

Robust Energy Management in Isolated Microgrids with Hydrogen Storage and Demand Response

Marcos Tostado-Véliz¹, Ahmad Rezaee Jordehi², Lázuli Fernández-Lobato¹, Francisco Jurado^{1,*}

1. Department of Electrical Engineering, University of Jaén, 23700 Linares, Spain (e-mail: mtostado@ujaen.es (M.T.-V.), lflobato@ujaen.es (L.F.-L.), fjurado@ujaen.es (F.J.)).
 2. Department of Electrical Engineering, Rasht Branch, Islamic Azad University, Rasht, Iran (e-mail: ahmadrezaeejordehi@gmail.com).
- * Correspondence: fjurado@ujaen.es

Abstract. Hydrogen is called to be one of the main energy vectors in future energy systems, especially for energy storage, where this carrier presents some interesting features. Its application in microgrids might help to improve economic, environmental and reliability indicators, providing greater storage capacity than other technologies, like batteries. Following this idea, this paper develops a robust energy management methodology for isolated microgrids considering hydrogen storage and demand response initiatives. The new proposal is raised as a nested max-min optimization framework. To reduce the original problem to a tractable single-level one, a master-slave scheme is developed by which binary variables can be fixed and thus the inner problem can be reduced to its equivalent Karush-Kuhn-Tucker conditions. Then, the overall optimization paradigm is solved in an iterative fashion used the Constraint-and-Column Generation Algorithm. The resulting tool is applied to a benchmark isolated microgrid, thus validating it for industry applications. Moreover, different relevant results are analysed in-depth. Thus, the role of hydrogen storage and demand response initiatives is discussed, concluding that flexible demand has a more notable impact on monetary savings than hydrogen storage, reducing the total cost by 6 % with respect to the base case. Some intrinsic issues are also identified. For example, it is observed that flexible consumers are more frequently called when the hydrogen chain is enabled, which may provoke undesirable effects like response fatigue.

Keywords. Demand Response; Energy Management; Hydrogen storage; Microgrid; Robust optimization.

Nomenclature

Indices and superscripts

t	Time $t \in \{1, 2, \dots, \mathcal{T} \}$
MT	Microturbine
DR	Demand response
Z	Electrolyser
FC	Fuel cell
NS	Non-served energy
$Curt$	Curtable demand
$Shed$	Sheddable demand
PV	Photovoltaic units
D	Non-flexible demand
Bal	Power balance
HSS	Hydrogen storage system
SOP	State-of-pressure
SOP_0/SOP_{end}	Initial/final state-of-pressure
$\underline{(\cdot)}/\overline{(\cdot)}$	Minimum/maximum value of a variable or parameter
$\widetilde{(\cdot)}/\widehat{(\cdot)}$	Forecasted/given parameters

Parameters and constants

$\Delta\tau$	Time step [h]
$c/v/m$	Fuel/energy/operation and maintenance (O&M) cost [\$/kWh]
k	Capital cost [\$/kW]
K	Lifecycle [h]
w	Shedding cost [\$/h]
q	Start-up and shutdown cost [\\$]
Y	Conversion factor [-]
η	Efficiency [pu]
LHV	Hydrogen lower heating value [kWh/kg]
Γ	Uncertain budget [-]

Decision variables

p	Power [kW]
y	Commitment status [Binary]
on/off	On/off status [Binary]
SOP	State-of-pressure [bar]
λ	Dual variables associated to equalities constraints [-]
μ	Dual variables associated to inequalities constraints [-]
β	Auxiliary variable for cost modelling [\\$]

Decision variables (vector notation)

\mathbf{x}	Vector of continuous primal variables
\mathbf{y}	Vector of binary primal variables
\mathbf{d}	Vector of uncertain variables $d_i \in \mathbf{d}, \forall i$

λ	Vector of dual variables associated to equalities constraints
μ	Vector of dual variables associated to inequalities constraints

1 - Introduction

1.1 - Context and motivation

In order to achieve carbon neutrality by 2050 [1], the European electricity sector must evolve towards massive integration of clean energy sources. Renewable generators are, however, difficult to manage due to their intermittent behaviour [2]. To overcome this issue, storage systems become essential in order to enable energy storage during periods of high renewable generation [3]. Mature battery technologies have a limited energy density, being few viable for medium and large-scale systems. In this context, hydrogen storage has emerged as a feasible solution [4]. Thereby, electrolysis and fuel cell (FC) technologies are continuously evolving to suppose a viable alternative to battery storage, in the sense that gaseous hydrogen storage has a notable energy density, much higher than batteries [5].

To optimally integrate renewable generators, storage systems and other emerging initiatives like demand response (DR), microgrids (MGs) are accepted to be a valuable framework [6]. Formally, a MG is a medium-scale energy system with sufficient capacity to fully satisfy its own demand in isolated conditions. MGs are frequently operated centrally, by an agent called MG operator, who decides the day-ahead scheduling program of her own assets with the aim of minimizing the overall cost of the system. Thus, this agent requires proper energy management tools, capable of handling with unpredictable behaviour of renewable generators and users. This paper focuses on this issue, in particular, on MGs including hydrogen storage.

1.2 - Related works

MG is not a new concept and multiple energy management and scheduling tools have been proposed over years (see Literature Review in [7]). However, we focus here on those works that consider MGs encompassing hydrogen as an active storage vector. In particular, we are especially interested in how uncertainties are modelled and handled in such frameworks. Despite the importance of uncertainties parameters in hydrogen-based systems, where the penetration of renewables is high, most of existing works assume deterministic conditions, thus neglecting the impact of uncertain parameters. A hierarchical control strategy for DC MGs was developed in [8]. Due to the nonlinearities presented in the mathematical model, the authors used the software HOMER® for optimal sizing the MG components, including hydrogen chain, photovoltaic (PV) units and batteries. A multi-objective day-ahead scheduling framework for MGs encompassing FCs was developed in [9]. Such methodology incorporates fuzzy decision rules to determine the best Pareto-oriented solution. Mehrjerdi designed in [10] and off-grid PV-powered refuelling/charging station, as well as a series of decision rules for its energy management. In [11], a two-layer model for optimal scheduling of MGs with hydrogen storage was proposed, in which the first layer incorporates detailed models of electrolyzers and FCs, while the second layer raises a model predictive control formulated as a Mixed-Integer-Linear programming (MILP). In [12], an energy management model was developed for multi-energy MGs incorporating FC vehicles. Xie, et al. [13] proposed a heuristic scheduling strategy based on greedy algorithm for MGs. This reference focuses

on near 100 % renewable MGs incorporating a hydrogen chain and batteries. Fang, et al. [14] developed a multi-time scale scheduling methodology for MGs encompassing hydrogen storage. In this regard, day-ahead and real-time decisions are taken on a holistic framework. In [15], an optimal energy management tool for a hydrogen-utility was presented. This model considers hydrogen consumers and PV production. However, deterministic conditions and inflexible demand were assumed.

A number of works model uncertainties using scenarios. This approach, commonly known as stochastic programming, is simple, but entails a high computational burden and does not lead to robust solutions as the worst-case scenario is hidden and generally not accessible. Within this category, Konstantinopoulos, et al. [16] proposed a metaheuristic-based energy management tool for grid-connected MGs incorporating hydrogen chain (electrolysis-storage-FC). In [17], a stochastic-based day-ahead energy management tool for hydrogen-oriented MGs was presented. The problem was formulated as a security-constrained unit commitment tool. Zhu, et al. [18] developed a scheduling strategy for energy trading among MGs encompassing hydrogen storage for fuelling vehicles. Daneshvar, et al. [19] developed an optimal scheduling model for hydrogen-based MGs incorporating DR initiatives. In [20], a two-stage decision-making process was proposed for MGs with hydrogen storage. The proposed structure encompasses day-ahead and real-time decisions. The authors in [21] focused on the role of electric vehicles and their random patterns when integrated in a MG with hydrogen storage, for which an optimal scheduling mechanism was developed. Such scheduling mechanism was raised as a nonlinear problem, which is difficult to solve using analytic methods. Rezaei, et al. [22] presented an energy management procedure for multi-MGs systems with hydrogen storage and DR. In this model, unexpected grid failures are considered. Stochastic representation of uncertainties was also considered in [23], where a joint planning-operation tool for MGs with hydrogen storage was developed. In [24], a decentralized algorithm based on the alternating direction of multipliers was developed for cooperative interaction among agents partaking in MGs. In this regard, various energy vectors (i.e. electricity, heat and hydrogen) were considered.

To overcome some difficulties of stochastic approaches, some techniques endow a certain degree of robustness seeking for risk-averse conditions calculated over a scenario-space for uncertainties. Such is the case of Wu, et al. [25], who developed an optimal scheduling model for hydrogen refuelling stations with onsite electrolyser units, using chance-constrained formulation to account for uncertainties. In [26], an optimal planning model for MGs was presented. In this reference, the authors considered MGs encompassing combined heat and power units together with FCs and hydrogen storage. In this reference, point-estimate methods are considered to accurately model uncertainties. Reference [27] focuses on the flexibility provided by FC vehicles, for which a MILP model was developed incorporating conditional value at risk (CVaR) constraints to reproduce a risk-averse result against uncertainties. This reference only considered flexibility provided by vehicles, ignoring other possible flexible resources and DR initiatives.

Alternatively, robust-based approaches seek for the worst-case realization of uncertainties and calculate the scheduling plan for the assets on the basis of such profiles. In [28], a robust model-predictive control was developed for optimal scheduling of MGs incorporating FC electric vehicles. Energy storage is enabled through vehicle-to-grid features of vehicles, while uncertainties are incorporated via min-max formulation, which

is further converted into a MILP framework under some assumptions. An optimal scheduling of multi-energy MGs was proposed in [29]. In this reference, the uncertainties are modelled via confidence intervals and integrated into the mathematical problem using a robust reformulation of the objective function and constraints. Mansour-Saatloo, et al. [30] presented a multi-objective day-ahead scheduling framework for MGs encompassing hydrogen storage. This reference focused on the role of intelligent parking lots providing flexibility to the system, whereas uncertainties were treated using the Information Gap Decision Theory (IGDT). Fan, et al. [31] presented a robust energy management framework for optimal scheduling of MGs with hydrogen storage, in which the impact of DR programs was ignored. The problem was presented as a master-slave structure solved using the constraint-and-column generation algorithm (C&CGA). An interval-based methodology was proposed in [32] for optimal scheduling of MGs with hydrogen storage incorporating different DR programs.

Lastly, some references combine different uncertainties modelling looking for gathering the advantages of different methodologies while their cons are diminished. In [33], an energy management model was developed for multi-energy MGs incorporating FC vehicles. This reference considers different uncertain models such as stochastic-based approaches or IGDT. A multi-objective scheduling strategy for MGs with hydrogen storage and curtailable loads was proposed in [34]. In this reference, multiple uncertainties are handled via a hybrid stochastic-robust approach. A risk-averse strategy for refuelling stations was developed in [35], which is based on modelling the uncertainties using IGDT. In this case, uncertainties from PV units are modelled in a pessimistic way while refuelling demand is treated via scenarios, by which a stochastic model is developed. For the sake of simplicity, Table 1 summarizes the main features of the studied literature.

1.3 - Research gaps and difficulties

This paper focuses on energy management in MGs encompassing hydrogen storage under uncertainty. This topic has been widely studied in the literature, as previously analysed. However, there are still some important issues in the existing literature. Energy management tools, need to be accurate, reliable and efficient in order to be easily implementable in industry tools. In this regard, existing works do not fully meet these requirements due to some of the following gaps:

- In optimization problems, MILP formulations are preferred due to three reasons: 1) this kind of problems can be solved using off-the-shelf solvers, which are widely available in conventional software like Matlab; 2) this kind of formulations are versatile and easily adaptable to different layouts and circumstances; 3) existing solvers are efficient and ensure the reachability of the global optimum. In this regard, some of the existing works present nonlinear formulations that do not reach the global performance of MILP problems.
- When dealing with uncertainties, probability or robust-based approaches can be considered. However, when risk-averse results are aimed, robust methodologies are preferred. This is due to scenario-based methodologies yield the most probable result over a scenario-space rather than the solution under worst-case realization of uncertainties. In addition, stochastic approaches present two important drawbacks: 1) normally, a large number of scenarios need to be evaluated, entailing computational issues; 2) one needs to know the probability features of

the uncertain parameter to generate accurate scenarios. On the other hand, among the different robust-based techniques, interval notation [32], semi-robust reformulation [34] and IGDT [35], have been widely employed. Nevertheless, these approaches are in fact simplifications of the original robust formulation based on min-max nested problems [28, 31], which is considered more reliable.

- Most of the studied papers either neglect or ignore DR programs or focus on only one type of DR initiative. In future energy systems, different DR programs such as shiftable demand or sheddable loads are expected to be implemented in order to provide flexibility to the system, being so necessary to model and evaluate the different DR initiatives jointly.

Table 1 - A summary of the related literature

Ref.	Model	Solver	Uncertainties modelling	DR	H ₂ storage
[8]	Nonlinear	HOMER + heuristic	Deterministic	No	Gaseous with onsite electrolysis and FC
[9]	MILP	Analytic		Shiftable	Only FC
[10]	Nonlinear	Heuristic		No	Gaseous vessels (only for fuelling vehicles)
[11, 14, 15]	MILP	Analytic		No	Gaseous with onsite electrolysis and FC
[12]	Nonlinear	Analytic		No	Gaseous with by-product H ₂ and FC
[13]	Nonlinear	Heuristic		No	Gaseous with onsite electrolysis and FC
[16]	Linear	Metaheuristic	Stochastic	No	Gaseous with onsite electrolysis and FC
[17, 19]	Nonlinear	Analytic		Shiftable	Gaseous with onsite hydrogen generation
[18]	Nonlinear	Lyapunov		No	Gaseous vessels (only for fuelling vehicles)
[20, 23]	MILP	Analytic		No	Gaseous with onsite electrolysis and FC
[21]	Nonlinear	Metaheuristic		No	Gaseous with onsite electrolysis and FC
[22]	MILP	Analytic		Curtable Sheddable	Gaseous with onsite electrolysis and FC
[24]	Quadratic	Analytic		No	Gaseous with onsite electrolysis and FC
[25]	MILP	Analytic		Chance constrained and distributed robust (hybrid)	No
[26]	Nonlinear	Metaheuristic	Point estimate method	No	Gaseous with onsite hydrogen generation
[27]	MILP	Analytic	Stochastic (CVaR)	Flexibility from vehicles	Gaseous with onsite electrolysis and FC
[28]	MILP	Analytic	Robust (min-max)	No	FC vehicles
[29]	MILP	Analytic	Robust	No	Gaseous with onsite electrolysis and FC
[30]	MILP	Analytic	IGDT	Flexibility from vehicles	Gaseous vessels (only for fuelling vehicles)
[31]	MILP	Analytic	Robust bi-level with C&CGA	No	Gaseous with onsite electrolysis and FC
[32]	MILP + Quadratic	Analytic	Interval	Curtable Sheddable	Gaseous with onsite electrolysis and FC
[33]	MILP	Analytic	Hybrid	No	Gaseous vessels (only for fuelling vehicles)
[34]	MILP	Analytic		Curtable	Gaseous with onsite electrolysis and FC
[35]	MILP	Analytic	IGDT + Stochastic	No	Gaseous vessels (only for fuelling vehicles)

1.4 - Contributions and paper organization

To overcome the gaps described above, this paper develops a novel robust energy management mechanism for MGs with hydrogen storage based on the original min-max formulation [36]. This particular formulation overcome the problems brought by other uncertainty models and approaches. Indeed, stochastic and other scenario-based methodologies as well as other robust-oriented approaches, as previously discussed. On the other hand, a solution algorithm based on C&CGA is proposed, which allows to decompose the overall problem into a master-slave structure in which the slave problem is kept fully linear and thus exchangeable by its Karush Kuhn Tucker (KKT) conditions. In addition, different DR initiatives are modelled keeping the model as a MILP, being in consequence versatile, portable and efficient to be easily accommodated in industry applications.

In this regard, our contributions may seem similar to those drawn in [31], since the developed solution algorithm is based on C&CGA. However, our study presents some important differences:

- Our solution algorithm is rather based on that developed in [36]. This algorithm only exchanges primal information between levels to build the different cuts. Hence, his methodology supposes a variant of the conventional C&CGA used in [31], whose convergence properties have been well proved in several references [37, 38].
- We assume a polyhedral representation of the uncertainty set, but omitting absolute values, as described in [36], resulting in a total linear formulation without employing linearization tricks. In this way, the resulting formulation is MILP, meeting the advantages previously mentioned for this kind of optimization problems.
- Instead of focusing in only one type of flexible load, different DR initiatives are specifically modelled. It allows to evaluate the effect of different DR initiatives jointly, which addresses with the probable situation in emerging energy systems. The necessary binary variables are previously fixed within an original master-slave structure.
- One of the main features of MGs is their capability of being operated in isolated conditions. In contrast to [31], we consider an isolated MG operation with the aim of providing the worst-case scenario for the operational stage.
- Our analysis is specifically focused on the role of DR and hydrogen chain in the energy management problem and how the level of uncertainty affects to these aspects. To this end, extensive simulations are performed under different scenarios.

For the sake of simplicity, we summarize the main contributions of this paper in the following three points:

- Proposing a robust-based energy management strategy for isolated MGs with hydrogen storage based on C&CGA.
- Incorporating different DR initiatives into the model by developing a master-slave solution methodology.
- Analysing the role and impact of DR programs and hydrogen storage in the energy management problem under uncertainties.

In the rest of this paper, Section 2 describes some preliminaries such as the MG layout and operational principle, its deterministic operational model and the uncertainty

modelling considered. Section 3 poses the developed robust reformulation and solution methodology based on a master-slave structure. Section 4 presents and discusses some numerical results. Lastly, the paper is concluded with Section 5.

2 - Preliminaries

2.1 - Description of the MG under study

Fig. 1 shows the pictorial representation of the isolated MG under study. It encompasses a hydrogen chain formed by onsite electrolysis, gaseous vessels and FCs. Electricity supply can be performed through renewable generators, i.e. PV units, and backup generation (e.g. microturbines). The consumers are divided into three categories [32]. Firstly, the non-flexible consumers, who are inhibited of the action of the scheduler tool and whose day-ahead demand is predicted rather than managed. Secondly, the curtailable consumers, who can adjust their consumption within acceptable limits receiving a compensatory payment for this service. Lastly, the sheddable consumers, who can be disconnected for convenience receiving a payment for each hour they are disconnected from the grid. The operation of the MG is centrally performed by the MG operator, who receives weather and non-flexible demand information and schedule the different assets and flexible consumers to minimize the cost. This agent is also responsible of uncertainty handling, as described later.

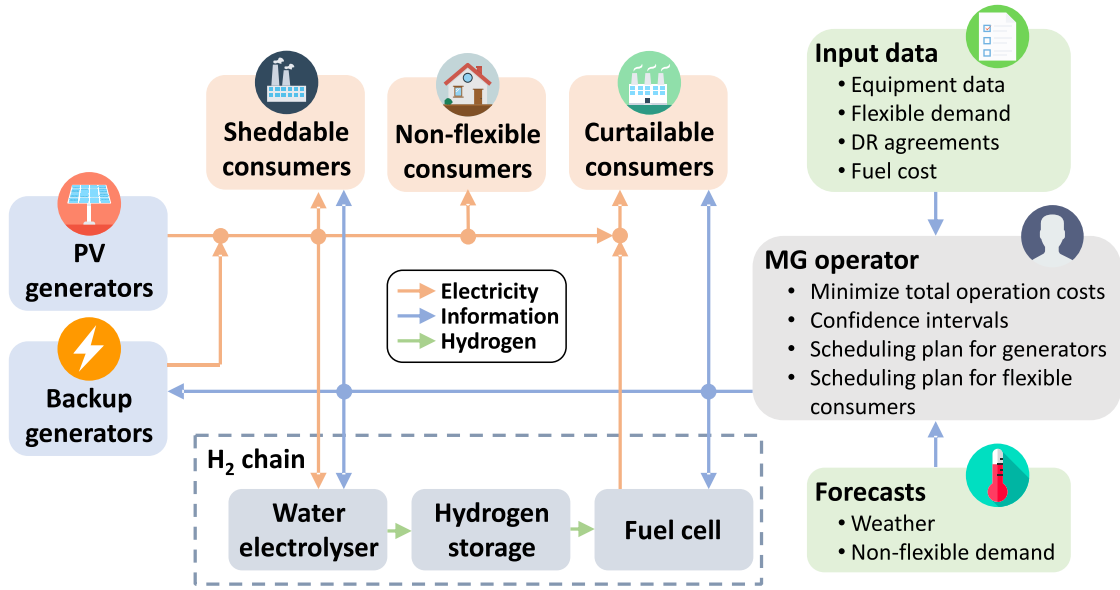


Fig. 1 - Pictorial representation of the MG under study

2.2 - MG deterministic operational model

In this section we present the mathematical model for the MG depicted in Fig. 1. The daily operation cost of the MG is given by:

$$\text{Cost} = f^{MT} + f^{DR} + f^Z + f^{FC} + f^{NS} \quad (1)$$

In (1), the first term represents the fuel cost of microturbines, the second term are the compensatory payments for applying DR, the third and fourth terms give the costs associated to electrolysers and FCs, respectively, while the last term stands for the cost of non-served load. These terms are respectively given in (2)-(5).

$$f^{MT} = \Delta\tau \cdot \sum_{t \in \mathcal{T}} \left\{ \underbrace{[c_t^{MT} \cdot p_t^{MT}]}_{\text{Fuel cost}} + \underbrace{\left[y_t^{DEG} \cdot \frac{k^{MT} \cdot \bar{p}^{MT}}{K^{MT}} \right]}_{\text{Capital cost}} \right\} \quad (2)$$

$$f^{DR} = \Delta\tau \cdot \sum_{t \in \mathcal{T}} \underbrace{v^{Curt} \cdot (\bar{p}_t^{Curt} - p_t^{Curt})}_{\text{Cost for curtailed demand}} + \Delta\tau \cdot w^{Shed} \cdot (|\mathcal{T}| - \sum_{t \in \mathcal{T}} y_t^{Shed}) \quad (3)$$

$$f^i = \Delta\tau \cdot \sum_{t \in \mathcal{T}} \left\{ \underbrace{[m^i \cdot p_t^i]}_{\text{O\&M cost}} + \underbrace{\left[y_t^x \cdot \frac{k^i \cdot \bar{p}^i}{K^i} \right]}_{\text{Capital cost}} \right\} + \underbrace{q^i \cdot \sum_{t \in \mathcal{T}} \{\text{on}_t^i + \text{off}_t^i\}}_{\text{Start-up \& shutdown cost}} ; i \in \{Z, FC\} \quad (4)$$

$$f^{NS} = \Delta\tau \cdot \sum_{t \in \mathcal{T}} v^{NS} \cdot p_t^{NS} \quad (5)$$

The deterministic operational model is completed by the constraints below, which are stated for power and hydrogen balances together with functional limits of the different units.

$$p_t^{MT} + p_t^{PV} + p_t^{FC} + p_t^{NS} = \tilde{p}_t^D + p_t^Z - p_t^{Curt} - y_t^{Shed} \cdot \bar{p}_t^{Shed} : \lambda_t^{Bal}; \forall t \in \mathcal{T} \quad (6)$$

$$y_t^i \cdot \underline{p}^i \leq p_t^i \leq y_t^i \cdot \bar{p}^i : \underline{\mu}_t^i, \bar{\mu}_t^i; \forall t \in \mathcal{T}, i \in \{MT, Z, FC\} \quad (7)$$

$$y_t^i - y_{t-1}^i = \text{on}_t^i + \text{off}_t^i; \forall t \in \mathcal{T} \setminus t > 1 \quad (8)$$

$$\underline{p}_t^{Curt} \leq p_t^{Curt} \leq \bar{p}_t^{Curt} : \underline{\mu}_t^{Curt}, \bar{\mu}_t^{Curt}; \forall t \in \mathcal{T} \quad (9)$$

$$0 \leq p_t^{NS} \leq \tilde{p}_t^D : \underline{\mu}_t^{NS}, \bar{\mu}_t^{NS}; \forall t \in \mathcal{T} \quad (10)$$

$$0 \leq p_t^{PV} \leq \tilde{p}_t^{PV} : \underline{\mu}_t^{PV}, \bar{\mu}_t^{PV}; \forall t \in \mathcal{T} \quad (11)$$

$$\text{SOP}_t^{HSS} = \text{SOP}_{t-1}^{HSS} + \Delta\tau \cdot \Upsilon \cdot \left(\frac{\eta^Z \cdot p_t^Z}{\text{LHV}} - \frac{p_t^{FC}}{\eta^{FC} \cdot \text{LHV}} \right) : \lambda_t^{SOP}; \forall t \in \mathcal{T} \setminus t > 1 \quad (12)$$

$$\underline{\text{SOP}}^{HSS} \leq \text{SOP}_t^{HSS} \leq \overline{\text{SOP}}^{HSS} : \underline{\mu}_t^{SOP}, \bar{\mu}_t^{SOP}; \forall t \in \mathcal{T} \quad (13)$$

$$\text{SOP}_{t=1}^{HSS} = \text{SOP}_{t=|\mathcal{T}|}^{HSS} = \overline{\text{SOP}}^{HSS} : \lambda^{SOP_0}, \lambda^{SOP_{end}} \quad (14)$$

$$y_t^Z + y_t^{FC} \leq 1; \forall t \in \mathcal{T} \quad (15)$$

The MG power balance is established in (6), taking into account the application of DR initiatives, while (7) and (8) model the power limits and establish coherency in the on-off status of dispatchable units, respectively. In (9), it is established that the dispatched curtailable demand must be within acceptable limits while in (10) the non-served load must be positive and lower than the expected non-controllable demand. The renewable generation is modelled in (11) and limited to the expected PV potential. In (12), the dynamics of the hydrogen storage are established by modelling its instantaneous state-of-pressure (SOP) [39], which must be within limits, as said (13). Since (12) is not defined for $t = 1$, its initial value is given in (14) and equal to the SOP at the end of the time horizon. Lastly, (15) establishes complementarity in the operation of the electrolyzers and FCs. It is worth noting that dual variables of the constraints above are written at the right-hand side of each equation and will be useful later.

For convenience, the deterministic operational model for the MG described in Section 2.1 is written in matrix form, below:

$$\min_{x,y} \mathbf{c}^T \mathbf{x} + \mathbf{b}^T \mathbf{y} \quad (16a)$$

Subject to:

$$\mathbf{Ax} + \mathbf{By} = \mathbf{E}\tilde{\mathbf{d}} \quad (16b)$$

$$\mathbf{Fx} + \mathbf{Gy} \leq \mathbf{K}\tilde{\mathbf{d}} \quad (16c)$$

$$y_i \in \{0,1\}; \forall i \quad (16d)$$

where \mathbf{c} and \mathbf{b} are the vectors of cost coefficients and $\mathbf{A}, \mathbf{B}, \mathbf{E}, \mathbf{F}, \mathbf{G}$ and \mathbf{K} are matrix of coefficients from inequality and equality constraints.

2.3 - Uncertainty modelling

In robust optimization problems, the space that collects the possible realization of uncertainties is known as uncertainty set. Adopting a proper uncertainty set representation is essential for an accurate evaluation of uncertainties. In the literature, one can find different uncertainty sets representation such as elliptical, polyhedral or ellipsoidal. Each one presents pros and cons, but polyhedral representations are considered suitable for energy management and other related problems because they offer a good trade-off between accuracy and simple formulation [31, 36].

In this paper we adopt a polyhedral representation of the uncertainty set. Given an uncertain parameter d , the associated uncertainty set is described by the following constraints:

$$d_i \in [\underline{d}_i, \bar{d}_i], \forall i \quad (17)$$

$$\frac{|\bar{d}_i - d_i|}{(\bar{d}_i - \underline{d}_i)} \leq \Gamma_i, \forall i \quad (18)$$

where $0 \leq \Gamma \leq 1$ is the uncertainty budget. The model (17) requires to estimate the upper and lower bounds of uncertainties. There are different options to estimate such limits (e.g. data driven approaches). In this paper, we assume that these limits can be modelled by imposing confidence intervals on forecasted profiles [32]. Note that the absolute value in (18) can be omitted when referring to renewable generation or demand and a risk-averse strategy is adopted [36]. Thus, the application of the model (17) and (18) to our problem is provided below:

$$0 \leq \tilde{p}_t^{PV} \leq \bar{p}^{PV}; \forall t \in \mathcal{T} \quad (19a)$$

$$\underline{p}_t^D \leq \tilde{p}_t^D \leq \bar{p}_t^D; \forall t \in \mathcal{T} \quad (19b)$$

$$\frac{\bar{p}^{PV} - \tilde{p}_t^{PV}}{\bar{p}^{PV}} \leq \Gamma^{PV}; \forall t \in \mathcal{T} \quad (19c)$$

$$\frac{\tilde{p}_t^D - \underline{p}_t^D}{\bar{p}_t^D - \underline{p}_t^D} \leq \Gamma^D; \forall t \in \mathcal{T} \quad (19d)$$

Note that we assume that the minimum PV potential is set to zero. This way, the PV potential may take values from zero and thus considering null generation. This circumstance is considered suitable to model renewable generation uncertainty since null potential collects two plausible situations. On the one hand, null PV potential during night. On the other hand, possible failure of PV panels, associated components (such as inverters) or sudden generation descent due to fully cloudy conditions.

3 - Robust reformulation of the problem

3.1 - Foundations

The robust reformulation of the deterministic problem (16) is given below in matrix form (see [36, 40] for further details):

$$\max_d \min_{x,y} \mathbf{c}^T \mathbf{x} + \mathbf{b}^T \mathbf{y} \quad (20a)$$

Subject to:

$$\mathbf{Ax} + \mathbf{By} = \mathbf{Ed} \quad (20b)$$

$$\mathbf{Fx} + \mathbf{Gy} \leq \mathbf{Kd} \quad (20c)$$

$$y_i \in \{0,1\}; \forall i \quad (20d)$$

Subject to:

$$\mathbf{Hd} \leq \mathbf{h} \quad (20e)$$

In the optimization problem above, (20a) and (20b)-(20d) are the objective function and constraints of the deterministic problem, respectively, while (20e) is the matrix notation of the set of constraints (19). Note that uncertain parameters are now declared as variables in (20). This way, the robust formulation (20) nests two problems. The inner sub-problem is identical to the deterministic problem (16), while the outer problem seeks for the worst-case realization of uncertainties, in order to orient the problem to a risk-averse perspective.

The bi-level problem (20) cannot be solved directly. Different approaches have been proposed in the literature to address this problem (e.g. see [41, 42]). In this paper we use the C&CGA proposed in [36], where it was successfully applied to transmission expansion problems. This approach consists on converting a bi-level framework into a single-level one by passing the inner level to the outer one through its KKT conditions. However, for our problem (20), the inner sub-problem cannot be directly reduced to its KKT conditions because the presence of binary variables. Indeed, the KKT conditions are necessary and sufficient for optimality when the problem is linear. Therefore, we cannot apply this procedure directly. To solve this issue, we raise a master-slave scheme, in which the binary variables of the inner problem are fixed at the master level, while the slave sub-problem solves the bi-level framework (20) by reducing the linear inner sub-problem to its equivalent KKT conditions. Subsequent sections are devoted on formally presented the different problems involved in the proposed master-slave structure as well as the designed C&CGA used for its solution.

3.2 - Master problem

The master problem calculates the scheduling plan of the MG assets assuming given values of uncertain parameters. This way, the master problem can be formulated, as follows:

$$\mathbf{y}^* \rightarrow \operatorname{argmin}_{x,y,\beta} \beta + \mathbf{b}^T \mathbf{y} \quad (21a)$$

Subject to:

$$\beta \geq \mathbf{c}^T \mathbf{x} \quad (21b)$$

$$\mathbf{Ax} + \mathbf{By} = \mathbf{E}\hat{\mathbf{d}} \quad (21c)$$

$$\mathbf{Fx} + \mathbf{Gy} \leq \mathbf{K}\hat{\mathbf{d}} \quad (21d)$$

$$y_i \in \{0,1\}; \forall i \quad (21e)$$

As result of the master problem (21), the optimal value of binary variables (\mathbf{y}^*) for a given realization of uncertainties ($\hat{\mathbf{d}}$) is obtained. In this regard, the problem (21) becomes

identical to (16) if $\widehat{\mathbf{d}} = \widetilde{\mathbf{d}}$. Additionally, the master problem incorporates the constraints (21b), which model the costs associated to continuous variables (fuel, payments to curtailable consumers, operation and maintenance and non-served load) being modelled and incorporated to the objective function through the auxiliary variable β . On the other hand, the costs associated to binary variables (capital costs, start-up and shutdown costs and payments to sheddable consumers) remain in the objective function.

Note that this paradigm corresponds to a solution framework based on Bender's decomposition. However, in contrast to conventional algorithms, only primal information is included in (21). In addition, it is worth noting that (21) is a MILP that can be efficiently solved using off-the-shelf solvers.

3.3 - Slave problem

Once the binary variables are fixed after solving the master problem, the inner sub-problem in (20) becomes linear and can be replaced by its KKT conditions, which are detailed below:

$$\Delta\tau \cdot c^{MT} + \lambda_t^{Bal} + \overline{\mu}_t^{MT} - \underline{\mu}_t^{MT} = 0; \forall t \in \mathcal{T} \quad (22)$$

$$\lambda_t^{Bal} + \overline{\mu}_t^{PV} - \underline{\mu}_t^{PV} = 0; \forall t \in \mathcal{T} \quad (23)$$

$$-\Delta\tau \cdot v^{Curt} - \lambda_t^{Bal} + \overline{\mu}_t^{Curt} - \underline{\mu}_t^{Curt} = 0; \forall t \in \mathcal{T} \quad (24)$$

$$\Delta\tau \cdot v^{NS} + \lambda_t^{Bal} + \overline{\mu}_t^{NS} - \underline{\mu}_t^{NS} = 0; \forall t \in \mathcal{T} \quad (25)$$

$$-\Delta\tau \cdot m^Z - \lambda_t^{Bal} + \overline{\mu}_t^Z - \underline{\mu}_t^Z - \lambda_t^{SOP} \cdot \frac{\Delta\tau \cdot \gamma \cdot \eta^Z}{LHV}; \forall t \in \mathcal{T} \quad (26)$$

$$\Delta\tau \cdot m^{FC} + \lambda_t^{Bal} + \overline{\mu}_t^{FC} - \underline{\mu}_t^{FC} + \lambda_t^{SOP} \cdot \frac{\Delta\tau \cdot \gamma}{LHV \cdot \eta^{FC}}; \forall t \in \mathcal{T} \quad (27)$$

$$\lambda^{SOP_0} - \underline{\mu}_t^{SOP} + \overline{\mu}_t^{SOP}; t = 1 \quad (28)$$

$$\lambda_t^{SOP} - \lambda_{t-1}^{SOP} - \underline{\mu}_t^{SOP} + \overline{\mu}_t^{SOP}; t > 1 \wedge t < |\mathcal{T}| \quad (29)$$

$$\lambda_t^{SOP_{end}} + \lambda_t^{SOP} - \lambda_{t-1}^{SOP} - \underline{\mu}_t^{SOP} + \overline{\mu}_t^{SOP}; t = |\mathcal{T}| \quad (30)$$

$$0 \leq \begin{matrix} p_t^i - \hat{y}_t^i \cdot p^i \perp \underline{\mu}_t^i \\ \hat{y}_t^i \cdot \bar{p}^i - p_t^i \perp \overline{\mu}_t^i \end{matrix} \geq 0; \forall t \in \mathcal{T} \wedge i \in \{MT, Z, FC\} \quad (31)$$

$$0 \leq \begin{matrix} p_t^{Curt} - \underline{p}_t^{Curt} \perp \underline{\mu}_t^{Curt} \\ \overline{p}_t^{Curt} - p_t^{Curt} \perp \overline{\mu}_t^{Curt} \end{matrix} \geq 0; \forall t \in \mathcal{T} \quad (32)$$

$$0 \leq \begin{matrix} p_t^{NS} \perp \underline{\mu}_t^{NS} \\ \tilde{p}_t^D - p_t^{NS} \perp \overline{\mu}_t^{NS} \end{matrix} \geq 0; \forall t \in \mathcal{T} \quad (33)$$

$$0 \leq \begin{matrix} p_t^{PV} \perp \underline{\mu}_t^{PV} \\ \tilde{p}_t^{PV} - p_t^{PV} \perp \overline{\mu}_t^{PV} \end{matrix} \geq 0; \forall t \in \mathcal{T} \quad (34)$$

$$0 \leq \begin{matrix} \text{SOP}_t^{HSS} - \underline{\text{SOP}}^{HSS} \perp \underline{\mu}_t^{SOP} \\ \overline{\text{SOP}}^{HSS} - \text{SOP}_t^{HSS} \perp \overline{\mu}_t^{SOP} \end{matrix} \geq 0; \forall t \in \mathcal{T} \quad (35)$$

where \perp stands for complementarity.

The collection of constraints (22)-(30) are the stationary conditions, obtained after equalling to zero the first partial derivatives of the Lagrangian function of the inner problem in (20), while (31)-(35) are the complementarity constraints associated to

inequality constraints (20c). Note that complementarity functions can be efficiently linearized using the big-M method, as described in [43].

After replacing the inner sub-problem in (20) by its KKT conditions (22)-(35), it can be passed to the outer level in (20) reducing the nested max-min original framework to the following single-level maximization problem:

$$\mathbf{d}^* \rightarrow \underset{x, \mathbf{d}}{\operatorname{argmax}} \mathbf{c}^T \mathbf{x} \quad (36a)$$

Subject to:

$$\mathbf{H}\mathbf{d} \leq \mathbf{h} \quad (36b)$$

$$\mathbf{c} + \mathbf{A}^T \boldsymbol{\lambda} + \mathbf{F}^T \boldsymbol{\mu} = \mathbf{0} \quad (36c)$$

$$\mathbf{A}\mathbf{x} + \mathbf{B}\hat{\mathbf{y}} = \mathbf{E}\mathbf{d} \quad (36d)$$

$$\mathbf{0} \leq \mathbf{K}\mathbf{d} - \mathbf{F}\mathbf{x} - \mathbf{G}\hat{\mathbf{y}} \perp \boldsymbol{\mu} \geq \mathbf{0} \quad (36e)$$

$$\boldsymbol{\lambda}: \text{free} \quad (36f)$$

$$\boldsymbol{\mu} \geq \mathbf{0} \quad (36g)$$

As seen, the slave problem (36) seeks for the worst-case realization of the uncertain parameters (\mathbf{d}^*). In practice, the value of uncertainties is not directly calculated and the vector \mathbf{d}^* is iteratively passed to the master problem until converging, as explained in the following sub-section. On the other hand, (36b) is the matrix notation of the uncertainty set (19), (36c) represents the stationary conditions (22)-(30). Constraints (36d) are the equality constraints of the master problem that ensure its feasibility while (36e) is the matrix notation of the complementarity constraints (31)-(35). Finally, the $\boldsymbol{\lambda}$'s are declared free variables by (36f), whereas (36g) imposes positivity on dual variables $\boldsymbol{\mu}$'s.

3.4 - Solution algorithm

To solve the master-slave structure depicted in Fig. 2, we propose a solution methodology based on C&CGA whose main steps are summarized below:

1. Fix the lower bound (LB) to $LB = -\infty$, the upper bound (UB) to $UB = \infty$ and the iteration counter $k = 0$.
2. If $k = 0$ solve the master problem taking $\hat{\mathbf{d}} = \tilde{\mathbf{d}}$. Otherwise, solve the master problem for $\hat{\mathbf{d}}$ obtained from the sub-problem. After running the master problem, the optimal solution tuple $\{\mathbf{x}^*, \mathbf{y}^*, \beta^*\}$ is obtained and the lower bound can be updated as $LB = \beta^* + \mathbf{b}^T \mathbf{y}^*$
3. Solve the slave problem (36) taking $\hat{\mathbf{y}} = \mathbf{y}^*$. After running this step, the solution tuple $\{\mathbf{x}^*, \mathbf{d}^*\}$ is obtained and the upper bound can be updated as $UB = \min\{UB, \mathbf{c}^T \mathbf{x}^* + \mathbf{b}^T \mathbf{y}^*\}$
4. Check convergence. If $(UB - LB)/UB \leq \epsilon$, then return \mathbf{x}^* and stop. Otherwise, $k = k + 1$, set $\hat{\mathbf{d}} = \mathbf{d}^*$ and go to step 2.

Note that ϵ is a positive real number that establishes the convergence criteria ($\epsilon = 0.5$ in this paper). Preliminary experiments performed by the authors revealed that the algorithm above normally converge within two or three iterations, being in concordance with the conclusions drawn in [37, 38] and other related papers. For the sake of simplicity, the 1-4 steps above are described in the flowchart of Fig. 2.

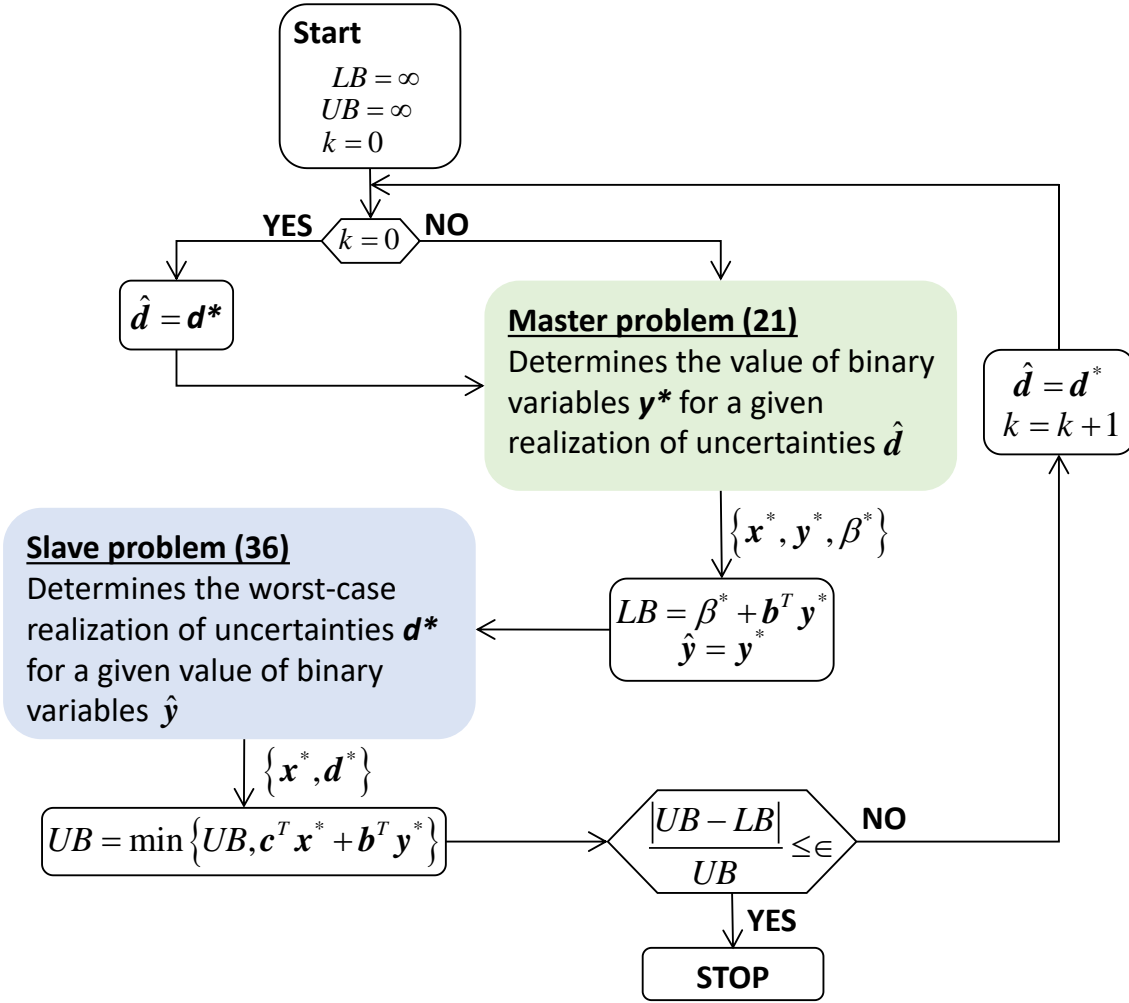


Fig. 2 - Flowchart of the proposed master-slave solution algorithm

4 - Case study

Throughout this section, we present and comment several numerical results. The objective of these simulations is twofold. On the one hand, we aim at validating the developed tool analysing that the results obtained are coherent. On the other hand, we analyse the role of hydrogen storage and DR in MG operation and how the level of uncertainty affects them. To this end, the optimization model presented in this paper was coded under Matlab R2021a and solved using Gurobi [44] on an Intel® Core™ i7-10700 K with 32.00 GB RAM. All the simulations were performed over a 24-h time horizon with 1-h time resolution (24 time slots in total).

4.1 - Input data

In this section, we focus on a benchmark MG such as that described in Section 2. Fig. 3 shows the expected profiles for PV generation and non-controllable/controllable demands. The PV potential was generated using the panel model described in [45] and taking weather parameters collected at Madrid (Spain) on May 3, 2016 [46], assuming a 2000 kWp PV array. The non-flexible demand was adapted from real data measured at La Palma Island (Spain) on May 3, 2016 [47], whereas the controllable demand was adapted from [32]. The minimum curtailable load was set at 60 % of the expected demand while the penalizations for curtailable, sheddable and unserved demand were set at 1.5 \$/kWh, 200 \$/h and 15 \$/kWh, respectively.

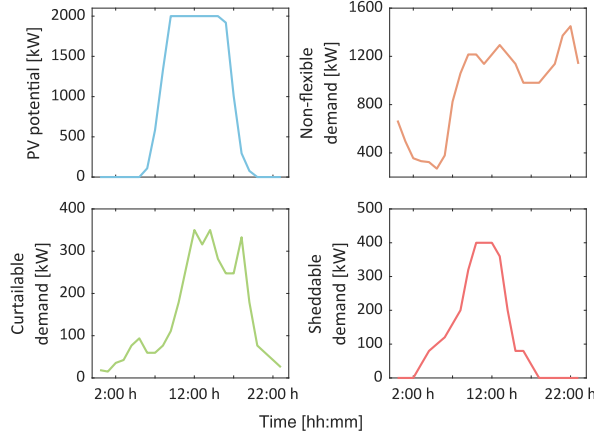


Fig. 3 - Expected profiles for renewable generation and demand

We considered two sources of uncertainties. On the one hand, the PV potential is uncertain because weather parameters cannot be predicted with total accuracy. On the other hand, the non-flexible demand, which is determined on the basis of unpredictable human decisions. To determine the upper and lower bounds of the non-controllable demand (necessary for uncertain constraints (19)), we imposed 20 % confidence intervals on predicted profiles. Lastly, curtable demand has been considered deterministic as it is normally agreed between consumers and operator. Nevertheless, these parameters could be considered unknown following the same models considered for renewable generation and non-flexible demand.

The MG under study is also equipped with microturbines as backup generators. The relevant data of these units are collected in Table 2. On the other hand, Table 3 collects the data referred to the hydrogen chain, which encompasses electrolysers, hydrogen storage and FCs.

Table 2 - Microturbines data [32, 36]

Parameter	Value
$\bar{p}^{MT}/\underline{p}^{MT}$	2500/200 kW
c^{MT}	1.5 \$/kWh
k^{MT}	340 \$/kW
K^{MT}	30,000 hours

Table 3 - Hydrogen chain data [4, 32]

Parameter	Value	Parameter	Value
\bar{p}^Z/\bar{p}^{FC}	750/750 kW	m^Z/m^{FC}	0.03/0.03 \$/kWh
$\underline{p}^Z/\underline{p}^{FC}$	25/25 kW	q^Z/q^{FC}	0.15/0.02 \$
η^Z/η^{FC}	0.65/0.77	$\underline{SOP}^{HSS}/\overline{SOP}^{HSS}$	2/10 bar
k^Z/k^{FC}	8.5/32 \$/kW	Υ	0.52
K^Z/K^{FC}	10,000/10,000 hours	LHV	39.72 kWh/kg

4.2 - Cases studied

This Section is thus devoted on studying an isolated MG such as that described in Section 2, encompassing hydrogen storage and enabling a variety of Dr programs such as sheddable and curtable loads. To this end, we aim at validating the developed

scheduling tool but also to analyse the role of hydrogen storage and DR programs in such networks. To address the latter objective, three cases are analysed, whose main characteristics are summarized below:

- Case 1: it corresponds with the most unfavourable case in which the hydrogen chain is not installed and DR is disabled. In this regard, curtailable and sheddable demands must be totally satisfied and all the demand could be considered inelastic. Under these circumstances, the flexibility of the system is low and storage capacity null, disabling the capability of energy arbitrage and surplus renewable management.
- Case 2: it is identical to the Case 1 but enabling DR. Thereby, although no storage is deployed, the MG can benefit from some flexibility provided by DR initiatives. In this sense, sheddable and curtailable consumers can adapt their consumption profiles for convenience, receiving a compensatory payment for their services.
- Case 3: it corresponds with the most favourable case considering full capabilities of the hydrogen chain and DR initiatives. Thus, this case is more favourable than the previous one since, under these circumstances, the MG can benefit from hydrogen storage and DR initiatives.

4.3 - Evaluating the effect of the uncertainty budget

Firstly, we study the effect of the uncertainty budget on the objective function and uncertain inputs. In this regard, Fig. 4 reports the total operational costs (objective function) for the different cases studied and values of the uncertainty budgets. As expected, the Case 3 supposes the most favourable conditions for MG operation, exploiting fully flexibility offered by the hydrogen chain and flexible consumers. Nevertheless, the monetary savings compared with the Case 2 were marginal, indicating that DR has a more direct impact on the monetary balance. In particular, the objective function was reduced by approximately 6 % and 9 % in the cases 2 and 3 when comparing with the Case 1, respectively.

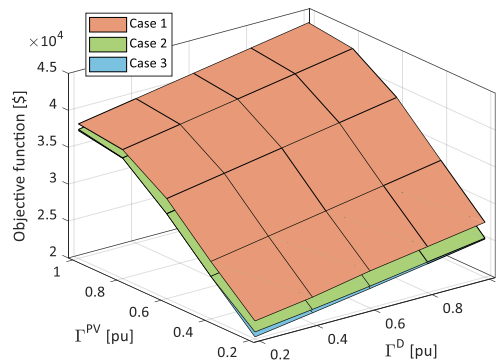


Fig. 4 - Objective function for different uncertainty budgets

In Fig. 4 it can be also studied the effect of the uncertainty budget. As seen, the total expenditures grow with both uncertainty budgets, but most notably when the PV potential is affected. Actually, the objective function increased by 41 % when Γ^{PV} grew from 0.2 to 1. In contrast, the objective function increased by 18 % in case of varying Γ^D . To better explain these results, let us analyse Fig. 5, where the PV potential and non-flexible demand are plotted for different uncertainty budgets (marginal differences among cases

were encountered when observing these indicators). As seen, the effect of uncertainties is much more notable in the PV potential, which was reduced by 76 % when Γ^{PV} increased, while the non-flexible demand grew by 17 %. This is explained in the fact that the considered uncertainty modelling considers possible failure of components, as explained in [36]. Indeed, the uncertainty modelling assumes a ~ 400 kW generation loss with $\Gamma^{PV} \geq 0.6$, which has a critical impact on the economy of the system. Note that this feature of the considered uncertainty modelling can be disabled by forcing the upper bound of the PV potential to be equal to the installed capacity. However, we preferred showing all the capabilities of the model. It is also worth noting that both uncertainties evolved in a risk-averse perspective when the uncertainty budgets increased, as expected.

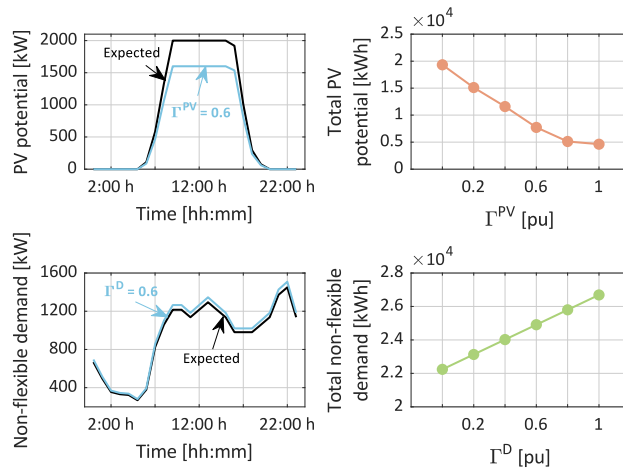


Fig. 5 - Analysis of the PV potential and non-flexible demand for different uncertainty budgets

4.4 - Evaluating the behaviour of the hydrogen chain

Next, we focus on the role and behaviour of the hydrogen chain, composed by electrolysers, storage and FCs. First of all, let us analyse the logical scheduling plan following by the hydrogen-based components, which is shown in Fig. 6 (only results with deterministic conditions were plotted to facilitate their analysis). As observed, FC was operated at night, exploiting the hydrogen stored at the beginning of the time horizon. During this period, the hydrogen vessels were discharged to their lower limit, to be posteriorly charged at evening. At this time, two favourable circumstances coincide; on the one hand, the PV potential is still high being thus exploitable by electrolysers; on the other hand, non-flexible demand is eventually low due to the afternoon valley period (see Fig. 5). Note that this is a logical procedure normally followed by other storage technologies like batteries [7]. However, it is important to note that, while batteries are frequently called to partake in the system, the hydrogen chain is only scheduled occasionally, due to its lower overall efficiency.

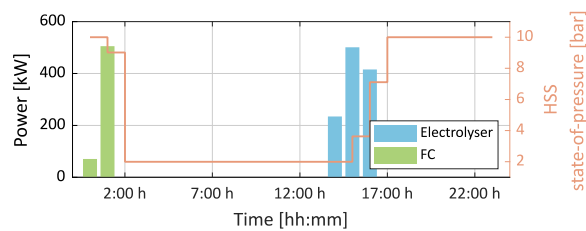


Fig. 6 - Scheduling result for the hydrogen chain under deterministic conditions

To better understand the role of the hydrogen chain, let us analyse Fig. 7, where the scheduling result for MG assets in the cases 2 (without hydrogen chain) and 3 (with hydrogen chain) are plotted. As seen, electrical generation from FCs allowed to disconnect backup generation at 1:00 h, while the energy supplied to electrolyzers totally proceeded from PV plants at evening. Thus, the hydrogen chain allowed to reduce the total expensive backup generation, as shown in Fig. 8. Indeed, the total backup generation was reduced by 20 % when comparing the cases 1 and 3. Nevertheless, DR has a more direct impact on this indicator, as seen in Fig. 8 and commented in the following sub-section.

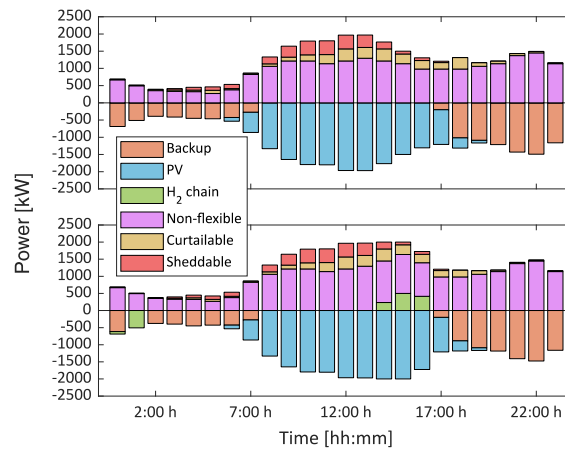


Fig. 7 - Scheduling result in the cases 2 (upper) and 3 (bottom) under deterministic conditions (negative power indicates generation)

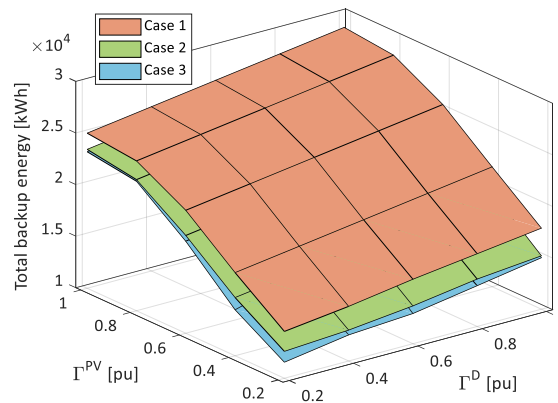


Fig. 8 - Total backup generation for different uncertainty budgets

In Fig. 8, one can also observe the effect of the uncertainty budget on total backup generation. As appreciated, the objective function was quite proportional to the backup generation, thus indicating that the fuel cost supposed the main expenditure in the study MG. In Fig. 8 it is also observed that differences between the cases 2 and 3 became minimal when the uncertainty budget increased. To better understand this result, Fig. 9 plots the total energy consumed/generated by electrolyzers/FCs for different uncertainty budgets. As seen, the hydrogen chain was only exploited with low uncertainty budgets, indicating almost deterministic conditions. As the effect of uncertainties becomes critical, the energy devoted on operating the hydrogen chain fell to zero. Thereby, the cases 2 and

3 became identical under robust conditions, as deduced in Fig. 8. Note that this is a logical result since electrolyzers were mainly exploited at evening, taking advantage of high PV generation. If renewable potential is assumed to be reduced, the use of the hydrogen chain becomes uneconomic because low efficiencies of current electrolysis and FC technologies [48]. Nevertheless, it is important to note that hydrogen chain may be more profitable under risk-seeker strategies. This is due to pessimistic conditions were assumed in this paper and thus low PV potential is expected as the uncertainty budget increases. Under these conditions, electrolyzers cannot exploit surplus renewable generation. In contrast, risk-seeker conditions assume optimistic values of uncertainties thus resulting in a more economic operation of the hydrogen chain and the entire system, as pointed out in [32].

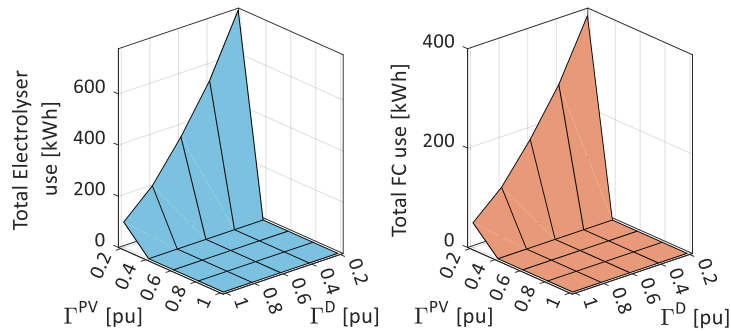


Fig. 9 - Total energy consumed/generated by electrolyzers/FCs for different uncertainty budgets

4.5 - Evaluating the impact of DR initiatives

Next, we evaluate the impact of DR initiatives. In this regard, we considered two kind of flexible demand, namely curtailable and sheddable loads, as explained in Section 2.1. Some important conclusions can be extracted from previous results. Indeed, in Fig. 4 it was observed that DR initiatives has a high impact on the economy of the system, being able to reduce the total operational cost by 6 % while a reduction of 3 % was only achieved by further including the hydrogen chain in the system. Similar conclusions were extracted after analysing Fig. 8, since the objective function resulted quite proportional to the total backup generation. Thus, we can conclude that DR has a higher impact on monetary savings than the hydrogen chain although, obviously, the best results were obtained when both facilities are enabled.

Therefore, we now focus rather on the impact of uncertainty in flexible consumers. In this regard, Fig. 10 shows the curtailable demand satisfied (in percentage) and total shedding hours for different uncertainty budgets. To facilitate the analysis, we only reported variation for $\Gamma^{PV} = \Gamma^D$. Regarding the total curtailable demand satisfied, it decreased with the uncertain level, as expected, since more unfavourable conditions are assumed when the uncertainty budget increased. Similar conclusions can be observed for the sheddable loads. Nevertheless, the effect is less appreciable on these consumers, just incrementing their response by 1-h when the uncertainty levels increased from 0.2 to 0.4 p.u. in the Case 2.

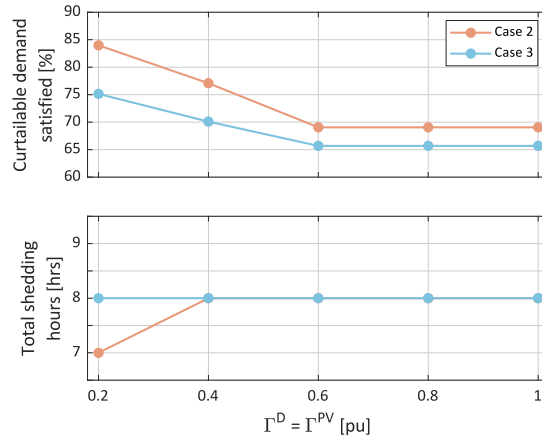


Fig. 10 - Total curtailable demand satisfied (upper) and shedding hours (bottom) for different uncertainty budgets

However, it is worth noting that worse results were obtained in the Case 3. It means that enabling the hydrogen chain might be, a priori, harmed to flexible consumers. This result may seem uncoherent. Nevertheless, it presents a simple interpretation. Indeed, the MG is operated with the aim of minimizing the total operation cost. Thus, when the hydrogen chain was enabled, electrolyzers were mainly operated at evening (see Fig. 7). This way, PV generation was further dedicated to supply electrolyzers rather than flexible consumers. From a pure economic point of view, this operational principle resulted more profitable for the MG operator, since the inclusion of the hydrogen chain allowed to reduce total backup generation. However, other factors should be taken into account, like the undesirable effects of response fatigue [49]. This issue will be considered in future works.

4.6 - Sensitivity analysis

Now, we provide a sensitivity analysis in order to show how the size of the hydrogen chain affects to the monetary balance of the system. To this end, the energy management problem was solved under deterministic conditions for various electrolyser/FC rated powers ranging from 0 to 1000 kW. Under such conditions, the value of the objective function is plotted in Fig. 11. To better analyse these results, the capital costs associated to the hydrogen chain were subtracted to the final value of the objective function. As seen in Fig. 11, the operation cost drastically reduced when the hydrogen chain is enabled (note that case with 0 kW installed is equivalent to ignore the hydrogen chain), thus demonstrating that the use of hydrogen storage in this kind of installations may result in substantial monetary savings. However, the cos reduction is actually marginal beyond 500 kW. This result evidences the necessity of optimally planning this kind of installations. This topic will be studied in future works.

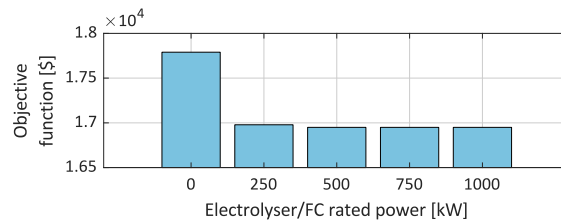


Fig. 10 - The value of the objective function under deterministic conditions and different sizes of the hydrogen chain

4.7 - Comparison with scenario-based approaches

Lastly, we present a comparison of the proposed robust methodology with conventional scenario-based approaches, such as stochastic programming [17]. To this end, a large number of scenarios for uncertainties were generated taking the same intervals considered in previous simulations. Then, the number of scenarios was reduced using the procedure described in [45]. Under these settings, the objective function obtained was compared with the proposed procedure in Fig. 11. As seen, our methodology is able to consider more pessimistic conditions. This is due to stochastic approaches consider all the possible realization of uncertainties, instead of seeking for the worst-case possible. On the other hand, computational burden of the stochastic approach was considerably higher, as shown in Fig. 12. This is because scenario-based approaches extend the variable space to the number of scenarios, which inevitably increment the computational cost of the optimization framework. It is also worth noting that the proposed procedure is quite efficient, being able to solve the case study in less than a minute. In this regard, considering uncertainties within the developed framework does not suppose a considerable extra effort when compared with the deterministic case.

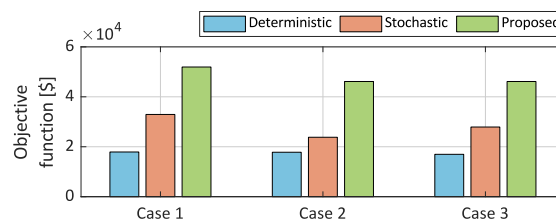


Fig. 11 - Comparison of the objective function assuming deterministic, stochastic or risk-averse (proposed) conditions

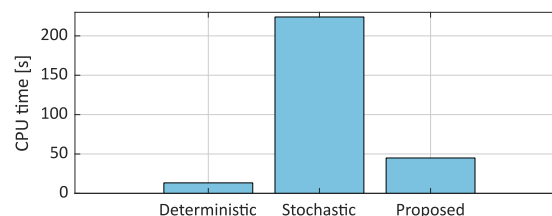


Fig. 12 - Comparison of the total CPU time assuming deterministic, stochastic or risk-averse (proposed) schemes

5 - Concluding remarks

A robust energy management methodology for isolated MGs including hydrogen storage and DR initiatives has been developed. The new proposal was raised as a max-min nested framework, which seeks for minimizing costs under worst-case realization of

uncertainties. To reduce the problem to a single-level framework tractable by off-the-shelf solvers, an original master-slave procedure has been presented, by which the value of binary variables is fixed and thus the inner problem can be reduced to its KKT conditions. Then, the overall framework is solved in an iterative fashion using the C&CGA.

The new tool was profusely tested on a benchmark isolated MG. The results obtained allow us to validate the developed methodology, thus resulting a valuable contribution for MG operation. In addition, we analysed the results obtained in depth with the aim of discussing the role of hydrogen storage and DR initiatives in MG operation. One of the most relevant conclusions are numerated below:

- Both DR initiatives and hydrogen storage had a positive impact on MG operation, reducing the total costs by 6 % and 9 % respectively. However, the impact of DR programs is notably higher.
- The level of uncertainty critically affects to the operation of the hydrogen chain, which resulted few profitable under robust conditions. In this regard, this facility was only exploited under deterministic assumptions, when renewable generation is high.
- The inclusion of hydrogen storage may be counterproductive for flexible consumers, who were more frequently called to provide the necessary flexibility for hydrogen production.

Given the good characteristics of the new proposal, we expect applying it to other similar tools like smart home schedulers. Moreover, results obtained here will be confirmed and further analysed over planning horizons.

References

- [1] European Commission. 2050 long-term strategy. Online, available at: https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2050-long-term-strategy_en, (accessed on Feb. 3, 2023).
- [2] Y. Song, M. Xia, Q. Chen, F. Chen. A data-model fusion dispatch strategy for the building energy flexibility based on the digital twin. *Applied Energy* 2023; 332: 120496. <https://doi.org/10.1016/j.apenergy.2022.120496>.
- [3] R. Masiello, R. Fioravanti, B. Chalamala, H. Passell. Electrification, decarbonization, and the future carbon-free grid: the role of energy storage in the electric grid infrastructure [point of view]. *Proceedings of the IEEE* 2022; 110(3): 324-33. <https://doi.org/10.1109/JPROC.2022.3146843>.
- [4] M. Tostado-Véliz, S.A. Mansouri, A. Rezaee-Jordehi, D. Icaza-Alvarez, F. Jurado. Information Gap Decision Theory-based day-ahead scheduling of energy communities with collective hydrogen chain. *International Journal of Hydrogen Energy* 2022 (In press). <https://doi.org/10.1016/j.ijhydene.2022.11.183>.
- [5] B. Zakeri, S. Syri. Electrical energy storage systems: A comparative life cycle cost analysis. *Renewable and Sustainable Energy Reviews* 2015; 42: 569-96. <https://doi.org/10.1016/j.rser.2014.10.011>.
- [6] M. McCullough. *Downtime on the Microgrid - Architecture, Electricity, and Smart City Islands*. Cambridge, MA: The MIT Press; 2020. <https://doi.org/10.7551/mitpress/11953.001.0001>.
- [7] M. Tostado-Véliz, S. Kamel, F. Aymen, A.R. Jordehi, F. Jurado. A Stochastic-IGDT model for energy management in isolated microgrids considering failures and demand response. *Applied Energy* 2022; 317: 119162. <https://doi.org/10.1016/j.apenergy.2022.119162>.
- [8] Y. Han, G. Zhang, Q. Li, Z. You, W. Chen, H. Liu. Hierarchical energy management for PV/hydrogen/battery island DC microgrid. *International Journal of Hydrogen Energy* 2019; 44(11): 5507-16. <https://doi.org/10.1016/j.ijhydene.2018.08.135>.
- [9] H. Pashaei-Didani, S. Nojavan, R. Nourollahi, K. Zare. Optimal economic-emission performance of fuel cell/CHP/storage based microgrid. *International Journal of Hydrogen Energy* 2019; 44(13): 6896-908. <https://doi.org/10.1016/j.ijhydene.2019.01.201>.

- [10] H. Mehrjerdi. Off-grid solar powered charging station for electric and hydrogen vehicles including fuel cell and hydrogen storage. *International Journal of Hydrogen Energy* 2019; 44(23): 11574-83. <https://doi.org/10.1016/j.ijhydene.2019.03.158>.
- [11] B. Li, H. Miao, J. Li. Multiple hydrogen-based hybrid storage systems operation for microgrids: A combined TOPSIS and model predictive control methodology. *Applied Energy* 2021; 283: 116303. <https://doi.org/10.1016/j.apenergy.2020.116303>.
- [12] J. Liu, X. Cao, Z. Xu, X. Guan, X. Dong, C. Wang. Resilient operation of multi-energy industrial park based on integrated hydrogen-electricity-heat microgrids. *International Journal of Hydrogen Energy* 2021; 46(57): 28855-69. <https://doi.org/10.1016/j.ijhydene.2020.11.229>.
- [13] Y. Xie, Y. Ueda, M. Sugiyama. Greedy energy management strategy and sizing method for a stand-alone microgrid with hydrogen storage. *Journal of Energy Storage* 2021; 44(B): 103406. <https://doi.org/10.1016/j.est.2021.103406>.
- [14] X. Fang, W. Dong, Y. Wang, Q. Yang. Multiple time-scale energy management strategy for a hydrogen-based multi-energy microgrid. *Applied Energy* 2022; 328: 120195. <https://doi.org/10.1016/j.apenergy.2022.120195>.
- [15] A.M. Abomazid, N.A. El-Taweel, H.E.Z. Farag. Optimal Energy Management of Hydrogen Energy Facility Using Integrated Battery Energy Storage and Solar Photovoltaic Systems. *IEEE Transactions on Sustainable Energy* 2022; 13(3): 1457-68. <https://doi.org/10.1109/TSTE.2022.3161891>.
- [16] S.A. Konstantinopoulos, A.G. Anastasiadis, G.A. Vokas, G.P. Kondylis, A. Polyzakis. Optimal management of hydrogen storage in stochastic smart microgrid operation. *International Journal of Hydrogen Energy* 2018; 43(1): 490-9. <https://doi.org/10.1016/j.ijhydene.2017.06.116>.
- [17] M.A. Mirzaei, A.S. Yazdankhah, B. Mohammadi-Ivatloo. Stochastic security-constrained operation of wind and hydrogen energy storage systems integrated with price-based demand response. *International Journal of Hydrogen Energy* 2019; 44(27): 14217-27. <https://doi.org/10.1016/j.ijhydene.2018.12.054>.
- [18] D. Zhu, et al. Energy trading in microgrids for synergies among electricity, hydrogen and heat networks. *Applied Energy* 2020; 272: 115225. <https://doi.org/10.1016/j.apenergy.2020.115225>.
- [19] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, S. Asadi. Transactive energy management for optimal scheduling of interconnected microgrids with hydrogen energy storage. *International Journal of Hydrogen Energy* 2021; 46(30): 16267-78. <https://doi.org/10.1016/j.ijhydene.2020.09.064>.
- [20] M. Shi, H. Wang, C. Lyu, P. Xie, Z. Xu, Y. Jia. A hybrid model of energy scheduling for integrated multi-energy microgrid with hydrogen and heat storage system. *Energy Reports* 2021; 7(6): 357-68. <https://doi.org/10.1016/j.egyr.2021.08.037>.
- [21] H. Eskandari, M. Kiani, M. Zadehbagheri, T. Nikman. Optimal scheduling of storage device, renewable resources and hydrogen storage in combined heat and power microgrids in the presence plug-in hybrid electric vehicles and their charging demand. *Journal of Energy Storage* 2022; 50: 104558. <https://doi.org/10.1016/j.est.2022.104558>.
- [22] N. Rezaei, Y. Pezhmani. Optimal islanding operation of hydrogen integrated multi-microgrids considering uncertainty and unexpected outages. *Journal of Energy Storage* 2022; 49: 104142. <https://doi.org/10.1016/j.est.2022.104142>.
- [23] S.M. Tatar, H. Akulker, H. Sildir, E. Aydin. Optimal design and operation of integrated microgrids under intermittent renewable energy sources coupled with green hydrogen and demand scenarios. *International Journal of Hydrogen Energy* 2022; 47(65): 27848-65. <https://doi.org/10.1016/j.ijhydene.2022.06.130>.
- [24] V. Khaligh, A. Ghezelbash, M. Mazidi, J. Liu, J.-H. Ryu, J. Na. A stochastic agent-based cooperative scheduling model of a multi-vector microgrid including electricity, hydrogen, and gas sectors. *Journal of Power Sources* 2022; 546: 231989. <https://doi.org/10.1016/j.jpowsour.2022.231989>.
- [25] X. Wu, S. Qi, Z. Wang, C. Duan, X. Wang, F. Li. Optimal scheduling for microgrids with hydrogen fueling stations considering uncertainty using data-driven approach. *Applied Energy* 2019; 253: 113568. <https://doi.org/10.1016/j.apenergy.2019.113568>.
- [26] M. Bornapour, R. Hemmati, M. Pourbehzadi, A. Dastranj, T. Nikman. Probabilistic optimal coordinated planning of molten carbonate fuel cell-CHP and renewable energy sources in microgrids considering hydrogen storage with point estimate method. *Energy Conversion & Management* 2020; 206: 112495. <https://doi.org/10.1016/j.enconman.2020.112495>.
- [27] A.S.G. Langeroudi, M. Sedaghat, S. Pirpoor, R. Fotouhi, M.A. Ghasemi. Risk-based optimal operation of power, heat and hydrogen-based microgrid considering a plug-in electric vehicle.

- International Journal of Hydrogen Energy* 2021; 46(58): 30031-47. <https://doi.org/10.1016/j.ijhydene.2021.06.062>.
- [28] F. Alavi, E.P. Lee, N. van de Wouw, B. De Schutter, Z. Lukszo. Fuel cell cars in a microgrid for synergies between hydrogen and electricity networks. *Applied Energy* 2017; 192: 296-304. <https://doi.org/10.1016/j.apenergy.2016.10.084>.
- [29] S. Nojavan, A. Akbari-Dibavar, A. Farahmad-Zahed, K. Zare. Risk-constrained scheduling of a CHP-based microgrid including hydrogen energy storage using robust optimization approach. *International Journal of Hydrogen Energy* 2020; 45(56): 32269-84. <https://doi.org/10.1016/j.ijhydene.2020.08.227>.
- [30] A. Mansour-Saatloo, et al. Multi-objective IGDT-based scheduling of low-carbon multi-energy microgrids integrated with hydrogen refueling stations and electric vehicle parking lots. *Sustainable Cities & Society* 2021; 74: 103197. <https://doi.org/10.1016/j.scs.2021.103197>.
- [31] F. Fan, R. Zhang, Y. Xu, S. Ren. Robustly Coordinated Operation of an Emission-free Microgrid with Hybrid Hydrogen-battery Energy Storage. *CSEE Journal of Power and Energy Systems* 2022; 8(2): 369-79. <https://doi.org/10.17775/CSEEJPES.2021.04200>.
- [32] M. Tostado-Véliz, S. Kamel, H.M. Hasanién, R.A. Turky, F. Jurado. A mixed-integer-linear-logical programming interval-based model for optimal scheduling of isolated microgrids with green hydrogen-based storage considering demand response. *Journal of Energy Storage* 2022; 48: 104028. <https://doi.org/10.1016/j.est.2022.104028>.
- [33] A. Mobasserí, M. Tostado-Véliz, A.A. Ghadimi, M.R. Miveh, F. Jurado. Multi-energy microgrid optimal operation with integrated power to gas technology considering uncertainties. *Journal of Cleaner Production* 2022; 333: 130174. <https://doi.org/10.1016/j.jclepro.2021.130174>.
- [34] Y.-P. Xu, R.-H. Liu, L.-Y. Tang, H. Wu, C. She. Risk-averse multi-objective optimization of multi-energy microgrids integrated with power-to-hydrogen technology, electric vehicles and data center under a hybrid robust-stochastic technique. *Sustainable Cities & Society* 2022; 79: 103699. <https://doi.org/10.1016/j.scs.2022.103699>.
- [35] M. Tostado-Véliz, A.A. Ghadimi, M.R. Miveh, M. Bayat, F. Jurado. Uncertainty-aware energy management strategies for PV-assisted refuelling stations with onsite hydrogen generation. *Journal of Cleaner Production* 2022; 365: 132869. <https://doi.org/10.1016/j.jclepro.2022.132869>.
- [36] C. Ruiz, A.J. Conejo. Robust transmission expansion planning. *European Journal of Operational Research* 2015; 242(2): 390-401. <https://doi.org/10.1016/j.ejor.2014.10.030>.
- [37] R. Jiang, J. Wang, M. Zhang, Y. Guan. Two-Stage Minimax Regret Robust Unit Commitment. *IEEE Transactions on Power Systems* 2013; 28(3): 2271-82. <https://doi.org/10.1109/TPWRS.2013.2250530>.
- [38] B. Zheng, L. Zhao. Solving two-stage robust optimization problems using a column-and-constraint generation method. *Operations Research Letters* 2013; 41(5): 457-61. <https://doi.org/10.1016/j.orl.2013.05.003>.
- [39] M.M. Lakouraj, H. Niaz, J.J. Liu, P. Siano, A. Anvari-Moghaddam. Optimal risk-constrained stochastic scheduling of microgrids with hydrogen vehicles in real-time and day-ahead markets. *Journal of Cleaner Production* 2021; 318: 128452. <https://doi.org/10.1016/j.jclepro.2021.128452>.
- [40] A. Khodaei, S. Bahramirad, M. Shahidehpour. Microgrid Planning Under Uncertainty. *IEEE Transactions on Power Systems* 2015; 30(5): 2417-25. <https://doi.org/10.1109/TPWRS.2014.2361094>.
- [41] D. Bertsimas, E. Litvinov, X.A. Sun, J. Zhao, T. Zheng. Adaptive Robust Optimization for the Security Constrained Unit Commitment Problem. *IEEE Transactions on Power Systems* 2013; 28(1): 52-63. <https://doi.org/10.1109/TPWRS.2012.2205021>.
- [42] Y. Li, B. Feng, B. Wang, S. Sun. Joint planning of distributed generations and energy storage in active distribution networks: A Bi-Level programming approach. *Energy* 2022; 245: 123226. <https://doi.org/10.1016/j.energy.2022.123226>.
- [43] J. Fortuny-Amat, B. McCarl. A representation and economic interpretation of a two-level programming problem. *Journal Operation Research Society* 1981; 32(9): 783-92. <https://doi.org/10.1057/jors.1981.156>.
- [44] Gurobi Optimization L.L.C. Gurobi Optimizer Reference Manual, 2021. Online, available at: <https://www.gurobi.com>, (accessed on Feb. 8, 2023).
- [45] M. Tostado-Véliz, A.R. Jordehi, S.A. Mansouri, F. Jurado. Day-ahead scheduling of 100% isolated communities under uncertainties through a novel stochastic-robust model. *Applied Energy* 2022; 328: 120257. <https://doi.org/10.1016/j.apenergy.2022.120257>.

- [46] European Comission. Photovoltaic Geographical Information System. Online, available at: https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html, (accessed on Feb. 8, 2023).
- [47] Red Eléctrica de España. 2021 Canary electricity demand in real-time. Online available at: <https://www.ree.es/en/activities/canary-islands-electricity-system/canary-electricity-demand-in-real-time>, (accessed on Feb. 8, 2023).
- [48] IRENA. Green Hydrogen Cost Reduction: Scaling up Electrolysers to meet the 1.5 °C Climate Goal. 2020. Online, available at: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Dec/IRENA_Green_hydrogen_cost_2020.pdf, (accessed on Feb. 8, 2023).
- [49] M. Tostado-Véliz, S. Kamel, H.M. Hasanien, R.A. Turky, F. Jurado. Uncertainty-aware day-ahead scheduling of microgrids considering response fatigue: An IGDT approach. *Applied Energy* 2022; 310: 118611. <https://doi.org/10.1016/j.apenergy.2022.118611>.