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A review on multi energy systems modelling and optimization

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ABSTRACT

Over the past decade, energy systems for the combined management of power vectors have been attracted the attention of the scientific community. Most of the published works aim at finding optimal design and operations of Multi Energy Systems (MES). In these works, the basic structure and assumptions of the formulation are often taken for granted. Consequently, approaching MESs for the first time, understanding how to guarantee the desired optimization detail with proper computational expenses, is a challenging and time-consuming task. The present work presents a novel approach to the analysis of the MES literature, since it is devoted to guide a practical development of MES optimization. Through the discussion of six case studies, the mathematical formulation is presented to provide a clear reference to build the model. Emphasis is placed on how the aspects investigated can change the nature of the problem and the choice of the solvers for the process execution. For each of these aspects, a literature review to identify and discuss the main proposals for its implementation is presented. Finally, a great attention is posed on the inclusion of thermal networks and storage in the optimization of multi-energy systems, discussing the different approaches used in the literature.

1. Introduction

1.1. MES definition and similar aggregation concept

The energy infrastructures are currently under a significant transformation due to the need to reduce the environmental impact in the energy sector and ensure affordable and clean power production. In this context, Multi Energy Systems (MES) propose an intelligent interconnection of energy infrastructures (i.e. production, conversion, transmission and storage technologies). MESs have been recognized as a promising option to exploit the links among different energy vectors (e.g. electricity, gas, hot/cold water) at various levels (e.g. spatial level, network level, etc. [1]). Combined management of renewable sources fluctuations and exploitation of other sources (such as waste heat) are among the main benefits.

In recent years, some terms devoted to defining aggregation concepts have been gaining importance, whose area of influence often overlaps with that of multi energy systems. Some examples are:

1. Energy Hub (EH), developed specifically to model generic MES from a technical point of view;
2. Combined Heat and Power (CHP) generation that can be considered as the simplest form of a multi energy system. In fact, besides combining the production of two or more energy carriers, it is also frequent the presence of additional components such as auxiliary boilers or thermal storage that are included in such systems;
3. Distributed Generation (DG), which indicates a multi energy system where technologies are typically small-scale (compared to centralized power plants) directly embedded in the distribution network or located close to the point of energy consumption;
4. other systems such as Micrograds (MG) and Virtual Power Plants (VPPs), which, although they typically focus on strictly electrical issues, are described using a mathematical formulation that is not too far from that of MES.

Multi Energy Systems can be constituted by any kind of technology for the production, consumption, storage and transportation of energy. Electric Generators (EG, [2]), Heat Only Boilers (HOB, [2]), Combined Heat and Power units (CHP, [3]), Combined Power and Cooling units (CPC, [4]), Electric Heat Pumps (EHP, [5]), Gas Heat Pumps (GHP, [6]), Fuel Cells (FC, [7]), Absorption Chillers (AC, [8,9]), PhotoVoltaic panels (PV, [10]), Solar Thermal panels (ST, [11]), Wind Turbines (WT, [12]), energy storages [13,14], Electric Networks (EN, [15]), and District Heating Networks (DHN, [15]) are the most common technologies

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Nomenclature

a	Binary variable (technologies connection)
C	Costs [€]
c	Specific costs [€/kW]
d	Decision variables (design)
F	Set of imported fuels
g	Inequality constraints
h	Equality constraints
I	Imported amount of fuel [kW]
l	Storage loss coefficient [kW/h]
m	Number of inequality constraints
N	Number of interval (linearization)
n	Number of equality constraints
o	Decision variables (operation)
oom	Order of magnitude
P	Power [kW]
SOC	State of charge [kWh]
s	Decision variables (synthesis)
t	Time instant
U	Set of technologies
V	Set of energy vectors
x	Function breakpoints (linearization)
w	Binary variable (existence of the technologies)
y	Binary variable (on/off state)
y'	Binary variable (selection of linearization interval)

Abbreviations

AC	Absorption Chiller
CAP	Storage capacity [kWh]
CHP	Combined Heat and Power system
CCHP	Combined Cooling, Heat and Power system
CFVT	Constant Flow Variable Temperature
CTVF	Constant Temperature Variable Flow
DG	Distributed generation
DH(N)	District Heating (Network)
DPR	Demand Response Program
FC	Fuel Cell
FRP	Flexible Ramping Product
EG	Electric Generator
EH	Energy Hub
EHP	Electric Heat Pump
EN	Electric Network
FEL	Following Electric Load
FTL	Following Thermal Load
GHP	Gas Heat Pump
HOB	Heat Only Boiler
HP	Heat Pump
LP	Linear Programming
MA	Memetic Algorithm
MES	Multi Energy Systems
MG	Microgrid
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
MIQCP	Mixed Integer Quadratically-Constrained
OUT	Exiting
MP	Master Problem
NLP	Nonlinear Programming
nZEB	Nearly Zero Energy Building
PV	PhotoVoltaic
RES	Renewable Energy Sources
RO	Robust Optimization
RP	Rated Power [kW]
SA	Simulated Annealing
SNO	Social Network Optimization
SP	Slave Problem
VFVT	Variable Flow Variable Temperature
VPP	Virtual Power Plant
WT	Wind Turbine

Greek letters

Δ	Difference
ξ	Random vector
π	Scenario probability
ω	Dummy continuous variable (linearization)

Superscripts

BUY	Bought from the grid
CH	Charging phase
DIS	Discharging phase
IN	Entering
INV	Investment
M	Maintenance
MIN,OFF	Minimum shut-down time
MIN,ON	Minimum start-up time
OP	Operating
SELL	Sold to the grid
ST	Storage
START	Initial value
RD	Ramp-down
RU	Ramp-up

Subscripts

c	cold
el	electricity
f	Index for imported fuels
gas	Natural gas
i	Index for energy vectors
j	Index for technologies
jc	Index for producers
jp	Index for consumers
k	Index for time instants
th	thermal
‘	First stage
‘’	Second stage

included as part of the MES investigated in the literature, but any other option can be considered as well. Since the discussion conducted in the present work concerns the Multi Energy Systems as a whole and does not consider a single real case study, a description of the technologies results to be unnecessary and only the aspects required for their mathematical modelling will be discussed in the next paragraphs.

1.2. Benefits and challenges of MES optimization

Multi energy systems are inherently complex and structured systems. The intermittency of renewable sources, the technical constraints of the components, the dynamic variation of energy prices and energy loads are only some of the elements that make their management a difficult task. As a consequence, optimization tools for the evaluation of these systems are indispensable. Among the most important benefits gained with the MES optimization, the followings are worth to be mentioned:

- lower consumptions of primary energy, and, consequently, operating costs and emissions. Based on the case studies proposed in the literature, the cost reduction in economic terms typically ranges from 5 % to 25 %. Significant advantages can be achieved as well when the optimization criterion is the primary energy reduction or the decrease of the CO_2 emissions (up to one half, [16–23]). Combined heat and power production is only an example of the benefits that can be achieved compared to separate generation [24,25];
- a better planning of component operation and the compliance of technical constraints respect the common practice operation set. In fact, in real applications load following techniques (e.g. Following Electric Load, Following Thermal Load, etc.), which manage the components operation according to a predefined hierarchy, are usually employed. Differently from an operation strategy, an optimization process allows to solve the unit commitment problem with a higher degree of freedom, since a hierarchy between the components operation is not defined. This typically results in smaller operation costs (from 5 % up to 25 % [17,23]);
- distributed generation can significantly reduce peaks and congestions in energy networks. This advantage is increased if its operation is the result of an optimization process. This is due to the lower amount of energy vectors requested to the grids thanks to the proximity of generators and users, which can be matched without resort to external networks. In addition, the capability to include network constraints in the optimization contributes significantly in avoiding operation criticalities (e.g. network congestion, [26,27];
- the most proper management of storage units, whose quality would be otherwise relatively poor in case of adoption of operation strategies.

From a theoretical point of view, therefore, the advantages of MES optimization have been amply demonstrated. Nevertheless, for optimal strategies to be put into practice in real scenarios, the optimization model must be able to realistically describe the energy system. Indeed, despite the undeniable benefits, modelling multi energy systems in a realistic way still presents several challenges that have to be met. The most important ones are:

- the intrinsic dependence of the solution to the initial assumptions, which can significantly affect the meaningfulness of the results. As a consequence, this can determine a non-complete applicability of the solution obtained in case the real conditions are excessively different from the simplified ones assumed. To guarantee a robust solution, the assumptions adopted should be adequate for any operation configuration in which the system could operate;
- the limited amount of real phenomena and practical aspects that can be implemented in the optimization model (e.g. components performance, decision variables, etc.). In fact, some features characterizing MESs are difficult to be considered because they require a complex modelling. Therefore, simplifications result necessary;
- computational times and convergence issues that arises when the problem reaches high dimensions. This can be caused by the need to consider long time periods in the analysis (e.g. as in the case of synthesis, design and operation optimization) or to include the uncertainties affecting the problem. In those cases, the model must be able to find a solution as close as possible to the global optimum in a reasonable amount of time.

1.3. Previous reviews on MES optimization

Given the enormous popularity of applying optimization tools to these types of systems, several works can be found in the scientific literature that provide comprehensive reviews on MES. The first review papers, written from 2006 to 2009 ([28–30]), discuss the concept of multi energy system and present the technologies that can be used for the combined generation. A holistic overview on MES, with a critical discussion on main characteristics, modelling approaches, aggregation concepts, and analysis tools for their operation and planning is presented in [1]. Concerning the synthesis and design problems for smart energy systems, a comprehensive analysis of optimization strategies can be found in [31] and [32], with references on decision-making processes. Some distinctions based on the size of the systems are made in [33–35], where the most common control strategies and optimization processes for MESs operation are discussed. Regarding large shares of renewable sources, [36] and [37] provide a comprehensive and detailed investigation of some important aspects, such as renewable energy availability analysis, load profile analysis, geographical domain and the choice of both time period and time step. In addition, relevant references are given for the different approaches typically used in the literature. Important aspects related to renewable sources are the uncertainty and flexibility of energy systems are reviewed in [38] and [39], considering both modelling and optimization purposes. Finally, the modelling alternatives, the problem formulation, and some exploitable solvers are presented in [40] and [41], highlighting pros and cons of the approaches found in literature. The evaluation of the system performance based on available data, thermodynamic simulation or dynamic modelling are discussed in [42], with a deepening on thermodynamic techniques for cooling and thermal system arrangements (trigeneration, multi-generation, etc.).

1.4. Goals of the present work

The reviews found in literature are comprehensive and feature an in-depth analysis of the scientific subjects. As a result, these sources are aimed towards researchers who already possess a solid understanding of the subject matter. However, they may not be the most suitable choice for researchers approaching this problem for the first time, even if they have expertise in energy. Furthermore, it is common for review articles to omit the mathematical formulation of the optimization problem typically found in research papers. Consequently, one can derive the mathematical formulation applicable to distinct case studies under precise underlying assumptions. This is a significant limitation as it does not take into account the impact of configuration modifications.

The main objective of this article is to provide the reader with a comprehensive guide to the creation of optimization models for multi energy systems. In order to achieve this goal, the authors identified and examined the factors that are typically associated with multi-energy systems and require adjustments in either their structure or mathematical formulation for optimization purposes. For each of these elements, which will be here called *discriminating elements*, relevant works from the scientific literature are cited, with the purpose of furnishing the reader with a compilation of articles where the proposed modelling framework has been employed. At the beginning, the formulation of an optimization problem for the operation of a multi-energy system assumed as base case is presented. Subsequently, additional instances are showcased in order to examine the integration of discriminating elements into the *base case* optimization model, as well as the challenges and benefits associated with their inclusion. Through the use of these modules, it is possible to incorporate any modifications into the mathematical formulation of the initial scenario, such that tailored optimization models can be developed. The inclusion of device's physical operation constraints to ensure practical and feasible results in real scenarios, the changes required to pass from an operation optimization to a synthesis and design optimization, the inclusion of uncertainty within the optimization framework, the possible flexibility measures to enhance the response of the energy system to changes in energy supply and demand are some examples of the topics covered by this review paper. Each discriminating element is analyzed independently, allowing for - easy isolation and examination. The authors thoroughly examined various analyses found in the literature, presenting the advantages and disadvantages of each approach. This enables readers to find an analysis that best suits their individual requirements. Moreover, most literature

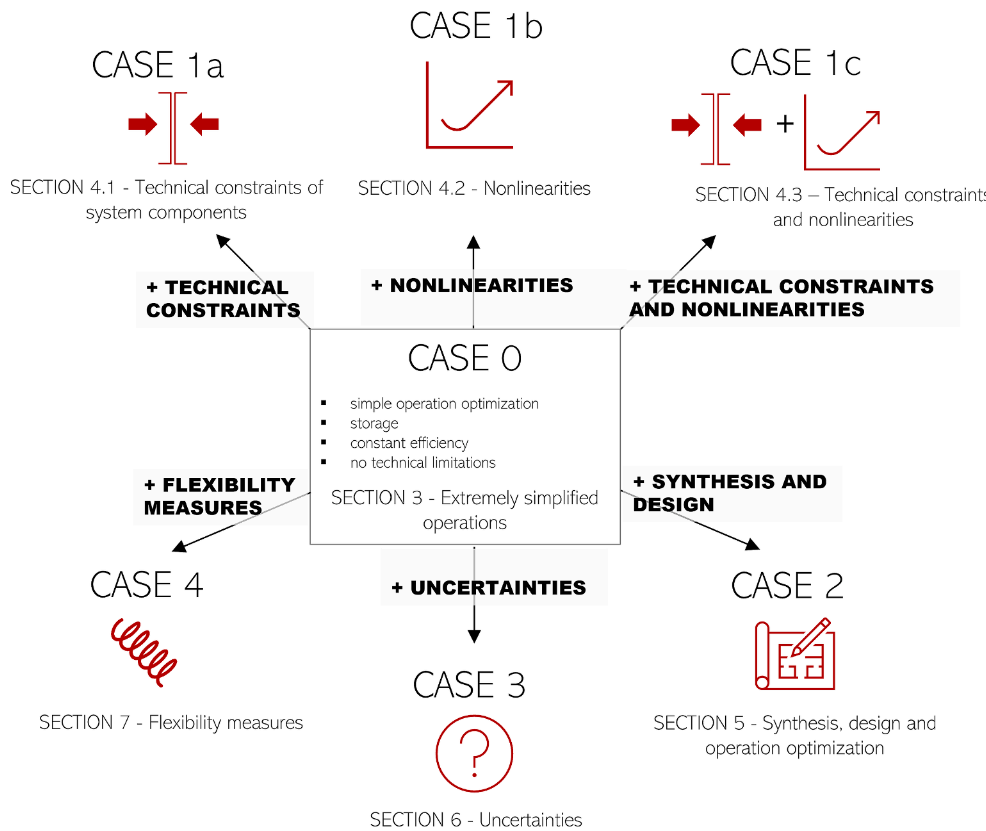


Fig. 1. Structure of the review paper.

reviews on multi-energy systems tend to focus mainly on the electrical aspects and often overlook the inclusion of heating and cooling networks in such systems. Our study aims to fill this gap by providing a comprehensive model that takes into account various forms of energy in the problem-solving process. Specifically, we investigate how to include thermal networks and energy storage in optimizing multi-energy systems and highlight the different methods used in existing research to achieve this.

Hence, the primary innovations introduced in this paper are as follows:

1. Emphasis on the factors that influence the nature of the optimization problem, the subsequent selection of the optimization solver, the associated computational challenges, and problem scale;
2. Presentation of a mathematically formulated approach, chosen for its practical applicability among the various alternatives found in the literature, with the intent to facilitate a discussion on the problem's characteristics;
3. A structured presentation format relying on case studies, suitable for model development. The computational complexity of the model depends on the desired level of detail;
4. A specific focus on thermal aspects within the context of Multi-Energy Systems optimization.

For each stage of this focus, pertinent research articles are cited as reference studies.

1.5. Structure of the paper

The structure of the paper has been developed to fit the purpose of the review analysis and to support the desire to focus the discussion on the modelling-related aspects.

The paper is structured as follows:

- Section 1, where the base case is presented, focusing on the operation optimization. This section includes the description of decision variables and objective function, mathematical formulation of constraints and storage modelling;
- Section 2 allows to include some real characteristics of energy systems into the model (e.g., real performance curves, technical constraints to account for system dynamism and the inclusion of maintenance costs);
- Section 3 focuses on the optimization purpose: from operation optimization to synthesis, design and operation optimization;
- Section 4 provides some insights into the introduction of uncertainty in multi energy system optimization problems;
- Section 5 discusses the different techniques that can be used to increase system flexibility;
- Section 6 draws the concluding remarks.

To further increase the clarity in the exposition of the paper's structure, Fig. 1 provides a graphical representation of the approach adopted in the present review analysis. Starting from an essential case study (Case 0), the discussion of the different modelling aspects of the MES optimization are exposed in separate case studies (Case1-4), which can be considered as independent among them. Notice that, for every case study, the corresponding section of the paper is reported.

ScienceDirect and Google Scholar have been used as databases for the research of the scientific papers discussed in the present review. In order to obtain an overview as wide as possible, no filters or limitations have been imposed in the research.

2. Discriminating elements

The *discriminating elements* are key characteristics of multi energy systems that strongly influence: a) the problem formulation; b) the optimization solution. In other words, they can change the nature of the

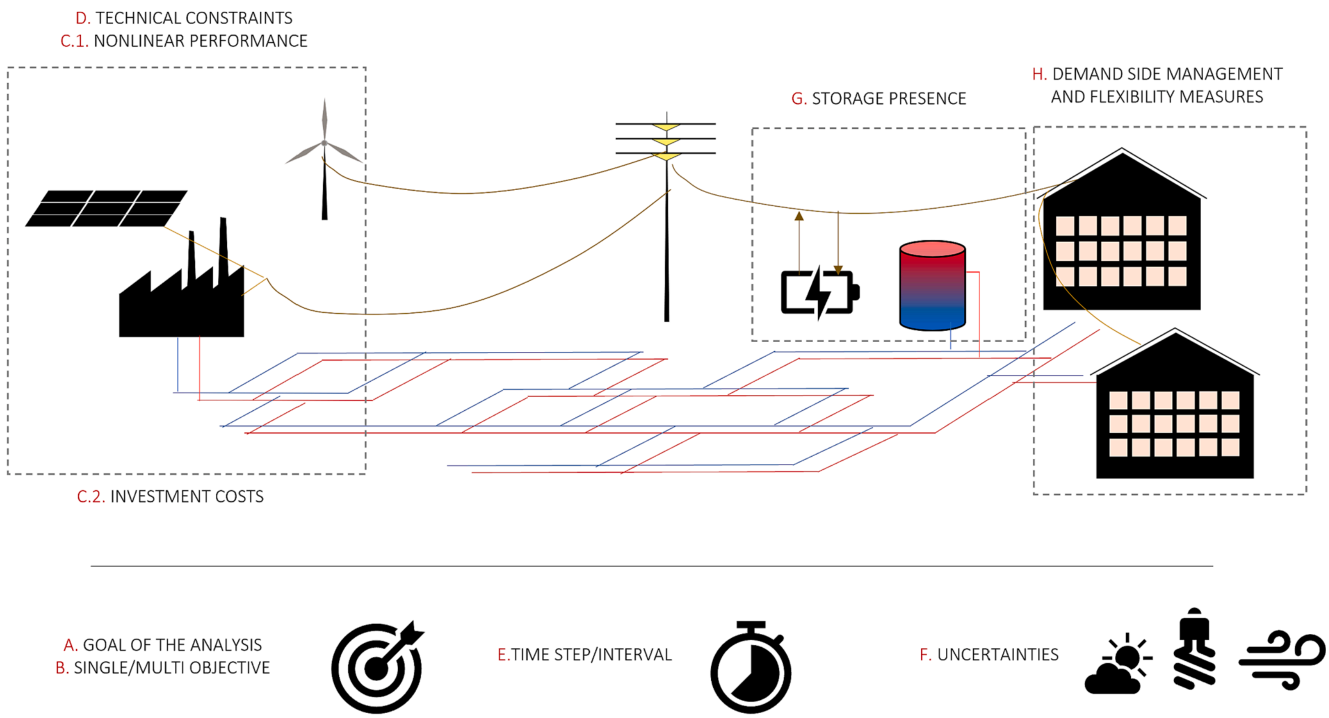


Fig. 2. General structure of an energy system with discriminating elements reported on the corresponding elements.

problem and, therefore, the way it can be solved.

The most important discriminating elements identified by the authors are (see Fig. 2):

A. Optimization purpose
The optimization process can include up to three different tasks:

1. Synthesis, when the objective is finding the most suitable components to employ for the combined production of the energy vectors, as well as establishing their interconnections.
2. Design, when the problem consists in the optimal dimensioning of the technologies selected by the synthesis process.
3. Operation, when the aim is to find a proper working schedule for the components (i.e., when a technology operates over time and its operating load).

B. Single-objective/multi-objective
The optimization can be done with a single objective function (e.g., cost, primary energy consumption, emissions) or a multi-objective function (a combination of two or more objective functions). This choice does not affect the problem formulation, but it could influence the choice of the solver. Longer computational times must be accounted for the multi-objective optimization, since multiple feasible solutions must be found, and their position in the Pareto curve must converge.

C. Nonlinearities
The problem to be solved can become nonlinear for different reasons:

1. Nonlinear performance of system components
   The performance of a component varies at partial load operation, in off-design conditions. Efficiencies usually have nonlinear trends, sometimes even non-convex. Therefore, nonlinearities are introduced in order to properly describe the performances of the components.
2. Nonlinear investment costs
   The investment costs vary nonlinearly with the size of the component, due to scaling phenomena and other economic aspects.

   The presence of nonlinearities strongly influences the formulation of the problem, the choice of the solver, the computational time and the reliability of the solution.

D. Technical constraints of system components
All components operating in energy systems are characterised by technical constraints. To represent the behaviours of the technologies, the problem formulation and the solver must be appropriate.

E. Time interval and time step
The length of the time interval that is taken in analysis (e.g., hours, days, years, etc.) can be very important. Considering longer periods means including a higher number of time steps and therefore a higher number of independent variables. By contrast, concerning the time step (15 min, 30 min, 1 h, 2 h. etc), larger values help reducing the problem size, but they bring a loss of precision in the operation simulation.

F. Uncertainties
Many inputs by the optimization process and referred to the future time periods can be difficult to be estimated (i.e., energy/fuels prices, energy demands, and availability of renewable sources). If the solution must include the effects of the uncertainties, suitable techniques must be adopted during the problem formulation. This increases the problem complexity and the computational cost.

G. Presence of energy storages
Energy storages allow decoupling the energy demand and generation, providing a higher degree of freedom to the system operation. However, their presence introduces a correlation between time steps, which can no longer be considered independent. Consequently, the optimization process moves from a series of small problems (several optimizations, each per time step) to a single problem (one optimization over all time steps). Therefore, the problem becomes larger in size. This makes the solution process more complex to solve due to the exponential relation that links computation time and problem size.

H. Flexibility measures
Beside energy storages, other solutions exist to increase the system flexibility. Among them are the adoption of demand response strategies and the exploitation of the infrastructure transients (e.g.,

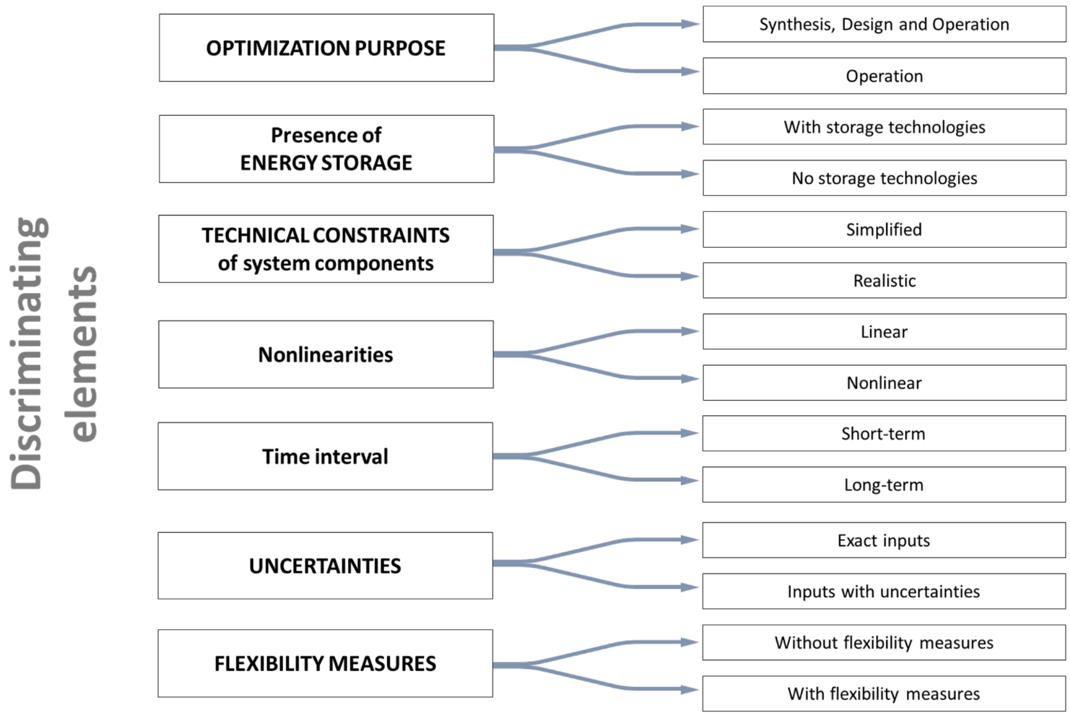


Fig. 3. Discriminating elements.

district heating network used as thermal storage). The inclusion of these aspects can be very complex, especially for the dynamic simulation of the network, where the presence of bilinear terms and high sizes of the problem must be addressed.

In addition, there are few other aspects that contribute shaping the formulation of the problem. These are not listed between the *discriminating elements* because they have a weaker influence on the problem formulation. As a consequence, the changes required to take them into account are minor. These are:

a. The typology of energy vector/product
Natural gas, electricity, heating, and cooling are by far the most common energy vectors, but others can be included, such as hydrogen, biofuels, desalted water, etc. As is easy to understand, every energy vector/product needs its balance. Each balance represents a constraint of the optimization problem. Therefore, adding or removing an energy vector from the operation of an energy system can be simply done by adding or removing the corresponding constraint.
b. The objective function
Minimization of primary energy consumptions, economic costs and CO_2 emissions are the most common criteria adopted, but other interesting objective functions are sometimes evaluated, such as peak shaving, social welfare, electric grid stability, curtailment of renewable power, etc. However, the type of objective function does not determine substantial differences in the problem definition. In fact, the issues that can be encountered in simulating the system are mainly referred to the constraints, while the objective function change is straightforward.
c. The presence of renewable sources in the energy system
RES generation cannot be arbitrarily modified since it depends on the availability of the source. This aspect represents an additional constraint (as renewable generation into an input data instead of a variable to optimize), but, even in this case, it does not modify the nature of the problem.

Discriminating elements are listed in Fig. 3 and for each of them the possibilities of analysis are summarised.

The importance to the identification of discriminating elements is driven by the fact that, influencing the mathematical formulation of the problem, they pose limitations on the selection of the optimization solver. As can be found in the scientific literature, high dimensional problems for MESs optimization are usually simplified and reformulated in order to be executed with deterministic solvers, which can reach better solutions compared to heuristic methods. This because they are able to guarantee the global optimality and can handle a much higher number of variables compared to heuristics. However, in order to fully exploit these advantages, the optimization problems should not include sources of non-convexity and, possibly, sources of nonlinearity. The classes of this kind of optimization are: Linear Programming (LP), Nonlinear Programming (NLP), Mixed Integer Linear Programming (MILP), and Mixed Integer Nonlinear Programming (MINLP). The differences of these categories are discussed further on, and are related to problem formulation, computational times and solution quality.

The following sections are devoted to the description of the case studies to discuss the implementation in an optimization model of the *discriminating elements* listed above. First of all, Case 0 is presented for providing the reader a mathematical formulation of a simple problem. Then, different *discriminating elements* are consecutively included; for each case, the changes of the nature of the optimization problem, the impacts on the choice of optimization solvers, as well as the increase of computational complexity and problem dimensions due to their inclusion, are discussed.

3. Case 0 - Simplified operations

Case 0 aims at defining the optimal scheduling of a multi energy system, consisting of generation, conversion, and storage technologies. The only specifications addressed are: a) the presence of energy storages; b) energy components have neither minimum operating load nor partial load operation; c) no uncertainty inclusion; c) the absence of other flexibility measures in the system. For a similar case, the most suitable time horizon is the short-term, which is usually addressed considering a

Table 1
Discriminant elements setup for Case 0.

Optimization purpose	Operation
Presence of energy storages	✓
Technical constraints of system components	×
Nonlinearities	×
Time interval	Short-term
Uncertainties	×
Flexibility measures	×

daily operation discretized with an hourly resolution [43]. Table 1 presents the *discriminating elements* setup for Case 0.

The authors' aim is not to detail the energy system (e.g., specifying energy components). The intention is to provide the reader with a general formulation that is as flexible as possible. However, an example of MES with the related mathematical formulation is provided in *the A. ppendix section*. This is done to help the reader understand the problem with a clear case reference.

More generally, concerning the discriminating elements described in Table 1, the reference model for this type of problem is a Linear Programming (LP) model that can be written in the standard form as reported in Eq. (1).

$$\min_{o} f(\boldsymbol{o})$$
$$s.t.\begin{cases} g_i(\boldsymbol{o}) \leq 0 \forall i \in \{1, \cdots, m\} \\ h_j(\boldsymbol{o}) = 0 \forall j \in \{1, \cdots, p\} \end{cases} \tag{1}$$
$$\boldsymbol{o} \in \mathbb{R}$$

where *o* is the vector containing the decision variables referred to the system operation, *f(o)* represents the linear objective function, *g(o)* and *h(o)* are the linear inequality and equality constraints, while *m* and *n* are the total number of inequality and equality constraints, respectively. In the following subsections, the definition of the decision variables (Section 3.1), the objective function (Section 3.2), and the constraints of the problem (Section 3.3) will be discussed.

For Case 0, since the use of integer variables is not necessary and the nonlinear equations are not present, it is possible to execute the optimization process using LP solvers, which are among the fastest algorithms able to reach the global optimum [44].

3.1. Definition of decision variables

In the type of problem described by Case 0, the decision variables are continuous. Often in the modelling of multi-energy systems, the operating power of each technology is described by a single decision variable. However, there are some units that, in some cases, may need to be described by two variables. This situation arises, for example, when modelling interactions with external networks like the power grid or district heating. In these cases, it is possible to employ two distinct variables—one for purchases from the network and another for sales to it. Alternatively, a single variable can be utilized, capable of assuming positive and negative values with different meanings (such as positive values for purchases and negative values for sales). The same applies to energy storages with regard to their charging and discharging phases.

Except for a few circumstances (see layout constraints in Section 3.3.3 and charging/discharging efficiency in Section 3.3.2), the two approaches can be generally considered equivalent, but each alternative has its pros and cons. The choice of using only one real variable implies a reduction of the number of variables and therefore a reduction in the computational effort. In addition, this choice allows the problem to be kept simple from a computational point of view. In fact, with the two-variables modelling, additional constraints to prevent simultaneous charging/discharging of the storage or simultaneous buying/selling from/to the grid must be included in the formulation. An exception concerns decision variables describing the energy networks when the optimization criterion is economic. In this case, two variables are needed since the purchase price and the selling price of the same energy carrier are always different. Furthermore, if the selling cost is lower than the buying cost (as is usually the case), no constraint needs to be added because the simultaneous buying and selling is intrinsically always disadvantageous.

3.2. Objective function

One of the most widely used objective functions is the economic one, here proposed as an example. As far as the operation optimization is concerned, the objective function includes only the operating costs, consisting of the costs of fuels imported into the energy system and the costs/revenues due to exchanges with energy networks. Consequently, a general form of the economic objective function can be written as Eq. *(2)*.

$$C^{OP} = \sum_{k=1}^{t^{end}} \left[\sum_{j \in U} \left(\sum_{f \in F} c_{f,j,k} I_{f,j,k} \right) + \sum_{i \in V} c_{i,k}^{BUY} P_{i,k}^{BUY} - c_{i,k}^{SELL} P_{i,k}^{SELL} \right] \tag{2}$$

Where F is the set of the fuels purchased (such as natural gas, hydrogen etc.), while V is the set of energy vectors managed within the system (heat, cold, electricity, etc.) and U is the set of generation and conversion technologies. Furthermore, I_f is the fuel imported in the time step considered and c_f is the related unit cost. In the same way, P_i^{BUY} and P_i^{SELL} represent the bought/sold power for each energy vector i, while c_i^{BUY} and c_i^{SELL} are the related unit costs.

Practical optimization problems often require minimizing or maximizing several conflicting objectives simultaneously. Multi-objective optimization methods attempt to find solutions that are as close as possible to the Pareto optimal front, defined as the set of non-dominated solution in the objective function space. Two main approaches can be identified for achieving this: Pareto-based approaches and aggregation approaches. Pareto-based approaches (e.g., Nondominated Sorting [45–50], Strength Pareto Evolutionary Approach [47,51,52] etc.) look for the Pareto front without making any choices among the selected solutions. In this case, multiple objectives are optimized simultaneously. Once the Pareto optimal set is found, decision-makers need to choose the "best compromise solution", based on the specific optimization problem or personal preferences. On the other hand, aggregation approaches (such as the weighted sum method [53–57], or constrained approach [57–61]) combine different objectives into a single objective function. These methods are widely used due to their ease of implementation. In this case, preferences are expressed before the optimization, which is why they are also referred to as "a priori methods". One critical aspect is that conflicting objectives often have different physical dimensions and variation ranges, so normalization is required. In this case, the multi-objective problem is transformed into a single-objective optimization problem, enabling the use of solution methods designed for single-objective problems. Aggregation approaches typically yield a single solution, but if the decision maker's preferences are expressed and optimizations are carried out iteratively, a set of solutions can be obtained.

3.3. Constraints

The fundamental constraints for this type of optimization problem are: a) the energy balances (Section 3.3.1); b) constraints for describing the behaviour of storage technologies (Section 3.3.2); c) constraints related to the layout of the system (Section 3.3.3).

3.3.1. Energy balances

As previously mentioned, for each energy vector, an equality constraint must be included in the mathematical formulation of the problem. The general form is reported in Eq. (3).

$$\sum_{j\in U}\left(P^{OUT}_{i,j,k}-P^{IN}_{i,j,k}\right)+P^{BUY}_{i,k}-P^{SELL}_{i,k}\pm P^{ST}_{i,k}-P^{LOAD}_{i,k}=0 \quad \forall i\in V,\ \forall k\in\{1,..,t^{end}\} \tag{3}$$

These sets of constraints state that, for each energy carrier i and at any time step k∈{1,..,t^{end}}, the sum of imported (P^{BUY}) and generated powers (P^{OUT}) must equal the sum of exported (P^{SELL}) and consumed powers (P^{IN}). In addition, power related to the charging and discharging phases of the storage (P^{ST}) should be included in the balance equation.

3.3.2. Energy storages

The main factors that need to be taken into account when modelling energy storages are:

- Limitation on charging/discharging powers;
- The storage capacity as maximum limit for the stored energy or, alternatively, the upper and lower limitations of the state of charge (typically used for electrical storage);
- The energy balance of the storage.

Moreover, other factors can be considered in the analysis, for example:

- Inclusion of charging/discharging efficiency of the energy storage;
- Inclusion of self-discharge due to energy losses;
- Impact of the ambient temperature (for thermal storage);
- Periodicity constraint (equilibrium of storage energy at initial and final hours of the simulation).

As already mentioned in Section 3.1, each energy storage, regardless of the typology, can be modelled by a single variable or by two variables. It is important to note that one case in which the two modelling approaches cannot be used indiscriminately is when a parameter changes, depending on the phase (charging and discharging). This occurs, for example, when two different values for the charging and the discharging efficiency should be included in the modelling of the energy storages.

The storage units can be described through linear equations. If only one variable is used for the modelling of these components, a possible formulation could be given by Eqs. (4)–(7) (ideal case) or Eqs. (6) – (8) (case with losses).

$$-P^{CH,max}_{i,k}\le P^{ST}_{i,k}\le P^{DIS,max}_{i,k}\forall i\in V,\forall k\in\{1,..,t^{end}\} \tag{4}$$

$$0\le CAP^{START}_{i}+\sum_{k=1}^{t}P^{ST}_{i,k}\Delta t\le CAP_i\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{5}$$

or

$$0\le(1-l_i)^{t}CAP^{START}_{i}+\sum_{k=1}^{t}(1-l_i)^{t-k}P^{ST}_{i,k}\Delta t\le CAP_i\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{6}$$

$$-CAP^{START}_{i}-\sum_{k=1}^{t}P^{ST}_{i,k}\Delta t\le 0\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{7}$$

or

$$-(1-l_i)^{t}CAP^{START}_{i}-\sum_{k=1}^{t}(1-l_i)^{t-k}P^{ST}_{i,k}\Delta t\le 0\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{8}$$

More in detail, Eq. (4) sets the upper and lower limits for charging/discharging power, while Eq. (5) ensures that physical storage limits, due to its finite capacity (CAP), are not violated. As an alternative to the previous equation, it is possible to impose that the state of charge (i.e., the available capacity expressed as a. percentage of its rated capacity) is within the permissible range in each time step. Finally, Eq.*7* ensures that the discharged energy was previously stored.

To account for energy losses over time, Eq. (6) must be used instead of Eq. (5), and Eq. (8) instead of Eq. (7); in this case the losses are modelled by the loss coefficient *l* that represents a percentage of energy that is lost in each time step and it takes into account that energy storage is not free over time. This phenomenon is particularly important for thermal storage and a method to estimate this parameter based on the ambient temperature and the storage capacity is described in [62]. However, if short term storage is under consideration, thermal losses can be typically neglected.

Concerning the electrical storage, charging, and discharging efficiencies are the most used parameters, with typical values between 0.75 and 0.90 [37]. Some examples of articles where single-variable modelling is selected in the analysis are [63–68].

The following equations (Eq.*9* – Eq.*14*) are also given for the modelling case with two decision variables linked to each storage. The binary variable y^{ST} is required to prevent simultaneous charging and discharging of the storage.

$$0\le P^{CH}_{i,k}\le y^{ST}_{i,k}\cdot P^{CH,max}_{i,k}\forall i\in V,\forall k\in\{1,..,t^{end}\} \tag{9}$$

$$0\le P^{DIS}_{i,k}\le\left(1-y^{ST}_{i,k}\right)P^{DIS,max}_{i,k}\forall i\in V,\forall k\in\{1,..,t^{end}\} \tag{10}$$

$$0\le CAP^{START}_{i}+\sum_{k=1}^{t}\left(P^{CH}_{i,k}-P^{DIS}_{i,k}\right)\Delta t\le CAP_i\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{11}$$

or

$$0\le(1-l_i)^{t}CAP^{START}_{i}+\sum_{k=1}^{t}(1-l_i)^{t-k}\left(P^{CH}_{i,k}-P^{DIS}_{i,k}\right)\Delta t\le CAP_i\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{12}$$

$$-CAP^{START}_{i}-\sum_{k=1}^{t}\left(P^{CH}_{i,k}-P^{DIS}_{i,k}\right)\Delta t\le 0\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{13}$$

or

$$-(1-l_i)^{t}CAP^{START}_{i}-\sum_{k=1}^{t}(1-l_i)^{t-k}\left(P^{CH}_{i,k}-P^{DIS}_{i,k}\right)\Delta t\le 0\forall i\in V,\forall t\in\{t^{start},..,t^{end}\} \tag{14}$$

Some specific cases of articles where two-variable modelling is selected for the study are [69–76].

In addition, the periodicity constraint can be included in order to impose the same storage level at the beginning and at the end of the considered time interval. The formulation of both modelling approaches is reported in Eqs. (15)–(16).

$$(1-l_i)^{t^{end}}CAP^{START}_{i}+\sum_{k=1}^{t^{end}}(1-l_i)^{t^{end}-k}P^{ST}_{i,k}\Delta t=CAP^{START}_{i} \tag{15}$$

$$(1-l_i)^{t^{end}}CAP^{START}_{i}+\sum_{k=1}^{t^{end}}(1-l_i)^{t^{end}-k}\left(P^{CH}_{i,k}-P^{DIS}_{i,k}\right)\Delta t=CAP^{START}_{i} \tag{16}$$

3.3.3. Layout constraints

Layout constraints are often overlooked, under the simplifying assumption that all components can be connected indiscriminately. However, parallel and series connections between different devices can be found in most of real applications. Furthermore, a particular example concerns heat generation technologies that operate at different temperature levels. In this case, the different circuits typically communicate via heat exchangers. On a practical level, in order to include the actual connections of the components in the mathematical formulation, the energy balances must be modified. For each energy vector, two types of constraints must be inserted. The first one (Eq.*17*) states that the output power of each generation/conversion technology must be less than the sum of the powers consumed by the interconnected technologies. On the other hand, the second constraint (Eq.*18*) expresses that the input power of each technology must be less than the sum of the powers produced by the interconnected generators.

$$P^{OUT}_{i,jp} \leq \sum_{jc \in U_c} P^{IN}_{i,jc} a_{jp,jc} \forall i \in V \tag{17}$$

$$\mathrm{P}^{IN}_{i,jc} \leq \sum_{\mathrm{jp} \in \mathrm{U}_p} \mathrm{P}^{OUT}_{i,jp} a_{jp,jc} \forall i \in V \tag{18}$$

In Eqs. (17)–(18), i represents the energy vector, jp and jc are subscripts to distinguish producer from consumer technologies and a indicates the state of the connection between the considered technologies (1 if connected and 0 otherwise). It should be noted that the set $\mathrm{U_p}$ includes not only producer technologies, but also purchase from the networks and discharging phase of storage. Similarly, the set $\mathrm{U_c}$ denotes both consumer technologies but also selling to networks and charging phase of storage. When layout constraints need to be included in the problem formulation, since it is necessary to distinguish the producers of each energy vector from its consumers, only double variable modelling can be used as modelling approach.

In the *A.ppendix section*, Eqs (17)–(18) are written in their extended form, referring to the proposed MES example.

3.4. LP models of multi energy systems in literature

The simplified description of energy systems, through Case 0 formulation, could bring to a representation far from the real one. As a result, there are few articles in the literature that perform the operational optimization using exclusively an LP formulation [77–82]. Among them, Georgiou et al. [83] propose a LP optimization scheme for the minimization of the net grid energy usage of a nearly Zero Energy Building (nZEB). However, the study proposes to include a further step at the end of the optimization: the import of the optimal dispatching in the software System Advisor Model (SAM), in order to address a more realistic modelling of storage and take into account the power conversion losses. More frequently, however, the use of the linear approach is embedded in a more complex optimization framework. In this case, the simplified linear approach allows the characteristics of the system to be broadly taken into account, allowing to analyse more complex aspects [84]. For example, Lauinger et al. [85] developed a decision-support tool in the form of a linear program in order to apply a stochastic programming approach, able to account for the uncertainty of the weather parameters. This choice is justified by the fact that stochastic programming increases the computational complexity in proportion to the number of considered weather scenarios, requiring the formulation of simple and fast operation problem. Another article that presents a similar methodological approach is [86]. Furthermore, a two-level nested optimization is presented by Capone et al. [87] in order to model the multi energy system taking into account the thermal dynamics of the district heating network. The upper-level uses the genetic algorithm to optimize the demand-side management, while the lower-level optimization uses a linear programming algorithm to find the best operation of the production plant. Finally, the short computational times characterizing LP problems can be particularly advantageous when the optimization process has to be repeated, for example for finding the Pareto curve in a multi-objective optimization [79].

4. Case 1 - Realistic modelling of the system components

Case 0 represents a highly simplified model since it neglects technical limitations that characterize the operation of the technologies, such that it is possible to say that the resulting formulation provides an ideal formulation of their operation. These simplifying assumptions are sometimes used even at the cost of significant impacts on model accuracy.

Table 2
Discriminating elements setup for Case 1a.

Optimization purpose	Operation
Presence of energy storages	✓
Technical constraints of system components	✓
Nonlinearities	×
Time interval	Short-term
Uncertainties	×
Flexibility measures	×

In general, the choice of whether to include technical constraints within the optimization can strongly influence the results of the optimal operation and load characteristics of individual technologies. In the present work, the more detailed description of the components operation obtained by including their technical features will be referred as “real performance”. In this section, these issues are addressed. More in detail:

a) Case 1a presents the modelling of technical constraints, thus analysing:
   - The minimum power constraints in Section 4.1.1;
   - Minimum up and down time constraints in Section 4.1.2;
   - Ramp rate constraints in Section 4.1.3;
   - Maintenance cost modelling in Section 4.1.4.
b) Case 1b the different possibilities to include nonlinearities are exposed. In particular:
   - Part load performance in Section 4.2.1;
   - Investment costs in Section 4.2.2.
c) Case 1c both operational constraints and actual performance are treated together.

4.1. CASE 1a - Technical constraints of system components

In order to include operational technical constraints of the technologies within the optimization problem, such as the discrete working ranges of technologies or their minimum operating period, a more complex mathematical formulation is required since binary variables become essential. Table 2 presents the *discriminating elements* characterizing Case 1a.

The formulation of the above-mentioned optimization problem turns out to be a Mixed Integer Linear Program (MILP) and it can be written in general form as in Eq. *(19)*:

$$\begin{gathered}\min_{o} f(\boldsymbol{o}) \\ s.t. \begin{cases} g_i(\boldsymbol{o}) \leq 0 \forall i \in \{1, \cdots, m\} \\ h_j(\boldsymbol{o}) = 0 \forall j \in \{1, \cdots, p\} \end{cases} \\ \boldsymbol{o} \in \{\mathbb{R}\} \vee \{\mathbb{Z}\} \vee \{0, 1\}\end{gathered} \tag{19}$$

where o is the vector containing the continuous and integer decision variables, f is the objective function, while g_i and h_i are the sets of inequity and equity constraints, respectively. In particular, *f, g* and h are linear functions, while o represents real or integer variables.

This formulation differs from the previously one presented in Section 3 due to the presence of the integer variables (that can appear both within the objective function and the equality/inequality constraints).

4.1.1. Minimum operating power

Most of the technical devices cannot operate in arbitrary low part load. Constraints on the minimum powers of the components can be included in the model by acting on the upper and lower boundary of the variables. In particular, the formulation is given in Eq. *(20)*.

$$P_{j,k}^{IN,MIN} y_{j,k} \leq P_{j,k}^{IN} \leq P_{j,k}^{IN,MAX} y_{j,k} \forall j \in U, \ \forall k \in \{1,..,t^{end}\} \tag{20}$$

Where y is the binary decision variable representing the on/off state of the technology and $P^{IN,MIN}$ and $P^{IN,MAX}$ are the extreme values of its working range. If the binary variable is set to zero, the only value that the P^{IN} variable can assume is 0 (and therefore the technology is off). If, instead, y is equal to 1, the technology is switched on at a level between its real minimum and maximum operating power.

It is worth to notice that the addition of this constraint is trivial for components whose performances have been piecewise linearized (Section 4.2.4), since the binary variables are already present, and therefore, considering the minimum operating powers does not increase the dimensions of the problem.

4.1.2. Minimum up and down time constraints

For some types of devices, the associated on/off schedule cannot assume arbitrary values. More in detail, each unit shall remain switched on for at least a predefined number of time periods after start-up. This constraint is called minimum up time constraint. Similarly, each unit must respect minimum down time constraints, remaining switched off for at least a predefined number of periods after shutting down. For example, this is typical of cogeneration units due to their slow dynamics. This technical constraint is important also because each unit, in addition to operating and maintaining costs, can have a start-up cost, incurred each time the unit is switched on. This cost is usually due to the inertia of the component (i.e., it consumes primary energy without producing any useful effect [88]). Consequently, neglecting these constraints may lead to erroneous estimates that may impact the feasibility of a technology in the energy system.

In the literature, three approaches can be found to manage this issue.

a) One possible way to set the minimum times for a technology to be switched on or off is to include the following constraints in the problem formulation (Eqs. (21)–(23)).

$$z_{j,k} = y_{j,k} - y_{j,k-1} \qquad \forall k \in \{2,..,t^{end}\} \tag{21}$$

$$\sum_{t=k}^{k+N\Delta t^{MIN,ON}} [y_{j,t}] \geq N\Delta t^{ON} - (z_{j,k} - 1)\cdot M \qquad \forall k \in \{2,..,t^{end} - N\Delta t^{ON}\} \tag{22}$$

$$\sum_{t=k}^{k+N\Delta t^{MIN,OFF}} [y_{j,t}] \leq (1 + z_{j,k})\cdot M \qquad \forall k \in \{2,..,t^{end} - N\Delta t^{OFF}\} \tag{23}$$

Where y is a binary variable equal to 1 if the device is on and 0 otherwise; z is a dummy variable to recognise the start-ups and shut-downs; $N\Delta t^{MIN,ON}$ and $N\Delta t^{MIN,OFF}$ are the minimum number of time steps in which the component must stay on and off, respectively; and M is an arbitrary big and constant number, usually called Big-M. These constraints allow the on/off vector to be scanned, relating the current instant to previous and subsequent ones, in such a way that the minimum time constraints are respected. It is worth to notice that, in order to compute the first z of the series, it must be provided a binary value for y as the initial state of the component (when $k = 0$). Obviously, these constraints require a single optimization over several time steps, as in case of storages (since the various time steps are linked by Eqs.21–22). This type of modelling is used in [58,76,72,89,90].

b) Minimum up and down time constraints can also be modelled in a less rigid way. This can be done by adopting some limitations or penalties to prevent the operation of components characterized by frequent starts and stops. In most cases, these effects are monetised by introducing in the objective function specific costs (known as "start-up and shut-down costs") for each component start and/or stop [91,92].

c) A less frequently used method is limiting starts and stops per day a priori [66,93,94].

The aforementioned methods for start/stop restrictions can also be applied simultaneously [16,95].

4.1.3. Ramp rate constraints

Another technical constraint that accounts for transitional behaviour of the devices is the ramp up/down constraint. In particular, it aims to limit the output power variation between each time step in order to represent a physical limit due to the real operation of the components and to improve the lifetime of the device. This type of constraint also handles information related to subsequent time steps, so it is not possible to adopt it within a series of separate optimizations. It can be written in the form reported in Eq. (24).

$$\Delta P_j^{RD} - (1 + z_{j,k})M \leq P_{j,k} - P_{j,k-1} \leq \Delta P_j^{RU} + (1 - z_{j,k})M \qquad \forall k \in \{2,..,t^{end}\}, \qquad \forall j \in U \tag{24}$$

Where ΔP^{RD} and ΔP^{RU} are the ramp-down and ramp-up powers, respectively. Notice that the constraints are not applied when startups or shutdowns take place. Concerning the scientific literature, [58,66,67,76,96] are some of the works that employ this kind of constraint in the analysis of the multi energy system operation.

4.1.4. Maintenance costs

The inclusion of maintenance costs within the optimization model can be done in different ways:

a) Maintenance costs are usually single-step costs unlike operating costs which scale with input power. As a consequence, they should only be added to the objective function only if the technology operates in the considered time step. This type of information can be managed only through the use of binary variables. The calculation of these costs is reported in Eq. *(25)*.

$$C^M = \sum_{j \in U} \left[\sum_{k=1}^{t^{end}} c_j^M y_{j,k} \right] \tag{25}$$

Where c_j^M is the specific maintenance cost of the j-th technology, while y is the binary variable that represents the on/off state of the component (equal to 1 if on, 0 otherwise).

b) Maintenance costs can be assumed to be proportional with the produced power and, consequently, with the operating cost [92,95] or, in other cases, they are given as a fraction of the capital cost ([73,97,98].

It should be noted that, with the modelling approach explained in point 2, maintenance costs are considered in a more approximate way, and, in this case, the use of binary variables is not necessary.

4.1.5. MILP models of multi energy systems in literature

Among the alternatives that address the scheduling optimization problem by taking into account the technical constraints that characterize these systems, the most commonly adopted formulation in literature for solving short-term operation is the Mixed-Integer Linear Programming ([16,17,53,68,99–108]). Brahman et al. [70] obtained a MILP model of a residential energy hub, focusing on advantages related to load shifting, load curtailing and flexible load modelling considering a maximum heating and cooling temperature deviation from desired set points. Several binary variables were used to represent the on/off states of the cogeneration unit and equipment identified as shiftable loads, along with the charge and discharge states of the storage units. Morais

Table 3
Discriminating elements setup for Case 1b.

Optimization purpose	Operation
Presence of energy storages	✓
Technical constraints of system components	✓
Nonlinearities	✓
Time interval	Short-term
Uncertainties	×
Flexibility measures	×

et al. [69] presented an optimal operation of a renewable micro-grid and the effectiveness of the presented methodology is demonstrated through its application to a real case study. The dispatching is formulated as a MILP problem since two variables are required for modelling the storage batteries. Daraei et al. [109] adopted the MILP method to evaluate the interaction between local renewable resources and CHP plants and its influence on the CHP production planning and energy demand. Finally, in this context, one of the most significant research works is presented by Wirtz et al. [110]. The authors of the paper investigated 24 MILP models with different levels of details for the design of MES and pointed out that, for the analysed case, considering part load efficiencies leads to lowest system costs but highest computational time. The large number of variables required for the linearization makes this model feature the one with the most impact on the optimization. In contrast, the features of minimum part load and start-up costs have a small impact on optimization.

4.2. CASE 1b - Nonlinearities

In this section the impact of nonlinearities on the energy system optimization model is analysed. More in detail, Case 1b aims at defining the optimal scheduling of a multi energy system, including in the mathematical formulation the off-design characteristics of the equipment and the investment costs. Table 3 presents the *discriminating elements* characterizing Case 1b.

The mathematical formulation for Case 1b is Nonlinear Programming (NLP) and its standard form for this kind of problem is expressed in Eq.*1*. It differs with respect to Case 0 for the presence of nonlinear relation in the objective function and/or in the constraints.

In the following section the above-mentioned sources of nonlinearity are described and different methodologies for dealing with nonlinearities are presented.

4.2.1. Part load performance

Although most models assume that the component efficiency is constant even when the system component is operating under off-design conditions, a critical aspect is the decrease of the nominal efficiency at part load. Unlike constant efficiency devices, nonlinear devices create a natural incentive to operate close to optimum efficiency, discouraging part-load operation. In addition, the inclusion of non-linear performance in the optimisation model not only allows fuel consumption to be minimized, but also allows the increase in emissions at part loads to be taken into account in the analysis. As a result, production planning and exchanges with storage and energy networks could change considerably.

In particular, modelling of off-design conditions is crucial when load profiles are highly variable. For example, the challenge for increasingly popular small-scale technologies (i.e., CHP units for residential applications) is to decrease the minimum load level and increase part-load efficiency to meet variable energy demands. Moreover, also on a large scale, this aspect is becoming important to model, as the operating regimes of central power plants are changing from pure base load to variable renewable energy balancing.

The constant efficiency approximation may be close to the reality for some technologies and operating conditions, but a very rough simplification for others. For example, among different prime movers used in cogeneration and trigeneration plants, the simple cycle gas turbine is characterized by the most pronounced degradation of efficiency (about 63 % of the nominal value at half load). Simple cycle gas turbines are followed by micro gas turbines and internal combustion engines (that have similar decreasing percentage, 88 % and 84 % respectively) [111].

4.2.2. Investment costs

The specific cost of many types of equipment typically decreases as size increases. In most cases this relation is nonlinear (e.g., wind turbine, internal combustion engine, simple cycle gas turbine, absorption chiller etc.)[111]. This nonlinearity is typically neglected and constant investment costs per unit of capacity are usually used [76,100]. In this case, the error made by assuming a linear relation between the two quantities can be non-negligeable when dealing with small-scale technologies. For example, with regard to the above-mentioned prime movers used in cogeneration and trigeneration plants, moving from a size of 10 kW to a size of 200 kW, a reduction in the unitary plant cost of 28 % for simple cycle gas turbines, 37 % for internal combustion engines, and up to 47 % for gas micro-turbines can be observed [111].

4.2.3. Nonlinearities and linearization of the NLP problem

Nonlinear optimization problems are intrinsically more difficult to solve and nonlinear programming procedures cannot guarantee that the solution is a global optimum, unless the optimization problem is convex. A possible alternative to always guarantee the global optimum and, at the same time, to exploit the advanced stage of development of MILP solvers, is the linearization of the nonlinear terms. This technique consists in replacing the original objective function and/or constraints with linear approximations. More in detail, any equation curve of second (or higher) order is divided into multiple regions in which the curve is approximated to a straight line. In this regard, a key factor is the choice of the number of regions. On one hand, if the efficiency curve is not divided into an adequate number of regions, the model does not

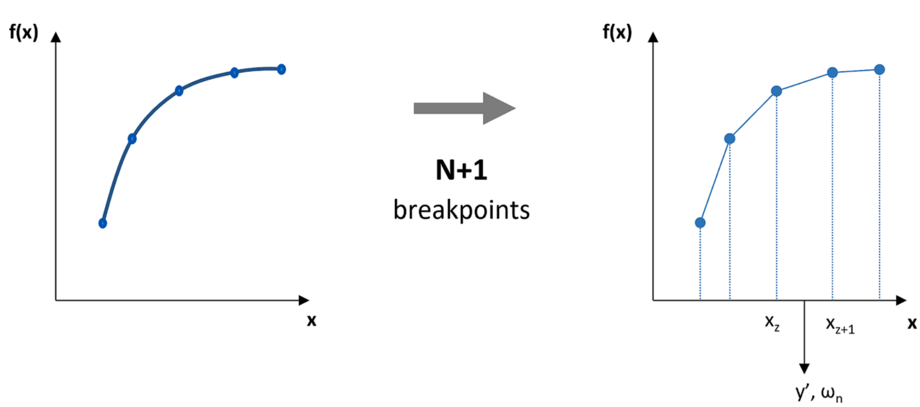


Fig. 4. Piecewise linearization.

Table 4
Discriminating elements setup for Case 1c.

Optimization purpose	Operation
Presence of energy storages	✓
Technical constraints of system components	✓
Nonlinearities	✓
Time interval	Short-term
Uncertainties	×
Flexibility measures	×

adequately account for nonlinearities in the system. On the other hand, if the number of regions becomes significant, the variables of the problem increase considerably and, consequently, so does the calculation time.

Advanced discussions about linearization techniques can be found in [112,113]. A basic algebraic formulation of a piecewise-linear approximation of a function f(x) is given hereafter. Fig. 4 shows graphically the piecewise linearization method.

First of all, known N as the number of intervals for the linearization, denote x_z ($z = 1,..,N + 1$) as the breakpoints of f(x). Then, it is necessary to include in the formulation N continuous variables ω and N binary variables y'. The field of existence of the variables ω is defined in Eq. *(26)*, while the limit for choosing no more than one interval at a time is addressed with Eq. *(27)*. Finally, the original parameters (x and $f(x)$) can be computed with Eqs. *28–29*, where f_n is the linear approximation of the curve in the n-interval.

$$x_z y'_n \geq \omega_n \geq x_{z+1} y'_n \tag{26}$$

$$\sum_{n=1}^{N} y'_n \leq 1 \tag{27}$$

$$x = \sum_{n=1}^{N} \omega_n \tag{28}$$

$$f(x) = \sum_{n=1}^{N} f_n(\omega_n) \tag{29}$$

4.2.4. NLP models in literature

As for linear models, there are not many research articles in the literature on nonlinear modelling approaches for MES management. Zhao et al. in [114] present the optimal scheduling of the energy systems under day-ahead electricity pricing. The authors point out that their proposed predictive control model based on an NLP algorithm is unable to take into account certain performance limits such as minimum load ratios of the technologies or the minimum water flow for the thermal storage. The NLP formulation is most used in decomposed problems for analysis with a wider extension. In fact, in problems where the number of variables to be optimized becomes considerable, one technique is certainly the decomposition of the integral problem into sub-problems. For example, an attempt of reducing the computational complexity of a problem can be found in [66], where the authors propose the optimal scheduling of a gas-electricity integrated distribution system and a multi-CCHP system. In this work, due to the detailed modelling of the networks and their integration within the energy system, a two-stage optimization is proposed. In particular, each phase is an NLP problem: the first presents all continuous variables, while in the second an on/off component model is obtained from the results of the previous phase.

4.3. CASE 1c - Technical constraints and nonlinearities

Case 1c describes an application in which both technical constraints and actual components performance are considered. *Discriminating elements* setup for Case 1c are reported in Table 4.

In the most general case, the mathematical formulation for Case 1c is a Mixed Integer Nonlinear Program (MINLP) and the standard form for this kind of problem is expressed in Eq. *(19)*. It differs with respect to Case 1a for the presence of nonlinear relation in the objective function and/or in the constraints. If, however, the nonlinearities of the system are treated through linear piecewise approximation, the modelling approach changes from MINLP to MILP and, consequently, the generic formulation becomes that given in Eq. *(19)*.

4.3.1. MINLP models in literature

Even though the MINLP approach requires an additional computational effort as it combines linear programming, nonlinear programming and integer programming algorithms, several papers use this methodology to model energy systems [115–119]. Moghaddam et at. [10] present a MINLP model for the 24-hour scheduling of a residential energy hub. One of the innovations of the paper is that the presented model takes into account part-load efficiency and is able to limit the start-up/shut-down of equipment. Deng et al. [120] proposed a MINLP scheduling model based on the input of real load and operation parameters of equipment. Both nonlinear input–output characteristics and discrete working ranges of energy equipment are considered. A comparative analysis with the existing scheduling strategy was conducted and it pointed out that the MINLP model proposed truly reflected the real operating condition of equipment.

On the other hand, a consistent number of studies using MILP approach presented in literature are not only able to handle the technical constraints of technologies but also nonlinearities (via the linearization technique presented in Section 4.2.3). Bischi et al. [94] include in the model the nonlinearity of the performance curves of the components through a piecewise linear approximation (thus transforming a MINLP into a MILP), also considering the impact of temperature on these curves. They solved the MILP optimization model with different levels of accuracy (5,10,20 intervals) of the piecewise linear approximation of the nonlinear performance curves. The results of the presented case study suggest that 10 intervals are a trade-off between accurate estimates of the optimal objective function and computational time. Almassalkhi et al. [103] developed a mixed integer piecewise linear programming formulation of an energy hub system considering nonlinear energy conversion processes, energy storage, and hub emission limits. Results highlight a reduction in effects inherent to constant efficiency assumption in supporting operational and planning decisions. For example, the traditional hub models can significantly undersize energy storage as compared to the piecewise linear energy hub formulation.

Finally, the choice of whether to include operational constraints and nonlinearities within the optimization can be of fundamental importance when performing combined synthesis, design, and operation optimization. Arcuri et al. [20] formulated a model for selecting the optimal typology, size, and operative strategy of a trigeneration system for the civil user, analysing different cogeneration plants. The mathematical model proposed is nonlinear since the analysis takes into account three nonlinear constraints: the variation in nominal efficiency and unit cost of the cogeneration plant in relation to its size and the decrease in nominal efficiency in part-load configuration. Marocco et al. [98] proposed the optimal design of a stand-alone renewable multi energy system, focusing on the feasibility of H2-based devices in remote areas. To this end, affine approximations to the electrolyser and fuel cell efficiency curves were included in the analysis to obtain a more detailed and accurate techno-economic estimate.

4.4. Comparison between different optimization approaches

As stated in the previous sections, several articles in the literature address the scheduling optimization problem by taking into account realistic modelling of system components, proposing MILP, MINLP and NLP optimization. In some cases, different optimization methods are applied to the same case study, resulting in comparable results from the

Table 5
Research papers that include real performances and operational constraints in the study.

Reference	MODELLING APPROACH	Nonlinear Performances	Minimum operating power	Minimum up/down time	Ramp rate
Di Somma et al.[53]	MILP		✓		
Morvaj et al. [93]	MILP		✓	✓	
Brahman et al [70]	MILP		✓	✓	✓
Bischi et al.[94]	MILP	✓	✓	✓	
Moghaddam et at. [72]	MINLP	✓	✓	✓	
Deng et al. [120]	MINLP	✓	✓		
Zhao et al. in [114]	NLP	✓			
Lu et al. [11]	MINLP	✓	✓	✓	
Moradi et al. [95]	MINLP	✓	✓	✓	
Jiang et al [66]	NLP	✓	✓		✓
Arcuri et al. [20]	MILP	✓			
Dvorak et al. [16]	MILP	✓	✓	✓	✓
Bertsimas et al. [122]	MILP	✓			
Zhou et al.[100]	MINLP	✓	✓		
Marzband et al.[75]	MINLP		✓	✓	✓
Polimeni et al. [123]	MILP		✓	✓	✓
Wald et al.[76]	MIQCP		✓	✓	✓

different approaches. Ommen et al. [121] examined the three most frequently used operation optimization methods (LP, MILP, and NLP) in order to investigate their impact on operation management of energy system technologies. Due to the added constraints in the MILP model (minimum powers, ramp rate and shut-up/shut-down constraints) and the NLP model (nonlinear performance curves) that limit the operation of the technologies under investigation, the number of operation hours of alternative units increases (+23 % for MILP, +39 % for NLP compared to the linear case). The changes are especially visible in case of using the NLP optimization, where efficiencies are reduced in conditions of part load. The results indicate that the MILP optimization is most appropriate from a viewpoint of accuracy and runtime. Lu et al. [11] proposed a MINLP model including in the analysis the nonlinear input–output characteristics of energy system components, discrete work intervals and limitations of their minimum operating period and the results are compared with an NLP optimization approach. Also in this case, the authors point out that, although the difference in terms of objective function between the two approaches is small, integer programming truly reflects the system actual operation. Although with a focus on more electrical issues, Nemati et al. [13] perform the optimal day-ahead unit commitment and economic dispatch in a microgrid by proposing two different algorithms (a genetic algorithm and a MILP algorithm). Both algorithms were adapted to the application under consideration; in particular, the MILP was combined with an external tool to correctly handle nonlinearities thus avoiding the complex resolution of a complete MINLP problem. Moradi et al. [95] employed an advanced dynamic programming method for a microgrid energy-scheduling. By applying the quadratic programming method to the system formulation, the model is divided into linear and quadratic terms only. Appropriate technical constraints, such as generation capacity constraints and the number of starts and stops, were included in the analysis. In addition, Zhou et al. [100] compared a MILP and a MINLP model to analyse the impacts of equipment off-design characteristics on the design and optimal operation of trigeneration systems. The results show that the assumption of constant efficiency has a rather small impact on the optimization results. This occurs provided several other devices are present in the system including thermal storage and grid connection. In this case it can be guaranteed that the efficiency of the power generation technology does not deviate significantly from its nominal efficiency.

In light of the works analysed, it is possible to draw a final consideration: the LP formulation allows to solve very quickly the operation problem at the price of a reduction in the precision of the simulation of the components. This can significantly decrease the precision of the solution since it does not adequately represent the energy system. The MINLP formulation provides the simulation of the system with the best quality, but finding the global optimum can be non-trivial, especially for nonconvex or high dimensional problems, exposing to the risk of convergence to local optima. Finally, the MILP formulation results to be a good compromise between these two alternatives, since it guarantees to find the global optimum of the problem and it ensures a satisfying accuracy of the components operation, provided that the linearization process is performed with an adequate precision.

Cited articles that include realistic modelling of system components in the analysis are reported in Table 5 also with the indication of their own modelling approach.

5. Case 2 - Synthesis, design and operation optimization

This case study is focused on the implementation of the synthesis, design and operation problems in the optimization process. This task is particularly meaningful from a practical point of view, since it represents the concrete problem that is required to be solved in order to properly build from scratch an energy system.

One of the first literature reviews that collected the main strategies developed for this purpose is [124], where the synthesis and design problems are posed at the centre of the discussion. The alternatives identified in this work are mentioned, discussed and referenced in the following subparagraphs. Another review [41] showed that, if only the synthesis and design problems are required to be solved, both deterministic and heuristic methods are adopted in the scientific literature, but when the operation must be also assessed, then the second ones may be not very efficient if used alone.

5.1. Time period selection

To correctly deal with the synthesis and design problems it is necessary to make an evaluation on a long-term period, theoretically (but not mandatorily) equal to the lifetime of the system. Obviously, considering the complete time period is not feasible in the practice, therefore, some representative days of the year are assumed with the aim of reducing quantitatively but not qualitatively the time steps. The period considered to perform the long term analysis can range from 5 years [125] up to 15 years [126], neglecting the differences between the single years. The yearly time period has been accounted with a number of representative days between 4 and 24 [12,127–132], typically with an hourly discretization. Some indications for correctly considering the transfer of information between simulated representative periods (e.g. energy storage) are contained in [76].

5.2. Problem definition

The most basic approach to deal with this problem consists in expanding the formulation developed for the operation optimization, including the synthesis and design variables, and the capital cost of the components for all the time steps considered. The synthesis variables are binaries that indicate the presence of a certain technology, while the design variables can be continuous or discrete and are referred to the size of the selected component. Capital costs and components' performances are typically nonlinear but can be piecewise linearized with the technique discussed in the previous paragraph.

5.3. Optimization techniques

As a result, the problem can be formulated as a single MINLP [133,134] or MILP [23,125,135–145,93,146], respectively. In these cases, the synthesis and design problems are addressed with the help of a superstructure, a theoretical layout that includes all the components that are described by the optimization variables.

5.4. Problem dimensions and computational cost reduction

The synthesis and design problems dimensions increase respect to the operation optimization (in the order of $10^4 \div 10^5$ variables, [93,136,140,147]). In fact, additional variables are required to represent the synthesis and design parameters, as well as to account the increase of time steps needed to represent the system lifetime. As an attempt to reduce the computational costs, different decomposition strategies have been developed and implemented. The most common one has been applied for the first time in order to optimize single CHP plants [148] and consists in dividing the single optimization in two nested levels (Master and Slave Problem, MP and SP respectively): in the outer stage (MP), synthesis and design are optimized with a heuristic solver, while in the inner stage (SP) the operation problem is solved with a deterministic solver. Therefore, the SP is optimized for any evaluation MP performs one iteration, but thanks to the SP small dimensions it is possible to take advantage from the exponential correlation between computational times and problem sizes. For the master problem, several heuristic algorithms are adopted and compared in [127]: the Tabu Search is faster in finding the optimum, but the Ant Colony Optimization reaches for first the convergence criterion. Genetic Algorithm is adopted also in [129,149,150,73], while Particle Swarm Optimization is employed in [151]. The choice of the heuristic solver must be evaluated according to the features that characterize the problem itself, in order to find the optimization method that better fits the case study under consideration. The problem decomposition is particularly advantageous when the time steps that constitute the representative days are not correlated between them (i.e. absence of energy storages or flexibility measures, etc.); in this case, the single optimizations become particularly fast (fractions of second) and can be executed in parallel.

In addition, there are other decomposition strategies that are less commonly applied but that are worth to be mentioned. A comparison between heuristic and semi-deterministic master problems is performed in [152], adopting respectively the evolutionarily stable strategy and the NLP derivative-free algorithm Particle Generating Set-Complex, resulting in a faster convergence of the latter one. The decomposition strategy is demonstrated to be advantageous, showing computational times equal up to the 5.4 % of those required by the full MILP formulation [127].

Another interesting development of the decomposition consists in avoiding the definition of a fixed superstructure for the addressing of the master problem [153–155]. The formulation is still similar to the case with the superstructure, but a higher degree of freedom can be reached.

5.5. Operation with following electric/thermal load

If the operation is managed with load following techniques (Following Electric Load, Following Thermal Load, etc.), and therefore the system operation is not optimized, the synthesis and design problems can be solved in a single stage with MINLP solvers [116,126], Genetic Algorithm [18,156–168], Owl Search Algorithm [169], Crow Search Algorithm [170] or Particle Swarm Optimization [27,171,172]. Typically, these problems have limited dimensions, therefore heuristic algorithms are the preferred choice thanks to their simple implementation, and their capability in dealing with nonlinear and non-convex objective functions or constraints.

5.6. Benefits of combined optimization

On the overall, solving the complete problem for the synthesis, design and optimization of the energy system allows to make a comprehensive analysis of the combined generation and a consistent comparison with the separate generation. The advantages of the combined generation are confirmed even on the long-term, with reductions of annual costs in the order of 12–17 % [136,173], a decrease of the emissions up to 56–66 % [136,173], or a lowering of the primary energy consumption of 10–34 % [131,144,173], according to the optimization criteria that is chosen.

5.7. Mathematical formulation

In light of all the elements collected from the scientific literature, the formulation proposed in the present work for the implementation of the synthesis, design and operation problem is in the decomposed form. A synthetic mathematical formulation is provided in Eq.30.

$$\min_{s,d} f(s,d,o)$$
$$s.t.\begin{cases} \min_{o} f(s,d,o) \\ s.t.\begin{cases} g_k^{SP}(o) \geq 0 \forall k \in \{1,\cdots,n\} \\ h_w^{SP}(o) = 0 \forall w \in \{1,\cdots,q\} \end{cases} \\ g_i^{MP}(s,d) \geq 0 \forall i \in \{1,\cdots,m\} \\ h_j^{MP}(s,d) = 0 \forall j \in \{1,\cdots,p\} \end{cases} \tag{30}$$
$$s,d,o \in \{\mathbb{R} V \mathbb{Z}\}$$

Where s and d are respectively the variables of the synthesis and design problem, respectively, while g^{SP}, h^{SP}, g^{MP} and h^{MP} are the inequalities and equalities of the Master Problem and Slave Problem. Regarding the master problem, the synthesis variables are binaries indicating the selection of a specific technology (w), while the design variables are discrete or continuous and represent the rated power of the selected component (RP). The boundary of the rated powers is defined with Eq. (31), where the multiplication between the binary variable and the upper and lower values (RP^{max} and RP^{min}) forces the rated power to zero in case the technology is not selected.

$$w_i \cdot RP_i^{min} \leq RP_i \leq w_i \cdot RP_i^{max} \forall i \in U \tag{31}$$

In case multiple components are available for each kind of technology, convergence problems often arise. This happens because the same MES configuration can be reached through different combinations of the MP variables [72]. This can be avoided by imposing hierarchy constraints [100] between the sizes of the components belonging to the same technology (Eq. (32)), which means that the components are not randomly selected, but their choice is made with order.

$$RP_{i,r} \leq RP_{i,r-1} \forall i \in U, \forall r \in \{2,\cdots,r^{max}\} \tag{32}$$

Where r^{max} is the maximum number of devices that can be installed for a single technology. In this case, the rated powers of the units belonging to the same technology are imposed to follow an ascending order.

Concerning the operation optimization of the SP, its formulation can be made in the same way described in the two previous paragraphs, considering the synthesis and design variables as known inputs of the problem.

6. Case 3 - Uncertainties

The correct management of the uncertainties is one of the most important aspects in the field of the energy systems for both short and long-term planning. Neglecting the uncertainties in the short-term optimization (e.g. day ahead analysis) can lead to a sub-optimal planning of the power production and even to critical or congested conditions, while the effect on the long-term optimization can be the undersizing/oversizing of the exploited technologies [174].

The implementation of uncertainties is often discussed in reviews on energy systems [37,1] and some works are completely focused on this topic. The parameters subject to uncertainty are recognized and discussed in [174]. A detailed overview on probabilistic, possibilistic, and combined methods, beside information gap decision theory is provided in [175], where both strengths and weaknesses are highlighted for each strategy. Deterministic and inexact optimization models are compared in [26], and precise considerations are provided regarding their limitations. Finally, a clear explanation of the criteria to follow to choose the most suitable method according to the data availability is provided in [176]. The gaps in the application of some techniques for addressing uncertainties in MESs are discussed, as well as the challenges represented by computational costs and mathematical formulation of more recent techniques for uncertainty management.

the most common sources of uncertainty on the input of the problem are: a) the prices of the energy vectors and their related environmental parameters such as emission factors; b) the energy demands; c) investment costs; d) the production from renewable sources; e) the ambient conditions [177]; f) the devices' performance [178,179]; and g) the operating reserve of power plants [180]. Furthermore, it is important to note that, although most research articles on the subject treat each uncertain parameter as independent from each other, in reality there may be potential correlation between them (e.g. between energy load and electricity price [89] or between different energy demands [181]). The interdependence between inputs can be defined by the covariance, which describes the correlation between two random variables.

6.1. Approaches to include uncertainty

Suitable forecasting models must be adopted to properly estimate the parameters affected by uncertainty [37]. This task is usually addressed in a separate analysis. Since the focus of the present work is devoted to the optimization problem, the strategies employed to develop a model able to generate input data according to the probabilistic phenomena are not furtherly discussed. The interested reader can find comprehensive discussions in [182–186].

When the research objective is to deal with data uncertainty in multi energy system optimization, two different approaches can be employed: i) uncertainty/sensitivity analysis, and ii) optimization under uncertainty. The first one aims at understanding the impact of uncertainty on model output, while the second method aims at identifying the optimal decision that should be taken "here-and-now" based on the uncertain parameters. Many research articles perform sensitivity analysis to identify which inputs have a major impact on optimization results [64,187,53,188]. This type of approach does not take into account the dynamic nature of decision-making under uncertainty and its information flow. The two main representatives for the inclusion of the uncertainties in the optimization are: a) stochastic programming; and b) the robust optimization. They differ on the basis of the information on the random events: in stochastic programming the probability distribution of uncertain data has to be known or estimated, while in robust optimization the uncertain data are assumed to be varying in a given uncertainty set.

However, there are many other methods in addition to stochastic programming and robust optimization. According to the degree of simplification, the complexity of the optimization model can significantly vary. A considerable number of tailored alternatives can be found in the scientific literature. Among these, scenario-based stochastic programming is one of the most employed strategies; this consists in defining some scenarios (i.e. sets of input data) and then, taking into account their respective probability of occurrence, finding the solutions that provide optimal strategy in facing each scenario ([21,189]). In other words, the goal is to find a solution that is feasible for all (or almost all) the possible parameter realizations and optimizes the expectation of some function of the decisions and the random variables. A relatively common strategy to coherently determine the different scenarios is to generate a high number of cases (order of 10^3 [180,190]) with the Monte Carlo method, and then reducing them to a small number (5 in [180], 9 in [191], 10 in [190,192], from 5 to 20 in [193]) with a clustering algorithm [194] or other techniques ([195,196]). Due to the dimensions of this problem, deterministic solvers (MILP and MINLP) are preferred by far to obtain low computational costs.

6.2. Security, reliability and availability

Other aspects related to the uncertainties that are often studied are the security, reliability, and availability of the energy system; many different models developed to include them in the optimization process can be found in the scientific literature. The N-1 principle consists in guaranteeing the security of the system even when one of the elements of the energy hub fails. This approach is applied in [197,198] with multistep optimizations. Robust Optimization (RO) ([177,178,198–200]) has the aim of finding a result that satisfies the worst case that could occur and is often used for reliability and availability.

Moreover, the two-stage formulation is widely used in stochastic programming. In this type of problem, the decision maker has to make some strategic decisions ("first-stage decisions") that are not easy to change on a short time scale and that can be made without full information on random events. After random events occur, corrective actions ("second-stage decisions"), that can be adapted on a short notice, are taken in response to each random outcome. The objective function of the optimization problem is composed of two parts: the cost of the first-stage decision and the expected cost of the second-stage decision taking into account the probability that each scenario has to effectively happen. If the number of scenarios is finite, the stochastic problem can be represented by its equivalent deterministic problem.

6.3. Mathematical formulation

Taking into account the advantages and complexities characterizing the inclusion of uncertainties in the optimization of multi energy systems, the scenario-based stochastic programming represents a good alternative for the implementation of uncertainties. Differently to other approaches, it has no peculiar constraints related to guaranteeing technical concepts such as security, reliability, or availability. Thanks to this degree of freedom, it can be found relatively often in the scientific literature.

For this reason, its mathematical formulation is proposed in the present work. In particular, the two-stage formulation is reported in Eq. (33) and is referred only to the operation problem.

$$
\begin{aligned}
&\min \overline{f}(o', o'', \xi) \\
&s.t. \begin{cases} g_i(o') \geq 0 \forall i \in \{1, \cdots, m\} \\ h_j(o') = 0 \forall j \in \{1, \cdots, p\} \end{cases} \qquad o' \in \{\mathbb{R} \vee \mathbb{Z}\} \\
&s.t. \begin{cases} g_{\sigma,i}(o'', \xi) \geq 0 \forall \sigma \in \{1, \cdots, r\}, \forall i \in \{1, \cdots, m\} \\ h_{\sigma,j}(o'', \xi) = 0 \forall \sigma \in \{1, \cdots, r\}, \forall j \in \{1, \cdots, p\} \end{cases}
\end{aligned}
\tag{33}
$$

$$\overline{f}(o) = f(o') + \sum_{\sigma=1}^{r}[\pi_\sigma \cdot f(o'', \xi_\sigma)] \tag{34}$$

Where ξ is the random vector of the uncertain data, σ is the index of the scenarios, r is the number of scenarios, π is the related probability, o' and o'' are the first-stage and the second-stage decision variables, respectively. The same equations already seen in the previous paragraphs (Eq.34) can be used for computing the objective function of every scenario.

Not only optimal operation, but also optimal design can be addressed adopting a two-stage stochastic programming. In this case, first-stage decision variables are the sizes of components, while second-stage decision variables are related to the demand pattern change (energy system scheduling) [193,201–203].

7. Case 5 - Flexibility measures

The degree of flexibility is the capability to guarantee the power balance of consumers and producers through efficient changes of operation. Some sources of flexibility are identified in [204], where an overview of the papers from the scientific literature treating this topic is given.

Energy storages are by far the most important flexibility source to the system since their influence on both the operation and the modelling of the optimization process is noticeable, as discussed in Section 3. The other measures that can increase the system flexibility are: i) energy substitution; ii) inertia of thermal networks and buildings; iii) Demand Response Programs (DRP); and iv) ancillary services.

7.1. Energy substitution

Energy substitution means to achieve the same energy product (e.g. cold) by adopting a different energy vector (e.g. absorption chiller fed by heat instead of electric chiller) ([205]). In this way it is possible to exploit another source to satisfy the same loads if an energy vector is no longer available.

7.2. Inertia of thermal networks and buildings

The inertia of District Heating/Cooling networks is a physical phenomenon determined by the hydraulic and thermal laws that rule the transport systems. This phenomenon can be appreciated because of the high masses that usually characterize DH networks. Different control strategies are exposed in [204], referred to the energy system configuration (centralized or distributed). Conservation laws have to be set out in order to simulate the physics of the network and three strategies can be found in scientific literature to address the DH inclusion in the MES optimization problem.

a) In some works the design problem of the TN is included in the optimization, but in a simplified form [22,137,206–208]. The TN is simulated with only the connection parameters (i.e. incidence/connectivity matrix) and the thermal powers flowing into the branches. Heat losses are addressed as a percentage (proportional to the distance between the nodes [146]) of the flowing energy and the sizing of the pipes is performed according to the maximum power reported in the time period analysed [143,209].
b) A more detailed optimization is obtained by simulating the operation of the thermal network with temperatures and flow rates. However, when both are considered as variables, the energy balance of the pipes becomes nonlinear. To overcome this issue and preserve the linearity of the model, the network can be assumed to operate under partially known conditions, such as Constant Flow Variable Temperature (CFVT) or Constant Temperature Variable Flow (CTVF). In the first case, the flow rates are considered as known and the temperatures have to be optimized, vice versa for the second case. CFVT is considered as the most applied in real operation and is assumed in [84,210–213], while CTVF is much less investigated [147].
The Variable Flow Variable Temperature (VFVT) configuration can be assumed, but complex models must be developed. The Newton-Raphson method is used in [214] for solving the nonlinear problem, while strong efforts for the linearization process are made in [191].
c) Despite the previously cited works include the DH in the optimization, none of them is formulated to consider the inertia of the network. However, in case of thermal networks of high dimensions, the effects of transients can be noticeable and cannot be neglected [215,216]. To fulfil this purpose, the concept of time delay must be introduced for each branch of the network, often requiring the addition of integer variables. In this case, for CTVF or CFVT configurations, an heuristic solver (Particles Swarm Optimization) is used in [217], while deterministic algorithms are employed in [218–221] (eventually including the building inertia [222]). An intermediate strategy is adopted in [188] and [189], where an heuristic Master Problem solves a Demand Response problem and, nested into the MP, the DH network is simulated with the node method and a simplified unit commitment problem is executed with Linear Programming. Obviously, the highest complexity of the problem is reached when both VFVT configuration and network inertia are considered. Finite volumes are used in [224] and finite differences are employed in [225] to simulate and optimize the DH with iterative processes. However, employing these methods with deterministic solvers is a very complex task because of the incompatibility between the strategies used for the solution of the matrix calculation and the algorithm of the solver itself [204]. Decomposition strategies are often proposed to optimize part of the problem with MILP/MINLP solvers. In [226], a quadratic solver is used to solve the DH problem in a Slave Problem coupled with an iterative Master Problem. A more complex model is developed in [138], where Benders decomposition, relaxed formulation and an iterative process are employed jointly with the simulation of the network based on a water mass method, which represents the network with the node method and accounts the thermal inertia by averaging the temperature at the outlet of the branches.

7.3. Demand Response Programs

Demand Response is a strategy aimed at modifying the user energy demand [227,228]). Demand Response increases the flexibility of an energy system and its effect can be enhanced by other flexibility measures, as pointed out in [229]. Compensation of renewable generation fluctuations, reduction of grid congestions, reduction of power import/export and cost reduction are the main benefits (identified in [230]) that can be attained with DRP. In more quantitative terms, a cost reduction between 1.7 % and 3.6 % is obtained in [205,223,231] and savings over 5 % are said to be expected for case studies with more suitable characteristics. However, lack of appropriate market mechanisms and market requirements of ahead planning are important challenges to deal with.

Concerning the DRP implementation in the optimization model, new variables for the time shifting of loads and, eventually, the percentage of participation have to be introduced, but without introducing other sources of nonlinearities [21,180,189,192,193,199,200,205,232–234]). As already mentioned, DRP are useful to reduce the effects of power fluctuations and deviations from the predicted loads; for this reason, most of the cited works include DRP in optimization with uncertainties. In addition, residential customer dissatisfaction can be defined in order to quantify the impact of the load modification [235].

7.4. Ancillary services

Ancillary services are operation techniques focused on the producers and are mostly referred to electricity networks. They consist in

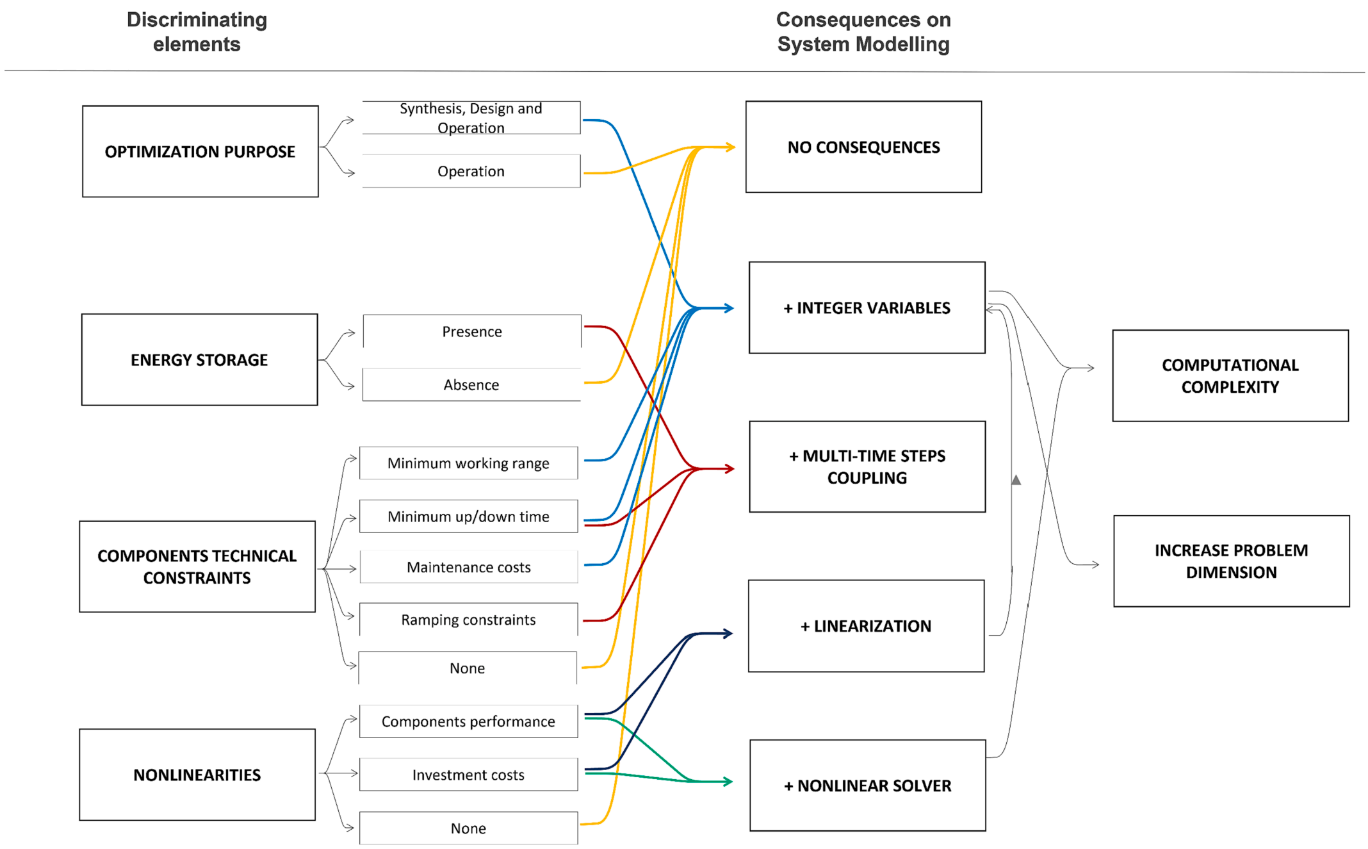


Fig. 5. Correlation between discriminating elements and consequences on system modelling.

guaranteeing a flexible generation capacity and the balance of the deviations of the loads from their predicted levels. The most common ones are power curtailment [236–239], operating reserve and Flexible Ramping Products (FRP, or ramping reserve). Power curtailment is performed for technical and economic reasons, but strong efforts are made in order to prevent this condition [240–242] because of its intrinsic inefficiency. Operating reserve is a production capacity that can be made available in a short period (from seconds to tens of minutes) in order to compensate an unbalance on the grid. Frequency response, spinning reserve and supplemental reserve are the main kinds of operating reserves [243]. A Flexible Ramping Product is a ramping capability commodity that can be dispatched in a 5-minute timeframe to meet demand changes on the network. Operating and ramping reserves are often included with simple constraints [190,218,220,244–248], which have the aim of ensuring a spinning/ramping reserve in the solution found by the optimization process. A more complex treatment must be developed if they are intended to be treated contemporary to the uncertainty [180,249,250].

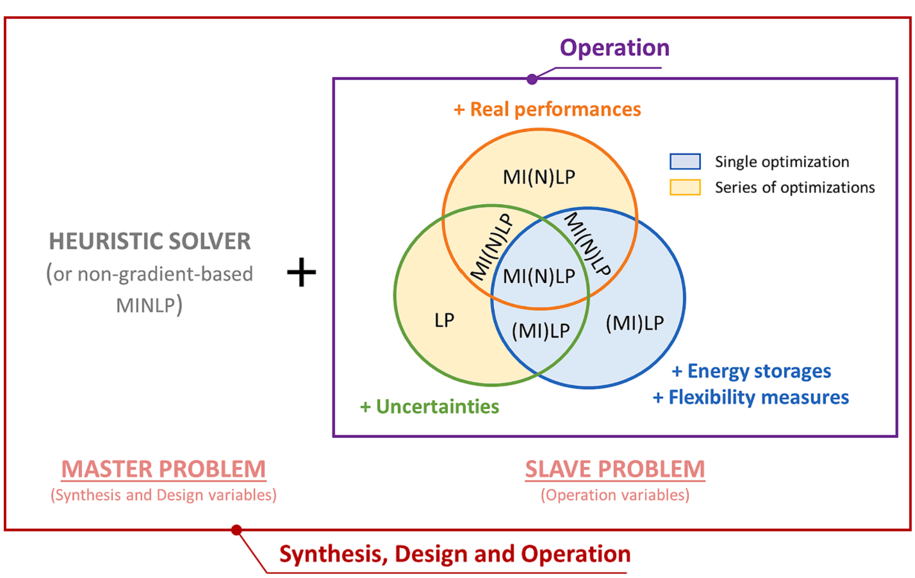


Fig. 6. Summary for the formulation of the optimization problem.

Table 6
Most popular solvers used in the field of energy systems optimization.

<table>
<tr><th>Method</th><th>Formulation</th><th colspan="3">Solvers</th><th>Max. size (oom)</th></tr>
<tr><td rowspan="4">Deterministic</td><td>LP</td><td>CLP</td><td rowspan="2">CBC
GLPK
CPLEX</td><td rowspan="2">GUROBI
Intlinprog
MOSEK</td><td>10^7</td></tr>
<tr><td>MILP</td><td></td><td>10^5</td></tr>
<tr><td>NLP</td><td>IPOPT
PATHNLP
CONOPT
MINOS</td><td rowspan="2">BONMIN
JUNIPER
SCIP
COUENNE
ANTIGONE</td><td rowspan="2">BARON
DICOPT
KNITRO
LINDO
XPRESS</td><td>$10^4 – 10^5$</td></tr>
<tr><td>MINLP</td><td></td><td>$10^3 – 10^4$</td></tr>
<tr><td rowspan="2">Heuristic</td><td>NLP</td><td>PSO ABC
ACO CS</td><td colspan="2" rowspan="2">GA
MA
BBO
SNO</td><td rowspan="2">10^2</td></tr>
<tr><td>MINLP</td><td></td></tr>
</table>

8. Discussion on the optimization model development

The present section has the aim of furtherly discuss the concepts explained in the previous paragraphs related to the discriminating elements, the effects of the initial assumptions on the problem formulation and the characteristics of the resulting optimization model. The changes to be introduced in the model in order to consider different aspects are highlighted, recognizing both advantages and challenges.

As discussed in the previous sections, a more detailed and realistic modelling of an energy system leads to an increase in the computational cost of the optimization problem with respect to the base case presented in Section 3. In Fig. 5, correlations between some of the discriminating elements and factors that modify the system modelling leading to a more complex and computationally intensive model are highlighted. The addition of synthesis and design problems in the operation optimization, minimum working ranges, number of components and maintenance costs make the inclusion of binary variables necessary. On the other hand, the inclusion of nonlinearities within the optimization problem to characterise real component performance and investment curves may also lead to the use of binary variables, in case they are piecewise linearized. Otherwise, if the model is kept nonlinear, a nonlinear (and, usually, non-convex) solver is required. Finally, the presence of storages, the control of components on/off frequency and ramp rate constraints determine a link between the time periods, so multi time steps coupling and the execution of a single optimization become necessary. The diagram also shows how some factors, such as the use of a nonlinear solver, have a direct impact on computational complexity, while others, such as the introduction of binary variables or multi-time steps coupling, lead in the first instance to an increase of the problem size and then to an increase in computational difficulty.

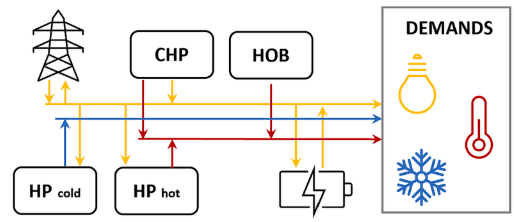
Fig. 6 summarizes the structure of the entire approach proposed in this review. As a starting point, it can be considered the operation optimization (on the right of the figure) performed in Case 0 but without the presence of energy storages, which represents the most simplified case and is formulated as a LP (since time steps are not linked between them). Then, according to the additional description of the energy system, the corresponding resulting formulation of the problem is reported with a Venn diagram. In order to address the real performances of the components (technical constraints, nonlinear performance curve, etc.) the problem turns into a MI(N)LP, where the nonlinearities can be piecewise linearized and, for this reason, the letter N is reported between brackets in the acronym. The same notation (i.e. reporting some letters of the acronym in brackets) is used in the figure when energy storages or other flexibility measures are added in the layout; in this case the formulation is turned into a (MI)LP, where integer variables can be avoided (at least in some circumstances), as discussed in the modelling of energy storages. In addition, the sets of the diagram are coloured according to the structure of the optimization process, i.e. if it is composed by a single optimization or a series of independent optimizations (one for each time step, which can be done when time periods are independent between them).

The other part of the schematic represents the cases in which synthesis, design along with operation are the optimization purposes. As already explained, different models are proposed in literature, but the one that has been reported in the present study expects the decomposition into Master and Slave Problems. The former is addressed for synthesis and design variables and is executed by a heuristic solver (because of the strong non-convexities, discontinuities and the nested SP), while the latter regards the operation problem and is treated as already discussed.

8.1. Optimization solver

The choice of the optimization solver is a crucial aspect since it can noticeably influence the computational times and the quality of the solution. A very high amount of solvers have been developed for each class of optimization problem. Table 6 represents a summary of the most employed solvers Table 6: these are grouped according to the optimization method and the problem formulation. Open-source software are written in green, while the ones in red require a commercial license. The names of the heuristic solvers are shortened with their acronyms: ACO (Ant Colony Optimization), ABC (Artificial Bee Colony), CS (Cuckoo Search), MA (Memetic Algorithm), BBO (Biogeography Based Optimization), SNO (Social Network Optimization). Knowing the maximum problem size (i.e. number of variables) that a solver is able to manage (without losing solution accuracy or requiring excessive computational times) can be very useful from a practical perspective. However, this is a complex information to achieve since it depends on many different and specific aspects. An attempt to answer this question is performed in the present study and an indication is provided in the table in terms of orders of magnitude (oom). These values have been taken according to the articles analysed for the review work, some benchmark studies found in literature [251–253] and other sources [254–256].

NLP and MINLP solvers can be adopted also for LP and MILP problems; however, this option is not considered since this is inefficient. In addition, some MILP solvers (e.g. CPLEX and GUROBI) are able to manage some kinds of nonlinearities, such as quadratic or conic terms. Nevertheless, since these are very specific and limited cases, they are not accounted as nonlinear solvers. Finally, in case of nonlinear formulation, it is fundamental to pay attention in recognizing if the problem is convex or not. Some solvers are not able to deal with non-convexity and the sizes of non-convex problem should be kept as low as possible to avoid



DECISION VARIABLES (i.e., technologies operating powers for each time-step)

- ELECTRIC GRID (IN/OUT) $P_{el}^{BUY}/P_{el}^{SELL}$
- ELECTRIC STORAGE $P_{el}^{ST,CHARGE}/P_{el}^{ST,DISCHARGE}$
- HEAT ONLY BOILER $P_{gas,HOB}^{IN}$
- CHP $P_{gas,CHP}^{IN}$
- HEAT PUMP (EL2HEAT) $P_{el,HP\ hot}^{IN}$
- HEAT PUMP (EL2COLD) $P_{el,HP\ cold}^{IN}$

\+ $y_{\mathrm{el}}^{ST} \in \{0,1\}$ for defining in each timestep if the storage is charging or discharging

GOAL

minimizing COSTS by finding the best technologies operating powers (decision variables)

OBJECTIVE FUNCTION

$$\sum_{k=1}^{t^{end}} c_{gas,\,k}P_{gas,CHP,k} + c_{gas,\,k}P_{gas,HOB,k} + c_{el,k}^{BUY}\,P_{el,k}^{BUY} - c_{el,k}^{SELL}\,P_{el,k}^{SELL}$$

Where c_{gas} and c_{el} are the specific costs of the energy vectors in each timestep

CONSTRAINTS

UPPER AND LOWER BOUNDARIES OF THE DECISION VARIABLES

$$0 \geq P_{el}^{BUY} \geq +\infty \qquad 0 \geq P_{gas,CHP}^{IN} \geq P_{gas,CHP}^{IN,MAX}$$

$$0 \geq P_{el}^{SELL} \geq +\infty \qquad 0 \geq P_{el,HP\ hot}^{IN} \geq P_{el,HP\ hot}^{IN,MAX}$$

$$0 \geq P_{el}^{ST,CHARGE} \geq P_{el}^{ST,CHARGE,max} \qquad 0 \geq P_{el,HP\ cold}^{IN} \geq P_{el,HP\ cold}^{IN,MAX}$$

$$0 \geq P_{el}^{ST,DISCHARGE} \geq P_{el}^{ST,DISCHARGE,max} \qquad 0 \geq P_{gas,HOB}^{IN} \geq P_{gas,HOB}^{IN,MAX}$$

ELECTRIC ENERGY BALANCE

$$\sum_{k=1}^{t^{end}} P_{el,\,CHP,\,k}^{OUT} + P_{el,\,k}^{BUY} - P_{el,\,k}^{SELL} - P_{el,\,EHP\ hot,\,k}^{IN} - P_{el,\,EHP\ cold,\,k}^{IN} - P_{el,\,k}^{ST,CHARGE} + P_{el,\,k}^{ST,DISCHARGE} - P_{el,\,k}^{LOAD} = 0$$

THEMAL ENERGY BALANCE

$$\sum_{k=1}^{t^{end}} P_{th,\,CHP,\,k}^{OUT} + P_{th,\,OHB,\,k}^{OUT} + P_{th,\,EHP\ hot,\,k}^{OUT} - P_{th,\,k}^{LOAD} = 0$$

COOLING ENERGY BALANCE

$$\sum_{k=1}^{t^{end}} P_{c,\,EHP\ cold,k}^{OUT} - P_{c,\,k}^{LOAD} = 0$$

STORAGE CONSTRAINTS

$$0 \leq P_{\mathrm{el},k}^{ST,CHARGE} \leq y_{\mathrm{el},k}^{ST} \cdot P_{\mathrm{el},k}^{ST,CHARGE,max} \qquad \forall\, k \in \{1,..,t^{end}\}$$

$$0 \leq P_{\mathrm{el},k}^{ST,DISCHARGE} \leq \left(1 - y_{\mathrm{el},k}^{ST}\right) P_{\mathrm{el},k}^{ST,DISCHARGE,max} \qquad \forall\, k \in \{1,..,t^{end}\}$$

$$0 \leq (1 - l_{el})^t CAP_{el}^{START} + \sum_{k=1}^{t} (1 - l_{el})^{t-k}\left(P_{\mathrm{el},k}^{CH} - P_{i,k}^{DIS}\right)\Delta t \leq CAP_{el} \qquad \forall\, t \in \{t^{start},..,t^{end}\}$$

$$-(1 - l_{el})^t CAP_{el}^{START} + \sum_{k=1}^{t} (1 - l_{el})^{t-k}\left(P_{\mathrm{el},k}^{CH} - P_{\mathrm{el},k}^{DIS}\right)\Delta t \leq 0 \qquad \forall\, t \in \{t^{start},..,t^{end}\}$$

Where the term l accounts for the losses

PROBLEM SIZE

$$number\ of\ decision\ variables \cdot total\ number\ of\ time\ steps$$

Example: daily operation optimization with hourly resolution → $9\,\frac{vars}{h} \cdot 24\,\frac{h}{day} = 216\,\frac{vars}{day}$

Fig. 7. Example of simplified Multi Energy System (MES) and related mathematical formulation.

convergence issues.

9. Conclusions

The present work represents a survey on optimization of Multi Energy Systems (MESs) from an engineering point of view. With this purpose, the main physical phenomena and technical constraints have been discussed. More in detail, this study addressed the inclusion of components technical constraints and their non-linear behaviours, the problem of synthesis and design, uncertainties and flexibility measures in a basic multi-energy system operation optimization model. In order to expose and discuss these concepts in a clear and ordered way, some case studies are identified and treated separately. With this structure it is possible to increase the focus on single elements. The literature review of the different alternatives proposed for the implementation in the optimization model of these aspects has been proposed, mentioning both advantages and challenges. In the authors' opinion, the mathematical formulation selected represented a good compromise between description accuracy and easiness of implementation. The approach adopted in the present review allowed to provide an overview on the strategies developed for the simulation and optimization of MESs and, at the same time, it represents a reference for the practical development of tailored optimization models.

In light of the articles examined during this review, some conclusions can be drawn regarding the state of art of the modelling and optimization of multi energy systems:

- The level of detail reached by most of the models presented in literature allows a realistic representation of the system operation; this is obtained by addressing the real performance of the components, including descriptive constraints (layout connections, ramping constraints, minimum operating times, etc.), and adopting a suitable time step ($\leq$1 h).
- Linearization techniques are often adopted in order to take advantage of the Mixed Integer Linear Programming (MILP) solvers, while decomposition strategies are commonly exploited when the synthesis and design optimization are addressed along with the operation problem.
- Several strategies are proposed to include the effects of uncertainties and, despite there is not a best one, in general no drastic changes are required in the problem formulation.
- Including the simulation of energy networks (in particular District Heating/Cooling) in the model has a high impact on the problem formulation. It allows to improve the optimization quality and it introduces another source of flexibility. Nevertheless, this leads to an increase of the number of variables and the addressing of nonlinear and non-convex equations.

Among the main research gaps are:

a) the lack of validation studies, even when the input data are taken from real case studies. The importance of this task is straightforward, since it would demonstrate on a practical way the advantages of MES optimization that are only theoretically proven. Therefore, validation is required both to assess the quality of the mathematical model developed to simulate the MES, as well as to prove that the resulting optimal operation can be applied in a real system;
b) the development of a suitable control system for the entire MES, its inclusion in the optimization model and the provision of results in a form that can be directly provided to the control system itself. This task would increase the description quality of the MES and allow the practical implementation of the optimization process. The complexity related to this task is due to the fact that it requires to operate the MES according to the schedule found with the optimization, but, at the same time, it must be possible to deal with any eventual deviation from the predefined operation;
c) a wider inclusion of flexibility sources in MES optimization processes. In fact, most of the models proposed in literature tend to apply considerable simplifications. On the other hand, when no assumptions are made, the resulting modelling becomes very complex and computationally intensive. The development of strategies able to ensure a good level of detail without being excessively time demanding would allow to achieve an advantageous implementation of more flexibility sources, which are a key element for MES operation. In this way, it would be possible to obtain reliable operating schedules with computational times that are compatible with the requirements of the real applications;
d) the integration of energy transport infrastructures in the MES simulation and optimization. In fact, the capability of transferring an energy vector from a producer to a consumer is usually taken for granted, despite it should be verified. The technical constraints and other physical phenomena that characterize the operation of energy transport infrastructures can pose important limitations to the purposes of the MES optimization.

Finally, some further extensions for the present work are identified:

a) Input data for the MES optimization are usually obtained from forecasting models specifically developed for this purpose. Including a research that presents the state of art of the methods used in this field can be a useful addition to the analysis here conducted;
b) The components constituting the MES are modelled with performance curves and technical constraints. Consequently, their mathematical formulation changes according to the assumptions made on their operation, with impacts on the nature of the problem and its convergence. Reporting an outlook of the different alternatives for modelling the components can be another interesting expansion to this review work;
c) A relatively new kind of element is becoming more common in energy systems, which is the prosumer. Its capability to alternatively act both as a producer and a consumer creates the necessity to develop devoted methods for its inclusion in the optimization problem. It would be worth to investigate how its mathematical formulation is addressed in the scientific literature.
d) Multi Energy Systems can have very different sizes, starting from small applications (single buildings) up to portions of a country. An analysis of the problem formulations adopted according to the dimensions of the case study considered could be of interest for understanding how the size of the application influences the optimization model.

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.

Appendix

Fig. 7 reports the mathematical formulation of the optimization model for a very simple MES, which is taken as an example. The system is composed by a CHP, a HOB, two HP (the heating and cooling production respectively), an electric storage and the communication with the electric grid. The reported equations are presented with the purpose of providing an example of how the generic formulation discussed in the paper appear in their extended form in a practical case. The variables to be optimized are: the power exchanged with the electricity grid, the input power of production and conversion technologies (combined heat and power unit, heat only boiler and heat pump, respectively) and the power exchanged with the electrical storage. For the simplified case presented, the two variables were used for electricity purchased and sold from/to the power grid and only one variable for the exchange with storage.

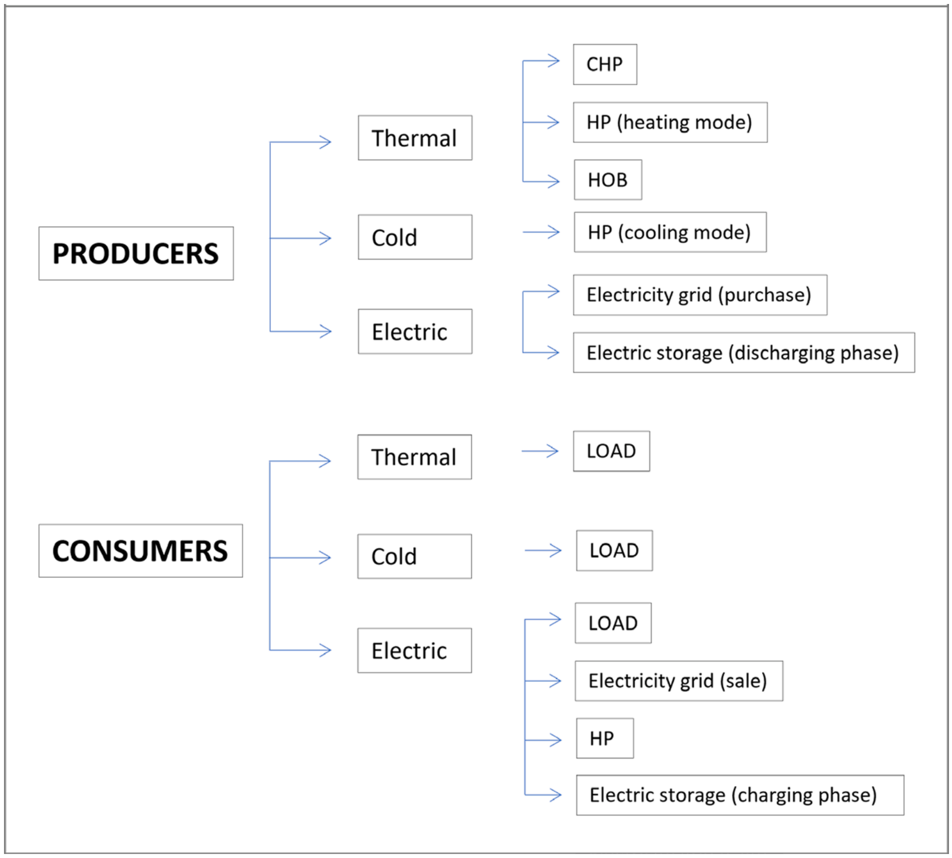


Fig. 8. Example of producers and consumers classification.

The economic objective function is composed of: a) the cost of the fuel needed to run the CHP and the only heat boiler; b) the cost of the electricity purchased from the power grid; c) the revenue from the electricity sold to the power grid. Finally, at the bottom of the figure, an indication of the size of the problem is given for the proposed example.

Layout constraints are written in their extended form for the proposed example. To this end, the technologies included in the system must be divided into: energy generators (U_c) and energy consumers (U_p). The obtained classification is shown in Fig. 8.

For example, if the electric heat pump is not physically connected with the electric storage and it can only be supplied by the electric grid, the new constraints describing this limitation are reported in Eqs. *35—36*.

$$P^{DIS}_{el,ST} \leq P^{IN}_{el,HP} 0_{HP,ST} + P^{SELL}_{el} 1_{POWERGRID,ST} + P^{CH}_{el} 1_{ST,ST} + P^{LOAD}_{el} 1_{LOAD,ST} \tag{35}$$

$$P^{IN}_{el,HP} \leq P^{OUT}_{el,CHP} 1_{CHP,HP} + P^{DIS}_{el} 0_{ST,HP} + P^{BUY}_{el} 1_{POWERGRID,HP} \tag{36}$$

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