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Optimization of energy and economic scheduling of a hybrid energy plant by using a dynamic programming approach

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ABSTRACT

An optimized energy and economic scheduling of hybrid energy plants can lead to a significant reduction of primary energy consumption and operational costs. Various optimization methods, with their own advantages and limitations, have been proposed in the literature. However, the scheduling optimization of complex hybrid energy plants that are composed of renewable, conventional and storage energy technologies is still an area which demands contribution. Dynamic programming has proved to be a powerful approach because of its ability to solve a variety of optimization problems with nonlinear objective functions and constraints, as well as to find global optimal solutions. Thus, this paper goes beyond previous analysis available in the literature by developing a novel methodology based on dynamic programming for the optimization of the energy and economic scheduling of hybrid energy plants. The hybrid energy plant considered in this paper includes renewable energy systems, fossil fuel energy systems and energy storage technologies. The actual fluctuation of the electricity prices is also considered in this work. The optimal scheduling was identified by considering the minimization of primary energy consumption or operational costs, as well as a hybrid scenario for meeting thermal, cooling and electrical energy demands of the user. Hybrid scenarios of minimizing both primary energy consumption and operational costs weighted by two different weight coefficients α and β, are also evaluated. The validity and capability of the optimization methodology is demonstrated by considering two case studies. The first case is a commercial building and the second case regards a University campus. Compared to commonly-used operation strategies, the energy scheduling optimization ($\alpha = 1$ and $\beta = 0$) by means of dynamic programming allows a primary energy saving between 3.8% and 8.3% for the first case study and a saving between 0.5% and 17.4% for the second case study. Moreover, the economic scheduling optimization ($\alpha = 0$ and $\beta = 1$) enables operational cost reduction in the range 11.7%–25.1% for the first case study and in the range 4.3%–14% for the second case study. For both case studies, the economic scheduling optimization shows that fulfilling the user energy demands by a combined heat and power is economically more convenient than importing electricity from the grid. Finally, unlike the operation strategies used as benchmarks, the dynamic programming methodology is flexible and able to solve scheduling optimization problems under different optimization constraints and can also allow customized hybrid solutions.

1. Introduction

A reduction of primary energy consumption is usually expected to contribute to increased sustainability of the residential and tertiary sectors. According to the European Commission [1], buildings are responsible for about 40% of the energy demand. Several strategies are adopted for reducing primary energy consumption, operational costs and pollutant emissions, such as: (i) increase the penetration of renewable energy systems, (ii) integration of thermal and electric energy storage technologies, (iii) improvement of the efficiency of energy generation systems. A major drawback of renewable energy systems is associated with their unpredictability because of the intermittent nature of the environmental conditions. This leads to fluctuations in energy production from renewable sources and thus the connection to the electric grid and the use of back-up systems is required to meet the required energy demands. In the current context, in order to reduce the consumption, costs and harmful emissions of fossil fuels there is a growing trend to use Hybrid Energy Plants (HEPs) [2]. Generally, a HEP is composed of different energy technologies which use two or more

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Nomenclature

Abbreviations

AB	auxiliary boiler
ABS	absorption chiller
AC	auxiliary chiller
ASHP	air source heat pump
CHP	combined heat and power
DP	dynamic programming
GSHP	ground source heat pump
HP	heat pump
HEP	hybrid energy plant
OC	operational costs
PEC	primary energy consumption
PV	photovoltaic system
S	summer
SOP	switch-on priority
STC	solar thermal collector
TES	thermal energy storage
W	winter

Symbols

A	area
c	coefficient
COP	coefficient of performance
E	energy
f	conversion factor
k	time variable
l	generic energy system
L	number of energy systems
$load$	ratio between actual thermal power and nominal thermal power
N	last time-step
P	power
t	time
T	temperature
U	input or decision variable
V	volume
x	state variable
y	function
α	weight of primary energy
β	weight of operational costs
η	efficiency

Subscripts and superscripts

cool	cooling
diss	dissipation
el	electrical
fuel	fuel
grid	national grid
in	entering
k	time variable
nom	nominal
op	optimal
out	outgoing
sent	sent to the grid
taken	taken from the grid
th	thermal

energy sources to meet the energy demands of a certain user.

The performance of a HEP can be affected by various factors, such as the operation strategy of the plant components and the climatic conditions. These factors influence the energy production of the systems and consequently the primary energy consumption and operational costs of the HEP. Therefore, implementing optimization methods for energy management and economic dispatch is a key factor to achieve the expected benefits from HEPs with lowest energy consumption and costs [3]. Indeed, a smart energy management helps to optimize the exploitation of fossil and renewable sources, reduce the pollutant emissions and minimize the energy costs [4]. The optimal energy management and economic dispatch of HEPs is a challenging task since the optimal solution depends on the renewable energy sources, environmental data, technical specifications of the energy systems and user energy demands [5].

A variety of optimization methods has been presented in the literature to solve the problem of operation optimization [6]. Among these methods, the most prominent are linear programming [7,8] and mixed integer linear programming [9]. In spite of the contributions of these methods to the operation optimization of energy systems, they are only suitable for linear problems, while for complex systems, such as HEPs, they are computationally expensive due to the large number of decision variables [10].

As the difficulties associated with the operation optimization of HEPs arise, mainly because the nature of these systems make the optimization problem strongly nonlinear, new and more efficient algorithms that are capable of tackling nonlinearities must be investigated for the management of HEPs. In fact, nonlinear constraints corresponding to the variation of the nominal efficiency of the energy units in relation to the external temperature and part-load operation and non-convexity corresponding to the binary nature of on/off decisions must be accounted for [11]. Otherwise, ignoring these effects may affect the reliability of the optimal operation strategy capable of minimizing primary energy consumption or operational costs. Regarding this issue, some optimization methods have been developed and proved to be effective in many applications and made the problem readily solvable [12]. Among these methods, genetic algorithm [13] and particle swarm optimization [14] methods are the most commonly used algorithms [12]. These optimization methods belong to the category of meta-heuristic optimization algorithms and they have the advantage of dealing with linear and nonlinear problems. Compared to mathematical programming techniques, which follow deterministic rules to find the optimal solution, in meta-heuristic optimization methods, the optimal solution is found by following a stochastic approach [11].

Meta-heuristic optimization methods proved their robustness and ability to solve nonlinear and non-differentiable problems. However, despite the contributions of these methods to the scheduling optimization of HEPs, they still suffer from some disadvantages such as high execution time for complex problems, premature convergence, trapping in local optima and need the definition of a high number of parameters [11].

Recently, Dynamic Programming (DP) has attracted lots of research in the area of energy systems [15]. Generally, DP is an optimization method that is used to solve problems in which decisions should be made sequentially by dividing the original problem into sub-problems [16]. The basic idea of this method is that the minimal cost solution of the original problem is found through multistage optimization where at each stage a decision is made in an optimum way from a finite number of decisions. DP method has been extensively used to solve scheduling optimization problems due its ability in dealing with non-convex, nonlinear and dynamic variables [17,18]. Moreover, it is capable of reaching the global optimal solution in the discrete state-space [19]. Chen et al. [20] presented a DP algorithm to solve the energy management problem of a combined heat and power system with energy storage. The study aimed to improve the energy efficiency of the system by considering a household as an application. The optimization is

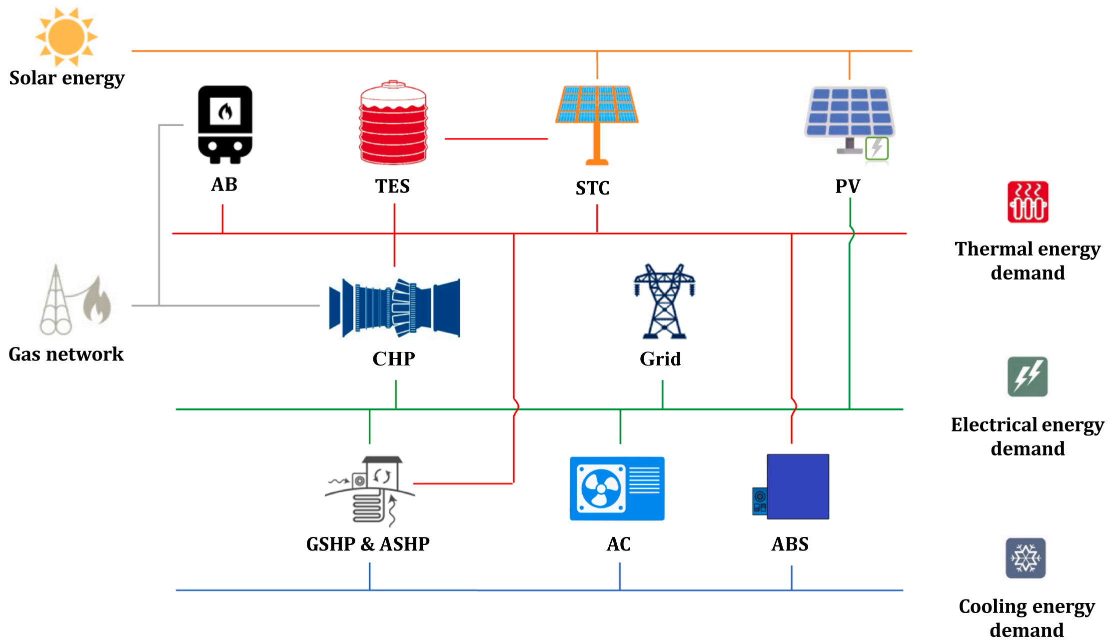

Fig. 1. Layout of the hybrid energy plant.

conducted on a short-term basis (24 h) and the results were compared to an experimental test. Results showed that DP allows to improve the overall energy efficiency of the system. However, in their study, attention has been only given to electrical and thermal energy demands and the option of integrating renewable energy sources is not evaluated. The optimal operating schedule of a tri-generation system with storage units was investigated in [21] by means of a DP algorithm. Plant operation was optimized by minimizing the operational costs considering off-design performance and randomness of renewables. The optimal schedule allowed a reduction of the operational costs over a time horizon of 24 h.

Facci et al. [22] developed a methodology to determine the optimal operation strategy of a fuel cell-based tri-generation plant. Energy and economic objective functions were optimized in their study and the analysis was carried out on a yearly basis. Moreover, hourly electrical, thermal and cooling energy demands for a small hotel were considered in their work. They found that the optimized control strategy allows to reduce the primary energy consumption and the operational costs of the plant. Similarly, in another work, the control strategy of a fuel cell-based combined heat and power system with boiler and mechanical chiller was optimized by the same authors [23]. They evaluated different combinations of building types, climatic conditions, energy costs and objective functions. Thiem et al. [24] developed and implemented a model predictive controller based on dynamic programming algorithm for the operation optimization of a cooling system composed of a compression chiller and an ice storage. The proposed model allowed lower operational costs compared to an open-loop control strategy. Further, DP has been used to control the operation in an organic Rankine cycle waste heat recovery system [25], showing that DP is suitable for real -time applications even though it is limited by dimensionality computation issues. The works mentioned before were able to tackle a number of challenges, such as the variation of systems efficiency with load, the effect of environmental conditions and the dynamic behavior of the considered systems. However, despite their contribution to the literature, these works did not consider the integration of renewable energy systems. Though renewable energy systems (such as solar thermal collectors and photovoltaic panels) depend on the availability of renewable sources and are non-controllable, they are widely used to meet building energy demands [26]. Therefore, their integration would be advisable, especially in combination with energy storage technologies.

Recently, Mahmoudimehr et al. [27] employed the DP method for the optimal performance management of a solar power plant equipped with thermal energy storage. The aim of the study was to optimize the daily electricity generation and revenue obtained from selling electricity. The daily operation (24 h) of the plant was optimized by deciding the amount of solar salt within the thermal tank. Compared to a genetic algorithm based method, DP allowed an increase of electricity generation and daily revenues up to 7.5% and 12.6%, respectively. Furthermore, the operation of a large scale hydro-photovoltaic hybrid power plant was investigated by Li et al. [28] by using a DP method. The study aimed to maximize the energy production and guaranteed rate by considering the carryover storage as an independent decision variable.

From the literature survey documented above, the DP method proved to be able to optimally schedule a variety of energy plants up to a good standard. However, the operation optimization of complex HEPs that are composed of renewable, conventional and storage energy technologies is still an area which demands contribution. Moreover, compared to linear programming and meta-heuristic optimization methods, the DP algorithm proves to be preferable for solving a variety of optimization problems because of: (i) its ability to deal with nonlinear objective functions and constraints, (ii) its capability of finding the global optimal solution due to its deterministic nature and (iii) its simple implementation [16]. This paper contributes to the literature by presenting a novel DP-based optimization method to solve the scheduling optimization problem of a complex HEP which comprises a Solar Thermal Collector (STC), Photovoltaic system (PV), Combined Heat and Power (CHP), Ground Source Heat Pump (GSHP), Air Source Heat Pump (ASHP), Absorption Chiller (ABS), Auxiliary Chiller (AC), Auxiliary Boiler (AB) and Thermal Energy Storage (TES). The applicability of the methodology is demonstrated by considering two case studies; the first case study is a tower composed of thirteen floors used for commercial purposes, while the second case study is a University campus. The optimization of energy, economic and hybrid scheduling are investigated in this paper. In the energy scheduling optimization, the optimal scheduling of the different HEP units is found by minimizing the Primary Energy Consumption (PEC). In the economic scheduling optimization, the optimal scheduling is found by minimizing the operational costs, while in the hybrid scheduling optimization the optimal scheduling is identified by minimizing a hybrid energy/economic objective function. Finally, it has to be considered that the sizes of the different systems considered in this study are fixed and consequently the investment costs are also fixed. Thus, only the primary energy consumption and operational costs are considered [29].

The scheduling optimization is conducted by considering the actual hourly fluctuation of the Italian electricity market during the year 2019. Moreover, the revenue obtained from selling the electricity to the grid is also considered. The optimization is conducted on hourly basis and throughout one year.

The rest of the paper is structured as follows: Section 2 gives details about the HEP components and describes the DP optimization method. Section 2 also presents the model of the HEP formulated in the state space and discusses the objective functions optimized in this paper. The case studies are outlined in Section 3. Section 4 presents the results and Section 5 concludes the paper.

2. Materials and methods

For real time applications, energy scheduling optimization studies are usually conducted by considering a short-term time horizon (e.g., 24 h), as illustrated in [29], while scheduling optimization problems during the design and planning phase of HEPs are usually addressed by considering one year of operation with an hourly resolution [30]. This is mainly due to the fact that high levels of spatial and temporal resolution may increase the required computing resources [30]. Moreover, models at the levels of the case studies considered in this paper generally use an hourly resolution because the dynamics of the thermal demand is very slow due to the large thermal inertia [31]. Therefore, in this paper, the scheduling optimization problem is solved by considering one year and the analysis is carried out on an hourly basis. For this purpose, a model for the simulation of the HEP is developed and implemented in Matlab®. The HEP components are modelled as grey-box models by means of power and efficiency curves. Nonlinearities associated with the variation of the performance of the considered systems according to both ambient conditions and load de-rating are also taken into account, as well as the start-up of the CHP and the thermal energy dissipation of the TES.

2.1. Hybrid energy plant description

Fig. 1 shows a scheme of plant layout. As mentioned before, the HEP is composed of a Solar Thermal Collector (STC), Photovoltaic system (PV), Combined Heat and Power (CHP), Ground Source Heat Pump (GSHP), Air Source Heat Pump (ASHP), Absorption Chiller (ABS) and Thermal Energy Storage (TES). Moreover, a gas Boiler (AB) and a compression Chiller (AC) are used as auxiliary systems. The heat pumps (GSHP and ASHP) are considered reversible, thus allowing to produce thermal energy in winter and cooling energy in summer.

From Eqs. (1), (2) and (3), thermal, cooling and electrical energy balances are satisfied at each time-step ($k = 1$ h) of the optimization time frame ($N = 8760$ h):

$$E_{AB,th\to user,k} = E_{user,th,k} - (E_{STC,th\to user,k} + E_{CHP,th\to user,k} + E_{GSHP,th,k} + E_{ASHP,th,k} + E_{TES,th,out\to user,k}) \tag{1}$$

$$E_{AC,cool,k} = E_{user,cool,k} - (E_{ABS,cool,k} + E_{GSHP,cool,k} + E_{ASHP,cool,k}) \tag{2}$$

$$E_{grid,el,taken,k} = E_{user,el,k} + E_{GSHP,el,k} + E_{ASHP,el,k} + E_{AC,el,k} - (E_{PV,el,k} + E_{CHP,el,k}) \tag{3}$$

In Eq. (1), the term $E_{\mathrm{user,th,k}}$ represents the thermal energy demand which is the sum of space heating and hot water energy demands. This can be met by the STC, CHP, GSHP, ASHP and TES. In Eq. (2), the term $E_{\mathrm{user,cool,k}}$ represents the cooling energy demand which can be met by the GSHP, ASHP and ABS. The electrical energy demand ($E_{\mathrm{user,el,k}}$) together with the electricity required by the heat pumps and compression chiller are met by the CHP and PV systems.

Finally, as reported in the balance equations, if the energy demands are not met by these systems, the AB ensures the fulfillment of the thermal demand ($E_{\mathrm{AB,th,k}}$), the AC ensure the fulfillment of the cooling demand ($E_{\mathrm{AC,cool,k}}$) while the remaining electrical energy demand is imported from the grid ($E_{\mathrm{grid,el,taken,k}}$). Moreover, the interaction with the electric grid is supposed to be bilateral, i.e., any excess of electricity, produced from the CHP and PV can be sent to the grid.

The thermal energy flows between the CHP, STC, AB, TES and ABS are expressed by the following equations:

$$E_{CHP,th,k} = E_{CHP,th\to user,k} + E_{CHP,th\to ABS,k} + E_{CHP,th\to TES,k} + E_{CHP,th\to diss,k} \tag{4}$$

$$E_{STC,th,k} = E_{STC,th\to user,k} + E_{STC,th\to ABS,k} + E_{STC,th\to TES,k} + E_{STC,th\to diss,k} \tag{5}$$

$$E_{TES,th,in,k} = E_{STC,th\to TES,k} + E_{CHP,th\to TES,k} \tag{6}$$

$$E_{ABS,th,in,k} = E_{STC,th\to ABS,k} + E_{CHP,th\to ABS,k} + E_{TES,th\to ABS,k} + E_{AB,th\to ABS,k} \tag{7}$$

In particular, Eq. (4) states that the thermal energy produced from the CHP is used to meet the user thermal energy demand, the ABS and to fill up the TES. The unrecovered thermal energy is supposed to be released to the environment ($E_{\mathrm{CHP,th\to diss,k}}$). The thermal energy produced from the STC is split in the same way as the CHP (see Eq. (5)). As stated in Eq. (6), the TES can be filled up by the STC and CHP system. The thermal energy required by the ABS is supplied by the CHP, STC, TES and AB.

2.2. Dynamic programming method

The DP method is based on Bellman's principle of optimality [16], according to which an optimal policy can be constructed sequentially [32]. The DP method requires the formulation of the optimization problem in the state-space as follows:

$$x_{k+1} = y(x_k, u_k) \tag{8}$$

$$E_k = g(x_k, u_k) \tag{9}$$

Eq. (8) is a discrete-time dynamic system where x represents the state variables which are used to describe the state of the HEP at each time interval of the time horizon and they include information about the sequence of decisions made so far. The term u stands for input or decision variables that are used to schedule the HEP components, while the term E of Eq. (9) represents the output variables of the controllable HEP components (i.e., energy production).

The aim of the optimization is to schedule the HEP components so that a cost function is minimized:

$$Z(x_0) = \sum_{k=0}^{N-1} h_k(x_k, u_k) + h_N(x_N) \tag{10}$$

where h_{N} is the final cost, while h_{k} is the intermediate cost of applying the control u_{k} at x_{k}. Let the optimal control policy be u^{op}, the optimal cost function is defined as follows:

$$Z^{op}(x_0) = \min_{u\in U} Z(x_0) \tag{11}$$

with U representing the space of all admissible control policies. Eq. (11) can be rewritten as:

$$Z^{op}(x_0) = \sum_{k=0}^{N-1} Z_k^{op} + Z_N^{op} \tag{12}$$

where

$$Z_k^{op} = \min_{u_k\in U_k} \{h_k(x_k, u_k, k) + Z_{k+1}^{op}\} \tag{13}$$

The relationship in Eq. (13), normally called Bellman equation, represents a formal statement of the principle of optimality. As stated before, the cost function expressed by Eq. (13) is solved by dividing the original problem into simple sequences of sub-problems and by moving backward in time starting from the time-step $k = N$-1 to time-step $k = 0$. Once the entire problem is solved for all $k \in \{0,\ldots,N\text{-}1\}$, the optimal scheduling policy can be found by tracking back the optimal policies which were found for the tail sub-problems. At the end of the recursion, the optimal scheduling policy that minimizes the cost function is tracked:

$$u^{op} = \{u_0^{op}(x_0), \ldots, u_{N-1}^{op}(x_{N-1})\} \tag{14}$$

2.2.1. Model representation in the state space

2.2.1.1. State variables. In this work, the state-space model is discretized with a time-step of one hour and two state variables are identified according to Eq. (15) and Eq. (16).

(1) Combined heat and power

$$x_{CHP,k+1} = \begin{cases} 1 & \text{if} \quad u_{CHP,k} \neq 0 \\ 0 & \text{if} \quad u_{CHP,k} = 0 \end{cases} \tag{15}$$

The state variable reported in Eq. (15) corresponds to the CHP system which is represented by binary values [0,1] describing the operating condition (on or off) of the CHP at the beginning of each time-step k. This state variable is introduced to model the start-up of the CHP.

(2) Thermal energy storage

As a second state, the state of charge of the TES is considered in the DP model. This is updated as follows:

$$x_{TES,k+1} = (1 - c_{diss})\cdot\left(x_{TES,k} + E_{TES,th,in,k} - E_{TES,th,out,k}\right) \tag{16}$$

As reported in Eq. (16), the heat dissipation is included in the storage model and assumed proportional to the stored energy. In particular, a dissipation coefficient of 0.5% is considered [33].

2.2.1.2. Decision variables. Five decision variables are identified to optimally schedule the components of the HEP. These correspond to the CHP, GSHP, ASHP, ABS and TES. The STC and PV systems are activated first, since the production of renewable energy systems clearly depends on ambient conditions. However, the energy produced from the STC system depends on the amount of energy to be stored in the TES and the energy produced from the PV system is auto-consumed, while the excess of electricity is sent to the grid.

(1) Renewable energy systems

The thermal energy and electric energy produced by the STC and the PV systems are calculated by means of Eq. (17) and Eq. (18), respectively:

$$E_{STC,th,k} = G_k \cdot A_{STC} \cdot \eta_{STC,k} \cdot \Delta k \tag{17}$$

$$E_{PV,el,k} = G_k \cdot A_{PV} \cdot \eta_{PV,k} \cdot \Delta k \tag{18}$$

with G representing the solar radiation expressed in [kW/m^2].

The efficiency of the STC is expressed as reported in Eq. (19) [34]:

$$\eta_{STC,k} = \eta_o - b_1 \cdot \left(\frac{T_{av} - T_k}{G}\right) - b_2 \cdot \left(\frac{T_{av} - T_k}{G}\right)^2 \tag{19}$$

where η_o stands for the optical efficiency of the collector (equal to 0.8), b_1 and b_2 two correction factors, G the solar radiation, T_k the external ambient temperature and T_{av} the average temperature. The latter is considered equal to 50 °C during winter and 80 °C during summer.

The overall performance of the PV system is calculated by the following equation [35,36]:

$$\eta_{PV,k} = \eta_{BoS} \cdot \eta_{M,ref} \cdot [1 - \lambda \cdot (T_{c,k} - T_{ref})] \tag{20}$$

with η_{BoS} is the balance of system (equal to 0.9), $\eta_{M,ref}$ the performance of the PV module at standard conditions (equal to 0.14), λ a penalty coefficient (equal to 0.005 [°C^{-1}]), T_{ref} the operating temperature of the cells at standard conditions (equal to 20 °C) and $T_{c,k}$ the effective operating temperature of the cell.

(2) Combined heat and power

The CHP system is a small scale gas turbine fed by natural gas. The thermal and electrical energy production of the CHP system at the k-th time-step are expressed by Eq. (21) and Eq. (22), respectively:

$$E_{CHP,th,k} = u_{CHP,k} \cdot P_{CHP,th,nom}(T_k) \cdot \Delta k \tag{21}$$

$$E_{CHP,el,k} = \eta_{CHP,el}(u_{CHP,k}, T_k) \cdot \frac{E_{CHP,th}(u_{CHP,k}, T_k)}{\eta_{CHP,th}(u_{CHP,k}, T_k)} \tag{22}$$

where;

$$u_{CHP,k} = \frac{P_{CHP,th,k}}{P_{CHP,th,nom}(T_k)} \tag{23}$$

As can be seen from Eq. (23), the decision variable for the CHP is defined as the ratio between the thermal power produced at the k-th time-step and the nominal thermal power of the CHP corrected according to the ambient temperature. The decision variable is discretized into equally spaced values in the modulation range of the CHP including the turned-off condition ($u_{CHP,th} = 0$). The fuel energy consumption for the CHP is calculated by taking into account the penalty for CHP start-up:

$$E_{CHP,fuel,k} = \frac{E_{CHP,th}(u_{CHP,k}, T_k)}{\eta_{CHP,th}(u_{CHP,k,}T_k)} + E_{CHP,fuel,start-up,k}(x_{CHP,k}, u_{CHP,k}) \tag{24}$$

where;

$$E_{CHP,fuel,start-up,k} = \left(\frac{P_{CHP,el,nom}}{\eta_{CHP,el,nom}}\right) \cdot (\Delta t_{start-up}); \quad \text{if} \quad x_{CHP,k} = 0 \quad \text{and} \quad u_{CHP,k} \neq 0 \tag{25}$$

The fuel energy consumed during a start-up ($E_{CHP,fuel,start-up}$) is assumed equal to the consumption of the system during a $\Delta t_{start-up}$ equal to 5 min at nominal conditions [37]. The effect of the ambient temperature and load on the CHP performance is also accounted for.

(3) Heat pumps

For the HP (i.e., GSHP or ASHP) unit, the thermal/cooling energy produced and the electrical energy consumed are represented by Eq. (26) and Eq. (27), respectively:

$$E_{HP,th/cool,k} = \begin{cases} u_{HP,k} \cdot P_{HP,th,nom}(T_k) \cdot \Delta k & \text{In winter} \\ u_{HP,k} \cdot P_{HP,cool,nom}(T_k) \cdot \Delta k & \text{In summer} \end{cases} \tag{26}$$

$$E_{HP,el,k} = \begin{cases} \dfrac{E_{HP,th}(u_{HP,k}, T_k)}{COP_{HP}(u_{HP,k}, T_k)} & \text{In winter} \\ \dfrac{E_{HP,cool}(u_{HP,k}, T_k)}{EER_{HP}(u_{HP,k}, T_k)} & \text{In summer} \end{cases} \tag{27}$$

where;

$$u_{HP,k} = \begin{cases} \dfrac{P_{HP,th,k}}{P_{HP,th,nom}(T_k)} & \text{In winter} \\ \dfrac{P_{HP,cool,k}}{P_{HP,cool,nom}(T_k)} & \text{In summer} \end{cases} \tag{28}$$

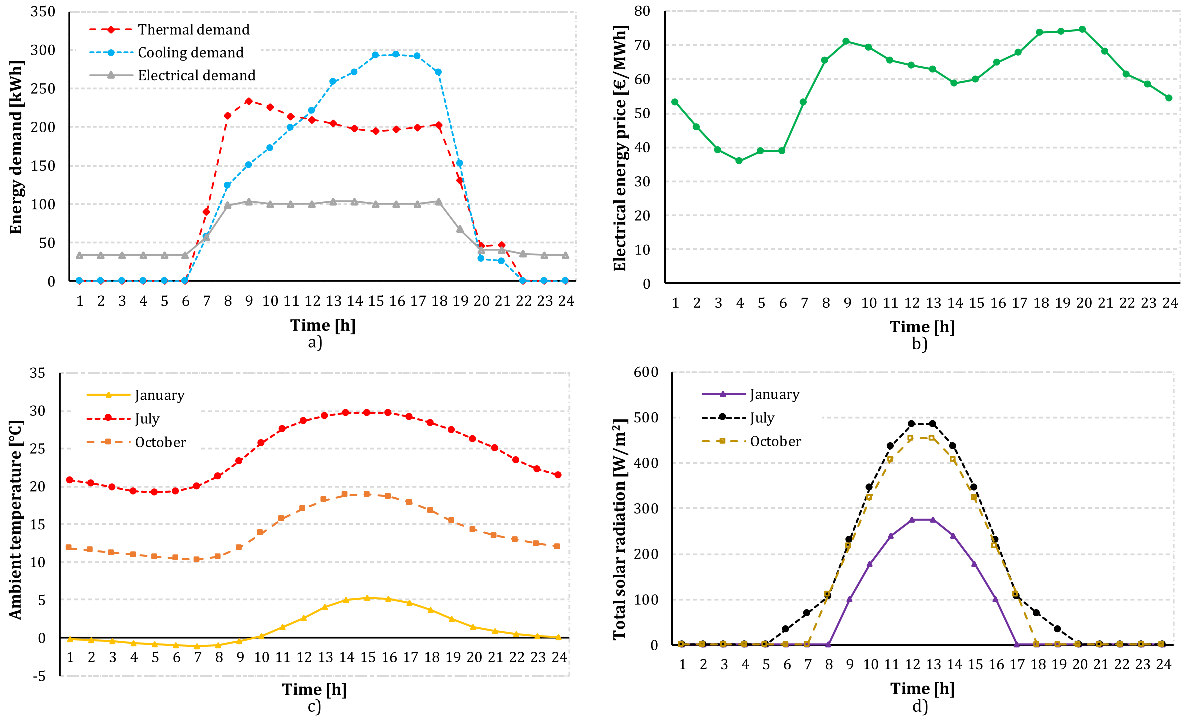

Fig. 2. Daily profiles for the energy demands (a), electricity price (b), ambient temperature (c) and total solar radiation (d).

As reported in Eq. (28), for both heat pumps (GSHP and ASHP), the decision variables (u_{GSHP} and u_{ASHP}) are defined as the ratio between the thermal power produced and the corrected nominal thermal power during winter, while they are defined as the ratio between the cooling power produced and the corrected nominal cooling power during summer. Moreover, T_k stands for the ground temperature for the GSHP, while it stands for ambient temperature for the ASHP.

Both heat pumps are able to modulate between 0% and 100% of the nominal thermal/cooling load. Moreover, the effect of the external temperature (air temperature for the ASHP and ground temperature for the GSHP) and the load on the heat pump performance is also considered [38].

(4) Absorption chiller

The fourth decision variable refers to the ABS unit, where the cooling energy produced and the thermal energy absorbed by the ABS are calculated as follows:

$$E_{ABS,cool,k} = u_{ABS,k} \cdot P_{ABS,cool,nom} \cdot \Delta k \quad (29)$$

$$E_{ABS,th,k} = \frac{E_{ABS,cool,k}(u_{ABS,k})}{EER_{ABS,K}} \quad (30)$$

where

$$u_{ABS,k} = \frac{P_{ABS,cool,k}}{P_{ABS,cool,nom}} \quad (31)$$

The ABS unit considered in this study is a single-effect H2O-BrLi with a nominal Energy Efficiency Ratio (*EER*) assumed equal to 0.7 [39].

(5) Thermal energy storage

A decision variable is also defined in order to control the amount of thermal energy used to meet the thermal energy demand. This is expressed by Eq. (32):

$$E_{TES,th,out,k} = u_{TES,k} \cdot x_{TES,k} \quad (32)$$

(6) Auxiliary systems

Finally, the remaining thermal and cooling energy demands not fulfilled by the systems reported above are met by the auxiliary systems, i.e., AB and AC:

$$E_{AB,th,k} = E_{AB,fuel,k} \cdot \eta_{AB,k} \quad (33)$$

$$E_{AC,cool,k} = E_{AC,el,k} \cdot EER_{AC,k} \quad (34)$$

2.2.2. Objective function

The optimal scheduling problem of the various energy technologies involved in the HEP is solved by investigating the following Hybrid Objective Function (*HOF*):

$$HOF(x_0) = \alpha \cdot NPEC(x_0) + \beta \cdot NOC(x_0) \quad (35)$$

α and β are two weights which can assume values between 0 and 1. *NPEC* and *NOC* are the normalized primary energy consumption and normalized operational costs, respectively. The case ($\alpha = 1$, $\beta = 0$) corresponds to the energy scheduling optimization, while the case ($\alpha = 0$, $\beta = 1$) corresponds to the economic scheduling optimization.

The Primary Energy Consumption (PEC) throughout one year of operation is expressed as reported in Eq. (36):

$$PEC(x_0) = \min_{u \in U} \sum_{k=0}^{N-1} E_{CHP,fuel,k}(x_k, u_k) + E_{AB,fuel,k}(x_k, u_k) + f_{grid \to user} \cdot E_{grid,el,taken,k}(x_k, u_k) - f_{user \to grid} \cdot E_{grid,el,sent,k}(x_k, u_k) \quad (36)$$

From Eq. (36), the PEC is defined as the sum of the fuel energy consumed by the CHP, the fuel energy consumed by the AB and the fuel energy related to the electrical energy taken/sent to the grid.

The Operational Costs (OC) associated with the operation of the HEP throughout one year is defined as follows:

$$OC(x_0) = FC_{HEP} + \min_{u \in U} \sum_{k=0}^{N-1} VC_{HEP}(x_k, u_k) + FUC_{HEP}(x_k, u_k) + EC_{HEP}(x_k, u_k) + EMC_{grid \rightarrow user}(x_k, u_k) - EMC_{user \rightarrow grid}(x_k, u_k) \quad (37)$$

The term *FC* stands for the fixed cost, *VC* stands for the variable cost, *FUC* is for the fuel cost, *EC* is for the emission cost and *EMC* refers to the cost of the electricity market. It should be mentioned that the *FC* does not depend on the scheduling strategy of the HEP components because these are fixed expenses on a yearly basis and they are calculated as a function of the system sizes:

$$FC_{HEP} = \sum_{l=1}^{L} SFC_l \cdot P_{l,nom} \quad (38)$$

with *SFC* and *P* representing the specific fixed cost and nominal size of the *l*-th system, respectively. The *VC* values are calculated as a function of the energy produced throughout one year:

$$VC_{HEP,k} = \sum_{l=1}^{L} SVC_l \cdot E_{l,k} \quad (39)$$

with *SVC* and *E* representing the specific variable cost and energy production of the *l*-th system, respectively. The *FUC* is calculated as follows:

$$FUC_{HEP,k} = SFUC \cdot (Fuel_{CHP,k} + Fuel_{AB,k}) \quad (40)$$

where *SFUC* is the specific cost of the natural gas. Similarly, the *EC* is calculated by using Eq. (41):

$$EC_{HEP,k} = SEC \cdot FE_k \quad (41)$$

with *SEC* and *FE* representing the specific emission cost and fuel emission, respectively. Finally, the cost of the electricity is calculated by considering the hourly trend of the electricity market:

$$EMC_{grid \rightarrow user,k} = (EEP_k + \Delta EEP) \cdot E_{grid,el,taken,k} \quad (42)$$

$$EMC_{user \rightarrow grid,k} = (EEP_k) \cdot E_{grid,el,sent,k} \quad (43)$$

The term *EEP* represents the hourly electricity price [€/MWh] of the Italian electricity market (see Fig. 2b). The revenue from selling electricity to the grid [€/MWh] is lower than the cost of the electricity bought from the grid by a fixed amount (*ΔEEP*) equal to 95 €/MWh which is specific to the considered Country.

2.2.3. Scheduling optimization

The discrete-time optimal scheduling problem of minimizing the primary energy consumption and operational costs over one year with an hourly time-step is formulated as follows:

$$\min_{\substack{\{u_{CHP}, u_{HP}, u_{ABS}, u_{TES}\} \\ \in [u_{min}, u_{max}]}} \sum_{k=0}^{N-1} \alpha \cdot NPEC\left(x_{CHP,k}, x_{TES,k}, u_{CHP,k}, u_{HP,k}, u_{ABS,k}, u_{TES,k}\right) + \beta \cdot NOC\left(x_{CHP,k}, x_{TES,k}, u_{CHP,k}, u_{HP,k}, u_{ABS,k}, u_{TES,k}\right) \quad (44)$$

s.t.

$$x_{CHP,k+1} = \begin{cases} 1 & \text{if} \quad u_{CHP,k} \neq 0 \\ 0 & \text{if} \quad u_{CHP,k} = 0 \end{cases} \quad (45)$$

$$x_{TES,k+1} = (1 - c_{diss}) \cdot \left(x_{TES,k} + E_{TES,th,in,k} - E_{TES,th,out,k}\right) \quad (46)$$

$$x_{CHP,0} = 0; x_{TES,0} = 0 \quad (47)$$

$$x_{CHP,N} = 0 \vee 1; x_{TES,min} \leq x_{TES,N} \leq x_{TES,max} \quad (48)$$

$$N = 8760 \quad (49)$$

In this paper, the scheduling optimization problem (Eqs. (44)–(49)) of the HEP components is solved by using a solver developed by Sundstrom and Guzzella in [19] that deals with discrete-time optimal-control problems using Bellman's DP algorithm. Both solver and plant model are implemented in Matlab® [40].

Table 1
Fixed and variable operational costs for the HEP components.

Technology	Fixed costs [€/(kW·year)]	Variable costs [€/kWh]	Reference
CHP	8.36	0.0150	[46,47]
GSHP	7.22	0.0005	[46]
ASHP	7.22	0.0005	[46]
ABS	9.20	0.0017	[46,48]
AB	2.21	0.0011	[46]
AC	7.22	0.0005	[46]

Table 2
Sizes of the HEP components [42].

Technology	Size	Value
PV	A_{PV} [m^2]	209
STC	A_{STC} [m^2]	119
CHP	$P_{el,CHP,nom}$ [kW_e]	100
	$\eta_{el,CHP,nom}$ [-]	0.27
	$P_{th,CHP,nom}$ [kW_{th}]	195
	$\eta_{th,CHP,nom}$ [-]	0.54
GSHP	$P_{th,GSHP,nom}$ [kW_{th}]	242
	$COP_{ASHP,nom}$ [-]	3.35
	$P_{cool,GSHP,nom}$ [kW_c]	198
	$EER_{GSHP,nom}$ [-]	4.6
ASHP	$P_{th,GSHP,nom}$ [kW_{th}]	17
	$COP_{ASHP,nom}$ [-]	2.8
	$P_{cool,GSHP,nom}$ [kW_c]	15
	$EER_{ASHP,nom}$ [-]	2.7
ABS	$P_{cool,ABS,nom}$ [kW_c]	109
	$EER_{ABS,nom}$ [-]	0.7
TES	V_{TES} [l]	1330

3. Case studies

3.1. Commercial building

The first case study considered in this work consists of a tower composed of thirteen floors where 1189 m^2 (corresponding to 5735 m^3) are used for commercial purposes and 4457 m^2 (corresponding to 20187 m^3) are used as offices. The tower is situated in northern Italy in the climatic zone "A" [41].

Fig. 2a shows the thermal, cooling and electrical energy demand profiles for the day in which the peak of the demands occurs [42]. Moreover, the heating period lasts from 15th October to 15th April, while the cooling period lasts from 15th June to 15th September. The energy demand for hot water (which is included in the thermal demand) and electricity are present throughout the whole year.

Fig. 2b reports the profile of a day-ahead (24 h) electricity price of the 2019 Italian electricity market [43]. Since the market price for electricity is determined according to supply and demands bids of market participants, the profile of the day-ahead electricity price changes throughout the year. Thus, in this study, the real profile of the 2019 electricity price of the Italian market is considered [43]. Figures 2c and 2d report the hourly ambient temperature and total solar radiation, calculated for the climatic zone "A", for a typical day of January, July and October. These were calculated by following the standard reported in [41].

According to the Italian market, the cost of natural gas is considered equal to 0.23 €/Stdm^3 [44]. Moreover, the cost for CO_2 emissions is assumed equal to 22 €/tCO_2 considering an emission factor equal to $1.972 \cdot 10^{-3}$ tCO_2/Stdm^3 [45].

Table 1 reports the fixed and variable costs associated with the operation and maintenance of the different HEP components. Since no

Table 3
Energy systems switch-on priority for winter and summer.

Winter	Summer
W1: TES, CHP, GSHP, ASHP	S1: ABS, GSHP, ASHP
W2: TES, GSHP, ASHP, CHP	S2: GSHP, ASHP, ABS
W3: GSHP, ASHP, TES, CHP	
W4: GSHP, TES, CHP, ASHP	
W5: TES, CHP, ASHP, GSHP	
W6: ASHP, GSHP, TES, CHP	
W7: ASHP, TES, CHP, GSHP	

Table 4
Sizes of the HEP components [50].

Technology	Size	Value
PV	$A_{PV}/A_{available}$ [-]	1
CHP	$P_{el,CHP,nom}/P_{el,campus,peak}$ [-]	0.57
	$P_{th,CHP,nom}/P_{th,campus,peak}$ [-]	0.32
	$\eta_{el,CHP,nom}$ [-]	0.30
ABS	$P_{cool,ABS,nom}/P_{cool,campus,peak}$ [-]	1
	$EER_{ABS,nom}$ [-]	0.7
AB	$P_{th,AB,nom}/P_{th,campus,peak}$	1
	$\eta_{th,AB,nom}$ [-]	0.93
AC	$P_{cool,AC,nom}/P_{cool,campus,peak}$ [-]	1
	$EER_{AC,nom}$ [-]	4
TES	$E_{th,TES,max}/P_{th,campus,peak}$ [h]	0.22

moving parts are presented in the STC, PV and TES, these costs are ignored for these systems. For instance, the maintenance costs for STC plants is lower than 1 €/MWh [46].

The yearly fixed costs, which are independent of the running time of the system and its operation strategy, are calculated as a function of the system nominal capacity. Moreover, they include the costs for administration, property tax, insurance and operational staff. The variable costs are calculated as a function of system energy production. It should be mentioned that fixed and variable costs do not include fuel costs, but only the costs related to the operation and maintenance of the system.

The sizes of the different plant components are summarized in Table 2. These sizes are obtained by optimizing the sizes of the HEP components by using a genetic algorithm. The AB and AC are sized by considering the peak of the thermal and cooling power demand, respectively.

The results obtained by the DP method are compared to commonly used operation strategies. The considered strategies are reported in Table 3. The term “W” stands for winter, while “S” stands for summer. The SOP strategies are constructed by considering all the possible combinations of the winter (W) and summer strategies (S). Thus, fourteen Switch-On Priority (SOP) strategies (7 W multiplied by 2 S) are used as benchmarks. It should be mentioned that for all SOP combinations, the renewable energy systems (STC and PV) are the first to be activated, while the auxiliary systems (AB and AC) are the last.

3.2. University campus

As a second case study the campus of the University of Parma (Italy) is considered in this paper [49]. The campus includes 21 buildings which are distributed over an area of approximately 77 ha. For the sake of brevity, thermal, cooling and electrical energy demands are not reported in this paper. More details about the energy demands, ambient conditions and description of the case study can be found in [50,51]. It has to be mentioned that energy demands were normalized with respect to their corresponding peak value because of confidentiality reasons.

In this case study, the HEP is composed of a PV, CHP (based on a medium scale gas turbine), ABS, AC, AB and TES. Table 4 presents the normalized sizes of the plant components which belong to the hybrid demand following “HDF-L” case reported in [50]. Moreover, battery

Table 5
Fixed and variable operational costs for the HEP components.

Technology	Fixed costs [€/(kW·year)]	Variable costs [€/kWh]	Reference
CHP	19.5	0.010	[46,52]
ABS	2	0.001	[46,48]
AB	2	0.001	[46]
AC	2	0.003	[46]

energy storage technologies are not considered, while the AB and ABS are sized by considering the peak of the thermal and cooling power demand, respectively. Fixed and variable costs associated with the operation and maintenance of the plant components are reported in Table 5.

For this case study, the results obtained by the DP method are compared to four operation strategies investigated in [50]. Two of the strategies are Thermal Demand Following (TDF1 and TDF2) strategies, while the other two are Electric Demand Following (EDF1 and EDF2) strategies.

The operation strategy TDF1 differs from TDF2 in that the cooling demand is first met by the ABS followed by the AC, while in TDF2 the starting order is the opposite. This difference also stands between EDF1 and EDF2.

Finally, all simulations have been carried out on a personal computer with 2 cores and 16 GB RAM. The time taken by the DP to solve the scheduling optimization problem is around 90 min.

4. Results and discussion

4.1. Commercial building

This section reports and discusses the results obtained from the energy, economic and hybrid scheduling optimization of the different energy technologies composing the energy plant. Fig. 3 shows the optimization results in terms of PEC and OC for the DP and SOP operation strategies by considering the energy scheduling optimization ($\alpha = 1$, $\beta = 0$) and economic scheduling optimization ($\alpha = 0$, $\beta = 1$). With reference to the energy scheduling optimization ($\alpha = 1$, $\beta = 0$), the DP method always allows better results in terms of primary energy saving compared to the SOP scheduling strategies. The achievable primary energy saving ranges from 3.83% (compared to W6S2) to 8.31% (compared to W7S1). The amount of primary energy consumed by the CHP falls almost in the middle between the W6S2 and W7S1 cases, which represent the best and worst cases in terms of PEC, respectively (see Table A1). Moreover, the electrical energy taken from the grid, when the DP is used, falls between these two cases. Therefore, it can be inferred that, in order to reduce the PEC, the DP algorithm optimally operates the systems which are fed by fossil fuel (such as the CHP and AB) and the systems powered by electricity (such as the GSHP, ASHP and AC). This can be clearly observed from the split of the energy consumption among the different energy systems composing the plant (see Table A1).

Furthermore, the economic scheduling optimization by using the DP strategy always allows a reduction of the operational costs. The cost reduction which can be achieved thanks to the DP algorithm ranges from 11.7% (W1S1, W2S1 and W5S1) to 25.1% (W3S2 and W6S2). By considering the best and worst SOP cases, i.e. W1S1 and W3S2, it appears that the electrical energy taken from the grid is the mostly responsible for the increase of the operational costs with about 43 k€ for the W1S1 and 71 k€ for the W3S2 (Table A4). In fact, by using the DP algorithm, the cost of the electricity taken from the grid decreases to about 15 k€. On the other hand, this causes an increase of the operational costs related to the fuel consumption and emission of the CHP. However, the use of the CHP is economically more convenient than fulfilling the energy demands by buying electricity from the grid. Thus, moving from the energy to the economic scheduling optimization, the

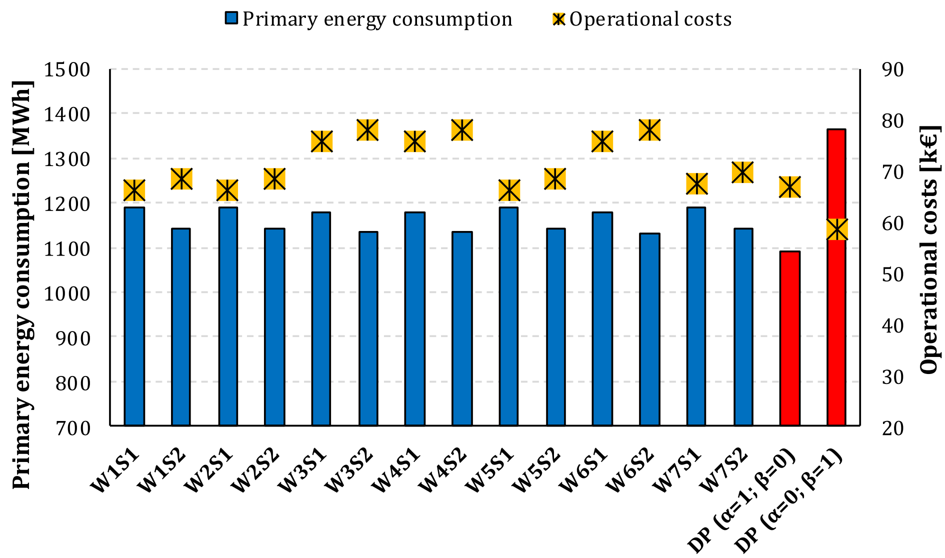

Fig. 3. Primary energy consumption and operational costs for the energy ($\alpha = 1$; $\beta = 0$) and economic ($\alpha = 0$; $\beta = 1$) scheduling optimization.

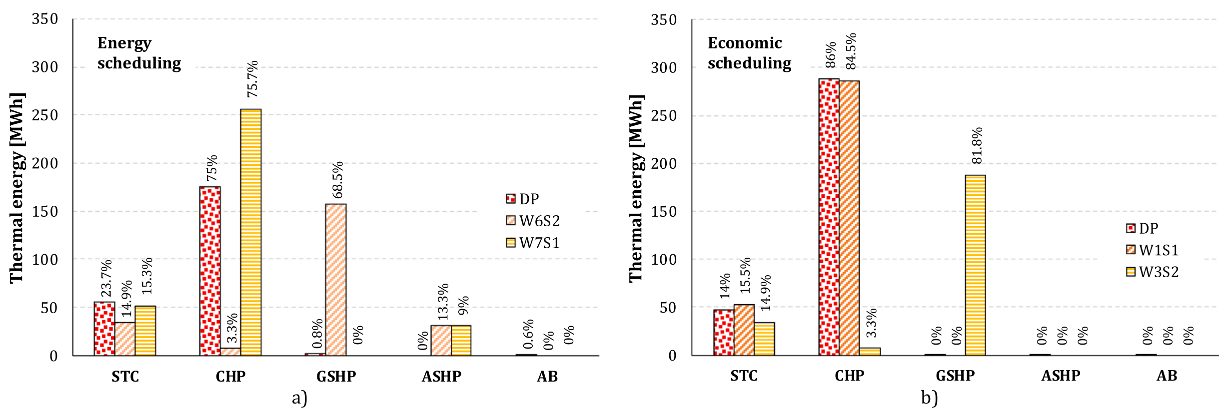

Fig. 4. Contribution of the HEP components to the thermal energy demand for the energy a) and economic b) scheduling optimization.

option of CHP-based energy production becomes an economically favorable option. However, the reduction of the operational costs occurs to the cost of an increase of the primary energy consumption, which is expected because in this case only the operational costs were minimized ($\alpha = 0$, $\beta = 1$), i.e. the optimization is mono-objective.

Another relevant finding regards the cost of the electricity exchanged with the grid. Results show that the average cost of the electricity taken from the grid is about 146 €/MWh for the DP case, about 148 €/MWh for W1S1 and about 150 €/MWh for the W3S2 strategy. This means that the DP algorithm allows electricity purchase from the grid with a lower cost compared to the SOP strategies.

Moreover, it was found that the average price of the electricity sold

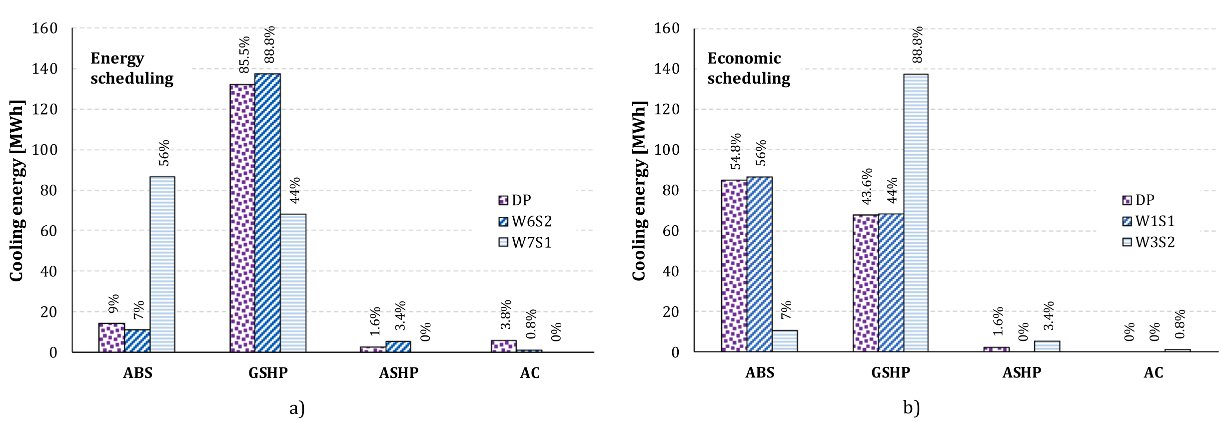

Fig. 5. Contribution of the HEP components to the cooling energy demand for the energy a) and economic b) scheduling optimization.

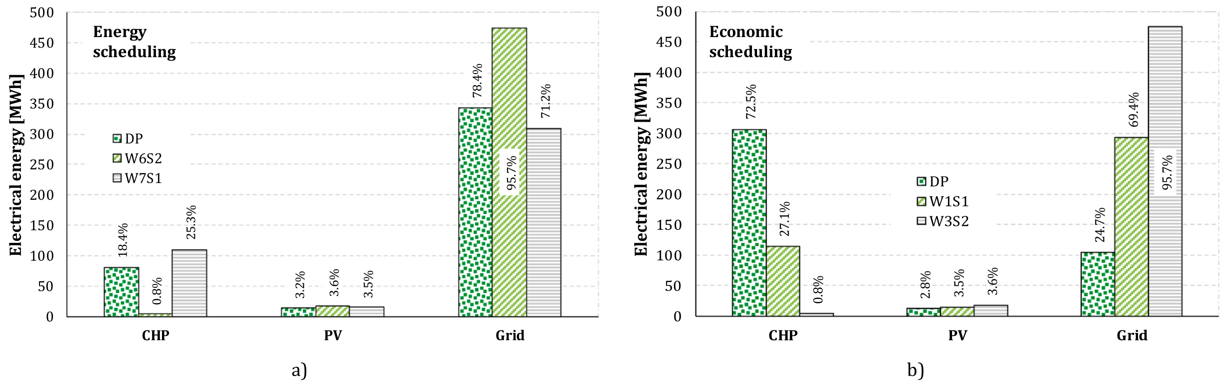

Fig. 6. Contribution of the HEP components to the electrical energy demand for the energy a) and economic b) scheduling optimization.

to the grid is about 66 €/MWh for the DP, about 60 €/MWh for the W1S1 and about 50 €/MWh for W3S2. Thus, when the DP strategy is adopted, the excess of electrical energy production is sold to the grid at a higher price. In fact, since the actual electricity market is considered in this work, the DP algorithm allows to optimize the interaction between the HEP and the grid by buying electricity from the grid during the hours of day when the price is lower and to sell electricity to the grid when the price is higher. In this work, the amount of electricity sent to the grid is small and consequently the revenue from selling electricity is negligible. However, the effect of the revenue from selling electricity would be more influencing when other renewable systems are integrated and large scale case studies (e.g. micro-grids) are considered.

Fig. 4 shows the production of thermal energy from the different HEP components for the energy and economic scheduling optimization. From Fig. 4a, the DP algorithm meets 75% of the thermal energy demand by exploiting the CHP and 23.7% by means of the STC. GSHP and AB systems are rarely used and just to cover thermal peak demands. Moreover, compared to the SOP strategies, the thermal energy met by the STC is higher; this means a higher utilization factor of renewable energy sources.

It worth to be noted that when the DP strategy is followed, the amount of energy lost through the storage is equal to about 12 MWh per year, while it is equal to about 22 MWh per year for both the W6S2 and W7S1 strategies. Indeed, since the energy dissipation is proportional to the energy stored in the TES, the DP tries to limit the amount of energy kept in the TES.

As highlighted in Fig. 4b, the economic scheduling optimization by means of DP increases the production of thermal energy from the CHP by about 112 MWh per year, compared to the energy scheduling optimization (Fig. 4a). This is because in addition to building thermal demand, the CHP is required to meet the thermal demand required by the ABS, which in turn meets a higher cooling energy demand when the systems are optimized by minimizing the operational costs (see Fig. 5b). In fact, as discussed at the beginning of this section, the use of the CHP is economically more convenient than fulfilling the energy demands by buying electricity from the grid. This is also confirmed by the W1S1 strategy (i.e., the SOP with lowest costs), in which the thermal energy demand is mostly fulfilled by the CHP system (Fig. 4b). Instead, for the W3S2-SOP (i.e., the SOP with highest costs), most of the thermal energy demand is met by the GSHP, while the remaining part is covered by the STC. Finally, it is worth noting that the AB is in practice never exploited, for both scheduling optimization.

Fig. 5a shows that, if the DP strategy is adopted, the cooling energy demand is mostly fulfilled by the GSHP followed by the ABS, when the systems are optimally operated by minimizing the energy consumption. A similar share of cooling energy between the HEP components is also found for the W6S2 strategy (i.e., the SOP with lowest energy consumption). Conversely, when the W7S1 is adopted (i.e., the SOP with

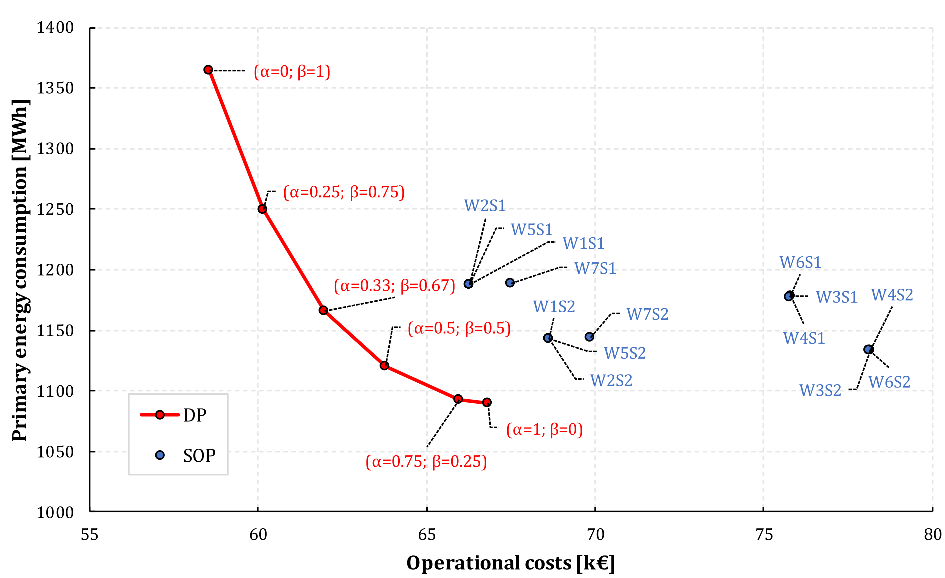

Fig. 7. Primary energy consumption and operational costs for the hybrid scheduling optimization.

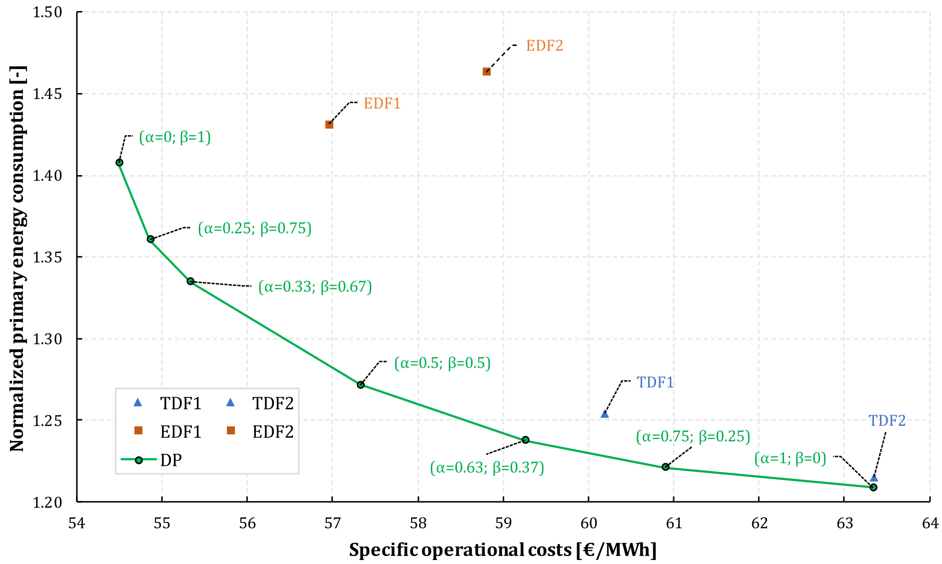

Fig. 8. Primary energy consumption and operational costs for the hybrid scheduling optimization.

highest energy consumption), the system which meets most of the cooling demand is the ABS, while the remaining part is fulfilled by the GSHP.

For the economic scheduling optimization, a similar behavior between the DP and W1S1 displays for the contribution of the HEP components to the cooling energy demand (Fig. 4b). More in details, since the ABS in the W1S1 case is the system which is activated first, this meets about more than half of the cooling energy demand by recuperating a fraction of the thermal energy produced by the STC and CHP systems. Then, the remaining part is met by the GSHP, which according to the W1S1, is the second system to be activated. Instead, when adopting the W3S2 strategy, the cooling demand is almost entirely met by the GSHP. From the analysis of these results, it seems that in order to reduce the operational costs, it is better to meet the cooling energy demand by using energy systems which are powered by thermal energy (i.e., the ABS) instead of systems powered by electricity (i.e., the heat pumps).

From Fig. 6, the electrical energy produced by the different HEP components and the electricity taken from the grid is mainly used to meet building electrical energy demand and to operate the GSHP, ASHP and AC units. With reference to energy scheduling optimization (Fig. 6a), almost the whole electrical energy demand is taken from the grid for the W6S2. Instead, for the W7S1 and DP strategies, a considerable part is also provided by the CHP system.

As clearly shown in Fig. 6b, the adoption of a DP strategy leads to a high production of electrical energy from the CHP, which allows to reduce the amount of electrical energy taken from the grid. This is mainly due to the high cost associated with the electricity taken from the Italian grid. The adoption of the W1S1 causes a 27.1% of production from the CHP and about 69.4% of electricity is taken from the grid. Regarding the W3S2, almost the whole building electricity demand and the electricity required by the heat pumps is taken from the grid. Consequently, higher operational costs are associated with the use of the SOP strategies (see Table A4). Finally, it has to be highlighted that the electrical energy produced from the PV and self-consumed is almost the same for the energy and economic scheduling strategies with about 22.2 MWh per year.

Fig. 7 reports the optimization results of the DP algorithm by considering a hybrid objective function with different combinations of the weights α and β, which further proves the effectiveness of the DP-based optimization strategy. Compared to the DP optimization of the energy scenario ($\alpha = 1, \beta = 0$), the optimization of the operational costs by means of the DP ($\alpha = 0, \beta = 1$) allows to reduce the operational costs by about 12%. However, this reduction of the operational costs occurs to the cost of an increase of the primary energy consumption of about 25%. Moreover, the optimization of the operational costs shows that the cogeneration of thermal and electrical energy from a CHP coupled with an ABS is economically more convenient than fulfilling the energy demands by heat pumps and importing electricity from the grid.

It should be mentioned that according to the European directives [53] the cogeneration efficiency of the CHP must be higher than 75%. However, passing from the case ($\alpha = 1$, $\beta = 0$) to ($\alpha = 0$, $\beta = 1$), the overall cogeneration efficiency decreases from about 82% to about 53%. As highlighted in Fig. 7, the best compromise between energy consumption and operational costs can be reached by considering the hybrid optimization cases ($\alpha = 0.5, \beta = 0.5$) and ($\alpha = 0.75, \beta = 0.25$). In fact, compared to the SOP strategies, the case ($\alpha = 0.5, \beta = 0.5$) allows a minimum primary energy saving of about 1.2% and a minimum cost saving of about 3.8%, while the case ($\alpha = 0.75$, $\beta = 0.25$) allows a minimum primary energy saving of about 3.6% and a minimum cost of 0.43%. Moreover, for both cases, the annual cogeneration efficiency is about 82%.

Finally, Fig. 7 clearly shows that the adoption of the DP strategy always allows better results than the SOP operation strategies. This is mainly due to the fact that when a SOP strategy is used, the starting order of the plant components is fixed and the systems are required to fulfill the energy demands in a predefined sequence. Instead, at each time-step of the considered time frame, the DP algorithm defines the operation strategy which minimizes the primary energy consumption and/or the operational costs. Moreover, due to its deterministic nature, DP is able to find the global optimal solution of the problem [16,19].

4.2. University campus

In order to further demonstrate the effectiveness of the proposed methodology, an additional investigation is made in this section by considering a second case study, represented by the campus of the University of Parma. Fig. 8 compares the optimization results of the DP algorithm by considering different combination of the weights α and β to the results of the thermal and electrical demand following strategies, i.e. TDF1, TDF2, EDF1 and EDF2. Moreover, because of confidentiality reasons, the primary energy consumption and operational costs are reported in Fig. 8 by dividing their values by the total thermal, cooling and electrical energy demands of the campus.

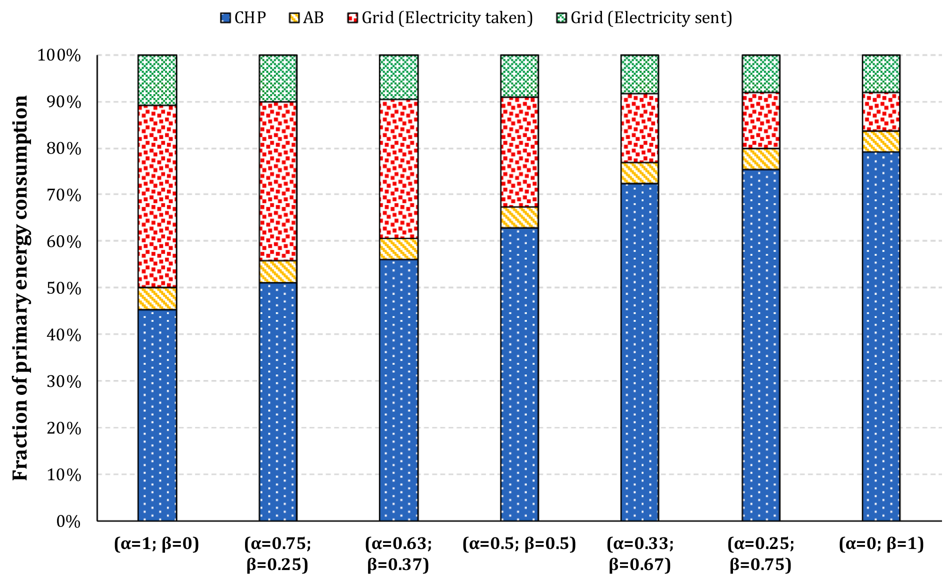

Fig. 9. Fraction of primary energy consumption for the DP optimization.

Results in Fig. 8 show that thermal demand following strategies (TDF1 and TDF2) are more convenient in terms of primary energy consumption than electrical demand following strategies (EDF1 and EDF2), which instead are more economically beneficial. In particular, among the strategies used as benchmarks, TDF2 is the strategy with the lower primary energy consumption, while EDF1 allows the lower operational costs. However, it is clear that energy scheduling optimization ($\alpha = 1$, $\beta = 0$) by means of DP allows a lower primary energy consumption than TDF2 as well as the economic scheduling optimization ($\alpha = 0$, $\beta = 1$) which allows lower operational costs compared to EDF1. More in detail, the energy scheduling optimization ($\alpha = 1$, $\beta = 0$) by means of DP allows a primary energy saving between about 0.5% (compared to TDF2) and 17.4% (compared to EDF2). Moreover, the economic scheduling optimization ($\alpha = 0$, $\beta = 1$) enables to reduce the operational costs by about 4.3% (compared to EDF1) and 14% (compared to TDF2).

Another interesting feature that makes DP superior to the operation strategies considered as benchmarks relies on its flexibility and ability to solve scheduling optimization problems under different optimization constraints. Indeed, DP proved its ability to handle hybrid objective functions by considering different combinations of weights α and β. In fact, the other operation strategies (TDF and EDF) fulfill the energy demands by following a predefined sequence of operation regardless of the optimization objective and constraints.

Fig. 9 describes the fraction of primary energy consumption of the different terms reported in Eq. (36). As for the other case study, Fig. 9 shows how the option of using a CHP becomes economically more beneficial when the objective is to optimize the operational costs ($\alpha = 0$, $\beta = 1$). This is clearly highlighted by the fraction of the primary energy consumption of the CHP which increases as the optimization objective passes from the energy ($\alpha = 1$, $\beta = 0$) to the economic ($\alpha = 0$, $\beta = 1$) scheduling optimization. On the contrary, passing from the energy to the economic scheduling optimization, the fraction of the electricity taken from the grid progressively decreases.

5. Conclusions

This paper presented a new general methodology based on a dynamic programming algorithm for the optimization of the energy and economic scheduling of a hybrid energy plant composed of renewable energy systems, fossil fuel energy systems and energy storage technologies. The developed optimization methodology was successfully applied to two different case studies, i.e. a commercial building and a University campus. The optimal scheduling was conducted by considering energy, economic and hybrid objective functions.

From the optimization results of the commercial building case study, compared to switch-on priority operation strategies, the energy scheduling optimization ($\alpha = 1$, $\beta = 0$) by means of dynamic programming allowed a primary energy saving between 3.8% and 8.3%. Instead, the economic scheduling optimization ($\alpha = 0$, $\beta = 1$) enabled to reduce the yearly operational costs by about 11.7% to 25.1%. Furthermore, the energy scheduling optimization results of the University campus showed that it was possible to achieve a primary energy saving between 0.5% and 17.4%, compared to commonly used thermal and electrical energy demand following strategies. Regarding the economic scheduling optimization, the saving of the operational costs was between 4.3% and 14%.

As the optimization objective moves from the energy scheduling to the economic optimization, for both case studies, it was possible to infer that fulfilling the user energy demands by using a combined heat and power system becomes economically more convenient than the option of importing electricity from the grid.

Finally, the results showed that both energy ($\alpha = 1$, $\beta = 0$) and economic ($\alpha = 0$, $\beta = 1$) scheduling optimization by means of dynamic programming always outperformed traditional operation strategies. The strength and superiority of the dynamic programming was also demonstrated in this paper by showing its ability to handle hybrid objective functions.

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.

Appendix A

See Tables A1–A4.

Table A1
Primary energy consumption for the DP and SOP operation strategies of the energy scheduling optimization.

	DP	SOP													
		W1S1	W1S2	W2S1	W2S2	W3S1	W3S2	W4S1	W4S2	W5S1	W5S2	W6S1	W6S2	W7S1	W7S2
$E_{CHP,fuel}$ [MWh]	351.1	559.7	383.7	559.7	383.7	205.6	29.5	205.6	29.5	559.7	383.7	205.6	29.5	507.2	331.2
$E_{AB,fuel}$ [MWh]	1.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$E_{grid,taken,fuel}$ [MWh]	805.6	690.1	820.0	690.1	820.0	985.4	1115.3	985.4	1115.3	690.1	820.0	984.9	1114.7	727.1	856.9
$E_{grid,sent,fuel}$ [MWh]	68.4	61.9	60.4	61.9	60.4	12.8	11.2	12.8	11.2	61.9	60.4	12.8	11.3	45.9	44.3
PEC [MWh]	1090	1188	1143	1188	1143	1178	1134	1178	1134	1188	1143	1178	1133	1188	1144
Saving [%]		8.27	4.69	8.27	4.69	7.51	3.88	7.51	3.88	8.27	4.69	7.47	3.83	8.31	4.74

Table A2
Operational costs for the DP and SOP operation strategies of the energy scheduling optimization.

	DP	SOP													
		W1S1	W1S2	W2S1	W2S2	W3S1	W3S2	W4S1	W4S2	W5S1	W5S2	W6S1	W6S2	W7S1	W7S2
FUC_{HEP} [k€]	8.45	13.42	9.20	13.42	9.20	4.93	0.71	4.93	0.71	13.42	9.20	4.93	0.71	12.17	7.94
EC_{HEP} [k€]	1.59	2.53	1.74	2.53	1.74	0.93	0.13	0.93	0.13	2.53	1.74	0.93	0.13	2.29	1.50
FC_{HEP} [k€]	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35
VC_{HEP} [k€]	1.62	2.19	1.47	2.19	1.47	0.96	0.24	0.96	0.24	2.19	1.47	0.96	0.24	2.04	1.31
$EMC_{grid,taken}$ [k€]	50.58	43.38	51.44	43.38	51.44	62.91	70.97	62.91	70.97	43.38	51.44	62.88	70.94	45.81	53.87
$EMC_{grid,sent}$ [k€]	1.76	1.60	1.57	1.60	1.57	0.28	0.25	0.28	0.25	1.60	1.57	0.28	0.25	1.15	1.11
OC [k€]	66.83	66.27	68.62	66.27	68.62	75.80	78.15	75.80	78.15	66.27	68.62	75.77	78.12	67.50	69.86
Saving [%]		−0.85	2.61	−0.85	2.61	11.83	14.49	11.83	14.49	−0.85	2.61	11.80	14.46	1.00	4.34

Table A3
Primary energy consumption for the DP and SOP operation strategies of the economic scheduling optimization.

	DP	SOP													
		W1S1	W1S2	W2S1	W2S2	W3S1	W3S2	W4S1	W4S2	W5S1	W5S2	W6S1	W6S2	W7S1	W7S2
$E_{CHP,fuel}$ [MWh]	1190.9	559.7	383.7	559.7	383.7	205.6	29.5	205.6	29.5	559.7	383.7	205.6	29.5	507.2	331.2
$E_{AB,fuel}$ [MWh]	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$E_{grid,taken,fuel}$ [MWh]	246.0	690.1	820.0	690.1	820.0	985.4	1115.3	985.4	1115.3	690.1	820.0	984.9	1114.7	727.1	856.9
$E_{grid,sent,fuel}$ [MWh]	72.6	61.9	60.4	61.9	60.4	12.8	11.2	12.8	11.2	61.9	60.4	12.8	11.3	45.9	44.3
PEC [MWh]	1364	1188	1143	1188	1143	1178	1134	1178	1134	1188	1143	1178	1133	1188	1144
Saving [%]		−14.9	−19.3	−14.9	−19.3	−15.8	−20.4	−15.8	−20.4	−14.9	−19.3	−15.9	−20.4	−14.8	−19.3

Table A4
Operational costs for the DP and SOP operation strategies of the economic scheduling optimization.

	DP	SOP													
		W1S1	W1S2	W2S1	W2S2	W3S1	W3S2	W4S1	W4S2	W5S1	W5S2	W6S1	W6S2	W7S1	W7S2
FUC_{HEP} [k€]	28.56	13.42	9.20	13.42	9.20	4.93	0.71	4.93	0.71	13.42	9.20	4.93	0.71	12.17	7.94
EC_{HEP} [k€]	5.39	2.53	1.74	2.53	1.74	0.93	0.13	0.93	0.13	2.53	1.74	0.93	0.13	2.29	1.50
FC_{HEP} [k€]	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35
VC_{HEP} [k€]	5.10	2.19	1.47	2.19	1.47	0.96	0.24	0.96	0.24	2.19	1.47	0.96	0.24	2.04	1.31
$EMC_{grid,taken}$ [k€]	15.24	43.38	51.44	43.38	51.44	62.91	70.97	62.91	70.97	43.38	51.44	62.88	70.94	45.81	53.87
$EMC_{grid,sent}$ [k€]	2.10	1.60	1.57	1.60	1.57	0.28	0.25	0.28	0.25	1.60	1.57	0.28	0.25	1.15	1.11
OC [k€]	58.53	66.27	68.62	66.27	68.62	75.80	78.15	75.80	78.15	66.27	68.62	75.77	78.12	67.50	69.86
Saving [%]		11.7	14.7	11.7	14.7	22.8	25.1	22.8	25.1	11.7	14.7	22.7	25.1	13.3	16.2

References

[1] European Commission, 2016. Buildings <https://ec.europa.eu/energy/en/topics/energy-efficiency/buildings>.
[2] K.S. Krishna, K.S. Kumar, A review on hybrid renewable energy systems, Renew. Sustain. Energy Rev. 52 (2015) 907–916.
[3] H. Bahlawan, M. Morini, M. Pinelli, P.R. Spina, Dynamic programming based methodology for the optimization of the sizing and operation of hybrid energy plants, Appl. Therm. Eng. 160 (2019) 113967.
[4] J. Xu, F. Wang, C. Lv, Q. Huang, H. Xie, Economic-environmental equilibrium based optimal scheduling strategy towards wind-solar-thermal power generation system under limited resources, Appl. Energy 231 (2018) 355–371.
[5] A.L. Facci, V.K. Krastev, G. Falucci, S. Ubertini, Smart integration of photovoltaic production, heat pump and thermal energy storage in residential applications, Sol. Energy 192 (2019) 133–143.
[6] A. Messac, Optimization in Practice with MATLAB®, Cambridge University Press, 2015.
[7] L. Moretti, E. Martelli, G. Manzolini, An efficient robust optimization model for the unit commitment and dispatch of multi-energy systems and microgrids, Appl. Energy 261 (2020) 113859.
[8] S. Nojavan, K. Saberi, K. Zare, Risk-based performance of combined cooling, heating and power (CCHP) integrated with renewable energies using information gap decision theory, Appl. Therm. Eng. 159 (2019) 113875.
[9] X. Wang, H. Tian, F. Yan, W. Feng, R. Wang, J. Pan, Optimization of a distributed energy system with multiple waste heat sources and heat storage of different temperatures based on the energy quality, Appl. Therm. Eng. 181 (2020) 115975.
[10] L. Urbanucci, Limits and potentials of Mixed Integer Linear Programming methods for optimization of polygeneration energy systems, Energy Procedia 148 (2018) 1199–1205.
[11] S.Y. Abujarad, M.W. Mustafa, J.J. Jamian, Recent approaches of unit commitment in the presence of intermittent renewable energy resources: A review, Renew. Sustain. Energy Rev. 70 (2017) 215–223.
[12] S. Twaha, M.A.M. Ramli, A review of optimization approaches for hybrid distributed energy generation systems: Off-grid and grid connected systems, Sustain. Cities Soc. 41 (2018) 320–331.
[13] L. Ling, Q. Zhang, Y. Yu, X. Ma, S. Liao, Energy saving analysis of the cooling plant using lake water source base on the optimized control strategy with set points change, Appl. Therm. Eng. 130 (2018) 1440–1449.
[14] M. Karami, L. Wang, Particle Swarm optimization for control operation of an all-variable speed water-cooled chiller plant, Appl. Therm. Eng. 130 (2018) 962–978.

[15] H.J. Chen, D.W.P. Wang, S.L. Chen, Optimization of an ice-storage air conditioning system using dynamic programming method, Appl. Therm. Eng. 25 (2005) 461–472.
[16] R.E. Bellman, Dynamic Programming, Princeton University Press, 1957.
[17] B. Ming, P. Liu, S. Guo, L. Cheng, Y. Zhou, S. Gao, H. Li, Robust hydroelectric unit commitment considering integration of large-scale photovoltaic power: A case study in China, Appl. Energy 228 (2018) 1341–1352.
[18] C. Saletti, A. Gambarotta, M. Morini, Development, analysis and application of a predictive controller to a small-scale district heating system, Appl. Therm. Eng. 165 (2020) 114558.
[19] O. Sundstrom, L. Guzzella, A generic dynamic programming Matlab function, in: Proceedings of the 18th IEEE CCA, Saint Petersburg, Russia, 2009, pp. 1625–1630.
[20] X.P. Chen, N. Hewitt, Z.T. Li, Q.M. Wu, X. Yuan, T. Roskilly, Dynamic programming for optimal operation of a biofuel micro CHP-HES system, Appl. Energy 208 (2017) 132–141.
[21] J. Kuang, C. Zhang, B. Sun, Stochastic dynamic solution for off-design operation optimization of combined cooling, heating, and power systems with energy storage, Appl. Therm. Eng. 163 (2019) 114356.
[22] A.L. Facci, S. Ubertini, Meta-heuristic optimization for a high-detail smart management of complex energy systems, Energy Convers. Manag. 160 (2018) 341–353.
[23] A.L. Facci, A. Ubertini, Analysis of a fuel cell combined heat and power plant under realistic smart management scenarios, Appl. Energy 216 (2018) 60–72.
[24] S. Thiem, A. Born, V. Danov, A. Vandersickel, J. Schäfer, T. Hamacher, Automated identification of a complex storage model and hardware implementation of a model-predictive controller for a cooling system with ice storage, Appl. Therm. Eng. 121 (2017) 922–940.
[25] B. Xu, D. Rathod, A. Yebi, Z. Filipi, A comparative analysis of real-time power optimization for organic Rankine cycle waste heat recovery systems, Appl. Therm. Eng. 164 (2020) 114442.
[26] H. Bahlawan, M. Morini, M. Pinelli, W.R. Poganietz, P.R. Spina, M. Venturini, Optimization of a hybrid energy plant by integrating the cumulative energy demand, Appl. Energy 253 (2019) 113484.
[27] J. Mahmoudimehr, P. Sebghati, A novel multi-objective Dynamic Programming optimization method: Performance management of a solar thermal power plant as a case study, Energy 168 (2019) 796–814.
[28] H. Li, P. Liu, S. Guo, B. Ming, L. Cheng, Z. Yang, Long-term complementary operation of a large-scale hydro-photovoltaic hybrid power plant using explicit stochastic optimization, Appl. Energy 238 (2019) 863–875.
[29] S.M. Moghaddas-Tafreshi, S. Mohseni, M.E. Karami, S. Kelly, Optimal energy management of a grid-connected multiple energy carrier micro-grid, Appl. Therm. Eng. 152 (2019) 796–806.
[30] C. Klemm, P. Vennemann, Modeling and optimization of multi-energy systems in mixed-use districts: A review of existing methods and approaches, Renew. Sust. Energ. Rev. 135 (2021) 110206.
[31] W. Mai, C.Y. Chung, T. Wu, H. Huang, Electric load forecasting for large office building based on radial basis function neural network, in: 2014 IEEE PES General Meeting | Conference & Exposition, National Harbor, MD, 2014, pp. 1–5.
[32] D.P. Bertsekas, Dynamic Programming and Optimal Control. Athena Scientific, Belmont, Massachusetts, third edition, 1 (2005).
[33] A. Gambarotta, M. Morini, N. Pompini, P.R. Spina, Optimization of load allocation strategy of a multi-source energy system by means of dynamic programming, Energy Procedia 81 (2015) 30–39.
[34] Rubini L., Sangiorgio S. Le energie rinnovabili. Hoelpi, Milano (2012).
[35] F. Kreith, D.Y. Goswami, Handbook of Energy Efficiency and Renewable Energy, CRC Press, 2007.
[36] Cocco D., Palomba C., Puddu P. Tecnologie delle energie rinnovabili. SG Editoriali, Padova (2008).
[37] M. Zachar, M. Trifkovic, P. Daoutidis, Design of combined heat and power microgrids, Comput. Aided Chem. Eng. 34 (2014) 657–662.
[38] Ente Italiano di Normazione, UNI TS 11300 (2012) (In Italian).
[39] E.S. Barbieri, Y.J. Dai, M. Morini, M. Pinelli, P.R. Spina, P. Sun, R.Z. Wang, Optimal sizing of a multi-source energy plant for power heat and cooling generation, Appl. Therm. Eng. 71 (2014) 736–750.
[40] https://it.mathworks.com/help/releases/R2019a/index.html.
[41] Ente Italiano di Normazione, UNI 10349, 2016, In Italian.
[42] E.S. Barbieri, M. Morini, E. Munari, M. Pinelli, P.R. Spina, R. Vecci, Concurrent optimization of size and switch-on priority of a multi-source energy system for a commercial building application, Energy Procedia 81 (2015) 45–54.
[43] https://www.mercatoelettrico.org/It/download/DatiStorici.aspx.
[44] https://ec.europa.eu/eurostat/statistics-explained/index.php/Natural_gas_price_statistics.
[45] https://www.minambiente.it/sites/default/files/archivio/allegati/emission_trading/tabella_coefficienti_standard_nazionali_11022019.pdf.
[46] Danish Energy Agency. Technology Data - Energy Plants for Electricity and District heating generation. Report 2016. http://www.ens.dk/teknologikatalog.
[47] K. Darrow, R. Tidball, J. Wang, A. Hampson, Catalog of CHP technologies - Section 5: Technology characterization - microturbines. U.S. Environmental Protection Agency Combined Heat and Power Partnership, 2017.
[48] U.S. Department of Energy. Absorption chillers for CHP. Combined heat and power technology fact sheet series. https://www.energy.gov/sites/prod/files/2017/06/f35/CHP-Absorption%20Chiller-compliant.pdf.
[49] M. Zatti, M. Gabba, M. Freschini, M. Rossi, A. Gambarotta, M. Morini, E. Martelli, k-MILP: A novel clustering approach to select typical and extreme days for multi-energy systems design optimization, Energy 181 (2019) 1051–1063.
[50] Bahlawan H., Gambarotta A., Losi E., Manservigi L., Morini M., Spina P.R., Venturini M., Sizing and operation of a hybrid energy plant composed of industrial gas turbines, renewable energy systems and energy storage technologies, J. Eng. Gas. Turbine Power (2021), GTP-20-1542, https://doi.org/10.1115/1.4049652 .
[51] H. Bahlawan, E. Losi, L. Manservigi, M. Morini, M. Pinelli, P.R. Spina, M. Venturini, Optimal design and energy management of a renewable energy plant with seasonal energy storage. 100% RENEWABLE: Strategies, technologies and challenges for a fossil free future, October 25-30, 2020, Pisa, Italy.
[52] U.S. Department of Energy. Distributed generation and combined heat and power system characteristics and costs in the buildings sector. https://www.eia.gov/analysis/studies/buildings/distrigen/pdf/dg_chp.pdf.
[53] Directive of the European Parliament and of the Council of 25 October 2012. Energy efficiency, amending Directives 2009/125/EC and 2010/30/EU and repealing Directives 2004/8/EC and 2006/32/EC.