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A novel approach for multi-stage investment decisions and dynamic variations in medium-term energy planning for multi-energy carriers community

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ABSTRACT

So far, energy planning methods faced several challenges in achieving a proper assessment due to the extreme variability of input conditions. To considerably decrease the computational efforts in achieving solutions, most of the analyses reported in the scientific literature assume constant costs and demand over the entire planning horizon in a typical year. However, results might not be perfectly aligned with real ones because of the incapability of some models to address several aspects like energy demand/production variability, energy and technology costs, efficiency degradation, and use of different energy carriers. This paper proposes a novel methodology that optimises both the long-term planning and short-term scheduling decisions in the management of a multi-energy carries community by means of a Mixed Integer Linear Programming model that also considers the modular design of technologies (e.g., technological devices selection from a discrete set of variants). Such a model has been applied to the case study of a University campus in Italy, whose historical demand data were used for its energy planning with a time horizon of 30 years. Three scenarios have been analysed: (i) the Business As Usual, (ii) the *Sector-coupling* scenario, and, finally, (iii) the *Hydrogen deployment* one. The results are obtained under different energy scenarios, showing the effectiveness of the methodology in dealing with multi-investment stages at different planning levels in a reasonable computational time. In particular, they showed that deploying more sustainable technologies would increase the cost of the electricity (between 43%–89%), while reducing other energy carriers' cost (about 60%) and lowering all energy carriers' carbon footprint (between 50%–80%). From a long-term perspective, (i) the use of sector-coupling technologies is beneficial from both economic and environmental points of view, and ii) dynamic variations of some parameters can strongly affect the deployment of high-cost technologies to be installed beyond 2030.

1. Introduction

In 2022, energy markets faced a significant skyrocketing trend in electricity and natural gas prices, particularly in Europe due to economic uncertainties and the unclear economic outlook. Important and strong policies are being now applied more than ever to move further in the advance of clean energy transitions to reduce the dependency on fossil fuels [1].

In response to future challenges in both energy generation and storage, energy planning has become crucial for developing long-range policies while assessing possible future scenarios. In light of this, energy systems modelling has gained more and more interest in the energy management sector [2]. Energy systems modelling enables to unlock the potential of Decentralised Energy Resources (DERs), Renewables Energy Sources (RESs), and Energy Storage Systems (ESSs) by assessing the interconnection between different energy carriers [3]. In such a context, Bartolini et al. [4] investigated synergies among different energy networks in a real residential district with a high share of Photovoltaic (PV) connected to different electric storage systems. This coupling proved to be a viable solution to exploit the excess of electricity production from PV only by undergoing local self-energy consumption. Jin et al. [5] developed an optimisation model for analysing the impact of the green hydrogen-natural gas blend into the Italian natural gas network in energy systems, hence to assess the the interaction and the integration of hydrogen and gas networks. Results led to an electrolyser capacity with a hydrogen volumetric concentration ratio in the mixture of 1.3–1.5 GWe/%vol. Energy planning models

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Nomenclature

AC	Absorption Chiller
BAU	Business As Usual
CHP	Combined Heat and Power
CTES	Cold Thermal Energy Storage
DER	Distributed Energy Resource
DHN	District Heating Network
DSO	Distribution System Operator
EC	Electric Chiller
EES	Electrical Energy Storage
EL	Electrolyser
ESS	Energy Storage System
FC	Fuel Cell
GB	Gas Boiler
HP	Heat Pump
HTES	Heat Thermal Energy Storage
LCOE	Levelized Cost of Energy
LEC	Local Energy Community
MILP	Mixed Integer Linear Program
O&M	Operation and Maintenance
OPEX	OPerational EXpenditure
PEM	Proton Exchange Membrane
PV	Photovoltaic
RES	Renewables Energy Sources
SH	Hydrogen Storage

can be classified according to different approaches. Klemm et al. [6] carried out a literature review of different energy system models and existing modelling tools. These models operate with a temporal resolution of at least 1 h and are based on bottom-up or hybrid approaches that use either Mixed Integer Linear Programming (MILP) or dynamic programming. As a result, they stated that there are a few modelling tools suitable for optimising energy systems in mixed-use districts such as those with multi-energy carriers. Ringkjøb et al. [7] reviewed and classified, under different perspectives (e.g., general logic, space and time granularity, technological and economic features), 75 energy modelling tools currently used for analysing energy and electricity systems. Although the review provides some insights into the tool selection process, there are still some challenges related to the space and the time variability that must be addressed. Beside the numerous open-source modelling tools, there are also commercial energy modelling software available in the market. Just to mention a few of them, the REopt web tool, which has been developed by the National Renewable Energy Laboratory (NREL) [8], is an online platform that performs energy systems analysis and provides the optimal mix of different technologies. However, REopt does not address hydrogen technologies included in this work. The same Lab also developed the energy planning tool ReEDS [9] that is used to perform national analyses and suggest expansion plans of infrastructure and technologies already deployed in the sector of the electric single-energy carrier. Gagnon et al. [10] used ReEDS to assess the evolution of the United States's electrical grid. Another commercial web-based tool, whose name is nPro [11], focuses on district-level technologies ,and in particular on the district heating connections. Generally speaking, the commercial solutions offer good user-friendly graphical interfaces and official support, and therefore they are particularly useful for energy policymakers and stakeholders that require accessible and easy-to-learn tools. However, the effectiveness or even the usability of most of them is jeopardised by the lack of flexibility from open-source alternatives like the possibility of defining specific technology types and spatial coverage.

Energy systems models are also classified on the base of other features like (i) top-down vs bottom-up approach, (ii) optimisation procedure, (iii) back-casting or forecasting methodology, (iv) MILP, (v) dynamic or stochastic algorithms, (vi) district or continental scale, and (vii) time resolution that ranges from seconds to hours. In this regard, Chang et al. [12] investigated the barriers of the current modelling status, highlighting the uttermost dependency of the results from energy demands data. They described the optimal planning of two real-world district multi-energy systems in China, namely Tongli's new energy town and Tongzhou's subsidiary administrative center. Results showed that investment decisions on energy conversion technologies involved in this study depended on different targets; for instance, the achievement of both carbon emissions reduction and renewables deployment goals would lead to a higher planning cost due to the increased number of considered constraints. The topic about the district-level planning by means of optimisation tools gained more and more interest over the last years thanks to the promotion effort of the European Commission [13] and the growth of both the Local Energy Communities (LECs) and Sector-coupling approach, , which are strongly dependent on the end-user electrification and cross-carrier sector-coupling pathways [14]. As stated in [6,12], most of the common tools for energy planning and modelling at a district and communities level consider a typical year for the whole planning horizon with a granularity of 1 h. The design of energy planning systems at the district level is often done by MILP approaches due to the inherent discrete nature of the involved entities. The assumption of linearity is required from both the design and computational perspective to achieve a good compromise between model meaningfulness and design/running time [15]. Wirtz et al. [16] analysed the variation of the results due to the fluctuation in both spatial and time resolution inputs, stating that not only the computational efforts have been considerably varied (from 10 s to 10 h) as well as the design objectives (about 5%).

Scenario analysis is a method to assess the improvement of different energy policies by comparing different possible outcomes. To deal with the uncertainty of the results, all the outcomes share the same model details of the benchmark case, which is known as Business As Usual (BAU). By means of the scenario analysis, Johannsen et al. [17] compared different optimisation and simulation strategies applied to a municipal case study, whereas Bhalawan et al. [18] investigated a design and operation methodology of a multi-generation energy system, achieving energy saving and cost reduction of 17-18% when compared to the BAU scenario. In both cases, a benchmark scenario has been first defined and then investigated using a step-wise and multi-objective approach. However, the previous results showed that there is not any standard modelling recipe and the design of a LEC should proceed by first considering a BAU scenario as a benchmark, and then deriving additional scenarios obtained by considering its alternative design constraints or objectives. Different types of inputs in energy systems models are subjected to high variability like the investment cost, especially those having a low Technology Readiness Level like hydrogen-related systems. In addition, the degradation rate of the technology and the energy demands variability over the years are important aspects to be aware of. To deal with these uncertainties, Piao et al. [19] developed an optimisation model that considers the oscillation of the electricity demand in Shanghai, China. The stochastic simulation-optimisation model did not only manage to predict the electricity demand perfectly, but it also allowed the assessment of the uncertainties such as interval values and probability distributions. Mavrotas et al. [20] combined both MILP and Monte Carlo approaches to consider the deviation of financial parameters (e.g., interest rate). Several probability functions have been obtained and provided to the decision-makers; as a result, the numerical solution of the stochastic program came out to be more time-consuming due to the additional complexity given by the statistical behaviour of the model. A dynamic multi-stage method for integrated energy systems planning has been proposed by Fan et al. [21]. The method, which consists of an initial stage, a linear development stage, and a further non-linear development stage has been successfully tested on three different case studies, proving the effectiveness of dynamic multi-stage energy planning. However, although the proposed approach considers the maturity of the technologies and their coupling degree, it does not include fluctuations of other key parameters such as energy demands and costs.

Indeed, to the authors' knowledge, a planning methodology addressing multiple energy carriers at the level of district energy communities and with multiple financial decision stages, which is able to support the investment decisions coherent with the dynamic of the energy market, the technology degradation, and the demand growth has not been deeply investigated so far. Moreover, most of the above-mentioned approaches assume continuous design variables that require a customisation of the equipment, with a consequent increase of costs or possible infeasible solutions. A more realistic, or at least less expensive, design of energy systems should require the use of integer decision design variables (e.g., power/capacity) able to capture the modular nature of the equipment of real energy systems; indeed, equipment and technologies are provided by manufacturers in distinct variants, each one with detailed specifications.

In this paper, a novel approach for the integrated short and long-term (decades) district-level planning of multi-energy carriers is introduced. In particular, a MILP-based two-step iterative method dealing with multi-stage investment decisions over the whole planning horizon of 30 years is proposed. Investment costs, energy demands, and each time-dependent data are assumed over the whole planning horizon. Such a time period is discretised into stages, one year each, and an energy system expansion plan is computed for each stage. In the first step, a MILP formulation is solved to set long-term investment decisions (the changes over time of the energy system configuration), while the short-term decisions (e.g., the operations on the technologies) are kept on a coarse-grained yearly scale. In the second step, a modified version of the MILP formulation provides the best scheduling of the deployed technologies in representative weeks of the time horizon, each one discretised into intervals of one hour. The MILPs employed in the two steps interact through linking inequalities, and they are embedded in an iterative scheme that leads to good integrated long/short-term solutions. The robustness and the computational efficiency of the proposed approach have been tested and validated with data coming from the case study of the campus of Marche Polytechnic University (UNIVPM) located in the center of Italy. Historical multi-energy carrier demands have been used to compute optimal energy plans over 30 years in three different scenarios: (i) BAU, (ii) *sector-coupling* scenario, and, finally, (iii) *hydrogen deployment*, the latter being the most-likely energy scenario in the next future since, according to the European REPowerEU strategy targets, 20 million tons of hydrogen will be needed by 2030, whose 10 million tons will be produced in Europe and the other 10 million tons will be imported [22]. Then, this work proposes an efficient computational approach for obtaining effective energy plans in the context of multi-energy carrier communities that consider dynamic multi-stage investments, fluctuating parameters, and realistic technology design. In particular, the main contributions are:

1. dynamic multi-stage investments: the proposed method takes into consideration the entire energy system at each year of the planning horizon, thus allowing for changes and expansions in response to ever-changing conditions. The objective function and operational conditions are the drivers of such adjustments;
2. variation of parameters over time: time fluctuating parameters, such as technology degradation and energy demand growth, are embedded into the model to ensure a more comprehensive and realistic energy planning process;
3. realistic modular design: the proposed approach adopts integer selection variables typical of the modular design instead of continuous variables describing the device features. Indeed, according to a more realistic representation of the technology deployment, the selection variables model the choice of a suitable device among a given number of available variants, each of them described by manufacturers' datasheets;
4. two-step iterative approach: the solution of MILPs within the proposed iterative scheme, on the one hand, trades off between the computational effort and the solution accuracy while, on the other hand, it makes viable the integrated long- and short-term planning over a wide time horizon of 30 years.

The paper is structured as follows: Section 2 describes in detail the methodology used for performing the energy planning analysis. Section 3 describes the case study of the UNIVPM campus. Section 4 explains and discusses the results of the different analysed scenarios from both planning and operation perspectives. Finally, Section 5 reports the conclusions of the work.

2. Material and methods

The optimisation approach described in this work aims to find solutions for multi-energy systems planning problems. A system layout is designed throughout the whole planning horizon, and selected technologies operate with technical constraints to fulfil the energy demand using different energy carriers. To explore multi-carrier energy communities, electricity, gas, heat, and cooling are considered as energy carriers along with water and hydrogen that are used only in the hydrogen deployment scenario.

Decisions are taken to minimise the overall economic cost, which is composed of investment, maintenance, and operative ones. A preliminary version of this approach has been described in [23] where it has been tested and validated for the energy planning of a residential district in the United States considering a multi-year horizon. The methodology has been further developed and refined to:

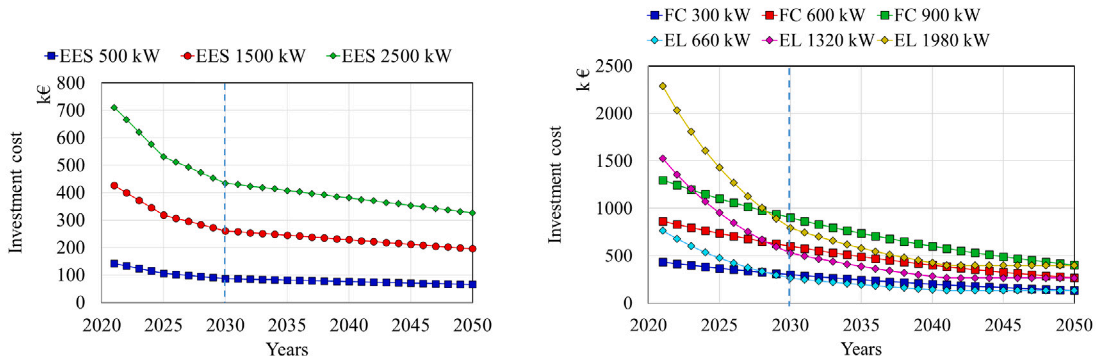
- make use of integer variables in the MILP approach for modelling investment choices;
- include the efficiency degradation of technologies over time and the discount rate of expenditures at present values;
- improve the exchange of information between the long- and short-term optimisation by means of refined constraints;
- integrate hydrogen systems with the other considered technologies.

2.1. Dynamic of parameters

The proposed approach considers the variations of several parameters over a planning horizon of 30 years. This time horizon has been chosen to reach 2050 when the net zero global targets should be achieved according to [24]. The following list provides an overview of the parameters involved in this study and explains how they have been chosen/considered:

- energy demand where, according to [25] and in line with the European Commission vision [26], the electricity one increases by 0.32%/year due to the electrification process, whereas other demands, e.g., natural gas, are kept constant according to [27];
- battery technology where both investment cost reduction and aging phenomena (e.g., capacity loss over time of 0.2%/day) have been modelled according to [28];
- efficiency degradation of technologies where all the involved technologies are subjected to a 1%/year of energy efficiency degradation, except Photovoltaic (PV) that has a degradation rate of 0.3%/year;
- hydrogen technology whose investment cost is based on the outcomes of [28].

The investment cost reduction of the involved technologies plays a key role in the analyses carried out in this work since the objective of the model is economic-driven. Fig. 1 shows that 2030 will be the turning point for the investment cost reduction of most of the involved technologies according to [25,26,28].



(a) Cost forecast of Electrical Energy Storage (EES) equipment available in the 3 variants of 500-1500-2500 kW [28]

(b) Cost forecast of hydrogen technologies: electrolyser and fuel cell devices are considered in 3 available variants of size [28]

Fig. 1. Outlook of the trends of investment costs: EESs and hydrogen technologies.

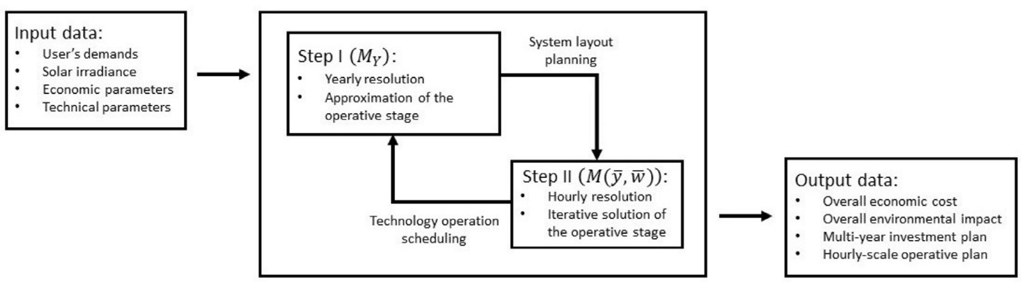


Fig. 2. Flowchart of the iterative MILP-based two-step approach.

2.2. The MILP-based two-step scheme

Solution models for multi-energy systems planning problems can be broadly divided into monolithic and decomposition-based approaches [29]. The former typically aims at founding optimal, or nearly optimal, solutions by relying on a single and very detailed description of the whole problem. However, since the related mathematical formulations typically embed time-indexed (binary) variables and constraints, such an approach rapidly becomes unviable as the size of the problem increases due to a wide time horizon and/or a refined time discretisation. As an example, a planning horizon of 10 years discretised in intervals of one hour corresponds to roughly 87 600 h. A formulation for a multi-energy system with 3 energy carriers and 20 technologies has at least $20 \times 87\,600 = 1752k$ variables and $3 \times 20 \times 87\,600 = 5256k$ constraints. Clearly, MILP solvers may struggle on such instances of only a moderate-size planning horizon. Decomposition-based techniques, as the two-step MILP approach described in this work, overcome such limits by leveraging in several possible ways the separation between the long-term decisions (investment stage) and the short-term ones (operative stage), still providing good quality solutions. The general structure and the pseudo-code of the approach are respectively reported in Fig. 2 and in Algorithm 1 at the end of Section 2.2.4. Table 2 in the Appendix reports the details of the mathematical notation.

2.2.1. First step : design of the system layout and planning of investments

In the first step, a MILP (M_Y) is solved to define the investment actions. Each year of the planning horizon represents a decision stage for the installation or the renewal of technological devices. The variables of M_Y decide the system layout (e.g., indicate which and how many devices, generally of different type and size) are selected among a set of available ones as well as the operation management. The latter (e.g., supply of external energy, device activation, energy conversion, and storage) are controlled on an aggregated scale of one year by the constraints of M_Y.

In particular, let Y be the set of intervals in a multi-year planning horizon K the set of available energy carriers, and $\hat{K} \subseteq K$ the subset of energy carriers (e.g., heat, cooling, and hydrogen in this case study) that cannot be fed from an external supply due to the lack of infrastructure. Moreover, let Q be the collection of deployable technological devices including both conversion and storage equipment and, in particular, let $S \subseteq Q$ be the set of storage devices. Finally, let ℓ_q be the expected lifetime of the technological device $q \in Q$. The model M_Y is defined upon the following variables for each year $y \in Y$ (notice: the amounts of energy are expressed in kWh):

- $x_{qy}, z_{qy} \in \mathbb{N}_0$: the number of devices of type $q \in Q$ purchased and active in year y, respectively;
- $p^k_{qy} \in \mathbb{R}^+$: the amount of energy by carrier $k \in K$ and produced by the conversion device $q \in Q \setminus S$ in year y;
- $r^{lk}_{qy} \in \mathbb{R}^+$: the amount of energy by carrier l converted into energy by carrier k through the conversion device $q \in Q \setminus S$ in year y;
- $s^k_{qy} \in \mathbb{R}^+$: the amount of energy by carrier k accumulated into the storage device $q \in S$ in year y;
- $f^k_y \in \mathbb{R}^+$: the amount of energy by carrier k and supplied from external sources at year y.

Variables are defined as non-negative because of the scenario, which corresponds to the case study where the energy system is one-way connected to the national grid and thus no surplus of energy can be sold. Moreover, alternative profitable strategies involving the sale of energy, possibly from non-dispatchable sources, to the external grid (e.g., *feed-in* or *net metering*) generally make ESS technologies economically disadvantageous. Clearly, $f^k_y = 0$ for energy of type $k \in \hat{K}$, see constraint (8).

According to the yearly granularity of the model, each parameter expresses a yearly aggregated value. In particular, the values of parameters $\bar{\boldsymbol{d}}, \bar{\boldsymbol{b}}, \bar{\boldsymbol{U}}$, and $\bar{\boldsymbol{C}}$ are computed as the rated hourly value times the total number $T_h = 8760$ of hours in one year. The model M_Y reads as follows:

$$\min \sum_{k\in K}\sum_{y\in Y} c_y^k f_y^k \cdot \frac{1}{(1+r)^y} + \Gamma \tag{1}$$

$$\bar{d}_y^k + \sum_{q\in S} s_{qy}^k + \sum_{q\in Q\setminus S}\sum_{l\in K\setminus\{k\}} r_{qy}^{kl} = \sum_{q\in S} e_q^k s_{qy-1}^k + \sum_{q\in Q\setminus S} p_{qy}^k + f_y^k \qquad \forall k\in K, \forall y\in Y \tag{2}$$

$$z_{qy} = \sum_{\tau=\max\{1,y-\ell_q+1\}}^{y} x_{q\tau} \qquad \forall q\in Q, \forall y\in Y \tag{3}$$

$$p_{qy}^k = \sum_{l\in K\setminus\{k\}} \phi_q^{lk} r_{qy}^{lk} + \bar{b}_{qy}^k \cdot \left(x_{qy} + \sum_{\tau=\max\{1,y-\ell_q+1\}}^{y-1} (1-\delta_q)^{(y-\tau)} x_{q\tau} \right) \qquad \forall q\in Q\setminus S, \forall k\in K, \forall y\in Y \tag{4}$$

$$p_{qy}^k \le \bar{U}_q^k z_{qy} \qquad \forall q\in Q\setminus S, \forall k\in K, \forall y\in Y \tag{5}$$

$$s_{qy}^k \le \bar{C}_q^k \cdot \left(x_{qy} + \sum_{\tau=\max\{1,y-\ell_q+1\}}^{y-1} (1-\delta_q)^{(y-\tau)} x_{q\tau} \right) \qquad \forall q\in S, \forall k\in K, \forall y\in Y \tag{6}$$

$$s_{q0}^k = 0 \qquad \forall q\in S, \forall k\in K \tag{7}$$

$$f_y^k = 0 \qquad \forall k\in \hat{K}, \forall y\in Y \tag{8}$$

$$x_{qy}, z_{qy} \in \mathbb{N}_0 \qquad \forall q\in Q, \forall y\in Y \tag{9}$$

$$p_{qy}^k, r_{qy}^{lk} \in \mathbb{R}^+ \qquad \forall q\in Q\setminus S, \forall l,k\in K : l\neq k, \forall y\in Y \tag{10}$$

$$s_{qy}^k, f_y^k \in \mathbb{R}^+ \qquad \forall q\in S, \forall k\in K, \forall y\in Y \tag{11}$$

Constraints (2) are the flow balancing equalities that hold for each energy carrier k and year y: the total amount of energy by carrier k and given by the user's annual demand plus the possible surplus of energy stored for being used afterward when required plus the energy converted into a different energy carrier must correspond to the total quantity given by the available charge of storage devices (e.g., heat thermal, electrical energy storage) at the previous year plus the production of installed devices plus the amount of energy purchased from external sources. The parameter e_q^k is the round-trip efficiency of the storage device q when accumulating the energy of type k, and assuming that both charging and discharging dynamics of ESSs are linear. Equations (3) link the number of operative devices to the number of those purchased in the past, also considering the device lifetime. For each energy carrier k and year y, the equality (4) sets the output of the conversion device q to the sum of two contributions. The former is the overall quantity of energy of type k obtained by the conversion from other kinds of energy carriers involved in the system, linearly weighted with the conversion efficiency ϕ_q^{lk} of the technology. The latter, instead, refers to the conversion from exogenous energy carriers that depends on exogenous factors that are all embedded into the annual base production value $\bar{b}_{qy}^k$ (e.g., renewable technologies like PV or wind farms are strongly dependent on weather conditions). The latter term also incorporates the parameter δ_q that expresses the annual degradation of the energy production efficiency (clearly, the contribution of δ_q increases as far as the device q gets older). Although the loss of efficiency also affects the conversion from energy carriers involved in the system, it has not been considered in the former contribution to avoid non-linearities, and therefore p_{qy}^k only approximates the output of the (set of) device: an exact expression is used in the MILP of the second step.

In any case, the production of each conversion device is limited by the scaled upper rated power $\bar{U}_q^k$ as prescribed by constraints (5).

Inequalities (6) bound the aggregated annual capacity of storage devices from above: the amount of energy of type k accumulated in one year by the storage device $q \in S$ must be no higher than the scaled rated capacity $\bar{C}_q^k$ amortised by the obsolescence of q. Moreover, all the operating storage devices are assumed to be empty at the beginning of the planning horizon, which is a constraint as reported in (7).

Since ESSs are generally used to absorb the peaks of production and because of the coarse-grained time resolution of the model, the s variables naturally would take the zero value (there is no economic convenience to store energy from one year to the other). To promote the investment and exploitation of energy storage devices, the model M_Y is fed by the linking constraints (see Section 2.2.3), with refined weekly-based data provided from the second step of the algorithm. Finally, besides the constraints (9)–(11) on the variables domains, further constraints are added to M_Y for modelling features and constraints of specific technologies employed in the case study (see Section 2.3). The objective function (1) minimises the overall yearly costs with a discount rate at present value r for the whole planning horizon of $|Y| = 30$ years. The first term refers to the buying costs of external energy supply (c_y^k is the cost of energy per kWh). The analytical expression of Γ is the following:

$$\Gamma = \sum_{\substack{q\in Q\\ y\in Y}} v_{qy} x_{qy} \cdot \frac{1}{(1+r)^{y-1}} + \sum_{\substack{q\in Q\\ y\in Y}} m_{qy} z_{qy} \cdot \frac{1}{(1+r)^y} - \sum_{\substack{q\in Q\\ y\ge |Y|+1-\ell_q}} \left[v_{qy} x_{qy} \cdot \frac{1-(1+r)^{|Y|+1-y-\ell_q}}{1-(1+r)^{-\ell_q}} \right] \cdot \frac{1}{(1+r)^{|Y|+1}}. \tag{12}$$

Investment v_{qy} and maintenance costs m_{qy} are summed up over the planning horizon for all the operating devices. The last term gives the total residual value of the owned equipment at the end of the planning horizon. Due to the features of the addressed case study (e.g., UNIVPM campus in Italy) and the choice of an economic-driven optimisation, revenues due to energy sales, costs for energy storage, and environmental costs have not been included in Γ. However, alternative/additional cost terms could be included in the objective function, or addressed by relying on multi-criteria optimisation methods (e.g., lexicographic, linear scaling, and ϵ-constraint), if they are relevant for case studies with different characteristics and/or located in different economic zones (e.g., environmental costs or costs in the U.S. market related to the maximum demand-based charge).

2.2.2. Second step: system operations scheduling

A solution $\boldsymbol{sol}^{\boldsymbol{Y}}$ provided by M_Y gives a full description of the system layout for the whole planning horizon. The second step of the optimisation computes a refined time scale schedule of the components chosen by M_Y, evaluates the actual total operative costs of the system, and assesses the operative feasibility of the layout. As reported in [30], a common approach adopted in energy systems modelling to control the computational viability consists in extracting a set of weeks through a κ-means clustering procedure [31], which is representative of the average weekly demands per each energy carrier and the average PV production. Therefore, a set W_y of representative weeks for each year $y \in Y$ of the planning horizon is considered in the second step. The weeks W_1 of the first year are directly obtained by clustering the historical data of the case study, whereas the representative weeks of the following years are obtained by considering the estimated data variations. After tuning the parameter κ, $|W_y|$ was set equal to 6. Each week in W_y is composed by 168 h and represents n_w original weeks.

For each year $\bar{y} \in Y$ and week $\bar{w}$ in $W_{\bar{y}}$, a second MILP formulation $M(\bar{y}, \bar{w})$ computes the hourly schedule of the energy system operations at minimum cost. Let $H_{\bar{w}}$ be the set of hours composing the week $\bar{w}$, $Q^{\bar{y}}$ the set of operating devices that $\boldsymbol{sol}^{\boldsymbol{Y}}$ indicates for year $\bar{y}$, and i_q the year of installation for each device $q \in Q^{\bar{y}}$. The set $Q^{\bar{y}}$ is obtained by adding a number $z_{q\bar{y}}$ of copies of the device q for conversion and storage operations at year $\bar{y}$, whereas i_q is given from the values of $x_{q\bar{y}}$ in $\boldsymbol{sol^Y}$. Finally, let $S^{\bar{y}} \subseteq Q^{\bar{y}}$ be the set of storage devices operating in year $\bar{y}$.

MILP $M(\bar{y}, \bar{w})$ does not perform investment decisions, thus design variables x_{qy} and the corresponding constraints are not used. Variables z_{qy} are restricted to be binary and re-indexed as z_{qh} to model the use of the device $q \in Q^{\bar{y}}$ at hour $h \in H_{\bar{w}}$. All the other variables (and constraints) are similarly re-indexed (e.g., $f_y^k \to f_h^k$). The formulation $M(\bar{y}, \bar{w})$ reads as:

$$\min \Omega_{\bar{y}\bar{w}} = \sum_{k \in K, h \in H_{\bar{w}}} c_{\bar{y}}^k f_h^k \cdot \frac{1}{(1+r)^{\bar{y}}} \tag{13}$$

$$d_h^k + \sum_{q \in S^{\bar{y}}} s_{qh}^k + \sum_{q \in Q^{\bar{y}} \setminus S^{\bar{y}}} \sum_{l \in K \setminus \{k\}} r_{qh}^{kl} = \sum_{q \in S^{\bar{y}}} e_q^k (1-\rho_q) s_{qh-1}^k + \sum_{q \in Q^{\bar{y}} \setminus S^{\bar{y}}} p_{qh}^k + f_h^k \quad \forall k \in K, \forall h \in H_{\bar{w}} \tag{14}$$

$$p_{qh}^k = \sum_{l \in K \setminus \{k\}} \phi_q^{lk} (1-\delta_q)^{(\bar{y}-i_q)} r_{qh}^{lk} + b_{qh}^k (1-\delta_q)^{(\bar{y}-i_q)} z_{qh} \quad \forall q \in Q^{\bar{y}} \setminus S^{\bar{y}}, \forall k \in K, \forall h \in H_{\bar{w}} \tag{15}$$

$$L_q^k z_{qh} \le p_{qh}^k \le U_q^k z_{qh} \quad \forall q \in Q^{\bar{y}} \setminus S^{\bar{y}}, \forall k \in K, \forall h \in H_{\bar{w}} \tag{16}$$

$$s_{qh}^k \le C_q^k (1-\delta_q)^{(\bar{y}-i_q)} z_{qh} \quad \forall q \in S^{\bar{y}}, \forall k \in K, \forall h \in H_{\bar{w}} \tag{17}$$

$$s_{qh_1}^k = s_{qh_{168}}^k \quad \forall q \in S^{\bar{y}}, \forall k \in K \tag{18}$$

$$f_h^k = 0 \quad \forall k \in \hat{K}, \forall h \in H_{\bar{w}} \tag{19}$$

$$z_{qh} \in \{0,1\} \quad \forall q \in Q^{\bar{y}}, \forall h \in H_{\bar{w}} \tag{20}$$

$$p_{qh}^k, r_{qh}^{lk} \in \mathbb{R}^+ \quad \forall q \in Q^{\bar{y}} \setminus S^{\bar{y}}, \forall l \neq k \in K, \forall h \in H_{\bar{w}} \tag{21}$$

$$s_{qh}^k, f_h^k \in \mathbb{R}^+ \quad \forall q \in S^{\bar{y}}, \forall k \in K, \forall h \in H_{\bar{w}} \tag{22}$$

The objective function (13) is the total discounted cost of the purchased energy, which is computed by considering the cost $c_{\bar{y}}^k$ per kWh of energy of type k at year $\bar{y}$. Constraints (14) are the balancing equations specifying the hourly requirements of the system and they refine (2) by introducing the hourly capacity loss ρ_q for storage. Constraints (15) and (17) are the analogous of (4) and (6), respectively, for a fixed year and equipment. However, the efficiency degradation δ_q in constraints (15) is considered in both the conversion efficiency ϕ_q^{lk} and base production b_{qh}^k. If the conversion devices q is operating at hour h (e.g., if $z_{qh} = 1$), inequalities (16) bound the energy output p_{qh}^k between the upper hourly rated power U_q^k and the lower partialisation bound L_q^k; otherwise, if the device q is not active (i.e., if $z_{qh} = 0$), p_{qh}^k will be set equal to zero. Finally, (18) ensures that during the week $\bar{w}$, which is only representative, the energy storage and consumption are balanced. Further constraints are considered based on specific technologies used in this work (see Section 2.3). A solution $\boldsymbol{sol^W}$ of the whole second step will be feasible if $M(\bar{y}, \bar{w})$ is feasible for each $\bar{y} \in Y$ and $\bar{w} \in W_{\bar{y}}$. In this case, its cost Ω is the sum of the costs $\Omega_{\bar{y}\bar{w}}$ of all the solutions $\boldsymbol{sol}(\bar{y}, \bar{w})$ of $M(\bar{y}, \bar{w})$, each one multiplied by $n_{\bar{w}}$.

2.2.3. Linking inequalities

The information obtained from the solutions of the $M(\bar{y}, \bar{w})$ programs is used through a feedback loop, which is implemented by the linking constraints (23) and (24), to guide M_Y towards different system layouts. A solution $\boldsymbol{sol}(\bar{y}, \bar{w})$ of $M(\bar{y}, \bar{w})$ can be either:

1. Infeasible due to the impossibility of satisfying the demand by exploiting the operating devices in case of shortage of external supply (e.g., k belongs to $\hat{K}$ and (19) hold), or
2. Feasible: in this case, it describes the hourly schedule of the device operations in the current week.

In the former case, a *feasibility cut* constraint of M_Y, which pursues the operative feasibility of the system layout on hourly scale (see line 22 in Algorithm 1), is updated. This constraint is defined for each non-purchasable energy carrier $k \in \hat{K}$ that do not fulfil the demand at a given hour $\hat{h}$ in at least a representative week of $W_{\bar{y}}$ for some years $\bar{y}$:

$$\hat{d}_{\bar{y}}^k \le \sum_{q \in Q \setminus S} \left[(1-\theta) U_q^k z_{q\bar{y}} + b_{q\hat{h}}^k \left(z_{q\bar{y}} - \sum_{\tau=\max\{1, y-\ell_q+1\}}^{\bar{y}-1} \delta_q^{(\bar{y}-\tau)} x_{q\tau} \right) \right] + \theta \sum_{q \in S} C_q^k \left(z_{q\bar{y}} - \sum_{\tau=\max\{1, \bar{y}-\ell_q+1\}}^{\bar{y}-1} \delta_q^{(\bar{y}-\tau)} x_{q\tau} \right). \tag{23}$$

In particular, considering the energy of type $k \in \hat{K}$ and year $\bar{y} \in Y$, let $\hat{d}_{\bar{y}}^k$ be the parameter indicating the largest demand per hour. $\hat{d}_{\bar{y}}^k$ is initialised to d_w^k and increased by $\hat{u}_{\bar{y}}^k$ (see lines 3 and 20 in Algorithm 1), where d_w^k is the largest demand per hour among the weeks in $W_{\bar{y}}$, $\hat{h}$ is the hour when the unmet demand of the infeasible solution is maximum, and $\hat{u}_{\bar{y}}^k$ is the value of such unmet demand. In (23), technical parameters of devices have an hourly scale, and the estimated base production b of renewable technologies is set to its value at hour $\hat{h}$. The hourly demand $\hat{d}_{\bar{y}}^k$ must be met by using renewable technologies together with a convex combination of the rated power U_q^k of energy conversion technologies producing k and the storage capacity C_q^k for k. Parameter $\theta \in [0, 1)$ defines the weight of each term of the combination and balances the ratio between conversion and storage. After preliminary experiments and tuning, its value was set equal to 0.4. Such a tuning made the investments into ESSs more profitable, hence overcoming the lack of convenience in storage technologies because of the aggregated annual scale of M_Y.

Moving to feasible solutions $\boldsymbol{sol}(\bar{y}, \bar{w})$, a constraint of M_Y which promotes the autonomy of the energy system by reducing the incoming supply from external sources, such as the national grid, and it is updated (line 23 in Algorithm 1). The inequality for a purchasable energy carrier $k \in K \setminus \hat{K}$ in year $\bar{y}$ reads as:

$$\tilde{d}_{\bar{y}}^k \le \frac{f_{\bar{y}}^k}{T_h} + \sum_{q \in Q \setminus S} \left[U_q^k z_{q\bar{y}} + b_{q\tilde{h}}^k \left(z_{q\bar{y}} - \sum_{\tau=\max\{1, \bar{y}-\ell_q+1\}}^{\bar{y}-1} \delta_q^{(\bar{y}-\tau)} x_{q\tau} \right) \right] + \sum_{q \in S} C_q^k \left(z_{q\bar{y}} - \sum_{\tau=\max\{1, \bar{y}-\ell_q+1\}}^{\bar{y}-1} \delta_q^{(\bar{y}-\tau)} x_{q\tau} \right). \tag{24}$$

The parameter $\tilde{d}_{\bar{y}}^k$ represents the request of energy linked to the peak of purchased external energy of type k recorded at year $\bar{y}$. It is initialised to zero at the beginning of the two-step algorithm. Then, the procedure looks for the hour $\tilde{h}$ of the feasible solutions $\boldsymbol{sol}(\bar{y}, \bar{w})$ when the maximum quantity of energy of type k ($\tilde{f}_{\bar{y}}^k$ in Algorithm 1) is bought, and updates the parameter $\tilde{d}_{\bar{y}}^k$ if its current value is quite smaller than $\tilde{f}_{\bar{y}}^k + d_{\tilde{h}}^k$ (see line 21 in Algorithm 1). The updating threshold is modulated by the parameter γ, which has been set equal to 0.6 after the parameter tuning. The idea of the constraint is to guide M_Y towards the selection of a set of devices able to meet the expected hourly residual demand, thus enhancing the autonomy of the system. The constraint (24) imposes the fulfilment of the energy request $\tilde{d}_{\bar{y}}^k$ by using only the mean value $f_{\bar{y}}^k / T_h$ of the annual external supply, thus limiting the peak of purchase. Similarly to (23), the presence of the terms associated with storage devices implicitly promotes the installation of ESSs in the system.

2.2.4. The whole procedure

A solution $\boldsymbol{sol}$ of the overall multi-energy system planning problem consists of both the long-term investment variables $\boldsymbol{sol^Y}[\boldsymbol{x}]$ and the short-term operative variables $\boldsymbol{sol^W}[\boldsymbol{z}, \boldsymbol{p}, \boldsymbol{r}, \boldsymbol{s}, \boldsymbol{f}]$. Its total cost C is given by the sum $\Gamma + \Omega$. If the current solution $\boldsymbol{sol}$ has the smallest cost obtained so far, the best total cost C^* and the best solution $\boldsymbol{sol}^*$ are then updated (see lines 22–24 in Algorithm 1). The two step procedure is repeated for a fixed number N of iterations (e.g., 5 in the experiments). The algorithm returns the best solution $\boldsymbol{sol}^*$ and the corresponding total cost C^* (see line 25 in Algorithm 1). The pseudo-code of the whole procedure is the following:

Algorithm 1 MILP-based two-step iterative algorithm

Initialise sets, parameters and variables;
Set $C^* = +\infty$;
Set $\tilde{\boldsymbol{d}} = \boldsymbol{0}$ and $\hat{d}^k_y$ to the largest hourly demand, for each $k \in \hat{K}$ and $y \in Y$;
for N times **do**
    Solve M_Y, update solution $\boldsymbol{sol^Y}$ and Γ;
    Set $\boldsymbol{sol^W} = \emptyset$ and $\Omega = 0$;
    for $\bar{y} \in Y$ **do**
        Initialise $Q^{\bar{y}}$, $S^{\bar{y}}$ from $\boldsymbol{sol^Y}[\boldsymbol{z}_{\bar{y}}]$; ▷ used technologies at year $\bar{y}$
        Set $\boldsymbol{i}$ from $\boldsymbol{sol^Y}[\boldsymbol{x}_{\bar{y}}]$; ▷ year of installation per technology
        Set $\hat{\boldsymbol{u}}_{\bar{y}} = \boldsymbol{0}$ and $\tilde{\boldsymbol{f}}_{\bar{y}} = \boldsymbol{0}$;
        for $\bar{w} \in W_{\bar{y}}$ **do**
            Solve $M(\bar{y}, \bar{w})$;
            if $\boldsymbol{sol}(\bar{y}, \bar{w})$ is infeasible **then**
                Update $\hat{u}^k_{\bar{y}}$ if hour $\hat{h} \in H_{\bar{w}}$ has the largest unmet demand, for each $k \in \hat{K}$;
                Set $\Omega = +\infty$;
            else
                Update $\tilde{f}^k_{\bar{y}}$ if hour $\tilde{h} \in H_{\bar{w}}$ has the largest quantity of purchased energy, for each $k \in K \setminus \hat{K}$;
                Set $\Omega = \Omega + n_{\bar{w}} \cdot \Omega_{\bar{y}\bar{w}}$;
                Set $\boldsymbol{sol^W} = \boldsymbol{sol^W} \cup \boldsymbol{sol}(\bar{y}, \bar{w})$;
        Set $\hat{\boldsymbol{d}}_{\bar{y}} = \hat{\boldsymbol{d}}_{\bar{y}} + \hat{\boldsymbol{u}}_{\bar{y}}$ and update (23);
        Set $\tilde{\boldsymbol{d}}_{\bar{y}} = \max\{\gamma \cdot (\boldsymbol{d}_{\tilde{h}} + \tilde{\boldsymbol{f}}_{\bar{y}}), \tilde{\boldsymbol{d}}_{\bar{y}}\}$ and update (24);
        if $C^* > \Gamma + \Omega$ **then**
            Set $C^* = \Gamma + \Omega$; ▷ update best solution cost
            Set $\boldsymbol{sol}^* = \boldsymbol{sol^Y}[\boldsymbol{x}] \cup \boldsymbol{sol^W}[\boldsymbol{z}, \boldsymbol{p}, \boldsymbol{r}, \boldsymbol{s}, \boldsymbol{f}]$; ▷ update best solution
return $(\boldsymbol{sol}^*, C^*)$

2.3. Technology-dependent constraints

Some of the technologies available in the case study under investigation need specific constraints to coherently model the requirements in M_Y and/or $M(\bar{y}, \bar{w})$; in particular:

- The Combined Heat and Power (CHP) unit needs a couple of equalities to model the simultaneous production of electricity (index el) and heat (index th) from the same natural gas supply with different conversion efficiencies. Let Q^{CHP} be the subset of deployable CHP devices in model M_Y; then, per each year $y \in Y$ the following equalities are imposed:

$$p^{el}_{qy} = \phi^{gas,el}_q r^{gas,el}_{qy} \tag{25}$$

$$p^{th}_{qy} = \phi^{gas,th}_q r^{gas,el}_{qy} \tag{26}$$

  Constraints are also included in $M(\bar{y}, \bar{w})$ after re-indexing on $h \in H_w$ when CHP units operate in a week represented by the model. An analogous formalisation is used to model the operations of a Proton Exchange Membrane (PEM) Fuel Cell (FC), which exploits hydrogen for the simultaneous production of electricity and heat;
- The size of the PV systems is constrained to an upper bound due to physical occupation, which is translated into a maximum deployable rated power in the system at each year $y \in Y$ for M_Y:

$$\sum_{q \in Q^{PV}} U^{el}_q z_{qy} \leq U^{PV}_{\max} \tag{27}$$

  where Q^{PV} is the collection of the PV systems of different sizes that can be installed;
- The Heat Pump (HP) provides alternative heating and cooling outputs. Let Q^{HP} be the collection of available HP technologies. Each $q \in Q^{HP}$ is differentiated as follows: q_1 can only generate heat, whereas q_2 generates the cooling energy. The different $q \in Q^{HP}$ share the same year of installation, and each of them contributes to half of the total costs of the device in the objective function of M_Y. For each $y \in Y$, the following equalities are added to M_Y to model the operation choice while observing the lifetime of the system:

$$z_{q_1 y} + z_{q_2 y} = \sum_{\tau=\max\{1, y-\ell_q+1\}}^{y} x_{q\tau} \tag{28}$$

  Given the binary nature of variables z_{qh}, a constraint for each hour $h \in H_w$ is introduced in $M(\bar{y}, \bar{w})$:

$$z_{q_1 h} + z_{q_2 h} \leq 1; \tag{29}$$

- The PEM ELectrolyser (EL) operates with electricity and water as inputs (index *wat*) for producing hydrogen (index *hyd*). The inequalities used to model its operations in M_Y are:

$$p^{hyd}_{qy} = \phi^{el,hyd}_q r^{el,hyd}_{qy} \tag{30}$$

$$\frac{\sum_{q \in Q^{EL}} p^{hyd}_{qy}}{\phi^{wat,hyd}_q} \leq f^{wat}_y \tag{31}$$

  per each $y \in Y$ (or $h \in H_w$ in $M(\bar{y}, \bar{w})$), with Q^{EL} subset of available EL technologies.

3. Case study

The case study under investigation focuses on the University campus of Marche Polytechnic University located in Ancona, Italy. It is a medium-scale campus that accounts for almost 17 000 people among students and academics, administrative, and technical staff. The UNIVPM campus hosts different faculties, namely Engineering, Agriculture, and Science: it is constituted by several facilities dedicated to offices, classrooms, and laboratories (see Fig. 3) that cover an area of about 31 000 m^2. The UNIVPM campus is connected to the national electric grid and to the natural gas grid. The connection with these infrastructures is one-way, meaning that it is only possible to withdraw these primary sources to fulfil part of the energy demand of the UNIVPM campus. Regarding the natural gas network, it is directly connected to the thermal power plant, which is located inside the campus and produces the thermal energy required by heating the different facilities within the campus. There are different energy networks that transport different energy carriers within the UNIVPM campus; indeed, besides the electrical and heat demands, there is also a cooling energy demand to be satisfied in the warm seasons. The electrical energy is satisfied by the constant production of the DERs, which is constituted by a CHP unit supported by the local grid distribution. The thermal energy, instead, is fulfilled mainly by the natural gas boilers and the heat produced by the CHP unit, which is distributed through a local District Heating Network (DHN); as for the cooling energy, both electric and absorption chillers powered by the heat energy from the DHN are used. Besides the connection to both electric and natural gas networks, the analysed energy system layout within the UNIVPM campus is constituted by:

- a PV system of 20 kW_p;
- a CHP unit with a rated power of 575 kW_{el}/610 kW_{th} connected to the DHN with a yearly average electrical and thermal efficiency of 0.415 and 0.44, respectively;
- eight natural Gas Boilers (GBs), each of them having a rated capacity of 1 MW_{th} and an average efficiency of 0.91;
- two Absorption Chillers (ACs) with an overall capacity of 500 kW_{th} and an average efficiency of 0.8;
- three Electrical Chillers (ECs) with a total capacity of 900 kW_{th} and an average Coefficient Of Performance equal to 3.

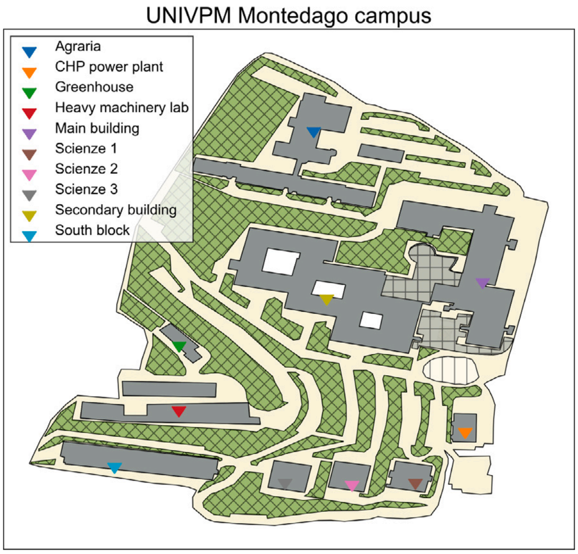


Fig. 3. Overall map of the UNIVPM campus (main facilities are highlighted).

The historical data used in this study refer to the year 2019 as shown in Fig. 4. The whole campus has been considered as a single end-user due to the lack of a monitoring system for each building. The energy demands, coming from the monitoring of gas and electricity consumption described in [32], consist of the three energy carriers previously mentioned. The type of monitoring is hourly base and it lasted for one year (2019). The overall electrical energy consumption was around 5 GWh_e with a power peak of 1.37 MW. Nearly 4 GWh_{th} have been consumed with a power peak of 4.4 MW occurred on the 4th of January 2019. This peak refers to the "rebound effect" caused by powering up the space heating infrastructure that was inactive during the Christmas holidays; thus, a considerable amount of heat was required to restore the set-point temperature of the UNIVPM facilities. Finally, the cooling energy demand occurred only in July–September when 0.5 GWh_{th} were absorbed with a power peak of 1.3 MW.

3.1. Modelling parameters

The parameters used in the scenario analysis are reported in detail in Appendix. Specifically, Table 3 provides values of energy supply costs, electrical demand variation per year, discount rates, and the environmental impact of each involved technology. For the sake of conciseness, only operational emissions (kg_{CO_2}/kWh), coming from the consumption of grid-imported electricity and gas, have been included. It is important to highlight that, whenever a technology relies on grid-imported resources, carbon emissions are generated based on the intensity of the energy consumption. It is also worth noting that a detailed Life Cycle Assessment (LCA) per each technology should be conducted for a comprehensive environmental assessment of the technologies. However, due to the limited accessibility to LCA data, this aspect has not been considered in this work. Tables 4 and 5 provide technical and economical parameters of the used technologies, reporting also the sizes of the different available devices in the "Rated power" and "Rated capacity" lists. Finally, Table 6 lists dynamic costs of ESS, FC, and EL with the estimated yearly rate of variation underlying the costs.

3.2. Scenarios definition

Different scenarios have been analysed to assess different future perspectives of the present case study from energy, environmental, and economic points of view. However, it is worth recalling that the MILP approach is economic-driven and does not optimise the environmental costs. The analysis started with the BAU scenario, which has been validated with real data and then used as a reference scenario before carrying on the other two studied scenarios, namely the *Sector-coupling* and the *Hydrogen deployment*. The former scenario provides insights into the impact of PV and ESSs, whereas the latter is more focused on the employment of hydrogen technologies along with their viability. In particular:

- *BAU*: this case consists of forecasting the energy planning based on the BAU scenario from today over 30 years, meaning that the energy will be mainly provided by the grid connection and already installed DERs. These technologies will be replaced with the same technologies once their lifetime will run out;
- *Sector-coupling*: in this scenario, a higher share of PV is introduced, which is constrained by the available surface area. Additionally, different types of ESSs are incorporated, including batteries and thermal energy storage, to mitigate PV production fluctuations. HPs are also included as cross-carrier sector coupling solutions to enhance the performance of the overall system;
- *Hydrogen deployment*: this scenario provides insights into the economical feasibility of the deployment of hydrogen technologies within the UNIVPM campus considering its production only with water electrolysis. Various ELs are available in the market such as Alkaline (ALK), PEM, Anion Exchange Membrane (AEM), and Solid Oxides (SOC). Among them, the PEM technology has been chosen for the proposed scenario due to its maturity and good performance in managing part-load operating conditions, which is warmly suggested when dealing with variable loads like in the present case study. The produced hydrogen is then stored in a pressurised tank and subsequently used to generate electricity through a PEM FC.

4. Results and comments

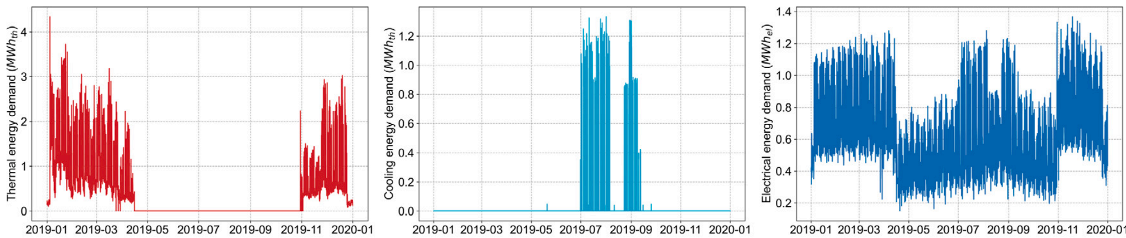
In this section, the results of both the planning (long-term) and the operational (short-term) perspective are reported and discussed. The assessment of the proposed approach has been performed by an analysis of the three scenarios previously mentioned. In particular, the capability of making multi-stage investments over the entire planning horizon and achieving an energy balance by a refined operational control have been evaluated. Regarding the computational aspects, the MILP-based two-step algorithm was implemented with AMPL (version 20221013, MSVC 19.29.30146.0, 64-bit) and solved by Cplex (version 12.10.0) with an integrality gap relative tolerance set to $2 \cdot 10^{-3}$ in the first step and to the default (i.e., 10^{-4}) in the second step. Each MILP was solved optimally within the time limit of 600 seconds. Experiments were carried out on an Intel® Core™ i7-7500U 2.90 GHz with 16 GB RAM.

4.1. Scenario analysis

In this Sub-section, results from planning and investment decisions are presented. The analysis on the three scenarios previously described assesses the capability of handling various technology matrices and adapts the decisions accordingly.

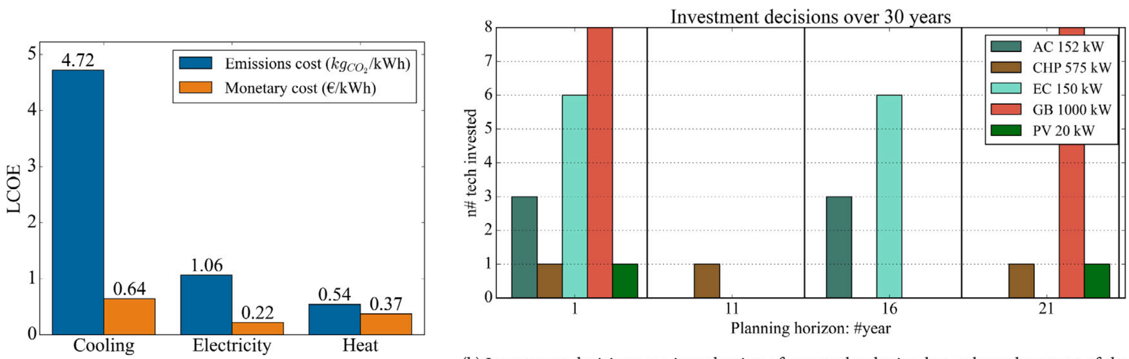
4.1.1. Results about the BAU scenario

Fig. 5 reports the results of the BAU scenario, highlighting both the economic and environmental Levelised Cost of Energy (LCOE) of each energy carrier (see in Fig. 5(a)). In particular, cooling energy is expensive in both economic and environmental terms since its demand is lower than other involved energy carriers. The economic LCOE of heat is higher than that of the electricity because it also includes the costs of locally installed equipment for energy conversion, while the



(a) Thermal energy (b) Cooling energy (c) Electrical energy

Fig. 4. Energy demands of the UNIVPM campus in 2019.



(a) Economical and environmental LCOE

(b) Investment decisions: no introduction of new technologies, but only replacement of the ones deployed at first year once their lifetime runs out

Fig. 5. BAU: levelised costs and investment stages.

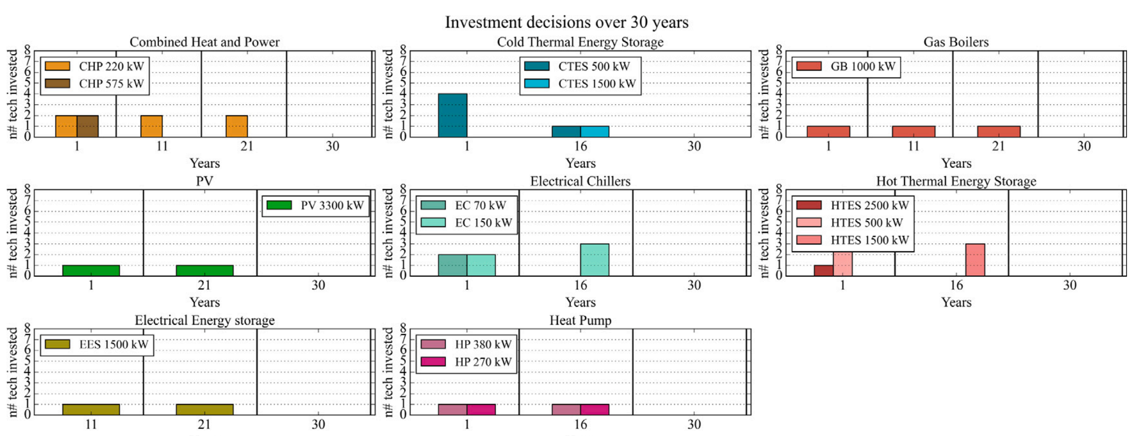


Fig. 6. Sector coupling scenario: multi-stage investment decisions.

electricity can be obtained from the national grid. However, the environmental LCOE of heat is lower because of (i) the high efficiency of energy conversion systems and (ii) the lower environmental impact of primary sources for its production. The investment plan over the entire planning horizon is reported in Fig. 5(b), where all the technologies are deployed in the first year and replaced once their lifetime runs out. The investment decisions beyond the 1st year have been strictly considered to satisfy the technical constraints rather than pursuing the economic strategies.

4.1.2. Results on the sector-coupling scenario

The maximum PV capacity is limited by the rooftop area, and it reaches a maximum value of 3300 kW_p. The optimal investment (actually replacement) plan considers a high share of PV and different types of ESS solutions, as reported in Fig. 6 where the economic-driven objective has been chosen to adopt the highest deployable PV installation capacity. Furthermore, the whole energy system fleet supports more diversified technologies to cover the energy demand; among them, different types of environmentally beneficial technologies have been selected such as HPs with sizes of 270 and 380 kW together with electric and cooling/thermal energy storages. Multi-stage investments have been also highlighted in Fig. 6; indeed, different changes occurred in the technologies deployment during the planning horizon. As evidence, not all the technologies deployed in the first year are replenished when their lifetime runs out. Some of these technologies

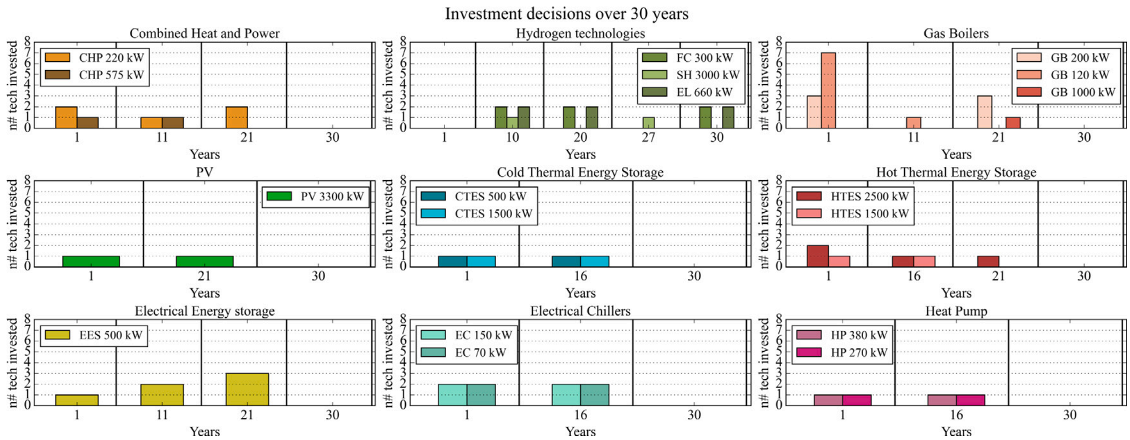


Fig. 7. Hydrogen deployment scenario: multi-stage investment decisions.

are replaced with different ones that can accommodate the required energy demands together with the investment of battery in the 11th year, which is the year 2031 when its investment cost is significantly lower than it was in the first year.

4.1.3. Results about the hydrogen deployment scenario

The results of this scenario are similar to those of the Sector-coupling one (see Fig. 1(b)). The hydrogen infrastructure is deployed in the 10th year (2030) when its cost will reach a rather low relative level. In particular, the whole hydrogen infrastructure, namely PEM EL, hydrogen storage (SH), and PEM FC, are deployed starting in the 10th year as shown in Fig. 7, when their investment costs will reach a threshold value that is economically and environmental convenient. Furthermore, both EL and FC must be re-bought every 10 years because of their 10 years lifetime. A key behaviour proving the model capability of capturing the dynamic conditions over the years is the decision of progressively increase the number of 500 kW ESSs devices to take advantage from the technology cost reduction and, at the same time, to pursue a more sustainable impact of the system since the copies of the natural gas boilers are contextually reduced (see Fig. 1(a)).

4.1.4. Scenarios comparison

The differential assessment has been done on the BAU benchmark scenario, using LCOEs as indicators, while the different investment decisions have been previously reported. Indeed, the economic levelized cost of electricity in the sector-coupling scenario grows by 43% compared to the BAU case, while the levelized cost of both heat and cooling energy reduces by 61 and 73%, respectively, thanks to the presence of Cold and Heat Thermal Energy Storage (CTES and HTES), see Fig. 8 and Table 1. Furthermore, such a scenario, which introduces new and sustainable solutions, has a positive impact from an environmental point of view, reaching a minimum environmental levelised cost reduction of 51% per each involved energy carrier. An higher reduction of the carbon footprint (80% compared to the BAU scenario) is reached by the hydrogen deployment scenario, since the hydrogen technologies integration is directly affected by the electricity. On the other hand, it leads to an increase of the economic cost by 89%.

Fig. 9 reports the overall costs of all the analysed scenarios over the whole planning horizon. It is observed that the hydrogen deployment scenario exhibits the minimum economic cost due to its higher independence from the grid. As a result, expenses related to grid imports are minimised. As regards the environmental benefits, the high share of PV and ESS integration together with the hydrogen deployment scenarios have similar effects, with the latter having a slightly further reduction; indeed, both of them have reached the maximum decolonisation allowable level that is constrained by the PV capacity.

Table 1
Scenarios analysis: LCOEs variation.

Scenarios	Energy carrier	Values	Variation (%)
Economic LCOE (€/kWh)			
BAU	Cooling	0.64	n.a.
	Electricity	0.22	n.a.
	Heat	0.37	n.a.
Sector coupling	Cooling	0.17	−73
	Electricity	0.31	+43
	Heat	0.15	−61
Hydrogen deployment	Cooling	0.18	−72
	Electricity	0.41	+89
	Heat	0.20	−47
Environmental LCOE (kg_{CO_2}/kWh)			
BAU	Cooling	4.72	n.a.
	Electricity	1.06	n.a.
	Heat	0.54	n.a.
Sector coupling	Cooling	1.89	−60
	Electricity	0.23	−79
	Heat	0.27	−51
Hydrogen deployment	Cooling	2.41	−49
	Electricity	0.21	−80
	Heat	0.26	−52

4.2. Results about operations' planning

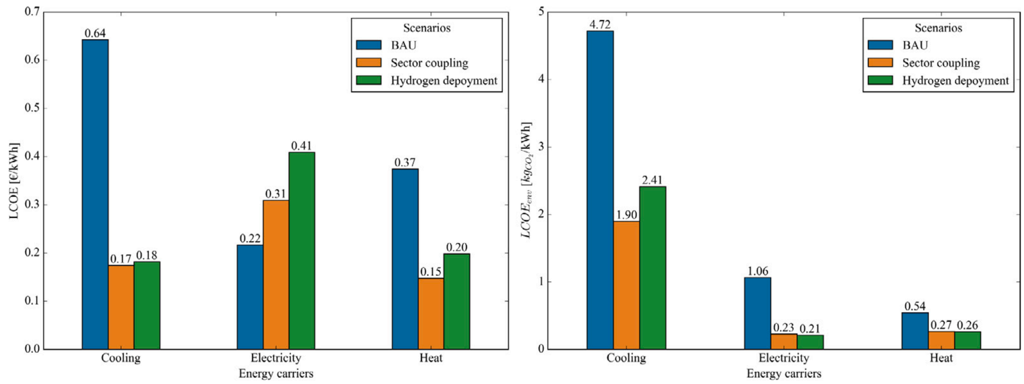
Results on various aspects of the case study operation's planning, such as hourly scheduling and energy balance, are illustrated in this section. For the sake of clarity and conciseness, only operational decisions of a day randomly selected are reported, instead of the complete 30-year span.

4.2.1. Multi-energy carriers balance

Fig. 10 displays the hourly energy balance for all the energy carriers being examined, even though there are only three energy demands. To provide a comprehensive overview, the report also includes the hydrogen deployment scenario, which encompasses a wide range of technologies. It is evident from the figure that all the energy carriers maintain a flawless balance, demonstrating the validity and robustness of the mathematical constraints of the model.

4.2.2. Load distribution over technological devices

Fig. 11 shows how the loads of the conversion and storage systems are distributed among the discrete set of available variants of each technological device. The mathematical model does not exhibit any preference for prioritising the operations of one variant over those of



(a) Economical LCOEs

(b) Environmental LCOEs

Fig. 8. Scenarios comparison: LCOEs of different energy carriers.

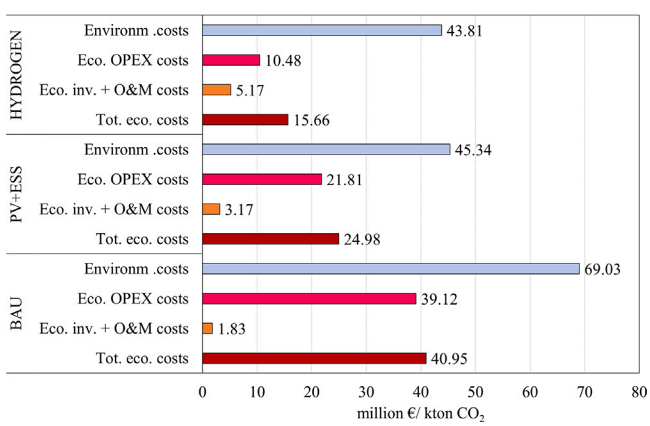


Fig. 9. Scenarios comparison with overall costs of the entire planning horizon.

others. Instead, the load distribution is scheduled randomly, while still adhering to all constraints, including size limitations.

5. Conclusions

In this work, a MILP-based two-step iterative approach for medium-term (30 years) multi-energy systems planning is presented. The approach suggests multi-stage investment decisions by taking into account the dynamic of different parameters throughout the planning horizon, as well as the modular design, and hence the availability of devices in a limited number of variants, of the involved technologies.

In the first step of the algorithm, each year of the planning horizon is considered as an investment stage where the new technologies procurement can be applied. In the second step, the operations of the designed system are then scheduled on an hourly basis along the whole planning horizon. The optimisation is devoted to the overall minimisation of economic costs. Such a methodology has been applied and validated using a real case study, namely the University campus of Marche Polytechnic University (UNIVPM) located in the center of Italy where historical energy consumption data have been used as input of the model.

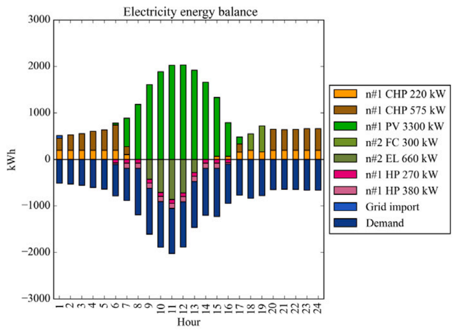
The results obtained on three different scenarios have been analysed to gain an extended assessment of the model capabilities and limitations under different conditions. Considering the overall planning horizon (30 years), the BAU case needs 40.95 million € of financial investment with a carbon footprint of 69.03 kton CO_2, while the two other analysed scenarios, namely the *Sector-coupling* and the *Hydrogen deployment*, have significantly reduced both economic and environmental costs, namely 24.98 million € and 45.34 kton CO_2 for the former and 15.66 million € and 43.81 kton CO_2 for the latter. In particular, a different study on the same case [32], where however the planning horizon is traditionally modelled by representative years, led to comparable results of LCOEs for the BAU scenario (0.22 €/kWh vs. 0.25 €/kWh obtained in [32] for the electricity and 0.37 €/kWh vs. 0.33 €/kWh obtained in [32] for the heat energy), so validating the proposed approach.

Indeed, the results show that it has not only captured different stages of investments, but it also handled well all dynamic variations of the involved parameters, e.g., an increasing number of ESSs devices are purchased over the years in the hydrogen deployment scenario, according to their investment costs reduction. Furthermore, hydrogen-related technologies become economically viable by acting as a cross-sector coupling solution in the 10th year based on the forecast of the investment cost reduction. Additional results on the operational side, such as the dynamic balance of all the energy carriers and the load distribution among the technologies, show the effectiveness of the method in capturing the expected behaviours of the energy system.

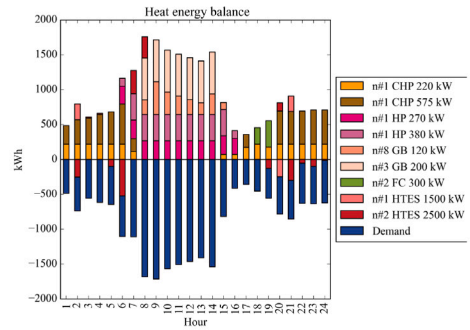
On the computational side, the proposed methodology efficiently provided optimised solutions in reasonable running time by leveraging the separations among investment and operation scheduling stages.

However, contrary to all-encompassing single-step MILPs, the two-step algorithm may lose effectiveness because of the heuristic decomposition. Moreover, parameters in (23)–(24) are partially sensitive to the case study features and hence require accurate tuning to allow the computation of high-quality solutions. Further investigations on the algorithmic side are needed to identify the settings of the well-performing parameters, possibly based on inference and/or learning. On the modelling side, several aspects of the energy systems have been simplified or neglected. Also input data, e.g., costs and demands, which clearly are neither deterministic nor completely predictable, require a more precise estimation and/or explicit handling by, e.g., stochastic programming, which will be investigated in future studies.

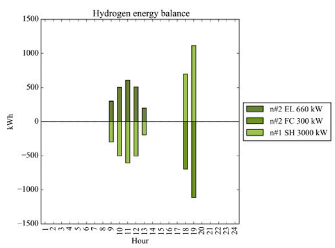
Another promising direction lies in linear programming decomposition schemes (e.g., Dantzig–Wolfe decomposition, Benders decomposition) that can provide useful duality gaps and optimal-guaranteed solutions while keeping the computational viability. Other aspects, like a detailed description of the environmental impact, the balancing of the same technologies' loads (and therefore prioritise one copy over



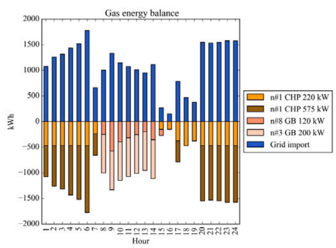
(a) Electricity energy balance



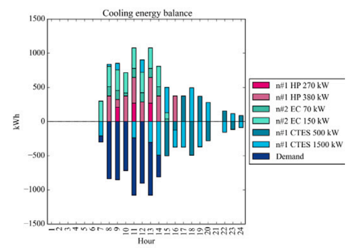
(b) Heat energy balance



(c) Hydrogen energy balance

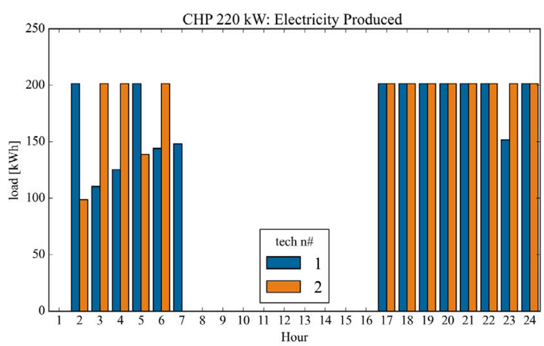


(d) Gas energy balance

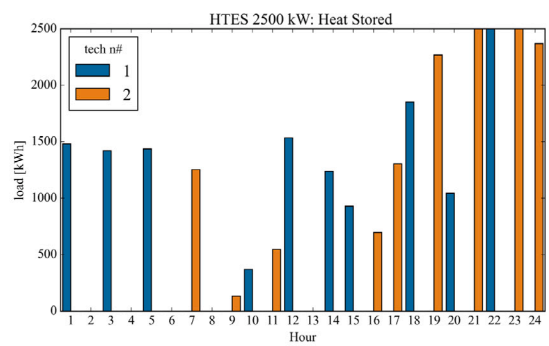


(e) Cooling energy balance

Fig. 10. Operations' results. For the sake of completeness, all energy balances considered in the methodology are reported. However, the cooling energy carrier and heat energy represent different days from *Hydrogen deployment* scenario.



(a) Conversion systems-CHPs production: No preference for any specific copies over others is exhibited. However, a slight rotating behavior among copies can be observed between 2:00 and 7:00. It is worth noting that this behavior is not explicitly accounted for in the mathematical model.



(b) Storage systems-HTES: No preferences for one copy over another can be observed.

Fig. 11. Examples of load distribution among the same technologies. Examples taken from the *Hydrogen deployment* scenario, year 1, week 2.

another) and among the loads of interconnected multi-energy systems will be further investigated in future works.

CRediT authorship contribution statement

Andrea Pizzuti: Conceptualization, Formal analysis, Methodology, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Lingkang Jin:** Conceptualization, Formal analysis, Methodology, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Mosè Rossi:** Investigation, Writing – original draft, Writing – review & editing. **Fabrizio Marinelli:** Supervision, Writing – original draft, Writing – review & editing. **Gabriele Comodi:** Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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Appendix

This section reports detailed tables about the mathematical notation (Table 2) and economic/technological parameters used in the discussed scenarios (Tables 3–6).

Table 2
Sets, parameters and variables of the MILPs M_Y and $M(\bar{y}, \bar{w})$.

Sets	
Common to M_Y **and** $M(\bar{y}, \bar{w})$	
K: energy carriers in the system (i.e., electricity, gas, heat, cooling, water, hydrogen)	
$\hat{K} \subseteq K$: non-purchasable energy carriers in the system (i.e., heat, cooling, hydrogen)	
only in M_Y	**only in** $M(\bar{y}, \bar{w})$
Y: years in the planning horizon	$H_{\bar{w}}$: hours in the week $\bar{w}$
Q: deployable technologies	$Q^{\bar{y}}$: installed technologies in year $\bar{y}$
$S \subseteq Q$: deployable storage devices	$S^{\bar{y}} \subseteq Q^{\bar{y}}$: installed storage devices in year $\bar{y}$
$Q^{CHP} \subseteq Q$: deployable CHP technologies	$W_{\bar{y}}$: representative weeks in year $\bar{y}$
$Q^{PV} \subseteq Q$: installable PV systems	
$Q^{HP} \subseteq Q$: deployable HP engines	

Parameters	
Common to M_Y **and** $M(\bar{y}, \bar{w})$	
c_y^k: cost per kWh of energy carrier k at year y	
e_q^k: round-trip efficiency of storage technology q accumulating energy carrier k	
ϕ_q^{lk}: conversion efficiency from energy carrier l to k of technology q	
δ_q: efficiency degradation of technology q	
b_{qh}^k: estimated base production in kWh of energy carrier k of technology q at hour h	
U_q^k: maximum rated power in kW of energy carrier k of technology q	
C_q^k: rated capacity in kWh of storage technology q accumulating energy carrier k	
ℓ_q: lifetime of technology q	
r: discount rate at present value	
only in M_Y	**only in** $M(\bar{y}, \bar{w})$
$\bar{d}_y^k$: aggr. demand in kWh of energy carrier k in year y	d_h^k: demand in kWh of energy carrier k at hour h
$\bar{b}_{qy}^k$: aggr. base production in kWh of energy carrier k of technology q in year y	ρ_q: hourly capacity loss of storage technology q
$\bar{U}_q^k$: aggr. maximum rated power in kWh of technology q producing energy carrier k	L_q^k: lower partialisation limit of power in kWh of technology q producing energy carrier k
$\bar{C}_q^k$: aggr. rated capacity in kWh of storage technology q accumulating energy carrier k	i_q: installation year of technology q
v_{qy}: investment cost in technology q at year y	$n_{\bar{w}}$: n. of weeks clustered in representative week $\bar{w}$
m_{qy}: maintenance cost of technology q in year y	$h_{\bar{w}}$: number of hours in week $\bar{w}$
T_h: total number of hours in an year	
$\hat{d}_y^k$: estimated peak of unmet demand in kWh of energy carrier $k \in \hat{K}$ at year y	
θ: sensitivity of constraint (23)	
$\tilde{d}_y^k$: estimated peak in kWh of requested energy carrier $k \in K \setminus \hat{K}$ at year y	
γ: sensitivity of parameter $\tilde{d}_y^k$	

Variables	
Common to M_Y **and** $M(\bar{y}, \bar{w})$, with $t \in Y$ in M_Y, $t \in H_{\bar{w}}$ in $M(\bar{y}, \bar{w})$	
$f_t^k \in \mathbb{R}^+$: flow of energy carrier k purchased at t	
$s_{qt}^k \in \mathbb{R}^+$: energy carrier k accumulated in storage of type q at t	
$p_{qt}^k \in \mathbb{R}^+$: energy carrier k produced by technologies q at t	
$r_{qt}^{lk} \in \mathbb{R}^+$: energy carrier l required for producing energy k by technologies q at t	
only in M_Y	**only in** $M(\bar{y}, \bar{w})$
$z_{qy} \in \mathbb{N}_0$: number of devices q operating in year y	$z_{qh} \in \{0, 1\}$: activation of device q at hour h
$x_{qy} \in \mathbb{N}_0$: number of devices q installed at year y	$\Omega_{\bar{y}\bar{w}}$: total discounted supply costs (i.e., OPEX) at week $\bar{w}$ of year $\bar{y}$
Γ: total discounted investment and maintenance costs (i.e., O&M)	

Table 3
Scenario parameters employed in the experimental study.

Parameters		CO_2 emission factors	
Electricity price [€/kWh][33]	0.195	Grid electricity [gCO_2/kWh] [34]	281.4
Natural gas price [€/kWh][33]	0.0695	CHP [gCO_2/kWh] [34]	353.3
Water price [€/m^3][33]	3.79	GB [gCO_2/kWh] [34]	231.1
Electrical demand per year increment [25,27]	0.32%		
Discount rate r	5%		

Table 4
Performance characteristics and cost coefficients of PV technology.

PV characteristics [35,36]	
Rated power [kW_p]	20, 500, 1000, 1500, 2000, 2500, 2700, 3300
Efficiency factor	17%
Efficiency degradation per year	0.3%
Lifetime [y]	20
Investment cost [€/kW_p]	1200
Maintenance cost factor	1.3%

Table 5
Performance characteristics and cost coefficients of conversion technologies.

Common					
Efficiency degradation per year	1%				
Partialisation limit of power	30%				
Conversion technologies	**Rated power [kW]**	**Conversion efficiency**	**Lifetime [y]**	**Investment cost [€/kW]**	**Maintenance cost factor**
CHP [37,38]	110 220 575	39% el (49% th) 43% el (47% th) 42% el (44% th)	10	900 600 321	2%
HP [39,40]	160 270 380	2.80 2.88 2.80	15	124 127 119	1%
AC [40]	131 152 316	80%	15	174	1%
EC [39,40]	70 120 150	2.74 2.71 3.00	15	121 124 125	1%
GB [41]	120 200 1000	88% 88% 91%	20	90	1.5%
FC [42]	300 600 900	50% el (34% th)	10	Table 6	Table 6
EL [42]	660 1320 1980	71% ($\phi_{EL}^{wat,hyd}$ 1.85)	10	Table 6	Table 6
Storage technologies	**Rated capacity [kWh]**	**Round-trip efficiency**	**Lifetime [y]**	**Investment cost [€/kWh]**	**Maintenance cost factor**
HTES/CTES [32,42]	500 1500 2500	75%	15	40	2%
ESS [28,42]	500 1500 2500	90%	10	Table 6	1%
SH [42]	1000 2000 3000	99%	18	30	2.3%

Table 6
Dynamic costs of storage technology ESS and PEM, and conversion technologies FC and EL for the 30-year planning horizon.

Years	ESS [28]	FC [28]		EL [28]	
	Investment cost [€/kWh]	Investment cost [€/kWh] rate [%/y] −3.97	Maintenance cost factor rate [%/y] −2.21	Investment cost [€/kWh] rate [%/y] −11.12 (−6.05)	Maintenance cost factor rate [%/y] 12.84
2021	284	1309	3.91	1155	6.21
2022	267	1257	3.83	1027	7.00
2023	248	1207	3.74	913	7.90
2024	231	1159	3.66	811	8.92
2025	212	1113	3.58	721	10.06
2026	204	1069	3.50	641	11.35
2027	197	1027	3.42	570	12.81
2028	189	986	3.35	506	14.45
2029	182	947	3.27	450	16.31
2030	174	909	3.20	400	18.40
2031	172	873	3.20	376	18.40
2032	169	838	3.20	353	18.40
2033	168	805	3.20	332	18.40
2034	166	773	3.20	312	18.40
2035	163	742	3.20	293	18.40
2036	161	713	3.20	275	18.40
2037	159	684	3.20	258	18.40
2038	157	657	3.20	243	18.40
2039	154	631	3.20	228	18.40
2040	153	606	3.20	214	18.40
2041	150	582	3.20	201	18.40
2042	148	559	3.20	200	18.40
2043	146	537	3.20	200	18.40

(*continued on next page*)

Table 6 (*continued*).

Years	ESS [28]	FC [28]		EL [28]	
	Investment cost [€/kWh]	Investment cost [€/kWh] rate [%/y] −3.97	Maintenance cost factor rate [%/y] −2.21	Investment cost [€/kWh] rate [%/y] −11.12 (−6.05)	Maintenance cost factor rate [%/y] 12.84
2044	144	515	3.20	200	18.40
2045	141	495	3.20	200	18.40
2046	139	475	3.20	200	18.40
2047	137	456	3.20	200	18.40
2048	135	438	3.20	200	18.40
2049	132	421	3.20	200	18.40
2050	131	404	3.20	200	18.40

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