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Power-to-Gas for energy system flexibility under uncertainty in demand, production and price

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ABSTRACT

The growing penetration of non-programmable renewable energy sources and the consequent fluctuations in energy prices and availability lead to the need to enhance energy system flexibility and synergies between different energy vectors. This can be reached through sector integration. Among the most relevant technologies used for this purpose, Power-to-Gas systems allow excess renewable electricity to be converted directly into fuels that can be then stored or used. A smart energy system, however, which includes these innovative solutions, requires intelligent management methods to optimize its operation. This work investigates the operational strategy of energy systems integrated with Power-to-Gas solutions for seasonal storage, by developing an optimization model for the system, formulated as Mixed-Integer Linear Programming problem. The algorithm tackles the uncertain nature of future disturbances, such as energy needs, generation and price using two-stage stochastic programming. The algorithm is tested on grid-connected and 100% renewable energy supply case studies. The novel stochastic algorithm allows a more robust optimization compared to a deterministic optimization, and system management is ensured under several future disturbances realization. Furthermore, the integration of Power-to-Gas solutions warrants the energy security of the energy systems and acts as a buffer to forestall unpredictable behavior of the disturbances.

1. Introduction

The imperative to decarbonize current energy systems, which arises from the need to mitigate the negative environmental impacts of fossil energy sources, is leading to a shift towards sustainable alternatives, which can ensure a cleaner and more resilient future for our planet. For this reason, the European Union set ambitious targets for the coming decades, that foresee a drastic reduction of greenhouse gas (GHG) emissions in order to reach a zero-carbon economy by 2050. To achieve these goals, radical changes in the current energy sector need to be performed [1]. This is leading to a change in the architecture of the energy systems and networks, due to the exploitation of novel energy sources and technologies, and the overall complexity of the systems is increasing. In this context, the key to evolve toward a cleaner and more sustainable energy system of the future is to develop integrated energy systems or Multi-Energy Systems (MES), namely systems in which multiple energy carriers (such as electricity, heat, fuels and cooling) interact with each other in an optimal way at different levels [2]. MES can perform better technically, economically and environmentally, when compared to traditional energy systems, in which each energy carrier is considered separately, and this is now recognized by many ongoing research activities on this topic [3].

As mentioned above, an essential step toward a carbon-neutral society is the integration of renewable energy sources (RES) into the energy systems to replace the use of fossil fuels. Nonetheless, given the variability of such sources, energy storage options are needed to allow their integration: it is in this framework that hydrogen applications may represent a promising solution [4]. Indeed, producing hydrogen with surplus RES means being able to store renewable electricity in a fuel which can be stored for a long time. Many studies exist which investigate how the integration of hydrogen production can perform in helping to decarbonize the energy sector. For instance, Bahlawan et al. [5] study how the production of hydrogen from electricity through electrolysis, and hydrogen seasonal storage can support the transition toward a clean energy supply in different countries,

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providing a procedure for optimal sizing of an MES. Other interesting results are obtained in [6], where the optimal design of an MES with hydrogen seasonal storage is investigated. The authors take into account the uncertainties in the future behavior of external parameters and they determine the system features for which the integration of Power-to-Gas (PtG), i.e. the generation of gaseous fuels, such as hydrogen, from electricity, becomes viable from an economic and environmental point of view. They find that this technology is useful in districts with a high ratio of seasonal thermal-to-electrical demand, as it helps to compensate for the long-term mismatch between RES production and energy demand.

When designing, planning or operating an MES, mathematical models, which reproduce the behavior of the system, are essential tools, and depending on the purpose of the study, different approaches can be employed. Among the existing models, Mixed-Integer Linear Programming (MILP) formulation is the most common mathematical programming technique to optimize MES at the design and operation level. Indeed, this method reveals to be a good optimization framework to model MES at a district scale as it can include the features of such systems with reasonable computational complexity [7]. Besides, during the modeling and optimization process of an energy system over a time horizon, the forecasts of the future external conditions in which the energy system will operate need to be taken into account. Usually, deterministic methods are used, and the prediction of future disturbances are considered as determined in advance. Indeed, due to model complexity and computational burden, many models usually pay limited attention to uncertainty. However, it is crucial to consider the intrinsically uncertain behavior of physical systems when predicting future disturbances (e.g. user needs, prices, RES generation) and performing optimal scheduling. Thus, assessing the uncertainties has become one of the main challenges of energy system optimization models [8].

In this work, a stochastic optimization algorithm based on MILP is developed, to investigate how the integration of PtG and hydrogen storage solutions in an MES can help to mitigate the impact of the uncertainties in several parameters.

1.1. Literature review

In the literature, there are many studies that focus on the development of planning and scheduling tools for the management of MES, in which uncertainties in energy needs, prices or production are considered, to obtain a more robust result. Several techniques are used to include the uncertainty in planning and optimization of energy systems: according to Chen et al. [9], the most popular optimization methods are robust optimization, stochastic programming and chance constraints programming.

Stochastic programming is formulated as a scenario-based mathematical model, in which the uncertainties are modeled through their probability distribution function (PDF), which allows recourse actions to hedge against infeasibility. In [10] the authors use this method to define an optimal dispatching strategy for integrated energy systems. On the contrary, when using robust optimization, the probability distribution information about uncertainties is not needed. An example of its utilization in the field of MES design is shown in [11]. The main feature of this approach is to ensure the feasibility of the problem against all possible realizations of uncertain parameters among a predefined uncertainty set, therefore this method is usually criticized because of its conservativeness, as it also considers the worst scenario in the set. Finally, chance constrained programming allows constraint violation: it does not apply a penalty on the objective function, but the probability of meeting the constraints is guaranteed to be satisfied with at least a specified confidence level. It is used for instance in [12] to develop a distributed optimization method for integrated electricity-natural gas distribution networks that takes into account the uncertainties in wind power generation. To use this method, the PDFs of the uncertainties must be known [9]. Each method has its own advantages and limitations, and the main features of them are presented in Table 1.

In this work, two-stage stochastic programming has been used to study the integration of Power-to-Gas in an MES to perform seasonal storage. In this type of model, the decision variables are distinguished into two groups: first-stage and second-stage variables. While the first have a deterministic behavior which must be the same for each of the future scenarios, i.e. the different future realization of the uncertain parameters, the management of the latter, on the contrary, depends on the realization of the uncertain parameters. Some relevant works which use this technique for the optimal operation and design of MES are presented below.

As shown in Table 2, two-stage stochastic programming is used in many studies to perform the optimal design of an MES, where multiple uncertainties are taken into account, such as demand profiles, market price, RES production. When dealing with design, the first-stage variables usually represent the selection and size of the technologies, while the second-stage variables are related to the operation of the system. Two-stage stochastic programming is also used to perform day-ahead scheduling of MES or microgrids, with the aim to find the optimal operation under multiple uncertainties. For all the applications, the optimization problem can be linearized, obtaining linear formulations (LP, MILP), otherwise nonlinear formulations can be used (NLP, MINLP). Nonetheless, although many nonlinear formulations exist in the literature, it is beneficial to maintain problem linearity, as shown in [14]. Indeed, for energy system scheduling and planning problems, even though nonlinear formulations may be more accurate, they are a lot more computationally demanding compared to linear formulations and may fail to find a feasible solution. On the contrary, a linear formulation can reach a good accuracy if properly developed and the optimal solution is guaranteed.

1.2. Scope of the present work

In light of the papers reviewed in the previous section, many works exist that perform day-ahead scheduling of MES or microgrids, considering the uncertainties in one or more parameters, as well as studies that, using a stochastic approach, aim at the design of an MES. Nevertheless, a lack of studies was found that consider the planning and optimization of an MES with the integration of PtG technologies to perform seasonal storage considering uncertainties in many parameters. Indeed, when treating the problem of seasonal storage, yearly prediction horizons are needed, to better understand the potential of this technology.

In particular, as far as the authors know, there are no studies involving the possibility to use a yearly planning algorithm as support for the implementation of a real-time controller on a system, with double time scale. This work aims at the development of an optimization algorithm, fast and adaptable to every MES, which takes the uncertainties in the future disturbances into account, to perform the yearly planning of an integrated energy system, in which the production of hydrogen and its storage are included.

The paper aims at answering the following research question: *To what extent can the integration of seasonal storage through PtG add flexibility and help mitigate the impact of uncertainties in energy price, generation and demand in the planning of an MES?*

The work was carried out with the perspective of adopting the developed algorithm in a supervisory controller based on Model Predictive Control (MPC). It could provide additional constraints regarding the correct long-term operation of the system to a lower level controller, which performs real-time management of the system. Indeed, to fully understand the possible role of PtG in the energy transition toward a sustainable energy framework, its potential as a long-term storage solution must be identified. Therefore, it is of paramount importance to investigate the smart energy management and control techniques which make it possible to implement such technology in real energy systems, fully exploiting its capabilities.

Table 1
Main features of the three optimization methods [9,13].

Optimization method	Stochastic programming	Robust optimization	Chance constraint programming
PDF	Needed	Not needed	Needed
Advantages	Sequential decision making	Computationally tractable	Relaxation of constraints
Limitations	Computationally expensive if large number of scenarios considered	Overconservative, cannot provide unified strategy	Computationally challenging
Applications	Long-term production planning and design	Short-term scheduling	Production planning, design and operation

Table 2
Literature linked to two-stage stochastic optimization applied to MES or microgrids.

Reference	Mathematical	Aim of optimization		Uncertainties			Optimization	Scenario	PtG
	model	Design	Planning	Needs	RES	Prices	horizon	generation	
[15]	MILP	✓		✓	✓	✓	Day-ahead	Roulette wheel method	
[16]	NLP	✓		✓	✓	✓	Year	Frank copula function	
[17]	NLP	✓		✓	✓	✓	Year	Moment matching	
[18]	MILP	✓		✓	✓		Year	k-means clustering	
[19]	LP	✓		✓			More years	Decision tree	
[20]	MILP		✓	✓	✓	✓	Day-ahead	Kernel density estimation	
[21]	MILP		✓	✓	✓	✓	Day-ahead	Errors from PDF	
[22]	MILP		✓	✓	✓	✓	Day-ahead	Errors from PDF	✓
[23]	MILP		✓	✓	✓	✓	Day-ahead	Errors from PDF	✓
[24]	MILP		✓	✓	✓		Day-ahead	Monte Carlo simulation	✓
[25]	NLP		✓	✓	✓		Day-ahead	Based on quantile	
[26]	NLP		✓	✓	✓	✓	Day-ahead	Roulette wheel method	
[27]	NLP		✓	✓	✓		Day-ahead	Roulette wheel method	
[28]	MINLP		✓	✓	✓		Day-ahead	Monte Carlo simulation	
This work	MILP		✓	✓	✓	✓	Year	Roulette wheel method	✓

The present paper analyzes the operation of the system, without considering investment for the infrastructures needed to generate and store hydrogen. Indeed, the aim of the study is to investigate if an energy system can benefit from an hydrogen seasonal storage in terms of energy security and flexibility.

The paper is structured as follows: in Section 2 the methods used are investigated and exposed, in Section 3 the application and case studies are described, while in Section 4 the results of the simulations performed are presented.

2. Methodology

This section describes the mathematical model and the optimization technique used in this work, as well as the method employed to include the uncertainties in the optimization and the procedure to generate and reduce the scenarios starting from their PDF.

2.1. Mathematical model

For the present application, MILP was used to model and optimize the energy system considered. Indeed, as mentioned above, linear formulations are preferred for these applications compared to nonlinear ones [14].

The algorithm was developed for a generic MES, such as the one schematically represented in Fig. 1, in which the different parts of the energy system interact with each other. The components involved are listed below:

Networks: the electricity grid or the gas network for instance. In the model they are described as entities with which the system can exchange energy, and the energy purchased from or injected into the networks can be associated with a certain economic cost.

Users: all those who have a certain energy need in the energy system. They are described as energy consumers, with the energy request given as input to the algorithm, corresponding to the user needs that must be fulfilled.

RES: the renewable energy sources involved. They are described as energy producers, and are associated with a certain amount of energy generated at each time-step, which enters the MES without additional costs.

Conversion systems: the components involved in the system, which can transform one or more energy vectors into one or more other energy vectors, such as combined heat and power plants, heat pumps or absorption chillers. They are described by linear equations that correlate the input and output energy flows of each plant, with specified performance parameters. The general equation that describes the input–output performance curve of a generic conversion system is as follows:

$$P_{\mathrm{out,j}}(t) = \alpha_{\mathrm{j}} P_{\mathrm{in,l}}(t)\,, \tag{1}$$

where j and l are different energy vectors, t is the time-step, and α_{j} is the performance parameter associated with the output energy vector j. In addition, the input power at each conversion system is constrained between a maximum and minimum value

$$P_{\mathrm{in,l}_{\mathrm{MIN}}}\delta(t) \le P_{\mathrm{in,l}}(t) \le P_{\mathrm{in,l}_{\mathrm{MAX}}}\delta(t)\,, \tag{2}$$

where $\delta(t)$ is the switch on/off binary variable related to the conversion system. It is worth noting that one conversion system can have more than one output energy carrier, with different performance parameters (as in the case of a cogeneration plant, which generates both electricity and heat and, therefore, has electrical and thermal efficiencies).

Storages: all the components that can perform energy storage, such as a battery, a thermal storage or a fuel storage. The energy stored in the storage at each time-step is related with the energy stored at the previous time-step through the following linear equation, which is valid for the energy vector l:

$$El(t) = \eta_{\mathrm{sd}} E_{\mathrm{l}}(t-1) + \left(\eta_{\mathrm{c}} P_{\mathrm{in,l}}(t) - \frac{P_{\mathrm{out,l}}(t)}{\eta_{\mathrm{d}}}\right)\Delta t\,, \tag{3}$$

where E_{l} is the energy stored in the form l, η_{sd} is the self-discharge efficiency of the storage, while η_{c} and η_{d} are the charge and discharge

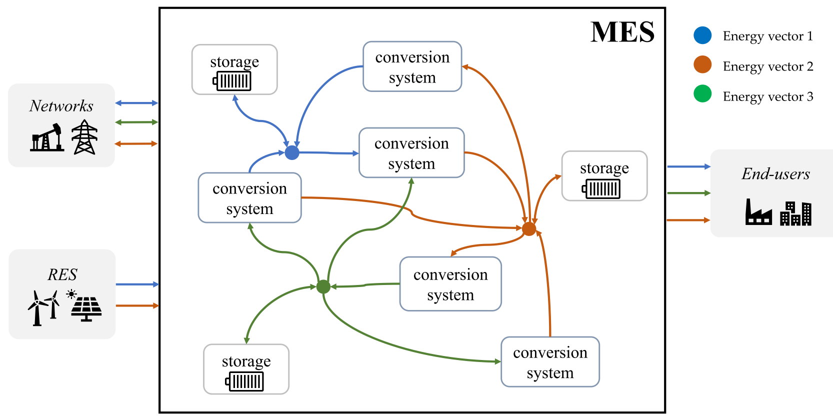


Fig. 1. Schematic diagram of a general MES.

efficiencies, and they model the energy losses when charging and discharging the storage, respectively, Δt is the time-step length.

For all the variables, lower and upper bounds are also set, according to the design of the energy system modeled. In addition, other constraints of the model are represented by the energy balances at each node of the system, indicated by dots in Fig. 1. For a general energy vector l, the balance is described by the following equation:

$$\sum_{n=1}^{N_{\text{in}}} P_{\text{in},l}(n,t) = \sum_{m=1}^{N_{out}} P_{\text{out},l}(m,t)\,, \tag{4}$$

where N_{in} and N_{out} are the number of energy flows of the energy vector l entering and exiting the node, respectively. They also include the energy exchanged with the networks, the energy produced by the RES and the energy used by the end-users.

2.2. Two-stage stochastic programming

Most of the problems that simulate the future behavior of real systems include some parameters which are to some extent uncertain. Indeed, when considering an MES, those parameters can be related to the end-user needs, to weather conditions, to energy prices or to the amount of energy produced by a certain renewable energy source. In this work, two-stage stochastic programming is used to tackle the uncertainties.

Stochastic programming is a framework for modeling optimization problems that involve uncertainty, by means of the creation of a finite number of scenarios for the uncertain parameters. Each scenario corresponds to a single realization of the random parameter throughout the time-span and to a probability of occurrence. Two-stage stochastic programming problems are a type of stochastic programming problem in which the decision variables are classified into two groups: first-stage and second-stage decision variables. While the first-stage variables are the same for each of the considered scenarios and therefore their behavior must fulfill the constraints for all the scenarios, the second-stage variables are repeated for each scenario and their management depends on the related scenario. In such problems, the cost function is built by means of the summation of the cost associated to all the scenarios ($f(x)$), and those associated with each of the possible future scenarios considered ($Q(x,\xi_s)$), where each term is multiplied by the probability of occurrence of the corresponding scenario, as described in the following equation:

$$\min g(x) = \sum_{s=1}^{N_s} Pr(s)[f(x) + Q(x,\xi_s)] = f(x) + \sum_{s=1}^{N_s} Pr(s)[Q(x,\xi_s)]\,, \tag{5}$$

where ξ_s are the future scenarios, $Pr(s)$ is the probability of occurrence of scenario ξ_s and N_s is the total number of scenarios considered.

In this work, since the initial deterministic problem is an MILP, the resulting two-stage stochastic programming problem is also an MILP, with the cost function built as described in Eq. (5), while the constraints involved are all the constraints related to the first- and second-stage variables.

2.3. Uncertainty modeling

As explained in the previous section, the aim of the proposed optimization model is to determine the optimal operation of an energy system over a future prediction horizon, with some of the parameters of the problem being uncertain at the time of decision. To do so, the uncertainties were described by means of scenarios over the optimization horizon, each corresponding with a single realization of the random parameter throughout the time-span and each associated with a certain probability of occurrence. In this way, all the stochastic parameters will be dependent on the considered scenario. The following sections describe the methods used in this work to generate the scenarios and to reduce their number.

2.3.1. Scenario generation

To generate the scenarios, a scenario generation method based on Monte Carlo sampling and the roulette wheel mechanism was used [27, 29]. When using this method, the forecast of the uncertain parameter over the period considered and its PDF must be known. The roulette wheel mechanism for scenario generation is described by the following steps and displayed in Fig. 2:

- The PDF of each uncertain parameter is discretized into a finite number of intervals, centered on the mean value, which corresponds to the forecast of the uncertainty at the considered time-step, as shown in Fig. 3. The length of each interval corresponds to the standard deviation of the distribution σ. For the purpose of this work, to model the uncertain parameters, the normal PDF is used [23], which is described by Eq. (6)

$$PDF(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}\,. \tag{6}$$

- The probability associated with each interval k is calculated using the following equation:

$$p_{\text{k}} = \int_{x_{\text{start}}}^{x_{\text{end}}} PDF(x)dx\,. \tag{7}$$

- The probabilities p_{k} are normalized in a way that their summation becomes equal to one, and each interval is associated with an accumulated probability, as shown in Fig. 3.

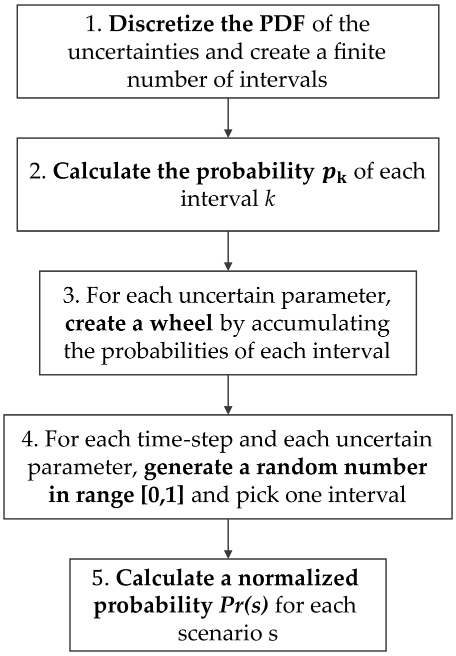


Fig. 2. Main steps of the roulette wheel mechanism.

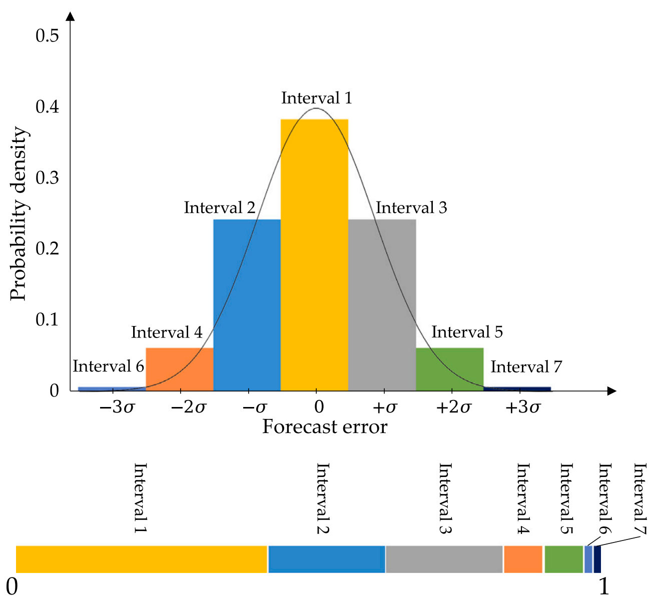


Fig. 3. Discretization of the PDF for the uncertain parameters, and accumulated normalized probabilities.

- To create the scenarios, for each time-step of the prediction horizon and each uncertain parameter, a number in range $[0, 1]$ is randomly generated, and one of the intervals is consequently picked. The probability associated with the point obtained corresponds to that of the interval, while the value for the random parameter becomes equal to the mean value associated with the interval picked at the time-step considered.
- Assuming that the uncertain parameters are independent of each other, the probability of each scenario s can be calculated as follows

$$Pr(s) = \frac{\prod_{u=1}^{N_u} \prod_{t=1}^{N_t} p_k(u,t)}{\sum_{s=1}^{N_s} \prod_{u=1}^{N_u} \prod_{t=1}^{N_t} p_k(u,t)}, \tag{8}$$

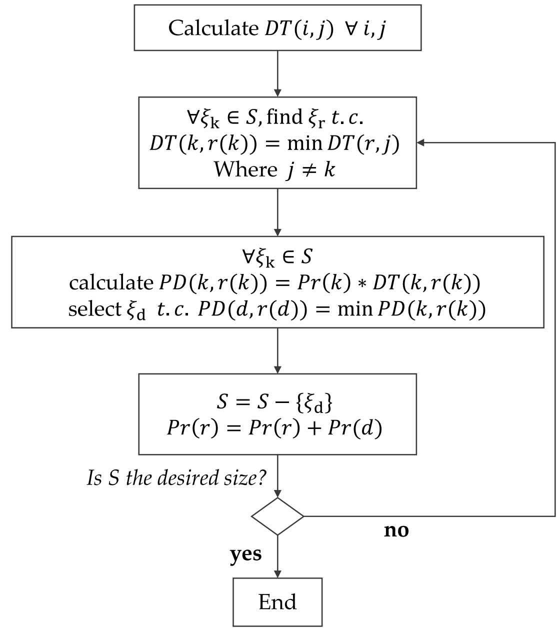


Fig. 4. Simultaneous backward scenario reduction method.

where N_t is number of time-steps, N_u is the number of uncertain parameters, N_s is the total number of scenarios generated and $p_{k(u,t)}$ is the probability associated with the value of the uncertain parameter u of the scenario at the time-step t.

2.3.2. Scenario reduction

In order for the representation of the uncertainties to be relevant through the scenarios, and to reproduce their probabilistic behavior in an appropriate way, a large number of scenarios is needed. Nevertheless, for the sake of optimization problem tractability, the number of scenarios needs to be reduced, and an appropriate scenario-reduction method must be chosen. Indeed, it is important to maintain an accurate representation of the uncertain behavior of the system. In this work, a simultaneous backward reduction method, which takes into account both the probability of the scenarios and their similarity to other existing scenarios, has been used [27,30]. With this kind of scenario reduction method, it is possible to select the scenarios which are more relevant among the initial set. Indeed, the reduction method allows the selection using a compromise between the similarity and the probability of scenarios, selecting the scenarios which are different from each other and at the same time more likely to occur.

Considering N_s different scenarios $\xi_i (i = 1, \ldots, N_s)$, each with a probability equal to $Pr(i)$, let $DT(i,j)$ indicate the distance between two different scenarios ξ_i and ξ_j, calculated as follows

$$DT(i,j) = \sqrt{\sum_{t=1}^{N_t} \sum_{u=1}^{N_u} \left(v_{t,u}^i - v_{t,u}^j\right)^2}, \tag{9}$$

where $v_{t,u}^i$ represents the value of scenario ξ_i for the uncertain parameter u at time t, N_t is the number of time-steps and N_u is the number of uncertain parameters. The procedure for the scenario reduction is shown in Fig. 4, and it is composed of the following steps:

Step 1: Let S be the initial set of scenarios to be reduced, which initially contains all the scenarios. Calculate the distances $DT(i,j)$ for all the scenario pairs.

Step 2: For each scenario $\xi_k \in S$, find the scenario ξ_r with the minimum distance from it.

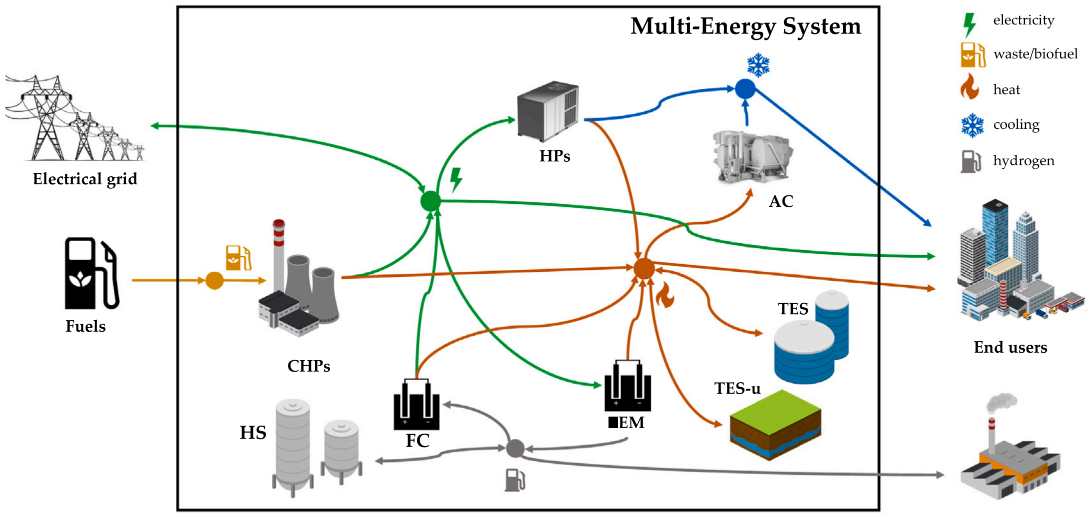


Fig. 5. Layout of the GC case studies (PEM, HS and FC are only present in the GC_Västerås_H2 case study).

Step 3: For each scenario $\xi_k \in S$, calculate $PD(k,r(k)) = Pr(k) * DT(k,r(k))$ and select the scenario ξ_d with $PD(d,r(d)) = \min PD(k,r(k))$. By weighting the distance with the probability, it is possible to take into account both probability of occurrence and distance from the other scenarios.

Step 4: Delete ξ_d from the set of scenarios S. Update the probabilities of the scenarios, adding the probability of the deleted scenario ξ_d to the probability of ξ_r: $Pr(r) = Pr(r) + Pr(d)$.

Step 5: Repeat the procedure from Step 2 to Step 4 until the desired number of scenarios is reached.

3. Application

The optimization algorithm with the stochastic approach presented in Section 2 was tested on different case studies: two grid-connected and two positive energy districts. They were used as virtual test benches, and the results were compared with the ones obtained using the deterministic approach, with the same boundary conditions. This section presents the case studies considered, how the optimization algorithm was applied to them, and how the uncertain parameters were modeled.

3.1. Grid-connected case studies

As a first case study, the city of Västerås was chosen, which is located in the south of Sweden. The energy system of the city is grid-connected (GC) and it is composed of three combined heat and power plants (CHPs), which convert residential waste, biofuels and renewable fuels into heat and electricity. In addition, there is an absorption chiller (AC) and two heat pumps (HPs), which contribute to the district heating network (DHN) supply together with the CHPs, and to the fulfillment of the cooling needs together with the AC. The energy system is also equipped with a water tank for heat storage (TES), while another bigger underground heat storage will be built in the near future (TES-u), to perform seasonal storage, and it is included in the optimization model. This first case study was named GC_Västerås.

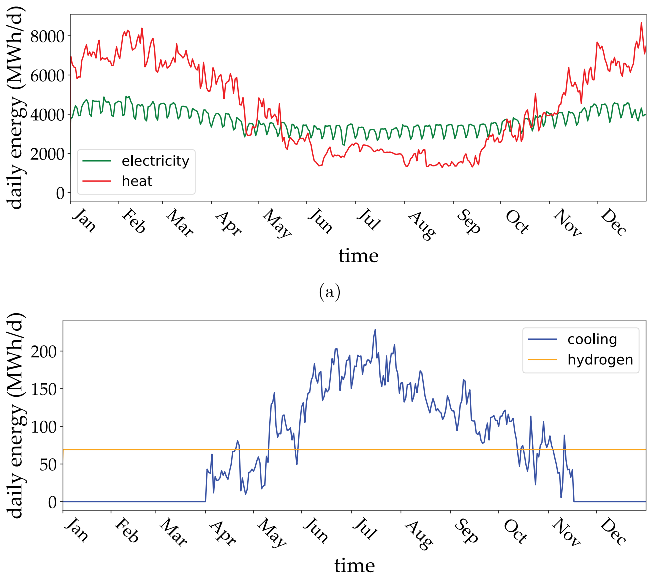
Starting from the reference system, a second case study was developed (GC_Västerås_H2), considering the installation of a PEM electrolyzer (PEM), together with a hydrogen storage tank (HS) and a fuel cell (FC) to convert the hydrogen into electricity and heat, with the aim to analyze the impact of the introduction of hydrogen seasonal storage on the existing MES. The configuration of this second case study is displayed in Fig. 5. It was also assumed to use part of the produced hydrogen to fulfill the needs of a steel mill in the area (the Hallstahammar steel mill [31]). The characteristics of the plants are presented in Table 3.

Table 3
Characteristics of the technologies of the GC case study.

Technology	Nominal inlet power	Performance parameters	Reference
CHP 5	200 MW	$\eta_{th} = 63\%$, $\eta_{el} = 27\%$	[32]
CHP 6	167 MW	$\eta_{th} = 63\%$, $\eta_{el} = 27\%$	[32]
CHP 7	150 MW	$\eta_{th} = 63\%$, $\eta_{el} = 27\%$	[32]
HP 1	5 MW	$COP = 3$, $EER = 1.4$	[33]
HP 2	4 MW	$COP = 3$, $EER = 2.5$	[33]
AC	9 MW	$EER = 0.78$	[33]
PEM	200 MW	$\eta_{H_2} = 60\%$, $\eta_{th} = 16.1\%$	[34]
FC	200 MW	$\eta_{th} = 25\%$, $\eta_{el} = 55\%$	[35]
HP-el	32.2 MW	$COP = 4$	[36]
Technology	**Nominal capacity**	**Performance parameters**	**Reference**
TES-u	13 000 MWh	$\eta_{sd} = 99.5\%$, $\eta_c = \eta_d = 95\%$	[37]
TES	1 200 MWh	$\eta_{sd} = 99.9\%$, $\eta_c = 95\%$, $\eta_d = 95\%$	[37,38]
HS	66 644 MWh	$\eta_{sd} = \eta_c = \eta_d = 100\%$	[38]

In the table, PEM efficiency also includes the compressor energy, to compress the produced hydrogen until the storage pressure (100 bar) [39], and HP-el represents an additional heat pump which is introduced to upgrade the heat produced at low temperature from the electrolyzer (at around 55 °C), to the temperature needed for the DHN (80 °C). For a clearer representation, this heat pump is not shown in Fig. 5. It is worth mentioning that a self-discharge efficiency η_{sd} equal to one is considered for the hydrogen storage, as it has been done in Refs. [5,38]. Given the state of knowledge and the purpose of the analyzes performed, this value was assumed, although for some storage technologies, due to the small size of the hydrogen molecule, the self-discharge efficiency might be lower. However, this does not affect the reliability of the developed algorithm.

The three CHPs work with different fuels: CHP 5 uses biofuel (19 EUR/MWh [40]), CHP 6 uses residential waste (−16 EUR/MWh [41]), and CHP 7 uses renewable fuels (9.5 EUR/MWh [40]). The residential waste is also imported from other cities in the Scandinavian countries, and it has a negative price since the plant owners receive a revenue for managing it. Part of the electricity needs of the city are covered by the CHPs; nevertheless, since the CHPs are heat-driven rather than electricity-driven, it is necessary to buy the remaining part of electricity from the national electrical grid. The prices of electricity are regulated by Nord Pool, which manages power exchange in the Nordic countries [42].



(a)

(b)

Fig. 6. Forecast of the energy needs for the GC case studies (the hydrogen need is only present in the GC_Västerås_H2).

Table 4
Characteristics of the technologies of the PE case studies [5].

Technology	Nominal inlet power		Performance parameters	
	Rome	Guangzhou	Rome	Guangzhou
GT	7.61 MW	5.28 MW	$\eta_{el} = 26\%$ $\eta_{th} = 60\%$	$\eta_{el} = 25\%$
ASHP	5.5 MW	7 MW	$COP = 3.3,\ EER = 2.8$	
AC	0.8 MW	2 MW	$EER = 0.75$	
PEM	11 MW	13 MW	$\eta_{H_2} = 55\%$	
Technology	Nominal capacity		Performance parameters	
	Rome	Guangzhou	Rome	Guangzhou
HS	3314 MWh	2038 MWh	$\eta_{sd} = \eta_c = \eta_d = 100\%$	
TES	92 MWh	66 MWh	$\eta_{sd} = \eta_c = \eta_d = 99.5\%$	
BES	10 MWh	30 MWh	$\eta_{sd} = 100,\ \eta_c = \eta_d = 95\%$	

The boundaries of the model comprise the power exchanged with the power grid, the heat, electricity and cooling demand of the entire city and the energy conversion plants previously mentioned. The electrical and thermal needs are estimated from historical data, while the district cooling needs are calculated in analogy with [43]. Indeed, the disturbances given to the optimization model are the energy needs of the entire city (displayed in Figs. 6(a) and 6(b)) and the energy prices (fixed for the fuels and variable for the electricity bought). For the latter, the forecast is estimated based on historical price data and it is shown in Fig. 7.

When employing the stochastic optimization, the behavior of the first-stage variable is defined a priori and cannot be changed depending on the scenario. Instead, the management of the second-stage variables is defined after the realization of the scenario and they represent a source of flexibility for the system. For this case study, the variables associated with the CHPs, PEM electrolyzer and AC management are considered as first-stage variables; while the ones related to the HPs, FC, storages and electricity bought from the electrical grid are taken as second-stage variables, and therefore the undesirable effects of the uncertain parameters can be adjusted through their management.

3.2. Positive-energy case studies

Two other case studies were simulated, taken from a study from Bahlawan et al. [5]: they are two districts with the same architecture

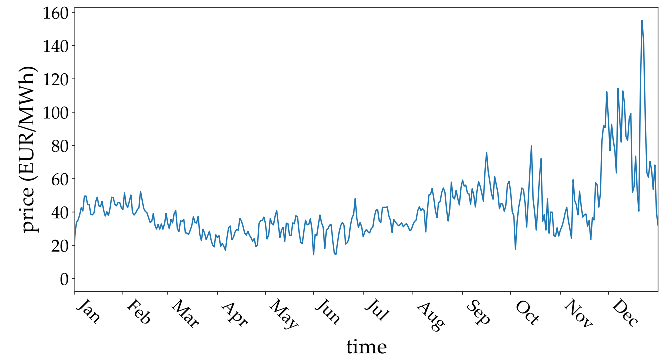


Fig. 7. Forecast of the electricity prices for the GC case studies.

Table 5
Case studies simulated.

Case study	Approach
GC_Västerås	Deterministic
GC_Västerås	Stochastic
GC_Västerås_H2	Deterministic
GC_Västerås_H2	Stochastic
PE_Rome_H2	Deterministic
PE_Rome_H2	Stochastic
PE_Guangzhou_H2	Deterministic
PE_Guangzhou_H2	Stochastic

but different ambient conditions, in particular it was assumed to locate the MES in Italy and in China, respectively in Rome (PE_Rome_H2) and in Guangzhou (PE_Guangzhou_H2). The layout of these case studies is presented in Fig. 8. They comprise a photovoltaic plant (PV), a PEM electrolyzer (PEM), a gas turbine (GT), which works with hydrogen, a heat pump (HP), an absorption chiller (AC), and storages for hydrogen (HS), heat (TES) and electricity (BES). The characterstics of the plants involved are shown in Table Table 4 for the two locations. While the HS is supposed to be used for seasonal storage, TES and BES are meant for daily energy fluctuations. The energy system designed in [5] was sized to be stand-alone and not connected to the electrical grid. However, in this work, it was assumed that the system can export the surplus electricity produced by the PV (although the electricity cannot be bought), in this way the system become a positive-energy (PE) district.

It needs to be highlighted that in these case studies, it is assumed that the waste-heat from the electrolyzer is not recovered, so that the results can be compared with those obtained in [5], and therefore the quality of the solution of the novel algorithm can be tested.

Both case studies have an electricity demand of 10 GWh/year, that corresponds to approximately 300 buildings, and the forecast of the energy needs for the two locations is shown in Figs. 9 and 10. The profiles were taken from [5], where the authors calculated the energy needs and the renewable energy production using the TRNSYS® software and monthly average data (see Table 4).

In these case studies, the energy stored in the BES and the management of PEM, AC and HP are the first-stage variables in the stochastic approach, while the energy stored in the HS and TES, the energy at the GT and the electricity exported are chosen to be second-stage variables and help to mitigate the effects of the uncertainties.

3.3. Optimization algorithm

The deterministic and stochastic optimization algorithms presented in Section 2 were adapted to the four case studies, leading to the eight case studies listed in Table 5.

The optimization algorithm was developed in the Python environment, and the problem was solved through the open-source solver

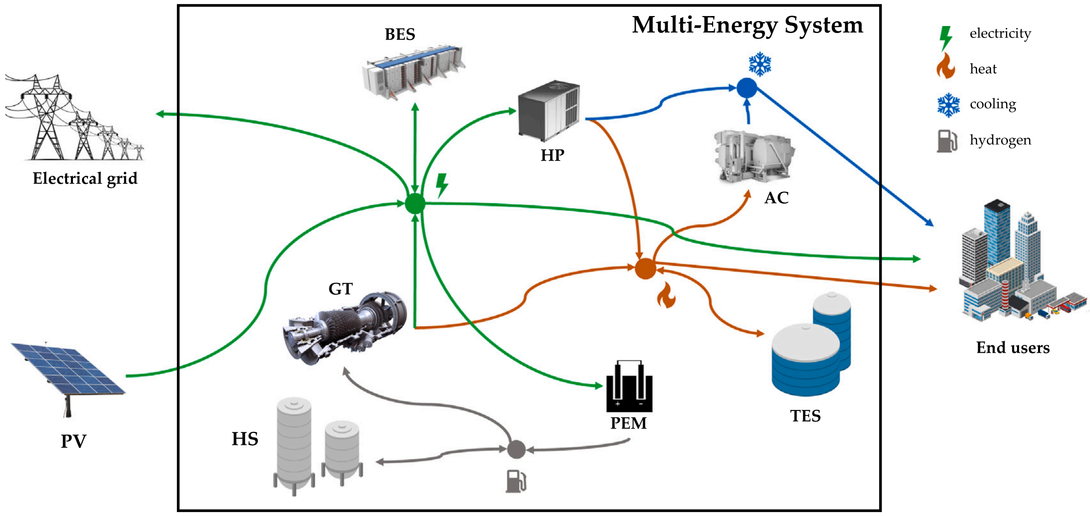


Fig. 8. Layout of the PE case studies.

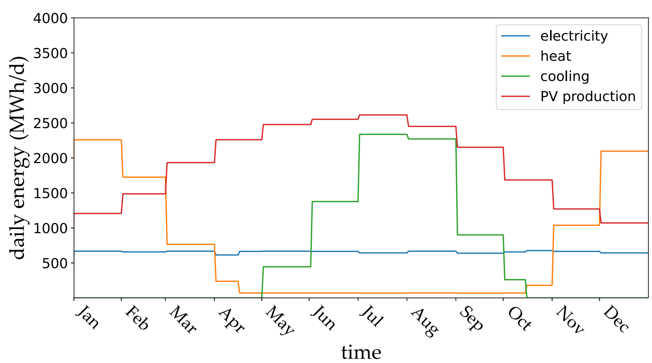


Fig. 9. Forecast of the energy needs and production for the PE_Rome_H2 case study [5].

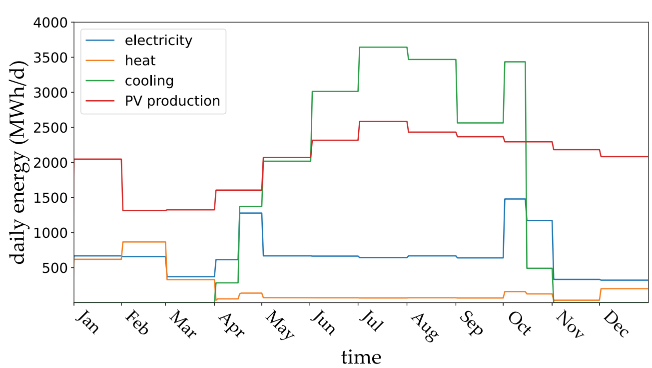


Fig. 10. Forecast of the energy needs and production for the PE_Guangzhou_H2 case study [5].

CBC [44]. The simulations were done over a period of one year, with a daily time-step. It is worth pointing out the reason why such parameters have been chosen: although this algorithm is now tested on virtual test-benches, it was developed with the intent of being used in a supervisory MPC module. Thus, the algorithm should have both a long-term vision of the system to be optimized, and the aim to give additional constraints to a short-term controller which operates the real-time control of the system. In this way, it is possible to have a control which also considers long-term objectives and performs better over time. In other words, this optimization algorithm needs to be fast, since it must be run every day and calculate the best control action to communicate to the real-time controller. Therefore the model was simplified and a daily time-step was employed. In addition, only an average efficiency was used for each plant, as the daily average power was considered. A similar work has been done by Saletti et al. [45].

The cost function implemented in the GC case studies is the minimization of the total economic cost, which is expressed for the stochastic approach by the following equations:

$$\min f_{\mathrm{obj_{GC}}}, \tag{10}$$

with

$$f_{\mathrm{obj_{GC}}} = \sum_{t=1}^{N_\mathrm{t}} \left[\sum_{f=1}^{N_\mathrm{f}} c_{\mathrm{f,bo}} P_{\mathrm{f,bo}}(t) + \sum_{s=1}^{N_\mathrm{s}} Pr(s) \Big(c_{\mathrm{el,bo,s}}(t) P_{\mathrm{el,bo,s}}(t) - c_{\mathrm{el,so,s}}(t) P_{\mathrm{el,so,s}}(t) \Big) \right] \Delta t\,, \tag{11}$$

where $c_{\mathrm{f,bo}}$ is the cost of purchasing the fuel f, while $c_{\mathrm{el,bo}}(t)$ and $c_{\mathrm{el,so}}(t)$ are the costs of buying and selling energy, expressed in EUR/MWh. In addition, $P_{\mathrm{f,bo}}(t)$ represents the amount of fuel f used by the CHPs, $P_{\mathrm{el,bo,s}}(t)$ is the amount of electricity bought from the grid, and $P_{\mathrm{el,so,s}}(t)$ is the electricity sold to the grid, in MW, N_t is the total number of time-steps considered in the optimization, N_f is the number of fuels, N_s is the number of scenarios, ξ_s is the scenario considered, $Pr(s)$ is its probability of occurrence and Δt the time-step length, in hour.

In the PE case studies, instead, the objective is the maximization of the total electrical energy exiting the MES, with the aim to utilize the renewable energy produced in the most efficient way. The stochastic cost function is as follows

$$\max f_{\mathrm{obj_{PE}}}, \tag{12}$$

with

$$f_{\mathrm{obj_{PE}}} = \sum_{t=1}^{N_\mathrm{t}} \sum_{s=1}^{N_\mathrm{scen}} Pr(s) P_{\mathrm{el,exp,s}}(t) \Delta t\,, \tag{13}$$

where $P_{\mathrm{el,exp,s}}(t)$ is the amount of excess electrical power at time-step t, for the scenario ξ_s, that can be exported and possibly injected into the grid. The cost function for the deterministic approach is easily obtained starting from the stochastic one, by considering a single scenario with probability equal to one.

3.4. Uncertainties

The uncertainties have been considered by means of the creation of scenarios for the uncertain parameters. First, the PDF of the uncertain

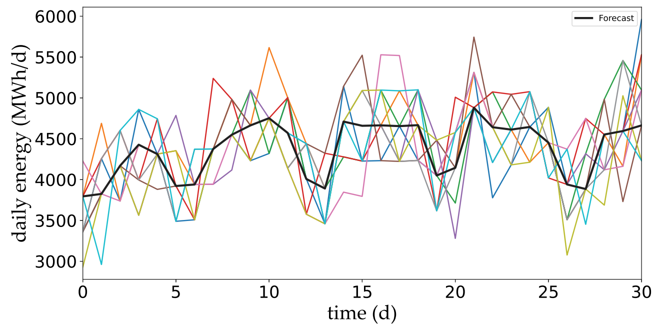


Fig. 11. Scenarios for electricity needs over one month, for the GC case studies.

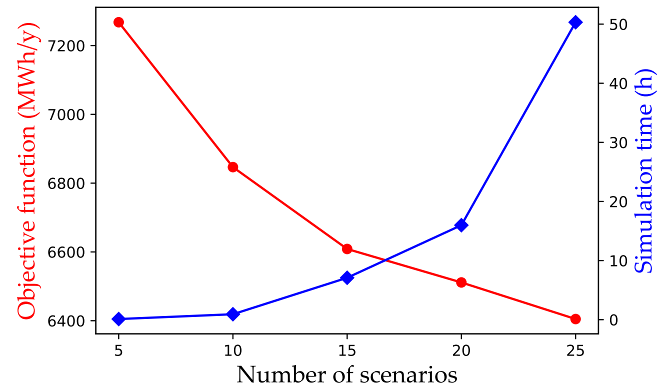


Fig. 12. Results of the sensitivity analysis for the PE_Guangzhou_H2 case study.

parameters was discretized into seven intervals centered on the forecasted value, each interval with a width equal to the standard deviation σ, as shown in Fig. 3 [26,27]. Then, a large number of scenarios was generated using the roulette wheel mechanism and, finally, this number was reduced to use them in the optimization model, following the procedure presented in Section 2.3. The uncertain parameters considered are the electricity price and user needs in the GC case studies, and PV production and user needs in the PE case studies. These parameters were considered as independent to each other, even though in real life this is not always the case. Nonetheless, this assumption does not affect the robustness of the approach. Similarly to what has been done in [26], the normal PDF was considered to model the deviation in the forecasted value for all the uncertain parameters. Indeed, although Weibull or Beta PDFs are generally adopted for wind speed and solar irradiance, with the roulette wheel scenario generation method, the scenarios are generated based on the difference between the forecasted value and the actual one, not the quantity itself, and therefore the normal distribution is adequate. The standard deviation was estimated based on historical data.

As an example, in Fig. 11 the scenarios for the electricity needs for the GC case studies are displayed, over one month, together with the deterministic forecast (represented by the black line).

4. Results

The algorithm was tested by applying it to the presented case studies. Both deterministic and stochastic models were employed, to compare the results obtained with the different approaches.

This section presents the results of this analysis. In particular, the outcomes of a sensitivity analysis are first described, which was performed to find the most appropriate number of scenarios to use when employing the stochastic approach; secondly, the results obtained from the simulations and the comparison between the different case studies are presented.

4.1. Sensitivity analysis

When solving a stochastic problem, the higher is the number of scenarios considered, the more the solution is robust. However, with high number of scenarios, the complexity of the problem increases, as well as the number of variables and this leads to greater computational effort. For this reason, it is important to use a number of scenarios that permits to obtain a reliable solution in a reasonable computational time. While reducing the scenarios, a sensitivity analysis was performed for the case study of the city of Guangzhou, with the aim of determining the number of scenarios taking account of the compromise between the computational time needed to find an optimal solution and the relevance of the solution. The simulations have been run with 5, 10, 15, 20 and 25 scenarios: the results obtained are shown in Fig. 12. The tests were carried out using a Core i7 system with 2.80 GHz CPU and 16 GB of RAM. Based on these results, it was decided to use 10 scenarios for the stochastic simulations. Indeed, with this number, an optimal result can be obtained in around one hour of calculation time, which is acceptable, if the algorithm is meant to be used for updating the yearly optimal scheduling every day. In addition, with a higher number of scenarios, the calculation time increases significantly, while the solution obtained is not affected in a relevant way.

4.2. Results for the grid-connected case studies

In this section, the results obtained from the simulations performed for the GC case studies are presented. Figs. 13(a) and 13(b) show the amount of electricity bought from the electrical grid in the two cases. The results of the stochastic approach are displayed in the form of bands, created by combining the maximum and minimum values obtained for the different scenarios. While in the GC_Västerås case study the amount of imported electricity presents some variations, but it is always lower than 4000 MWh/day, in the GC_Västerås_H2 case study there are peaks of electricity purchased when the electricity price is lower. This happens thanks to the introduction of the electrolyzer in the system, which allows hydrogen production when the electricity price is low enough. In this way, more flexibility is added by the integration of hydrogen production in the energy system. In addition, looking at the differences between deterministic and stochastic approaches, it can be noted that the results obtained using the deterministic approach are mainly contained in the stochastic bands, showing that with the stochastic approach the results are coherent with what is achieved in a deterministic way.

Given the high variability of the electricity price in this region of Sweden, the integration of this kind of technology can be helpful in saving money and in the exploitation of the large availability of renewable energy in the country during some periods of the year, which leads to low electricity prices. Indeed, as shown in Table 6, the value of the objective function, namely the total economic cost of the system, is lower in the GC_Västerås_H2 case study, even if in this case study part of the produced hydrogen is used to fulfill additional hydrogen needs. It is worth underlining that it was possible to compare the results of the deterministic approach and the stochastic approach in terms of cost function value because the difference in percentage between the data used for the deterministic simulations and the weighted values obtained with the scenario approach over the whole year was not significant.

Fig. 15 displays the cumulative costs and revenues of the system over the year in the four simulations. For the stochastic approach, a weighted value for the cost of electricity was calculated and the percentage indicated refers to the total positive economic cost (excluding revenues). It is possible to notice that the cost of electricity represents more than half of the total cost for all the simulations, followed by renewable fuel and biofuel. Residential waste, on the other

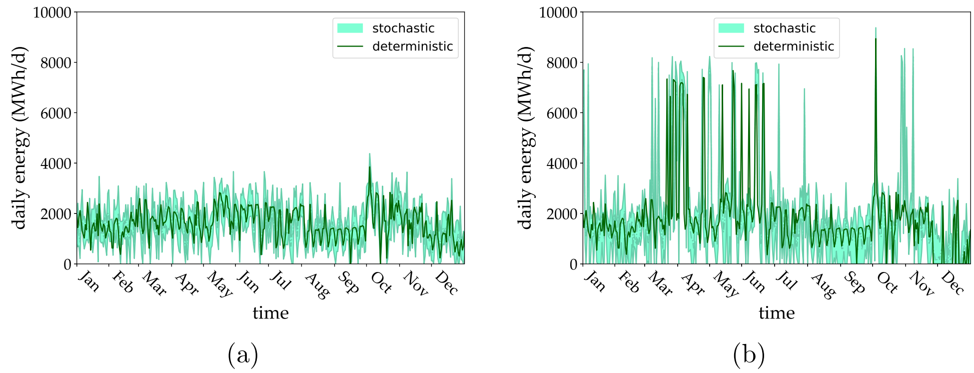


Fig. 13. Electricity bought from the grid in the (a) GC_Västerås and (b) GC_Västerås_H2 case studies in the deterministic and stochastic approach.

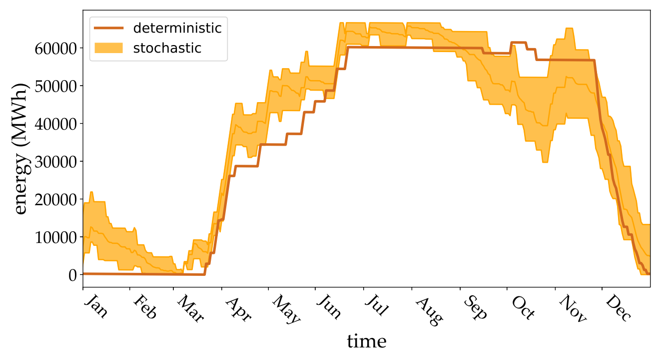


Fig. 14. Management of the hydrogen storage in the GC_Västerås_H2 case study in the deterministic and stochastic approach.

Table 6
Objective function obtained for the GC case studies.

Simulation approach	Cost function value (EUR)		Cost reduction
	GC_Västerås	GC_Västerås_H2	
Deterministic	19 496 164	18 475 391	5.2%
Stochastic	19 636 593	17 164 267	12.6%

hand, allows for great savings, since the revenues deriving from its use cover more than half of the expenses. By comparing deterministic and stochastic approaches, it can be seen that the cost of electricity is the main cost saving factor for the GC_Västerås_H2 case studies. As already mentioned, in fact, with the introduction of the electrolyzer it is possible to better exploit periods of low electricity prices and avoid purchasing electricity at high prices.

Fig. 14 shows the management of hydrogen storage in the GC_Västerås_H2 case study with the two approaches. A few considerations can be made: with the deterministic approach, the storage is kept empty during the first months of the year, when it is not used, and this obviously leads to lower flexibility of the system, as in the case of a sudden price increase, there is a lack of stored hydrogen available to produce electricity; nevertheless, the stored hydrogen in the stochastic approach is not always greater than in the deterministic approach, since the energy security of the system does not need to be guaranteed, as the plant is connected to the power grid.

Among the results, it is also obtained that the HP-el produce 0.7% of the heat for the DHN supply in the deterministic approach, while this number increases to 1.4% in the stochastic approach, showing that the waste heat from the PtG plant, even if in modest quantities, also allows for thermal energy to be used in the city's DHN.

4.3. Results for the positive-energy case studies

The following results were obtained from the simulations for the PE case studies. First of all, in Figs. 16 and 17, the electricity exported to the grid is displayed: for the stochastic approach, the results are shown in the form of bands of operation, as for the GC case study. It needs to be highlighted that the maximum amount of electricity exported from the system was constrained to be less than 24 MWh per day. This was set for two reasons: first, since maximization of exported electricity is the objective of the optimization, if the maximum amount of exported electricity is not constrained, seasonal hydrogen storage could be used less, mainly with the deterministic approach, reducing the energy security of the system; secondly, considering the integration of these positive energy districts with the electrical grid, this allows for a lower impact on the stability of the electrical grid. The systems, in fact, are considered self-sufficient, with the possibility of feeding (if available) surplus renewable electricity into the electrical grid. It is clear that, to integrate such positive energy systems into the existing energy networks, they need to maintain their self-sufficient characteristics and without impacting negatively on external networks.

These results show that in both cases the average amount of electricity sold using the stochastic approach (the dotted line) is lower than the electricity sold using the deterministic approach, which also leads to a lower cost function value for the stochastic approach (see Table 7). This management is due to the variability added through the scenarios both in energy production and utilization, which causes a more conservative behavior of the system, a lower export of electricity and therefore the storage of a greater amount of energy.

An interesting result concerns the management of the PEM electrolyzer in the two approaches, displayed in Figs. 18 and 19. It is possible to see that more hydrogen is produced in the stochastic approach in both case studies, leading to a higher amount of hydrogen stored, as shown in Figs. 20 and 21. This is important because the hydrogen storage is used from the optimizer to help mitigate the impact of the uncertainties on the energy system. Indeed, by keeping it fuller, the system is more robust against unpredictable events (such as a sudden decrease in the energy production or an unexpected high energy request from the end-users) and the energy security of the system is higher.

Another significant result of this study regards the different management of the hydrogen storage in the two locations. Indeed, while in Rome the storage is emptied during the spring (see Fig. 20), and the hydrogen is mainly used to fulfill the thermal needs during the winter season, in Guangzhou the storage is filled during the winter and the hydrogen is used to fulfill the high cooling needs during the summer (see Fig. 21). Especially, it can be seen that the storage is emptied rapidly is the first half of October: here, as it can be seen in Fig. 10, the electrical and cooling needs are high, while the PV production starts to decrease because of the coming of the winter season. This shows the algorithm is successful regardless of the geographical location or

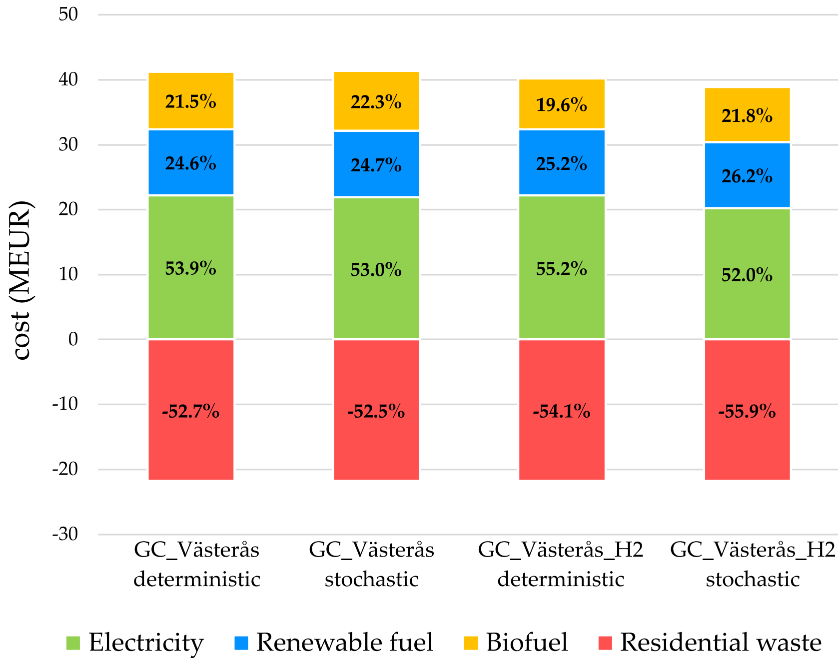


Fig. 15. Economic analysis for the GC_Västerås and GC_Västerås_H2 case studies in the deterministic and stochastic approach.

external conditions, which lead to a different energy demand, as shown in Figs. 9 and 10.

Furthermore, when looking at the management of the GT (displayed in Figs. 22 and 23), which was considered as a second-stage variable and therefore behaves differently for each of the scenarios, it can be noted that the behavior obtained using the deterministic approach is largely contained in the bands of operation derived for the management of this plant in the stochastic approach.

Nevertheless, when comparing the deterministic and the stochastic results, it can be seen that the solution obtained from the deterministic model can be misleading. Indeed, when considering the uncertainties, less electricity is sold to the grid in the stochastic approach, leading to a higher operational energy cost, showing that the solution of the deterministic approach could be unrealistic and is vulnerable to uncertainty. On the contrary, with the solution obtained from the stochastic approach, if any of the scenarios happen, the management of the MES is possible. Finally, analyzing the results obtained with this optimization strategy, it can be seen that the trends and the management of the hydrogen storage are in line with what was obtained by Bahlawan et al. [5]. Nonetheless, when the system is optimally managed, using both the approaches presented, the results show that the system is oversized: in fact, part of the electricity is always exported. In addition it is obtained that the AC is not used in the PE_Rome_H2 case study, meaning that it is more convenient to use the renewable electricity to fulfill cooling needs through the ASHP. In the PE_Guangzhou_H2 case study, instead, the AC is used around 25 days per year in both the approaches, during April and October, which is quite a short amount of time. It was demonstrated that even when this plant is removed from the energy system, its management is feasible, which means that the AC could also be omitted from the design of the system in both the locations.

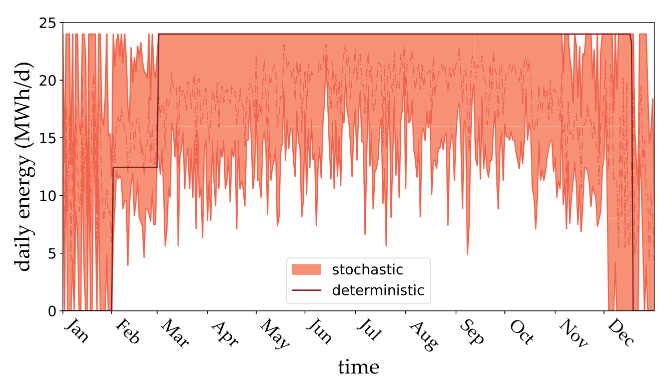


Fig. 16. Electricity exported in the PE_Rome_H2 case study in the deterministic and stochastic approach.

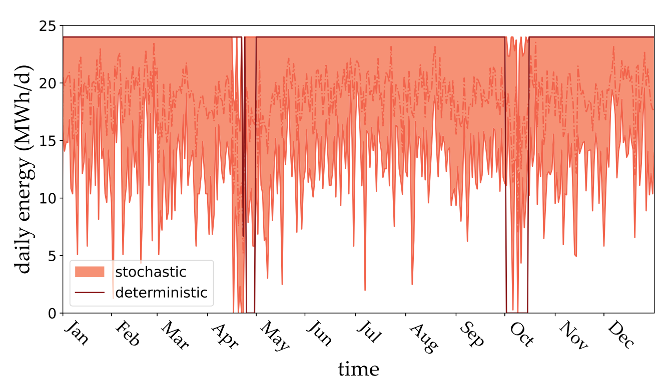


Fig. 17. Electricity exported in the PE_Guangzhou_H2 case study in the deterministic and stochastic approach.

5. Conclusions

The increasing complexity of current energy systems leads to the need to find efficient optimization strategies to manage them in an intelligent way. In this work, an optimization algorithm based on Mixed-Integer Linear Programming is proposed, which is a useful tool when considering the management of a complex Multi-Energy System, to determine its optimal operation. The novelty of this research is to introduce the uncertainty in various external parameters in a conventional energy planning algorithm, to study the integration of a Power-to-Gas solution for seasonal storage. This leads to a problem in which the objective function considers the expected cost of the different

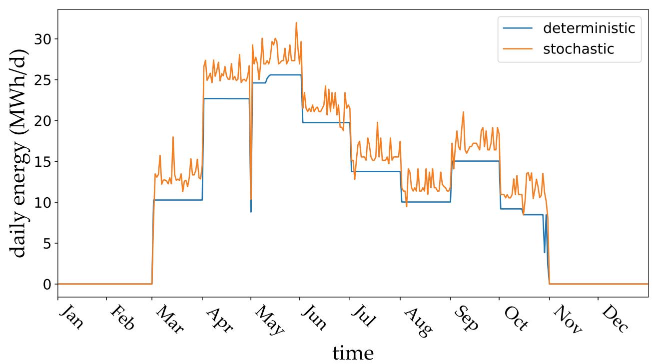


Fig. 18. Management of the PEM electrolyzer in the PE_Rome_H2 case study in the deterministic and stochastic approach.

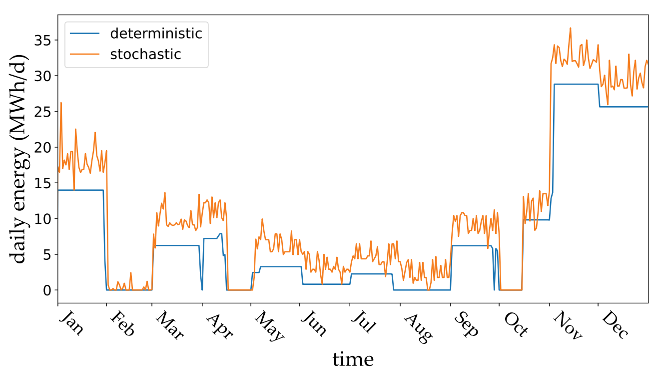


Fig. 19. Management of the PEM electrolyzer in the PE_Guangzhou_H2 case study in the deterministic and stochastic approach.

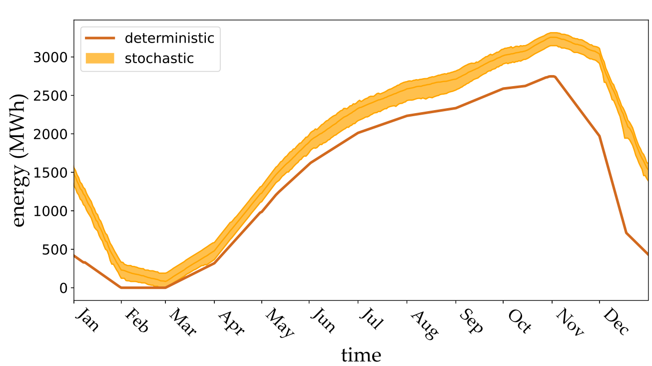


Fig. 20. Management of the hydrogen storage in the PE_Rome_H2 case study in the deterministic and stochastic approach.

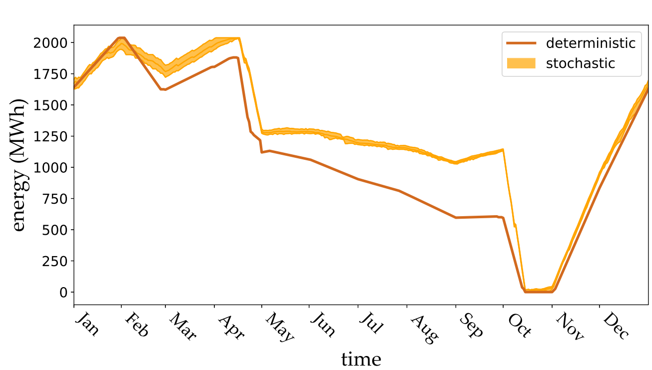


Fig. 21. Management of the hydrogen storage in the PE_Guangzhou_H2 case study in the deterministic and stochastic approach.

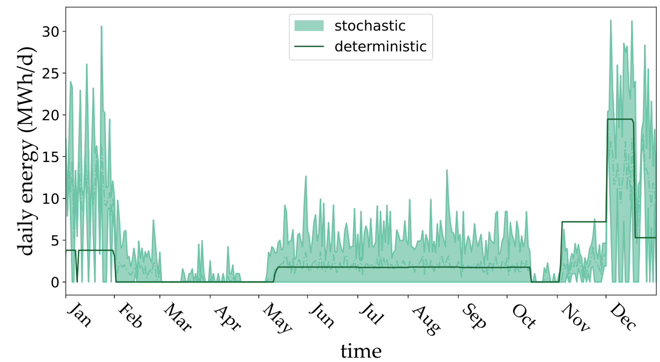


Fig. 22. Management of the GT in the PE_Rome_H2 case study in the deterministic and stochastic approach.

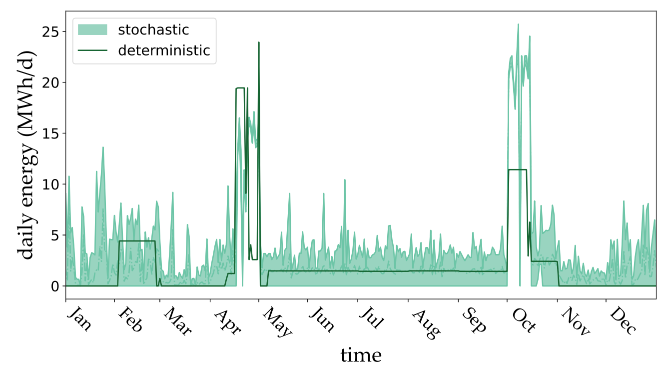


Fig. 23. Management of the GT in the PE_Guangzhou_H2 case study in the deterministic and stochastic approach.

Table 7
Objective function obtained for the PE case studies.

Case study	Cost function value (MWh)		Difference
	Deterministic	Stochastic	
PE_Rome_H2	7356	6443	−12.4%
PE_Guangzhou_H2	8263	6847	−17.1%

considered scenarios, and the aim is to use the developed algorithm in a novel controller to optimize the management of an energy system.

Indeed, while it is simple to implement and solve a deterministic model, the main disadvantage of these models is their inability to consider the uncertainties in the parameters of the optimization, which, however, is possible when employing stochastic programming. The proposed method showed its efficiency in dealing with large-scale problems by applying a precise stochastic modeling of the uncertain parameters and the Mixed-Integer Linear Programming approach.

The case studies considered involved the integration of Power-to-Gas technologies to provide seasonal storage, both in positive energy districts and in grid-connected energy systems. Indeed, the algorithm was applied to four different case studies, with different configurations and boundary conditions: this made it possible to obtain a wide range of results and to test its efficiency. The results obtained using both a deterministic and the novel stochastic algorithm were compared, showing the ability of the latter to optimize the management of the system considering uncertainties in energy production, prices and needs, and providing higher flexibility. The research led to the following main results:

- The hydrogen seasonal storage ensured energy security in the positive-energy case studies, and different climate conditions led to different ways of managing the storage.

- In a grid-connected case study, its management is both related to climate conditions and electricity prices, and makes it possible to reduce the cost of purchasing electricity over one year.
- The exploitation of this technology acts as a buffer to forestall unpredictable behavior of the disturbances and can help to prevent any undesirable disservices due to this unexpected behavior. Therefore, the flexibility of the system is increased, and the impact of the uncertainties on its management is mitigated.
- When using the stochastic approach, the optimal management of the system is robust to the uncertain boundary conditions and optimal bands of operation can be obtained for the decision variables, by combining the results for each scenario.

The developed algorithm is easily applicable to other case studies, revealing to be a useful tool to study various applications at different scales. Indeed, depending on the case study considered, a different business model can be taken into account, by changing the goals and the objective function implemented. However, the algorithm could be improved further, for example by taking into consideration the interdependence of the uncertainties or by performing a multi-objective optimization, to address different purposes.

The results show that it is worth investing in these technologies to perform seasonal storage in terms of energy management and operating cost: further studies need to be done to investigate the economics of the systems also taking into account the investment costs.

Future studies will include the usage of this optimization algorithm in a Model Predictive Controller, to optimally control the energy system considered, using the operational bands obtained with the stochastic approach to bind a real-time controller and provide it with indications on the long-term optimal operation of the system.

Nomenclature

c	energy cost, EUR/MWh
$DT(i,j)$	distance between scenarios ξ_i and ξ_j, –
E	energy, MWh
f_{obj}	objective function, MWh/EUR
N_s	total number of scenarios, –
N_t	total number of time-steps, –
N_u	total number of uncertainties, –
p_k	probability of occurrence of interval k, –
$PD(k,r(k))$	distance between scenarios k and $r(k)$ times probability of scenario k, –
$Pr(s)$	probability of occurrence of scenario s, –
t	time, hour
Δt	time-step, hour
$\upsilon^{i}_{t,u}$	value of the scenario ξ_i at time t for uncertain parameter u, –
δ	binary on–off variable, –
η	efficiency, –
μ	mean of the normal distribution, –
σ	standard deviation of the normal distribution, –
ξ_s	scenario s, –

Subscripts and superscripts

bo	bought
c	charge
d	discharge
el	electricity
ext	external
f	fuel
H_2	hydrogen
s	index for scenario
sd	self-discharge
so	sold
th	thermal
u	uncertain parameter

Acronyms

AC	Absorption Chiller
ASHP	Air Source Hear Pump
BES	Battery Electric System
CHP	Combined Heat and Power plant
COP	Coefficient Of Performance
DHN	District Heating Network
EER	Energy Efficiency Ratio
FC	Fuel Cell
GC	Grid-Connected
GT	Gas Turbine
HP	Heat Pump
HS	Hydrogen Storage
LP	Linear Programming
MES	Multi-Energy System
MILP	Mixed-Integer Linear Programming
MPC	Model Predictive Control
NLP	Nonlinear Programming
PDF	Probability Distribution Function
PE	Positive-Energy
PEM	Proton Exchange Membrane
PtG	Power-to-Gas
PV	Photovoltaics
RES	Renewable Energy Sources
TES	Thermal Energy Storage

CRediT authorship contribution statement

Emanuela Marzi: Conceptualization, Methodology, Software, Investigation, Writing – original draft, Visualization. **Mirko Morini:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing – review & editing. **Costanza Saletti:** Conceptualization, Methodology, Writing – review & editing. **Stavros Vouros:** Methodology, Writing – review & editing. **Valentina Zaccaria:** Methodology, Writing – review & editing. **Konstantinos Kyprianidis:** Supervision, Funding acquisition, Writing – review & editing. **Agostino Gambarotta:** Supervision, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Konstantinos Kyprianidis reports financial support was provided by ERA-Net Cofund scheme. Mirko Morini reports financial support was provided by ERA-Net Cofund scheme. Costanza Saletti reports financial support was provided by PON.

Data availability

Data will be made available on request.

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