. This finding also demonstrates that it is more cost-effective to meet the electrical energy demand by means of the CHP system instead of taking electricity from the grid. Moreover, it was found out that in the DRP30 scenario, the CHP efficiency in the DRP30 scenario is approximately 75 %, i.e., it is lower than in the case of minimization of primary energy consumption. Once again, load shifting is in practice always fully exploited, with the exception of just 2 % of weekdays in the DRP30 scenario. This means that load shifting is more effective for the minimization of MES operating costs than for PEC minimization.

The key finding of this paper is that, whatever the minimization target (primary energy consumption or operating costs), both primary energy consumption and operating costs can be lowered by approximately 1 % and 8 % respectively in the DR30 scenario, compared to the case in which the load is not shifted.

As a future work, the analysis of the interaction between energy production and user demand will be addressed by employing clustering techniques coupled with a hybrid objective function that takes into account the simultaneous minimization of primary energy consumption and operating costs. An optimal management strategy based on demand response program will also be investigated in order to optimally size the available storage systems. Since the uncertainty of renewable energy sources, as well as energy demands, may play an important role in the short-term and long-term planning of the system, the stochastic behavior of both RES and energy demand will be taken into account by the authors in a future work. This limitation of the current study will be overcome in future research activities. An additional future work will be the comparison of MILP formulation to other optimization algorithms.

CRediT authorship contribution statement

Hilal Bahlawan: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Giulia Anna Maria Castorino:** Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Enzo Losi:** Validation, Formal analysis, Writing – review & editing, Visualization. **Lucrezia Manservigi:** Validation, Formal analysis, Writing – review & editing, Visualization. **Pier Ruggero Spina:** Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing, Visualization, Supervision, Project administration. **Mauro Venturini:** Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix 1

To highlight the novelty of this paper, this Appendix includes a synoptic Table which allows the direct comparison of this paper to already-available literature studies (ranked in ascending order in the bibliography).

The comparison is made by addressing the considered objective function, optimization algorithm, optimization variables, technologies, energy demand, DRP presence and time frame of the analysis.

As can be grasped, the main novelty is represented by the application of the demand response program over one entire year of operation for electrical, thermal and cooling energy demands, while the studies that investigate the potential benefits of DRP usually consider one or few days. Another feature that differentiates this paper from other literature studies is that this paper investigates both energy and cost minimization, while most studies consider just one optimization target.

Appendix 2

Figs. A1 through A6 show the energy production during one year, by highlighting the contribution of the different technologies to the electrical and thermal energy demand. The negative values for the TES and the BES stand for the respective energy entering the storage, while the negative values for the PV production means that PV power is sent to grid. The contribution of the different technologies to the cooling energy demand is not reported since only ASHP and AC are involved (Fig. 6c and 11c).

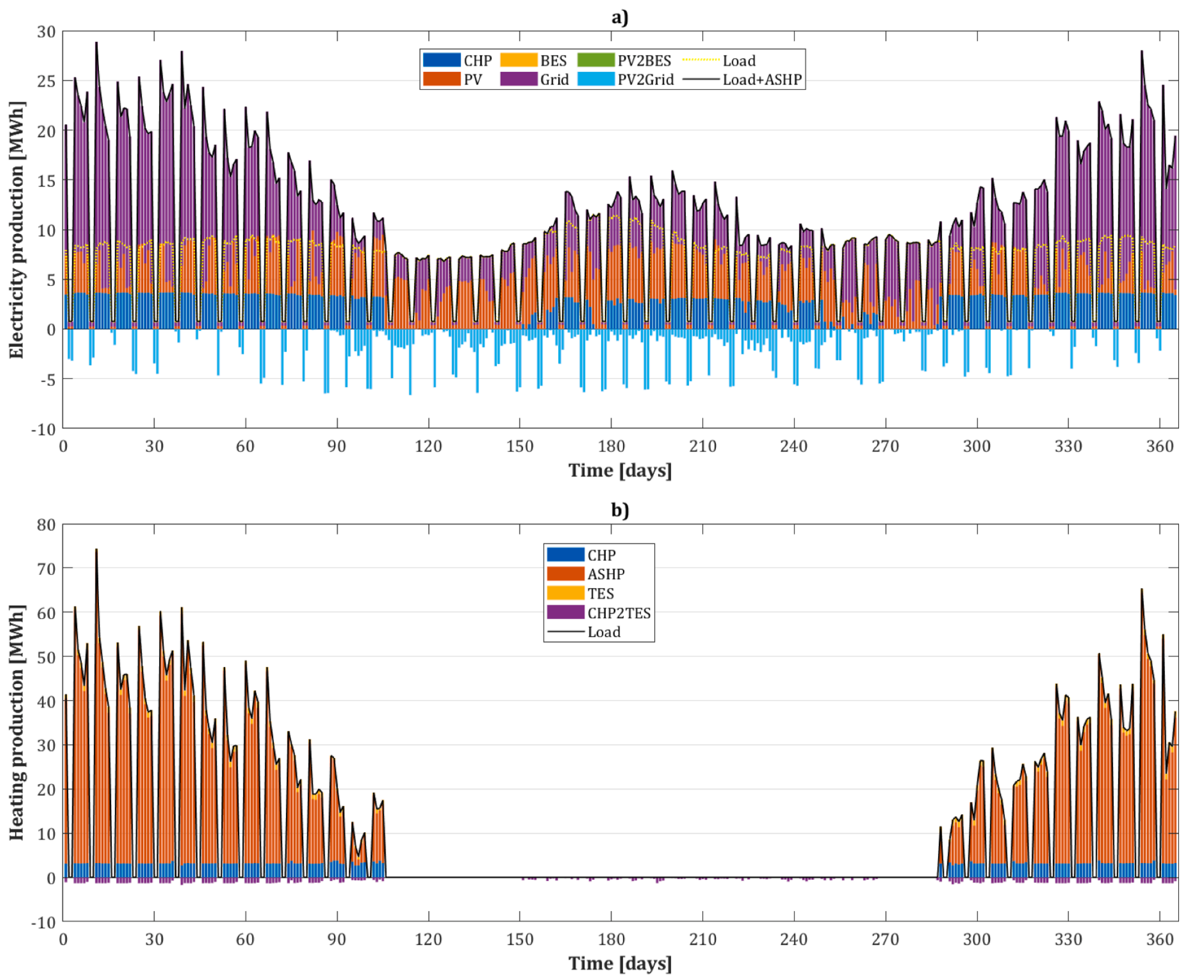

Fig. A1. Production of electrical (a) and thermal (b) energy during one year (Baseline scenario; Minimization of primary energy consumption).

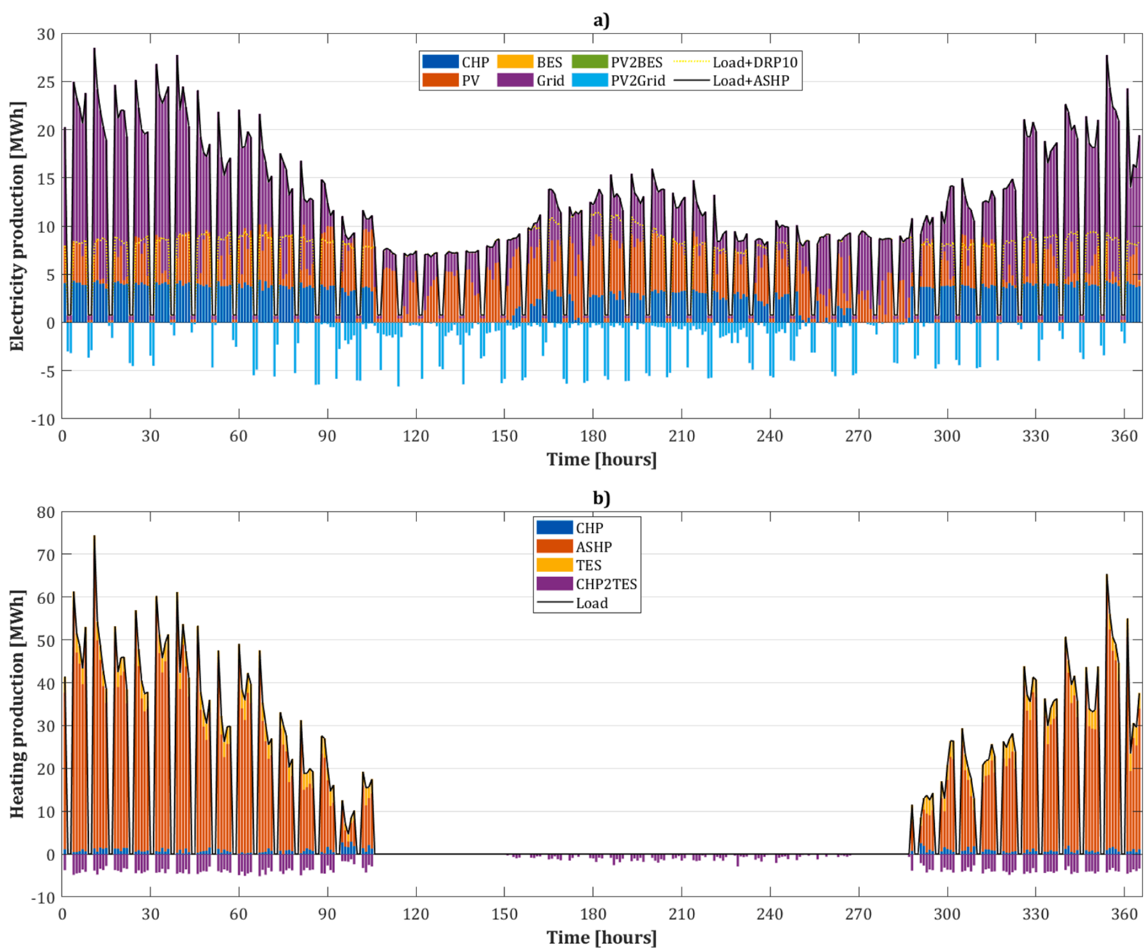

Fig. A2. Production of electrical (a) and thermal (b) energy during one year (DRP 10 scenario; Minimization of primary energy consumption).

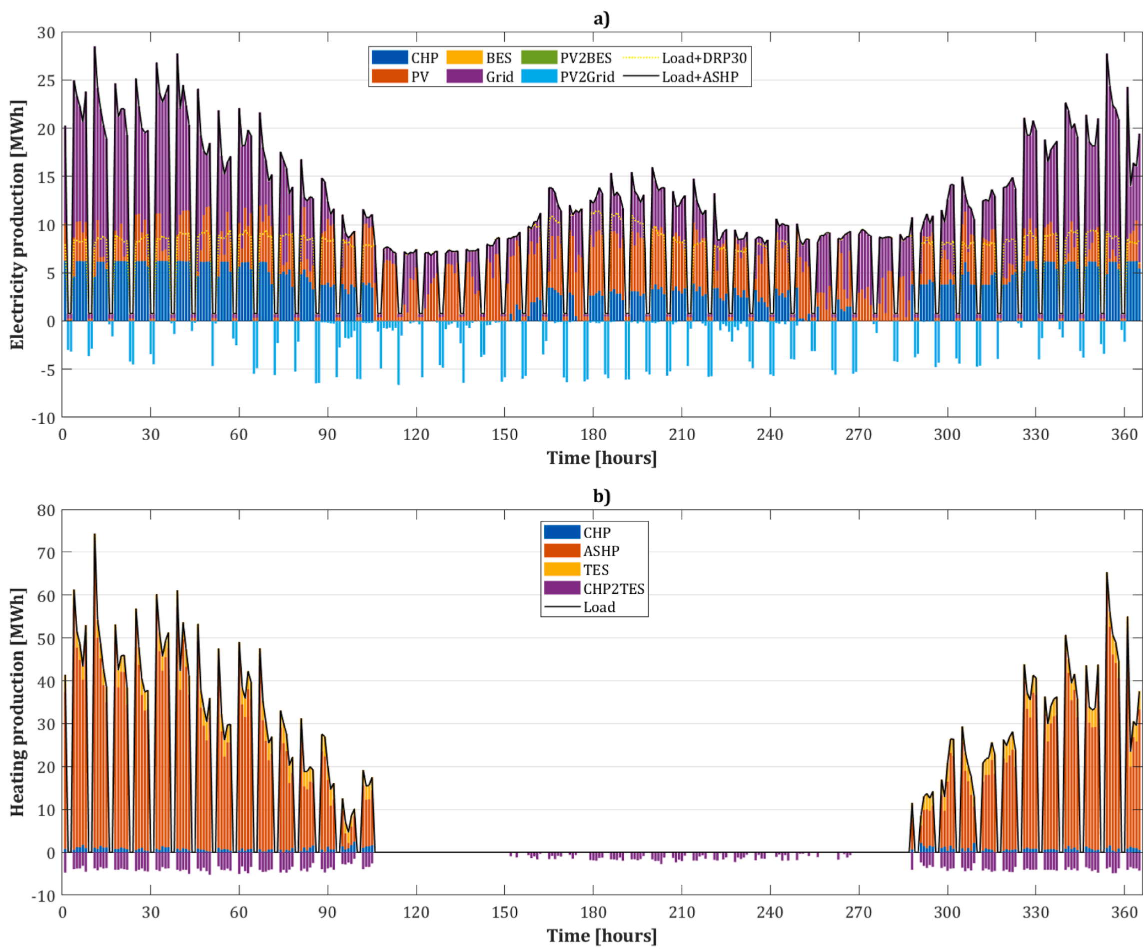

Fig. A3. Production of electrical (a) and thermal (b) energy during one year (DRP 30 scenario; Minimization of primary energy consumption).

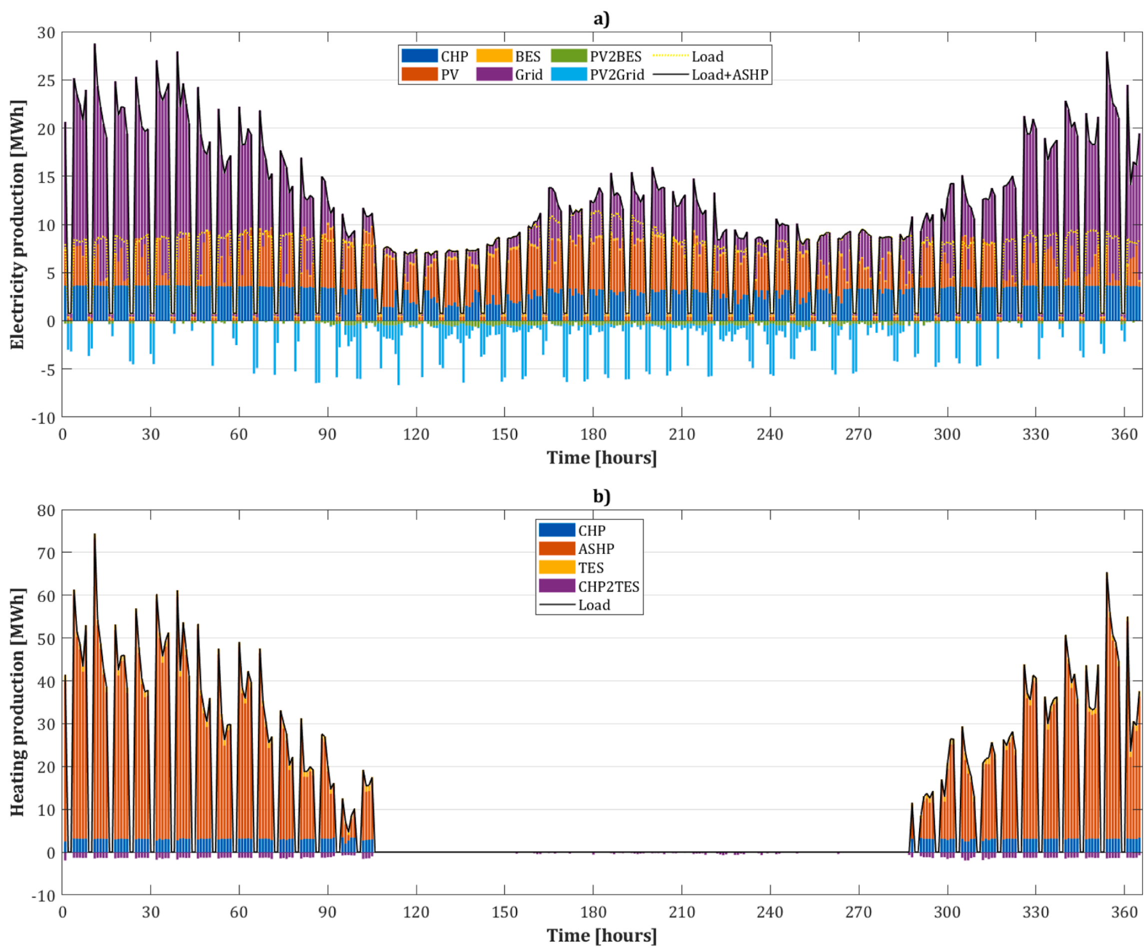

Fig. A4. Production of electrical (a) and thermal (b) energy during one year (Baseline scenario; Minimization of operational costs).

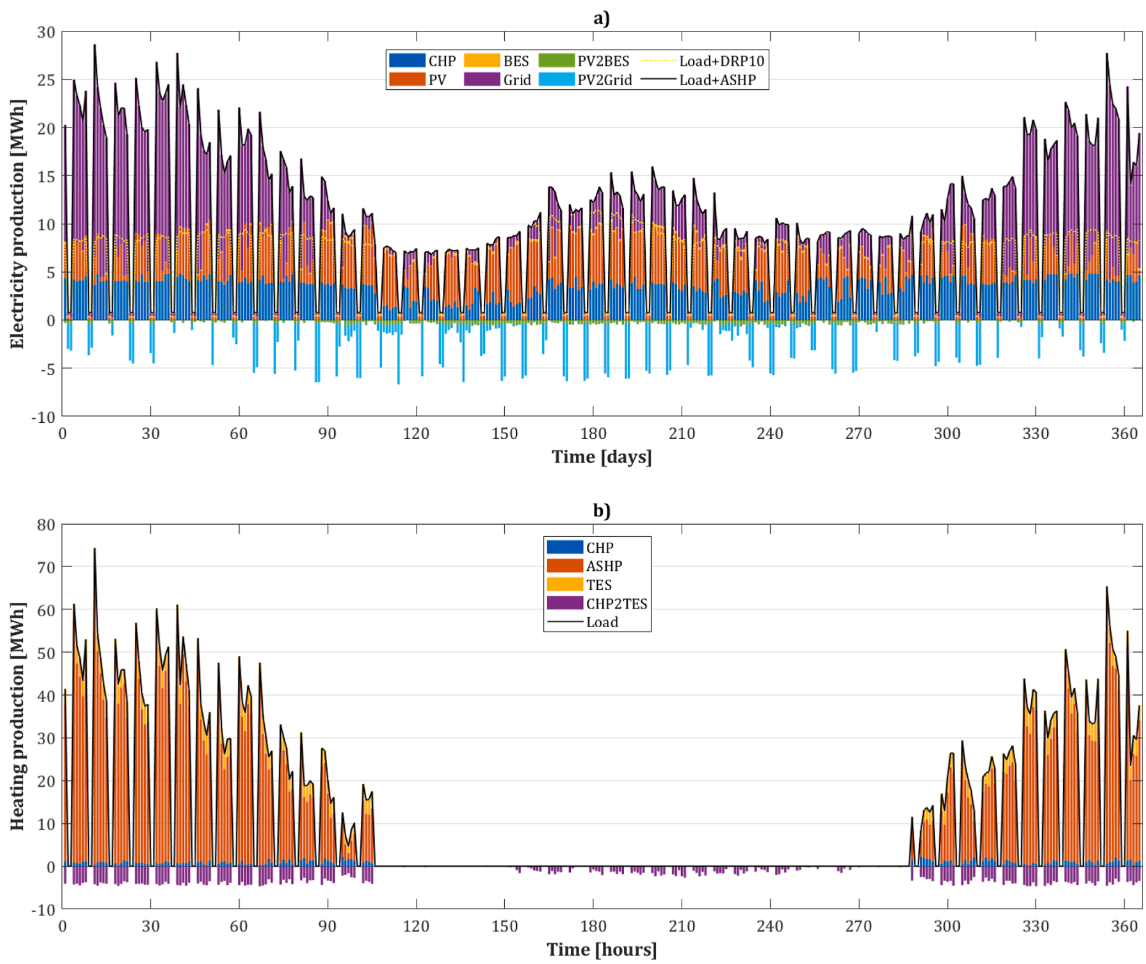

Fig. A5. Production of electrical (a) and thermal (b) energy during one year (DRP 10 scenario; Minimization of operational costs).

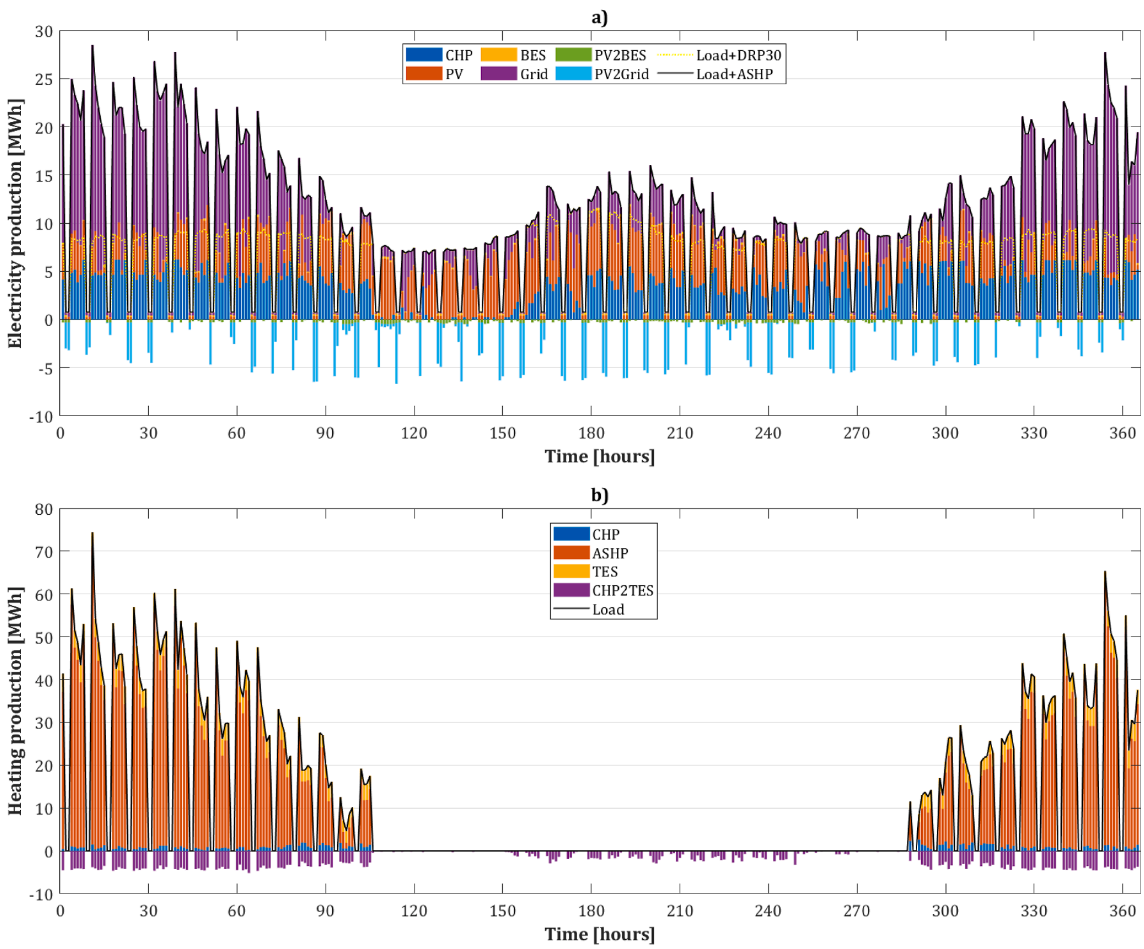

Fig. A6. Production of electrical (a) and thermal (b) energy during one year (DRP 30 scenario; Minimization of operational costs).

Table A1
Comparison of this paper to literature studies.

Reference	Objective function	Optimization algorithms	Optimization variables	Technologies	energy demand	DRP	Timeframe
This paper	PEC or OC minimization	MILP operation optimization	simultaneous optimization of operation and demand	TES, PV, BES, CHP, ASHP, AC, Grid, NG	electrical, thermal and cooling demand	✓TOU	1 year
[5]	single OF: PEC or Costs minimization	SMO + DP	sizing and operation optimization	STC, TES, PV, CHP, ASHP, AC, EC, GB, Grid, NG	electrical, thermal and cooling demand	×	1 year
[11]	costs minimization Nonlinear OF	DEROP iterative algorithm	management optimization	BES, Grid	electrical demand	×	1 day
[12]	multi-OF: PEC and Costs minimization	TRNSYS + GA	design optimization	STC, AC, TES	thermal and cooling demand	×	1 year
[13]	multi-OF: Costs and CO2 emission minimization	TRNSYS + neural network + GA	design optimization	PV, WT, H2S, AE, FC, Grid	electrical demand	×	1 year
[14]	multi-OF: Costs and CO2 emission minimization	GA	design optimization	PV, WT, STC, TES, HPT, BES, DG	electrical and thermal demand	×	1 year
[16]	PEC minimization	GA	design optimization	STC, PV, GSHP, TES, STES, BES	electrical, thermal and cooling demand	×	1 year
[18]	PEC minimization	DP	sizing and operation optimization	STC, PV, CHP, GSHP, ASHP, AB, TES, Grid, NG	electrical and thermal demand	×	1 day
[19]	OC minimization	PSO + Monte Carlo method	operation optimization	MT, FC, H2S, GB, RB, ARR, Grid, NG	electrical and thermal demand	×	1 day
[21]	multi-OF: Costs and CO2 emission minimization	MILP	sizing and operation optimization	AE, FC, GT, GB, HPT, BES, TES, H2S, NG	electrical and thermal demand	×	1 year
[22]	multi-OF: Costs, CO2 and NOX emission minimization	MILP	operation optimization	DG, MGT, NG	electrical demand	×	1 day
[23]	PEC minimization	DP	operation optimization	AB, TES, BES, DHG, Grid, NG	electrical and thermal demand	×	1 year
[24]	single OF: PEC or Costs minimization	DP	operation optimization	STC, PV, CHP, GSHP, ASHP, AC, EC, GB, TES, Grid, NG	electrical, thermal and cooling demand	×	1 year
[28]	costs minimization	RHO	operation optimization	PV, WT, DG, BES	electrical demand	✓TOU	4 days
[29]	maximization of the final profit	MILP	operation optimization	STC, TES, CES, PV, WT, CHP, ASHP, AC, EC, GB, Grid, NG	electrical, thermal and cooling demand	✓	1 day
[30]	costs minimization	DSM algorithm + Monte Carlo	design optimization	PV, BCHP GB, Grid, NG	electrical and thermal demand	✓ TOU	1 summer day 1 winter day
[31]	costs and CO2 emission minimization	RMILP	operation optimization	PV, WT, AC, EC, BES, TES, CES, STC, GB, GT, NG	electrical, thermal and cooling demand	✓TOU, RTP	1 day
[32]	cost minimization	CPLEX – robust optimization	design optimization	BES, Grid, PV, WT	electrical demand	✓CPP, TOU	4 days
[34]	the MG profit maximization and cost minimization	MINLP	management optimization	MT, PV, Grid, WT, NG	electrical demand	✓RTP, HPDR, TOU	1 day
[35]	cost minimization	HOMER tool	sizing optimization	HPT, PV, RB, WT, BES, DG	electrical demand	✓TOU	1 summer day 1 winter day
[36]	cost minimization	robust optimization NSGA-II algorithm	operation optimization	WT, GB, CCHP, GT, BES, TES, CES, GB, AC, EC, NG	electrical, thermal and cooling demand	✓IBDR	4 days (one per season)
[38]	cost minimization	mathematical model	operation optimization	WT, Grid	electrical demand	✓ RTP	1 year

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