Dynamic programming based methodology for the optimization of the sizing and operation of hybrid energy plants

Hilal Bahlawan[a]*, Mirko Morini[b], Michele Pinelli[a], Pier Ruggero Spina[a]

[a]*Dipartimento di Ingegneria, Università degli Studi di Ferrara, Via Saragat, 1, 44122 Ferrara, Italy*
[b]*Dipartimento di Ingegneria e Architettura, Università degli Studi di Parma, Parco Area delle Scienze 181/a, 43124 Parma, Italy*

ABSTRACT

The dynamic programming method is mainly used to deal with energy management and optimal control problems of hybrid energy plants. This paper extends the application of this method and documents the development of a dynamic programming based methodology for the optimization of both the sizing and operation of hybrid energy plants. The optimization problem is carried out with the aim of minimizing primary energy consumption over the simulation period. Moreover, in order to demonstrate the validity and usefulness of the optimization methodology presented in this paper, a comparison with an optimization methodology developed by the same authors is made. The optimization methodology used as a benchmark is based on the genetic algorithm and is commonly used in the literature. A case study consisting of a building located in the north of Italy is considered to demonstrate the developed methodology. The hybrid energy plant used to fulfil the energy demands of the building comprises a photovoltaic panel, solar thermal collector, combined heat and power, ground and air source heat pumps, hot water storage and auxiliary boiler. Compared to the genetic algorithm based methodology, the proposed methodology allows a primary energy saving and computation time saving of about 5.4 % and 41 %, respectively. In addition, compared to a traditional plant composed of a boiler and the grid, the developed methodology allows a primary energy saving of about 24 %. The proposed methodology is fast, easy to implement and also addresses the non-linearity associated with the optimization problem of hybrid energy plants.

Keywords: *Dynamic programming; Hybrid energy plant; Optimization; Primary energy consumption.*

Nomenclature

a	correction factor
c	coefficient
COP	coefficient of performance
$\mathcal{E}$	energy
F	function
G	function
k	time variable
N	last time step
P	power
PE	primary energy consumption
T	temperature
U	input or control variable
V	volume
$\mathcal{X}$	state
π	control policy
η	efficiency
φ	incident radiant power

Acronyms

AB	auxiliary boiler
ASHP	air source heat pump
CHP	combined heat and power
DP	dynamic programming
GA	genetic algorithm
GSHP	ground source heat pump
HEP	hybrid energy plant
LHV	lower heat value
LP	linear programming
load	ratio between actual power and nominal power
MILP	mixed integer linear programming
PSO	particle swarm optimization
PV	photovoltaic
STH	solar thermal collector
STORAGE	hot water storage
SOP	switch-on priority
TP	traditional plant
XSHP	generic heat pump

Subscripts and superscripts

av	average
AB	auxiliary boiler
ASHP	air source heat pump
BoS	balance of system
c	cell
CHP	combined heat and power
diss	dissipation
el	electric
fuel	fuel
GSHP	ground source heat pump
in	entering
k	time-step
max	maximum
min	minimum
nom	nominal
o	optical
out	outgoing

PV	photovoltaic panel	taken	taken from the grid
ref	reference	th	thermal
sent	sent to the grid	XSHP	generic heat pump
STH	solar thermal collector	z	generic technology
STORAGE	hot water storage	*	optimal

1. Introduction

A reduction in energy consumption and especially primary energy consumption will contribute to increased sustainability in buildings. One of the strategies for reducing primary energy consumption is to improve the efficiency of hybrid energy plants (HEPs). This result may be achieved through the correct sizing and the optimal management of the technologies involved in the energy plant. Furthermore, these two issues are deeply interrelated, because the definition itself of optimal management strongly depends on the actual sizing of the employed technologies. In order to manage such complex issues, it is necessary to define methods and guidelines that help to optimize the sizes of the systems used and the operating strategy, in order to optimize the exploitation of fossil and renewable sources.

The sizing and operation optimization problem of the HEP components must be based on efficient correspondence between the energy supply and demand of the building. In order to obtain optimal solutions, the best practice is to use numerical optimization. A variety of methods has been developed to solve optimization problems [1]. The most prominent of these methods is Linear Programming (LP), which has the disadvantage of its incapability to address non-linearity while many problems are non-linear [2].

Other classes of optimization methods have been presented in the literature and proved to be effective in many cases [3]. Concerning the optimization problem of the sizing and operation of HEPs, most of these methods solve the problem by coupling two optimization methods such as evolutionary methods and LP techniques [4]. Despite the effectiveness of some of these methods, there are still some disadvantages such as (i) long execution time, (ii) high memory usage and (iii) not being able to address the non-linearity in the objective function, constraints or characteristics of the HEP [5].

Another optimization method which has recently attracted lots of research in the area of energy systems is dynamic programming (DP). Generally, DP is a method which can efficiently deal with linear and non-linear objectives and constraints and obtain global optimal solutions in the discrete state space [6]. This method is based on the principle of optimality: "*An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision*" [6]. The basic idea of DP is a multistage optimization problem in the sense that, at each time-step, a decision is made from a finite number of decisions based on the adopted optimization criterion. This is a general approach for making a sequence of interrelated decisions in an optimal way and is suitable for dynamic systems.

The DP method is mainly used to solve optimal control problems where the behavior of a physical system is described by a state variable and can be controlled from outside by a control variable [7]. The DP method is widely used to solve energy management problems and to make decisions regarding HEP operation [8, 9]. In fact, it is currently only adopted for energy management and system scheduling applications. Therefore, the diffusion of its use for management applications makes it necessary to be taken into consideration also during the sizing phase.

This paper proposes a new DP based optimization method, called the DP-DP method, to solve both the optimization problems of the sizing and operation of HEPs. The optimization problem is made on an energy-based criterion, i.e. with the aim of minimizing primary energy consumption over the simulation period. The proposed method is fast, easy to implement and also addresses the non-linearity associated with the characteristics of the plant.

The rest of this paper is organized as follows: Section 2 provides an overview of the literature regarding optimization methods of HEPs. Section 3 introduces the original DP-DP optimization method, presents the mathematical models of the HEP components considered in this study (solar thermal collector, photovoltaic panel, combined heat and power, ground and air source heat pumps, auxiliary boiler and hot water storage) and describes the state-space model and the optimization procedure. The case study is outlined in Section 4. Finally, Sections 5 and 6 discuss the results and conclude the paper.

2. Literature review

In recent years, HEPs have gained a great deal of attention in the scientific literature for primary energy saving and greenhouse gas emission reduction in building demand fulfillment. Several authors have analyzed the combination of different technologies which use renewable, partially renewable and fossil energy sources. In [10] the authors studied the combination of a wood boiler, condensing boiler, heat pump, solar thermal collector and photovoltaic panel. Sontag and Lange [11] combined cogeneration with solar energy and wind energy. Moghaddam et al. [12] presented a model for scheduling a residential energy hub including a heat pump, auxiliary boiler, absorption chiller, combined heat and power, electrical and thermal energy storage. An HEP composed of wind turbines, solar panels, fuel cells and a battery pack is designed in [13]. Lee et al. [14] studied an integrated renewable energy system composed of a solar thermal collector, photovoltaic panel, ground source heat pump, electric chiller and gas fired boiler. Wu et al [15] presented a study for the optimization of an integrated renewable energy system composed of a biomass combined heat and power plant, photovoltaic panel, heat pump and hot water storage.

A key factor for saving as much primary energy as possible is the correct sizing of the various technologies of the HEP. Moreover, in residential applications, thermal and electrical demands vary significantly depending on the time of year, and even the time of day, and they are not synchronized. For these reasons, there is a need for a tool to manage and optimize the operation of HEPs. A large variety of methods was proposed for the sizing and operation optimization of HEPs. These can be classified as heuristic methods and mathematical programming methods. Among the heuristic methods, the genetic algorithm (GA) and Particle Swarm Optimization (PSO) are considered to be the most used methods for the optimization of energy plants [16]. For instance, Barbieri et al. [17] developed a model to study the effect of different climatic scenarios on multi-source energy plant sizing using a GA with the goal of minimizing primary energy consumption. The size of an HEP composed of a wind generator, photovoltaic panel, battery and inverter is optimized in [18] by using an adaptive GA. An optimization model based on the use of a GA is adopted in [19] to optimize hybrid renewable energy system sizing. The system consists of a photovoltaic panel, wind turbine and cogeneration system. Yousefi et al. [20] used a GA to optimize the size of a hybrid system consisting of a combined heat and power unit, photovoltaic/thermal panels and an internal combustion engine. In [21], a GA based system sizing method is developed, with the aim of minimizing initial total system costs. The system includes air conditioning equipment, photovoltaic panels, wind turbines, thermal energy storage and electrical energy storage. A multi-objective optimization approach using GA is employed in [22] to determine the optimal design variables of solar heating and cooling systems by minimizing the primary energy consumption and annual cost of the system. Ling et al. [23] proposed a GA for the optimization of the control strategy for a cooling plant that uses lake water. The study is conducted with the aim of exploring energy saving potentials by optimizing the operation of the considered energy plant. The efficiency improvement of a polygeneration hybrid solar and biomass system is investigated by Sahoo et al. [24]. In their study, the authors proposed a GA model for the improvement in efficiency and payback period of polygeneration plants. Sharafi et al. [25] proposed the PSO approach for the optimal design of a hybrid renewable energy system and to minimize the total system cost, unmet load and fuel emissions. Sakawa et al. [26] proposed GAs to approximate the solution of Mixed Integer Linear Programming (MILP) with the aim of optimizing the operational planning of a district heating and cooling plant. The optimal operation of a chiller plant is discussed in [27] and a PSO algorithm is employed to find the optimal control parameters. The goal of the study is to minimize plant energy consumption throughout the simulation period. In another example, an optimization model based on the PSO algorithm is presented by Moghaddas-Tafreshi et al. [28] to schedule the components of a multiple energy carrier by minimizing the operational costs a day ahead. Despite the advantages behind the use of heuristic methods for optimization purposes, the GA and PSO methods still have their own drawbacks. In fact, GA can be time-consuming when it is used for the optimization of complex HEPs, inaccurate and trapped into local optima [29]. While the main disadvantages of the PSO algorithm are the difficulty in defining the initial parameters, such as the initial position and velocity of the particles, and the premature convergence into a local minimum for complex systems [16].

Considering the mathematical programming methods, Linear Programming (LP) and Mixed Integer Linear Programming (MILP) are widely presented in the literature. An LP algorithm is used in [30] to optimally plan the operation of a system composed of a co-generator system fed by biomass and an energy storage system. The optimization problem is solved with the objective of minimizing the overall net acquisition cost for energy. Carpaneto et al. [31] developed a procedure for the optimization of unit commitment in a network with different power sources. In their work, they focus on minimizing the overall operational cost by using MILP techniques. Another MILP method is presented in [32] for the sizing and plant layout optimization of trigeneration systems. Ghorab [33] applied an MILP technique to investigate smart energy network optimization and to minimize energy consumption and environmental impact by enhancing the overall efficiency of the energy technologies. Evins [34] addressed the optimization of an energy plant design and operating variables applying a multi-level optimization approach. The plant design variables are optimized using a GA and its operational variables are optimized using MILP techniques. A similar approach is used by the authors of [35]. They developed an optimization model with an evolutionary algorithm and MILP and split the model into two levels (i.e. master and slave). In spite of the LP and MILP contributions to the sizing and operation optimization of HEPs, they are only suitable for linear objective functions and constraints [29]. Moreover, for complex systems, they require large computation time due to the very large number of decision variables [16].

DP is another type of mathematical programming widely used in dealings with the optimization of HEPs. Marano et al. [36] applied a DP method to the optimal management of an HEP composed of wind turbines, photovoltaic panels and compressed air energy storage considering energy, economic and environmental aspects. Similarly, Bianchi et al. [37] used DP for managing wind variability with pumped hydro storage and gas turbines. They found that DP allows natural gas consumption to be minimized unlike the other control strategies. Facci et al. [38] optimized a trigeneration system operation strategy by means of a DP algorithm. The optimization is carried out to determine the economically optimal plant state that maximizes total profit over one day. The optimal daily generation scheduling of a hydro-photovoltaic power plant is investigated in [39]. The study used DP techniques to determine the optimal dispatch strategies of the hydro unit while meeting the load characteristics and minimizing water consumption. Mahnmoudimehr et al. [40]

employed the DP algorithm for the optimal performance management of an energy plant composed of a solar thermal collector and an energy storage system. The major objective of their study was to validate the superiority of the proposed DP algorithm approach over conventional methods used in the literature. The results showed that the developed DP algorithm attains higher values in terms of revenue compared to other methods, such as GA. Table 1 shows some of the benefits and limitations of the optimization methods reviewed in this section.

Table 1. Comparison between the optimization methods.

Optimization method	Benefits	Limitations
GA	• Suitable for linear and non-linear problems • Suitable for discrete and continuous problems	• Time-consuming for complex problems • Global optimum not guaranteed
PSO	• Suitable for linear and non-linear problems • Suitable for discrete and continuous problems • Fast convergence	• Difficult to define initial parameters • Global optimum not guaranteed
LP/MILP	• Simple to implement • Suitable for discrete and continuous problems • Accurate	• Only suitable for linear problems • Long computation time
DP	• Suitable for linear and non-linear problems • Suitable for discrete and continuous problems • Suitable for complex systems • Global optimum guaranteed	• Only suitable for situations where decisions are made in stages.

The above review of the literature shows that DP algorithm is preferable for solving the optimization problem of complex HEPs [40]. Compared to other optimization methods, the main advantage of the DP algorithm is its ability to handle linear and non-linear objective functions and constraints [6]. Moreover, the implementation of the DP algorithm is simple and always guarantees that the global optimum is found [36]. However, this method has not been used simultaneously for the sizing and operation of HEPs. Thus, this paper contributes to the literature by introducing a new methodology, called the DP-DP method, for the optimization of HEPs. The proposed work extends the use of the DP method and attempts to apply it to solve both the sizing and operation optimization problem of HEPs. The advantages of the proposed optimization methodology are demonstrated by comparing it with one of the most used optimization methods, i.e. the GA method. For this purpose, a building located in the north of Italy is considered as a case study. Compared to a GA method published by the same authors, called the GA-SOP method, the methodology developed in this paper is easier to implement, allows greater primary energy saving and has a considerably lower computation time.

3. Methods and materials

A new method based on the DP algorithm is presented in this study for the sizing and operation optimization of HEPs. The optimization of the HEP is conducted by minimizing primary energy consumed throughout the simulation period. However, a different objective function, such as pollutant emissions or total cost, may also be implemented. A model for the simulation of the HEP is implemented in Matlab®. The model takes into account variability in terms of the performance of the considered systems according to both external air temperature and load. The analysis is carried out on an hourly basis.

3.1 The hybrid energy plant

Figure 1 shows a schematic representation of the HEP used to fulfill the energy demands of the building. The HEP is composed of a solar thermal collector (STH), photovoltaic panel (PV), combined heat and power (CHP), ground source heat pump (GSHP), air source heat pump (ASHP), auxiliary boiler (AB) and hot water storage (STORAGE).

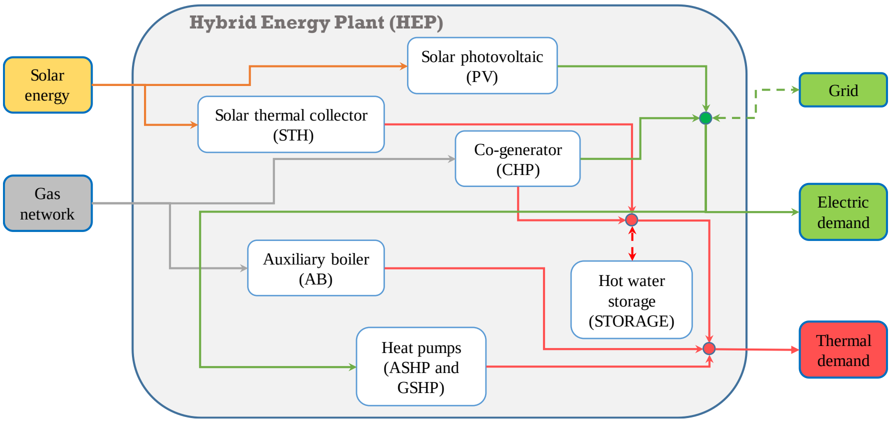


Fig. 1. Schematic representation of the HEP

Equation (1) and (2) represent thermal and electrical energy balances:

$$\varepsilon_{\mathrm{AB,th},k} = \varepsilon_{\mathrm{th},k} - (\varepsilon_{\mathrm{STH,th}\to\mathrm{th},k} + \varepsilon_{\mathrm{CHP,th}\to\mathrm{th},k} + \varepsilon_{\mathrm{GSHP,th},k} + \varepsilon_{\mathrm{ASHP,th},k} + \varepsilon_{\mathrm{STORAGE,th,out},k}) \quad (1)$$

$$\varepsilon_{\mathrm{grid,el},k} = \varepsilon_{\mathrm{el},k} + \varepsilon_{\mathrm{GSHP,el},k} + \varepsilon_{\mathrm{ASHP,el},k} - (\varepsilon_{\mathrm{PV},k} + \varepsilon_{\mathrm{CHP,el},k}) \quad (2)$$

$$\varepsilon_{\mathrm{CHP,th},k} = \varepsilon_{\mathrm{CHP,th}\to\mathrm{th},k} + \varepsilon_{\mathrm{CHP,th}\to\mathrm{STORAGE},k} \quad (3)$$

$$\varepsilon_{\mathrm{STH},k} = \varepsilon_{\mathrm{STH,th}\to\mathrm{th},k} + \varepsilon_{\mathrm{STH,th}\to\mathrm{STORAGE},k} \quad (4)$$

$$\varepsilon_{\mathrm{STORAGE,th,in},k} = \varepsilon_{\mathrm{STH,th}\to\mathrm{STORAGE},k} + \varepsilon_{\mathrm{CHP,th}\to\mathrm{STORAGE},k} \quad (5)$$

These energy balances ensure the fulfillment of thermal and electrical energy demands at each time step (equal to one hour). As can be seen from Eq. (1), the building thermal energy demand ($\mathcal{E}_{\mathrm{th},k}$) is fulfilled by the thermal energy produced by the STH ($\mathcal{E}_{\mathrm{STH,th}\to\mathrm{th},k}$), CHP unit ($\mathcal{E}_{\mathrm{CHP,th}\to\mathrm{th},,k}$), GSHP ($\mathcal{E}_{\mathrm{GSHP,th},k}$), ASHP ($\mathcal{E}_{\mathrm{ASHP,th},k}$) and STORAGE ($\mathcal{E}_{\mathrm{STORAGE,th,out},k}$). The subscript th → th means that the thermal production of the specific system directly meets the thermal demand (i.e. space heating and hot water). If the thermal demand is not fulfilled by the previous systems, the remaining part will be fulfilled by the AB ($\mathcal{E}_{\mathrm{AB,th},k}$). From Eq. (2), the electricity produced by the PV ($\mathcal{E}_{\mathrm{PV,el},k}$) and CHP ($\mathcal{E}_{\mathrm{CHP,el},k}$) systems is used to meet the building electricity demand ($\mathcal{E}_{\mathrm{el},k}$) and the electricity required by the GSHP ($\mathcal{E}_{\mathrm{GSHP,el},k}$) and ASHP ($\mathcal{E}_{\mathrm{ASHP,el},k}$) systems. If the PV and CHP systems are not able to fulfill the required electricity, the remaining part is imported from the grid ($\mathcal{E}_{\mathrm{grid,el},k}$). Otherwise any excess electricity is sent to the grid. Moreover, as shown from Eqs. (3) and (4), the thermal energy produced by the CHP and STH may be used to fulfill the thermal demand and to fill up the STORAGE (Eq. 5).

The primary energy consumed throughout the simulation period to be minimized is defined as follows:

$$PE = \sum_{k=0}^{N-1} PE_{\mathrm{fuel,CHP},k} + PE_{\mathrm{fuel,AB},k} + \Delta PE_{\varepsilon_{\mathrm{el},k}} \quad (6)$$

where

$$\Delta PE_{\varepsilon_{\mathrm{el},k}} = PE_{\varepsilon_{\mathrm{el,taken},k}} - PE_{\varepsilon_{\mathrm{el,sent},k}} \quad (7)$$

As can be seen from Eqs. (6) and (7), primary energy consumption (PE) is defined as the sum of the consumption of the CHP ($PE_{\mathrm{fuel,CHP},k}$), AB ($PE_{\mathrm{fuel,AB},k}$) and the primary energy associated with the electrical energy exchanged with the grid ($\Delta PE_{\mathcal{E}_{\mathrm{el},k}}$).

3.2 Plant components models

The energy systems comprising the HEP are defined by power and efficiency as grey-box models. For each technology, the basic correlations are summarized below.

Photovoltaic panel

The total efficiency of the photovoltaic panel takes into account the efficiency of the photovoltaic panel ($\eta_{PV,ref}$) and the efficiency of the inverter and electrical connections (η_{BoS}). Their design condition values are 0.12 and 0.9, respectively [41]. The efficiency of the PV system is calculated by Eq. (8):

$$\eta_{PV} = \eta_{PV,ref} \cdot \eta_{BoS} \cdot \left[1 - \beta \cdot \left(T_c - T_{c,ref}\right)\right] \tag{8}$$

where β is a temperature penalty coefficient and T_c and $T_{c,ref}$ are the operating and reference temperature of the cell, respectively. The output power of the photovoltaic panel is not controlled by any device and only depends on radiant power and electrical efficiency.

Solar thermal collector

The efficiency of the solar thermal collector is calculated as follows [42]:

$$\eta_{STH} = \eta_o - a_1 \cdot \left(\frac{T_{av} - T_k}{\varphi}\right) - a_2 \cdot \varphi \cdot \left(\frac{T_{av} - T_k}{\varphi}\right)^2 \tag{9}$$

where η_o is the optical efficiency, a_1 and a_2 correction factors, T_{av} the average temperature assumed equal to 50 °C, T_k the temperature at the k-th time step and φ the incident radiant power. Like the PV system, the output power of the STC is not controlled by any device and only depends on external conditions.

Combined heat and power

The combined heat and power technology considered is based on an internal combustion engine. The nominal electrical efficiency and thermal power are calculated using Eqs. (10) and (11) obtained by carrying out a market survey on CHP technologies with nominal electrical capacities within the range 0÷100 kW_e [17]:

$$\eta_{CHP,el,nom} = 0.232 \cdot \left(P_{CHP,el,nom}\right)^{0.084} \tag{10}$$

$$P_{CHP,th,nom} = 2.5 \cdot \left(P_{CHP,el,nom}\right)^{0.91} \tag{11}$$

A linear variation of the performance of the CHP with external air temperature and thermal load variation is assumed [17]. The minimum thermal load is assumed to be equal to 10 % of the nominal load [43]. In order to reflect the physical behavior of the CHP during start-up, a penalty corresponding to the fuel consumed in five minutes at nominal conditions is added.

Heat pumps

The GSHP and ASHP systems are considered and modelled. It was assumed that the nominal performance of both systems is affected by the temperature of the external and internal heat exchangers and the thermal load according to [44, 45]. For both heat pumps, the minimum load is assumed equal to 10 % of the nominal thermal load [17, 46].

Hot water storage

The hot water storage tank is linked with both the STH and CHP systems and can be filled up by any excess energy produced by these systems. The heat dissipation is also included in the storage model and assumed proportional to the stored energy. In particular, a dissipation coefficient of 0.5 % is considered according to [47].

Auxiliary boiler

An auxiliary condensing boiler is considered and used to meet the thermal energy possibly not fulfilled by the other systems. The variation of the performance of the AB is also taken into account and it is assumed that the performance varies linearly with load variation. The nominal efficiency of the AB (on an LHV basis) is assumed equal to 1.06 [17].

3.3 Optimization model

In this context, the optimal size and control of the HEP are found by performing two runs of the DP algorithm. The main difference between the two runs lies in the way in which the technologies are modelled. The first run of the DP algorithm allows the combination of sizes considered as an optimal solution to be calculated, while the second run defines the optimal operation strategy of the different technologies.

3.3.1 State-space model representation

In this research, the optimization problem is implemented using a Matlab® solver developed by Sundstrom and Guzzella [48] that deals with discrete-time optimal-control problems using Bellman's DP algorithm. The formulation of the optimization problem requires a state-space representation of the model as follows:

$$\chi_{z,k+1} = F\left(\chi_{z,k}, U_{z,k}, k\right) \tag{12}$$

$$\varepsilon_{z,k} = G\left(\chi_{z,k}, U_{z,k}, k\right) \tag{13}$$

where $\mathcal{X}$ represents the state variables, U the input variables and $\mathcal{E}$ the output variables of the technology z at time step k. In this study, the state-space model is discretized with a time-step of one hour. Two states are identified, $\mathcal{X}_{\text{CHP}}$ and $\mathcal{X}_{\text{STORAGE}}$, corresponding to the CHP operating condition and the storage state of charge, respectively. The CHP state ($\mathcal{X}_{\text{CHP}}$) is represented by the binary numbers 1 and 0 which represent the on-off condition of the CHP at the beginning of the k-th time step. The state of the CHP is updated as follows:

$$\chi_{\text{CHP},k+1} = \begin{cases} 1 & if \quad U_{\text{CHP},k} \neq 0 \\ 0 & if \quad U_{\text{CHP},k} = 0 \end{cases} \tag{14}$$

The storage state of charge is updated as follows:

$$\chi_{\text{STORAGE},k+1} = \left(1 - c_{\text{diss}}\right) \cdot \left(\chi_{\text{STORAGE},k} + \varepsilon_{\text{STORAGE,th,in},k} - \varepsilon_{\text{STORAGE,th,out},k}\right) \tag{15}$$

Input variables U are used to control the HEP and they represent the fraction of maximum energy output of the controllable technologies involved in the plant. For each technology the power output can be represented by the following equation:

$$\varepsilon_{z,k} = U_{z,k} \cdot \varepsilon_{z,k,\max} \tag{16}$$

$\mathcal{E}_{z,k,\max}$ is the maximum energy which can be produced by the technology z at the k-th time step. For the definition of the problem, the constraints and discretization of states and inputs should be defined as follows:

$$\chi_{z,k} \in \left[\chi_{z,\min}, \chi_{z,\max}\right] \tag{17}$$

$$U_{z,k} \in \left[U_{z,\min}, U_{z,\max}\right] \tag{18}$$

$\mathcal{X}_{z,\min}$ and $\mathcal{X}_{z,\max}$ are the minimum and maximum states that technology z can assume. While, $\mathcal{U}_{z,\min}$ and $\mathcal{U}_{z,\max}$ represent the minimum and maximum load.

Four input variables U_{CHP}, U_{GSHP}, U_{ASHP} and U_{STORAGE} are used to control the HEP plant and they represent the fraction of maximum energy output of the CHP, GSHP, ASHP and STORAGE systems. In particular, for the CHP system, the output thermal energy and electrical energy at the k-th time step are described by the following equations:

$$\varepsilon_{\text{CHP,th},k} = U_{\text{CHP},k} \cdot P_{\text{CHP,th,max},k} \cdot \Delta k \tag{19}$$

$$\varepsilon_{\text{CHP,el},k} = \eta_{\text{CHP,el}}(U_{\text{CHP}}, k) \cdot \frac{\varepsilon_{\text{CHP,th}}(U_{\text{CHP}}, k)}{\eta_{\text{CHP,th}}(U_{\text{CHP}}, T_k, k)} \tag{20}$$

For the GSHP and ASHP systems, the output thermal energy is represented by Eq. (21), while the consumed electrical energy is expressed by Eq. (22):

$$\varepsilon_{\text{XSHP,th},k} = U_{\text{XSHP,k}} \cdot P_{\text{XSHP,th,max},k} \cdot \Delta k \tag{21}$$

$$\varepsilon_{\text{XSHP,el},k} = \frac{\varepsilon_{\text{XSHP,th}}(U_{\text{XSHP}}, k)}{COP_{\text{XSHP,th}}(U_{\text{XSHP}}, T_k, k)} \tag{22}$$

where XSHP stands for GSHP and ASHP.

The thermal energy taken from the storage and used to fulfill the thermal energy demand is calculated as follows:

$$\varepsilon_{\text{STORAGE,th,out},k} = U_{\text{STORAGE},k} \cdot \chi_{\text{STORAGE},k} \tag{23}$$

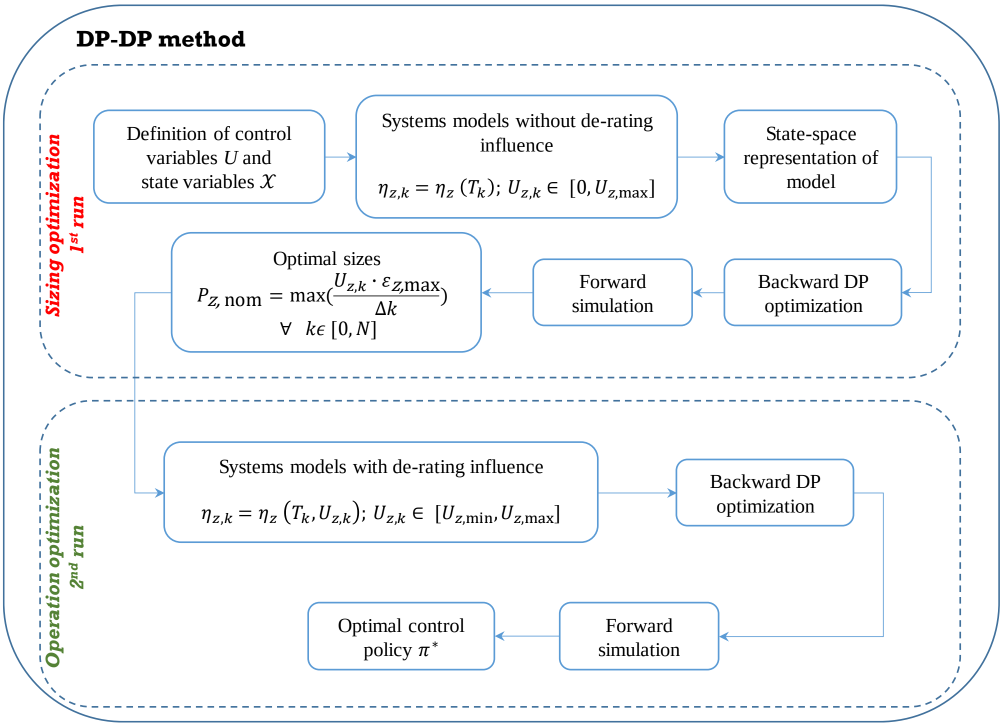


Fig. 2. Optimization flowchart of the DP-DP method

Figure 2 outlines the methodology for the sizing and operation optimization of HEPs.

3.3.2 Sizing optimization

As highlighted in Fig. 2, the first run of the DP is conducted considering only the variability of the efficiency (η_z) of the technology with external air temperature, i.e. assuming that load variation has no effect on the performance of the various technologies.

$$\eta_{\mathrm{CHP,el},k} = \eta_{\mathrm{CHP,el},k}(T_k) \tag{24}$$

$$COP_{\mathrm{XSHP},k} = COP_{\mathrm{XSHP}}(T_k) \tag{25}$$

Moreover, the technological limit of the technologies is ignored assuming that the systems are able to operate at a load $\mathcal{U}$ lower than their minimum load as reported in the following equations:

$$U_{\mathrm{CHP},k} \in \left[0, U_{\mathrm{CHP},max}\right] \tag{26}$$

$$U_{\mathrm{XSHP},k} \in \left[0, U_{\mathrm{XSHP},max}\right] \tag{27}$$

The sizing optimization range, for the considered technologies, is defined by calculating the maximum power that can be produced by the CHP, GSHP and ASHP systems:

$$\varepsilon_{\mathrm{CHP,el,max}} = \max(\varepsilon_{\mathrm{el},k}) \qquad \forall\, k \in \left[0, N\right] \tag{28}$$

$$\varepsilon_{\mathrm{XSHP,th,max}} = \max(\varepsilon_{\mathrm{th},k}) \qquad \forall\, k \in \left[0, N\right] \tag{29}$$

$\mathcal{E}_{\mathrm{CHP,el,max}}$ and $\mathcal{E}_{\mathrm{XSHP,th,max}}$ represent the upper limit of the sizing optimization range for the CHP, GSHP and ASHP systems. Thus, during the first run of the DP algorithm, the abovementioned technologies are free to modulate between 0 and $\mathcal{E}_{\mathrm{CHP,el,max}}/\mathcal{E}_{\mathrm{XSHP,th,max}}$ without load de-rating. From Eqs. (28) and (29), depending on the type of technology, the term $\mathcal{E}$ on the right side, could be a thermal, cooling or electrical energy demand. It should be mentioned that, during the first run, the performance of the CHP, GSHP and ASHP systems is fixed considering their maximum load.

Once the first run is performed, the optimal size of each technology z, is defined by calculating the maximum power allocated to each technology as follows:

$$P_{z,\text{nom}} = \max\left(\frac{U_{z,k} \cdot \varepsilon_{z,\max}}{\Delta k}\right) \quad \forall k \in [0, N] \tag{30}$$

3.3.3 Operation optimization

The second step of the DP-DP optimization method consists of optimizing the operation of the HEP once the optimal combination of sizes is found by the previous step. In this step, the optimal control policy is defined by considering that both external air temperature and load influence the performance. Therefore, the operation optimization step is performed by modifying Eqs. (24) and (25) to the form expressed in Eqs. (31) and (32), respectively:

$$\eta_{\text{CHP,el},k} = \eta_{\text{CHP,el},k}(T_k, U_{\text{CHP},k}) \tag{31}$$

$$COP_{\text{XSHP},k} = COP_{\text{XSHP}}(T_k, U_{\text{XSHP},k}) \tag{32}$$

Therefore, the performance of the CHP, GSHP and ASHP systems become a function of both external air temperature and load. Moreover, the control variables U are set again so that they can assume values in the actual interval of loads in which each technology can modulate:

$$U_{\text{CHP},k} \in [U_{\text{CHP,min}}, U_{\text{CHP,max}}] \tag{33}$$

$$U_{\text{XSHP},k} \in [U_{\text{XSHP,min}}, U_{\text{XSHP,max}}] \tag{34}$$

3.3.4 Optimal policy evaluation

The sizing and operation optimization steps are conducted with the aim of finding the optimal policy which minimizes primary energy consumption expressed by Eq. (6).

Let π^* be the optimal policy, which corresponds to:

$$\pi^* = \arg\min_{\pi \in \Pi} PE_\pi(\chi_0) \tag{35}$$

where

$$PE_\pi(\chi_0) = \sum_{k=0}^{N-1} PE_{\text{fuel,CHP}}(\chi, U, k) + PE_{\text{fuel,AB}}(\chi, U, k) + \frac{\varepsilon_{\text{el,taken}}(\chi, U, k)}{\eta_{\text{el,taken}\to PE}} - \frac{\varepsilon_{\text{el,sent}}(\chi, U, k)}{\eta_{\text{el,sent}\to PE}} \tag{36}$$

$\eta_{el,taken\to PE}$ and $\eta_{el,sent\to PE}$ are the conversion efficiencies considering values of 0.40 [49] and 0.43 [50], respectively. The optimization problem is solved by constructing a sequence of interrelated decisions called backward DP optimization. In other words, the DP algorithm begins by defining a small part of the whole problem and determining an optimal solution to it. Then, the algorithm slightly extends the small part and finds an optimal solution for it using the optimal solution which was found before. This procedure is then repeated by the algorithm until the current problem turns into the entire problem. Finally, when the entire problem is solved, the optimal control policy π^* can be found by a forward simulation, i.e. by tracking back the optimal solution which were found for the small problems.

The optimal control policy representing the optimal energy scheduling over the simulation corresponds to:

$$\pi^* = \{U_0, U_1, \ldots, U_{\text{N}-1}\} \tag{37}$$

where

$$U_k = [U_{\text{CHP},k}, U_{\text{GSHP},k}, U_{\text{ASHP},k}, U_{\text{STORAGE},k}] \tag{38}$$

4. Case study

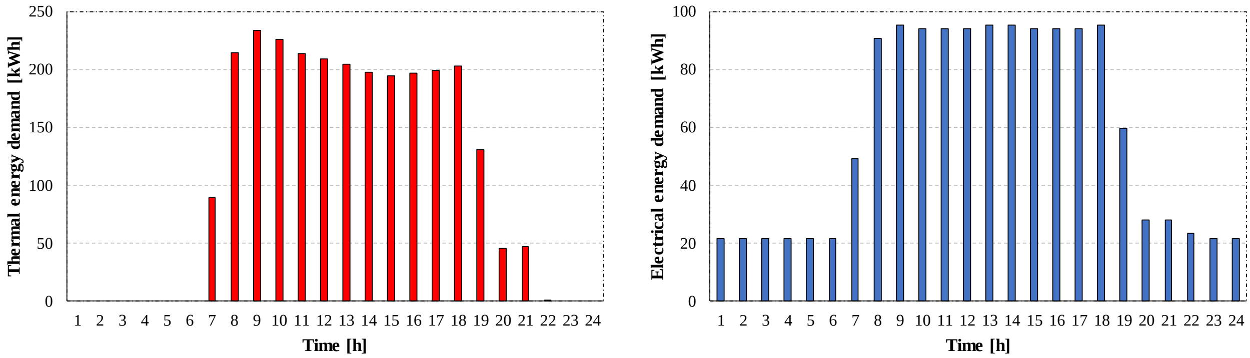
The case study considered in this work is a building intended for commercial and office use in the north of Italy. The building is composed of thirteen floors: i) the basement is designated for storage and a garage, ii) the ground and first floor are designated as a commercial area, iii) the 2nd to 12th floors are designated for office use.

The sizing and operation optimization problem is carried out for an HEP composed of technologies that can be used for the production of electricity, space heating and hot water. Therefore, the sizing and operation optimization is carried out with the aim of minimizing primary energy consumption during the winter and mid-season, since the thermal energy demand required during the summer is lower than in the winter and mid-season. Thermal demand for heating is considered during the winter season, whereas thermal demand for hot water and electrical energy demand are considered throughout the whole time frame.

4.1 Energy demands

The heating period for the Italian climatic zone "A" where the building is located runs from October 15th to April 15th. The thermal energy demand for heating and hot water is obtained using the software for stationary simulations EdilClimaEC700® on a monthly basis. Then the monthly thermal energy demand is transformed to calculate the hourly demand using non-dimensional profiles taking into consideration the type of user.

The electrical energy demand is for lighting, appliances and elevator operation. The thermal and electrical energy demands distributed on an hourly basis on a typical winter day are shown in Fig. 3.



a) b)

Fig. 3. Thermal a) and electrical b) energy demands on a typical winter day.

4.2 Optimization variables

Since the purpose of this study is to optimize both the size and operation of HEPs, only controllable technologies are involved in the optimization problem. Renewable energy technologies (i.e. STH and PV) are not controllable, so their optimization is not considered. In particular, PV and STH can exploit a total area of 328 m^2. STH covers an area of 2.5 m^2, while the remaining part is occupied by the PV system. Moreover, the capacity of the AB is set equal to the peak of the thermal energy demand (i.e. 234 kW), because a back-up system must always meet the thermal energy demand when the other systems are not working or turned off. The volume of the STORAGE (V_{STORAGE}) depends on the size of the CHP and STH technologies. It is calculated according to [51] considering a coefficient of 0.04 m^3/m^2 for the volume allocated to the STH and a coefficient of 2 kWh/kW_{th} for the volume assigned to the CHP.

In this case, the size of the CHP is represented by the nominal electric power $P_{\text{CHP,el,nom}}$, while the GSHP and ASHP are both represented by the nominal thermal power, $P_{\text{GSHP,th,nom}}$ and $P_{\text{ASHP,th,nom}}$, respectively. The peak in demand, calculated using Eqs. (28) and (29), is 95.97 kW_e for the electricity and 233.73 kW_{th} for heating. Therefore, the upper limit of the optimization range, for the CHP nominal power, is rounded up to 100 kW_e, whereas the upper limits for GSHP and ASHP are both rounded up to 250 kW_{th}. The upper STORAGE volume limit ($V_{\text{STORAGE,max}}$) was calculated considering the maximum electric power of the CHP, i.e. 100 kW_e.

As previously mentioned, the CHP state ($\mathcal{X}_{\text{CHP}}$) is represented by the binary numbers 1 and 0 which represent the on-off condition of the CHP at the beginning of the *k*-th time step. The stored energy ($\mathcal{X}_{\text{STORAGE}}$) is limited within the range $[0, \mathcal{E}_{\text{th,STORAGE,max}}]$ and is discretized in 10 equally spaced values.

For the sizing optimization step, input variables U, for the CHP, GSHP, ASHP and STORAGE systems are discretized in 10 equally spaced values within the range $[0, U_{\max}]$. Instead, for the operation optimization step, the input variables are discretized in 9 equally spaced values within the range $[U_{\min}, U_{\max}]$ and a tenth value ($U_z = 0$) is also added to the inputs representing the off condition. Moreover, for the CHP, GSHP and ASHP systems, the maximum load $\mathcal{U}_{\max}$ corresponds to the nominal load, while the minimum load $U_{\text{z,min}}$ is assumed equal to 10 % of the nominal load (See Section 3.2).

Finally, the state-space model is discretized with a time-step of one hour and the time horizon N for the winter and mid-season period is equal to 4391 hours. Moreover, for the sizing and operation optimization steps, the states at the beginning are set so that the co-generator is off and the STORAGE is empty, while the final states are free. The optimization was conducted on a cluster with 24 Gb of RAM and a 4-core processor.

5. Results

The results of the DP-DP method are compared to those obtained from a traditional optimization method called the GA-SOP method which is developed by the same authors in other works [17, 44]. In the GA-SOP optimization framework, the sizing optimization is conducted using GA, whereas the starting order of the different technologies comprising the energy plant is defined by a Switch-On Priority (SOP) mapping which minimizes the primary energy consumed over the simulation period. For more details, the development procedure of SOP mapping is described in a previous work [44]. For the optimal combination of sizes found by the GA, the SOP for the different technologies is as follows:

1. Renewable energy technologies (i.e. solar thermal collector and photovoltaic panel);
2. Hot water storage;
3. Combined heat and power;
4. Ground source heat pump;
5. Air source heat pump;
6. Auxiliary boiler.

Table 2 lists the optimal sizes obtained using the GA-SOP and DP-DP methods. As can be seen, the optimal CHP capacity defined by the DP-DP method is greater (100 kW_e) than the GA-SOP method (90 kW_e), while the size of the GSHP (44 kW_{th}) is smaller than the result found using the GA-SOP method (60 kW_{th}). As can be noted, the results obtained from the two methods are different, which is expected because the GA-SOP and DP-DP methods use different algorithms to solve the sizing optimization problem. Furthermore, the two sizing optimization problems were implemented differently, i.e. the GA method is applied on a continuous optimization problem, while the DP-DP method solves a discrete optimization problem. Moreover, in the sizing optimization step, the GA-SOP method defines the control logic of the different technologies using the SOP mapping, while in the other case, the control logic is defined by the DP itself.

Table 2. Optimal sizes for the GA-SOP and DP-DP methods.

	$P_{CHP,el,nom}$ [kW_e]	$P_{GSHP,th,nom}$ [kW_{th}]	$P_{ASHP,th,nom}$ [kW_{th}]
GA-SOP method	90	60	0
DP-DP method	100	44	0

Table 3 lists the primary energy consumption and time execution for the GA-SOP method, DP-DP method and the case of a Traditional Plant (TP). In the TP case, the thermal energy demand is fulfilled by a boiler with a nominal power equal to the peak (234 kW), while the electrical energy demand is taken from the grid. It can be seen that the primary energy consumed during the winter and mid-season in a TP is equal to 735.9 MWh. Due to the higher complexity of the plant and the introduction of renewable energy systems, the consumption in the GA-SOP and DP-DP methods is reduced to 585.9 and 554.3 MWh, respectively. As can be noted, the DP-DP method gives a further advantage in terms of primary energy consumption compared to the GA-SOP method. In particular, compared to the GA-SOP method, the DP-DP method allows a primary energy saving of 5.4 % to be achieved. Moreover, compared to the TP case, a primary energy saving of about 24.7 % may be achieved.

Table 3. Primary energy consumption for the GA-SOP and DP-DP methods.

	TP	GA-SOP method	DP-DP method
Primary energy consumption [MWh]	735.9	585.9	554.3
Computation time [h]	-	31	18

It would be interesting to compare the computation time between the GA-SOP and DP-DP methods. As can be noted from Table 3, there is a huge difference in computation time (the computation time is represented by the wall-clock time) between the two methods which can be explained by the fact that the GA takes more time than DP to solve the sizing optimization problem. Indeed, for the presented case study, the use of the DP-DP method allows a computation time saving of around 41.4 % compared to the GA-SOP method.

Figures 4a and 4b show the fraction of thermal energy demand allocated to each technology of the HEP plant and the fraction of thermal energy which is lost to the atmosphere for both the GA-SOP and DP-DP methods. The fraction of thermal energy demand fulfilled by the CHP is the highest for all cases with 91.5 % for the GA-SOP method and 95.6 % for the DP-DP method. The production of the GSHP varies from 2.6 % to 5.3 % and in all cases is used to meet the peak thermal energy demand. The minimum fraction is found in the DP-DP method because the HEP is characterized by larger CHP and smaller GSHP units. The AB is only used in the DP-DP method (0.2 %).

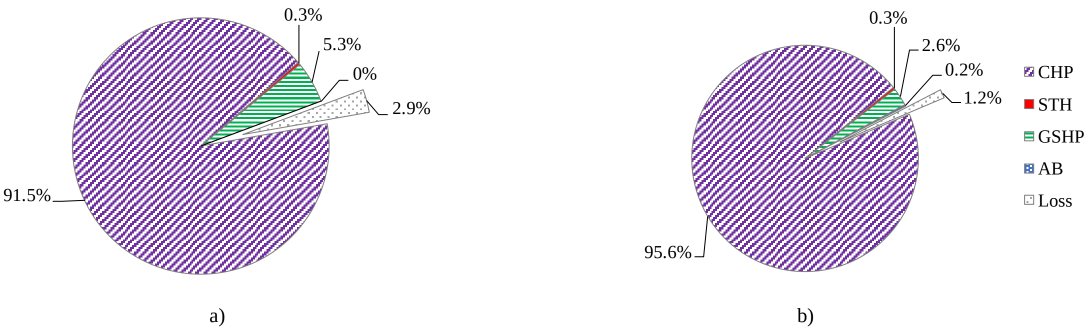


Fig. 4. Fraction of thermal energy demand met by the different HEP components for the GA-SOP a) and DP-DP b) methods.

The operating time of the CHP and GSHP systems for the GA-SOP and DP-DP methods is illustrated in Fig 5. As shown, the CHP is the system employed the most for all cases. Furthermore, the operating time of the technologies is lower when using the DP-DP method compared to the GA-SOP method. The CHP is able to meet a larger fraction of thermal demand even when working fewer hours and this may reduce the maintenance costs of the CHP.

The average performance of the CHP and the GSHP is another interesting point to highlight. The average efficiency of the CHP ($\eta_{\mathrm{el,CHP,av}}$) and the average coefficient of performance of the GSHP ($COP_{\mathrm{GSHP,av}}$) were calculated over the winter and mid-season period. It can be noted that, when using the DP-DP method, CHP and GSHP work at a higher average performance compared to the other case with values of 0.354 and 3.564, respectively. In other words, the DP-DP method tries to keep the CHP and GSHP working at full load and a higher efficiency than the GA-SOP method and this allows primary energy consumption to be minimized.

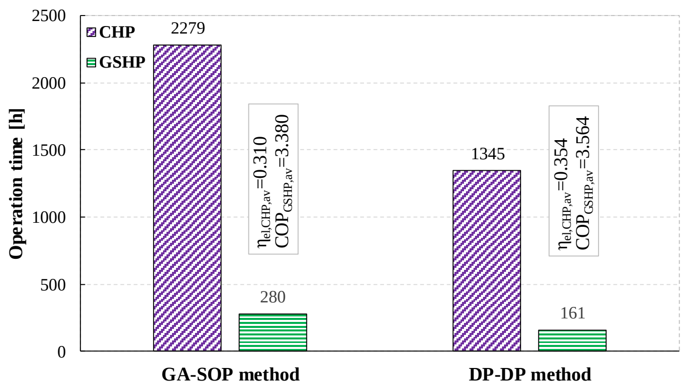


Fig. 5. The operating time of the CHP and GSHP during the simulation period.

The operational results of the GA-SOP and DP-DP methods are reported in Fig. 6 and Fig. 7 for a typical winter and mid-season day. They show the optimal operating strategy of the technologies defined in both methods.

As can be noted from Figs. 6 and 7, there is a big difference between the operational results obtained from the two methods. Indeed, for the GA-SOP method, the operation is defined by an SOP mapping, while the DP-DP method defines the optimal control policy by means of a DP algorithm which leads to a reduction of 5.4 % in primary energy consumption. From Fig. 6, with reference to the DP-DP method, a higher fraction of the thermal energy demand is fulfilled by the CHP which is greater in size than the GA-SOP method. Moreover, Figs. 6 and 7 show that the control policy defined by the DP tries to directly meet the thermal energy demand by the CHP system storing any excess. This prevents the system from operating at part loads, thus minimizing the number of start-ups. The stored energy is then used two or three times a day, when this is enough to meet the thermal energy demand. For both methods, Fig. 6 shows that the GSHP is employed during peak days when the CHP and the stored energy are not sufficient to fulfill the whole energy demand.

It is interesting to note that, following the DP optimal policy, the amount of energy in the storage is always lower than in the GA-SOP case (see Figs. 6 and 7). Indeed, as the thermal energy lost to the atmosphere through storage is proportional to the amount of stored energy, the DP-DP algorithm tries to limit the thermal dissipation by reducing the amount of energy kept in the storage. In fact, it can be seen from Fig. 4 that the lost energy is reduced by 2.9 % for the GA-SOP method and 1.2 % for the DP-DP method.

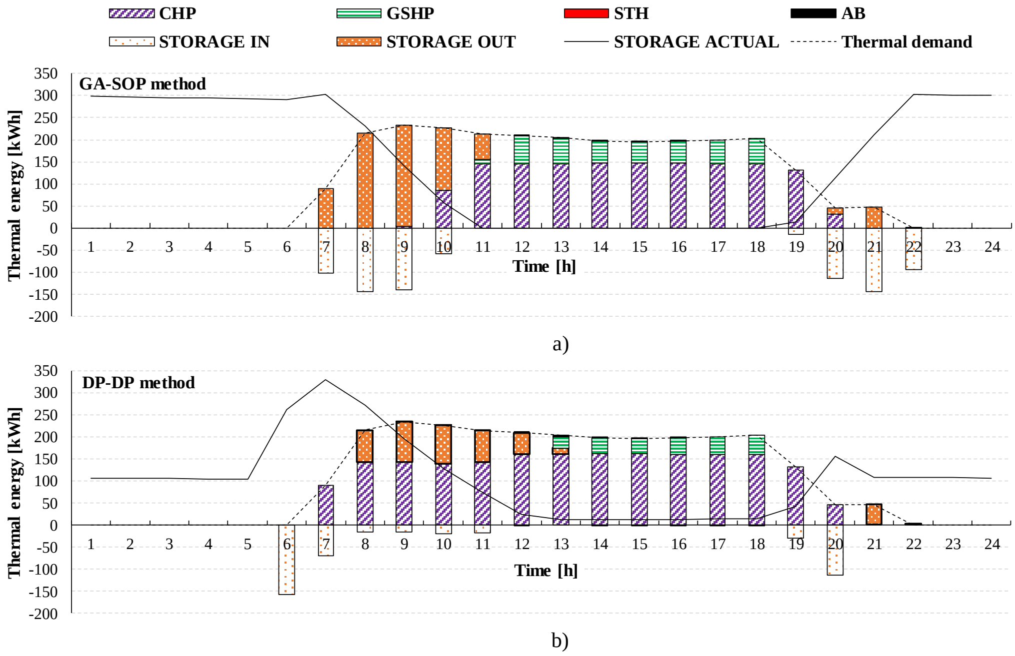


Fig. 6. Contribution to thermal energy demand of the HEP components for the GA-SOP a) and DP-DP b) methods on a winter day.

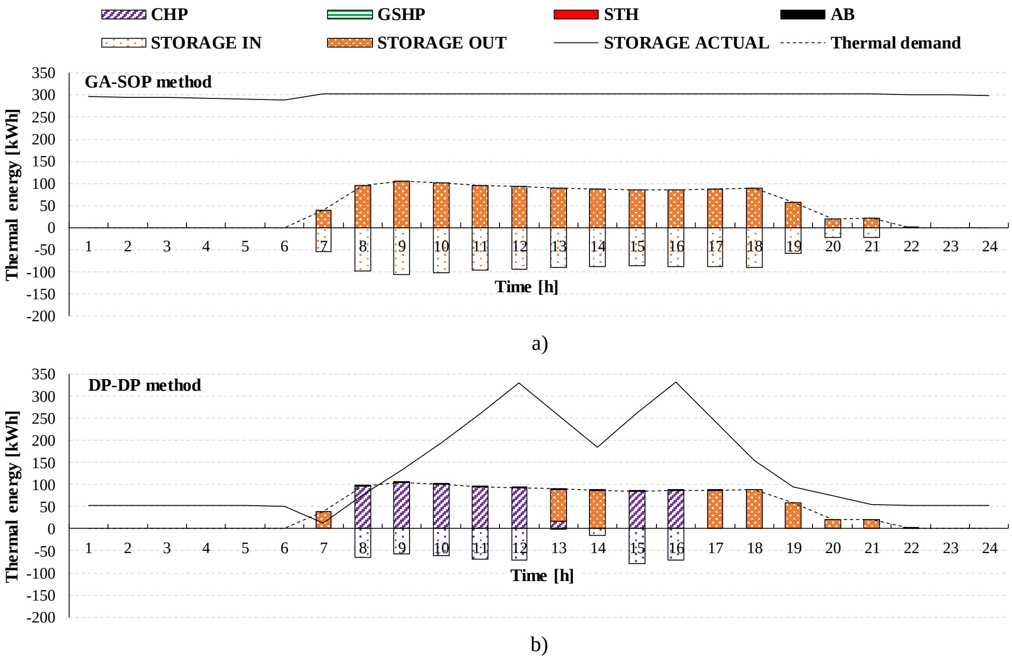


Fig. 7. Contribution to thermal energy demand of the HEP components for the GA-SOP a) and DP-DP b) methods on a mid-season day.

6. Conclusions

The issue of sizing and operation optimization was investigated in this paper, where a new general methodology based on the dynamic programming method is discussed. The study attempted to extend the use of dynamic programming techniques, which are mainly used for optimal control problems, by applying them to both the sizing and operation optimization of HEPs. The developed optimization framework is successfully applied on a hybrid energy plant which is employed to fulfill the energy demands of a case study. The superiority of the proposed method is demonstrated by comparing it with a commonly used optimization method, the genetic algorithm. The optimal combinations of sizes found by the two methodologies are different. This is due to the different characteristics and working procedure of the genetic algorithm and dynamic programming. It may be that the objective function that is minimized has a shallow minimum around which many configurations are nearly equivalent.

The optimization results showed that the proposed method is superior and requires relatively lower computation time compared to a traditional method based on the genetic algorithm. Moreover, compared to the genetic algorithm based method, the optimization method developed in this paper allows primary energy saving and computation time saving of about 5.4 % and 41 %, respectively. Finally, compared to the consumption of a traditional plant composed of a boiler and the electric grid, the optimization model developed in this paper allows about 24.7 % energy saving to be achieved.

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