Uncertainty-Aware Day-Ahead Scheduling of Microgrids considering Response Fatigue: an IGDT Approach

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Abstract - The implantation of demand response programs may be unsuccessful due to a variety of reasons. One of the most important is the so-called response fatigue, which refers to the discouragement experienced by consumers when they received an excessive number of signals from the operator. This circumstance is, however, typically ignored in energy management tools of electrical energy systems. To solve this issue, this paper proposes an uncertainty-aware day-ahead optimal scheduling tool for grid-connected microgrids based on information gap decision theory, which incorporates additional constraints to bound the duration of demand response signals. Thereby, the harmful effects caused by response fatigue are lessened. The developed optimization problem is formulated as a Mixed-Integer-Linear programming, which is solvable using standard solvers and versatile enough to be adapted to different system layouts. A benchmark case study serves to show the effectiveness of the developed methodology to manage with uncertainties, while the effect of response fatigue in consumers is bounded to acceptable thresholds. As a sake of example, the developed methodology is able to determine a scheduling plan with a total renewable generation 50% lower compared with the deterministic case, while the total demand is overestimated by ~20%, in which the effect of response fatigue is kept within acceptable bounds yet. Accurateness and efficiency of the new proposal are also checked by making a comparison with other uncertainties modelling.

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Nomenclature

Acronyms

MG	Microgrid
DR	Demand response
PV	Photovoltaic
WG	Wind generator
SOC	State-of-charge
MILP	Mixed-integer linear programming
IGDT	Information gap decision theory
WT	Wind turbine
BES	Battery energy storage
SOS1	Special ordered set 1

Indexes (Sets)

$t(\mathcal{T})$	Time
$s(\mathcal{S})$	Sheddable consumer
$c(\mathcal{C})$	Curtailable consumer
$\Omega^{-/+}$	Set of favourable/unfavourable uncertainties ($\Omega = \Omega^- \cup \Omega^+$)

Superscripts/Functions

$Buy/Sell$	Purchased/sold energy from/to the upstream grid
PV	Photovoltaic units
WG	Wind generation units
$BES, ch/dch$	Battery energy storage in charging/discharging mode
LD	Local demand
$\overline{(*)}/\underline{(*)}$	Maximum/minimum value of a variable or parameter

$\widetilde{(*)}$	Uncertain parameter
$\mathrm{E}(*)$	Expected value of an uncertain parameter

Parameters

$\Delta\tau$	Time step (h)
λ	Energy cost ($/kWh)
σ	Cost of DR programs ($/h or $/kWh)
R	Ramp rate limit (kW)
η	Efficiency (pu)
ϑ	Solar irradiation (kW/m^2)
θ	Temperature (ºC)
γ	Wind speed (m/s)
a, b	Coefficients of the speed-power curve of a wind turbine ($kW/(m/s)^3$, -)
α	Uncertain radius (pu)

Variables (deterministic)

p	Power (kW)
u	Commitment status (Binary)
ε	Energy stored (kWh)

Vectors/matrix notation

$\boldsymbol{v}$	Vector of continuous decision variables
$\boldsymbol{u}$	Vector of binary decision variables
$\mathbf{A}$	Matrix of uncertain radiuses
$\mathbf{\Delta}$	Vector of margins of increase

Linearization of nonlinear terms (further information is provided in formulation)

M	Large positive number ($\sim 10^6$)

n_1, n_2	Number of divisions (segments) of piecewise representation of nonlinear terms
s, x, y	Generic continuous variables
ϱ	Generic integer variable
$\hat{q}, \hat{x}, \hat{y}$	Grid-points of piecewise representation of nonlinear terms
ξ, ζ, ς	SOS1 variables for piecewise representation of nonlinear terms
$\delta_{\hat{x}_i}, \delta_{y_i}, \delta_z$	Continuous variables for piecewise representation of nonlinear terms
β, z	Dummy linear variables to replace nonlinear terms

1 - Introduction

1.1 - Context and motivation

With the increasing interest in decarbonizing energy systems, microgrids (MGs) have emerged as an invaluable framework for massive integration of renewable sources and storage facilities [1, 2]. From an operational point of view, a MG is an autonomous small-scale electrical system with the capability of being operated in grid-connected or isolated modes [3]. In the case of MGs, optimal scheduling of on-site assets is of vital importance to reach an efficient operation of the system [4]. In this regard, MG operators may also recur to the active participation of final consumers, in order to enable a higher degree of flexibility and therefore being able to improve economic and environmental results [5].

To encourage the active participation of consumers in grid operation, system operators are putting into practice a variety of demand-response (DR) programs, by which the customers are heartened to modify their consumption routines on the basis of price or incentive-based signals [6]. The capability of DR programs on incrementing the flexibility of grid operation and thus enabling a more efficient and reliable management of available resources, has been well reported in various references [7, 8]. However, there are numerous reasons by which the implantation of a DR initiative may result unsuccessful [9, 10]. One of them is the so-called response fatigue [11], which refers to the discouragement experienced by consumers when they received an excessive number of DR signals from the operator. Thereby, customers may be reluctant to adopt DR initiatives, if this entails a large number of actions from their side. In this sense, MG operators should take into account the effects of response fatigue in their operating plans. In particular, this task becomes a challenge if the uncertain behaviour of demand and renewable sources is considered, which requires the use of robust specific tools [12]. This paper is focused on this issue.

1.2 - Literature review

Recently, various works have dealt with the optimal operation of MGs in presence of DR programs. In [13], a stochastic programming tool for day-ahead energy management of a rural isolated MG was developed. In this case, the grid incorporates a pumped-hydro storage unit to manage with the intermittent nature of photovoltaic (PV) and wind generators (WGs), however, this reference only contemplates incentive-based DR programs, thus neglecting the possible flexibility provided by incentive-based initiatives. Similarly, the authors of [14], proposed an energy management tool for a MG in both isolated and grid-connected modes, in which only price-based DR initiatives were modelled and the influence of other kind of flexibilities were not fully considered. The considered system comprises various electric and thermal loads and generators in combination with DR programs. Uncertainties in generation and energy pricing are treated via stochastic programming, incorporating a scenario-reduction stage for alleviating the computational cost of the optimization problem. In [15], the authors developed a methodology for energy management of a grid-connected MG in presence of uncertainties. An improved incentive-based DR mechanism was proposed to better balance generation-consumption profiles while the uncertainties were modelled through stochastic programming and copula functions. The scheduling problem was formulated as a bi-objective optimization problem. To solve the optimization problem, the authors used the Multi-objective Group Search Optimizer, which is a metaheuristic technique that are normally more rigid than linear formulations. The references above use stochastic-based approaches to model uncertainties, which are computationally expensive [3].

However, other models do not proper model the effect of uncertainties, like the fully decentralized energy management system for MGs presented in [16]. This approach is suitable for systems with high renewable penetration and DR, in which various agents must participate in a coordinated way. To this end, a game-based solution framework is developed, by which the Nash equilibrium point is found. Ali, et al [17] addressed the problem of multi-MG optimization in the absence of market price signals (islanded mode). Since in this case DR programs cannot be triggered by price signals, the authors proposed a DR mechanism that it is based on welfare maximization rather than price-based programs. Thereby, the potential surplus generated in each MG is shared among the other systems, which may suffer from shortage issues. In [18], a multi-objective optimization approach for energy management of grid-connected MGs was proposed. The optimization model encompasses the minimization of the operating cost and the maximization of the utility benefit, by which the confidence-based velocity-controlled particle swarm optimization is combined with a fuzzy-clustering technique to find the best compromise operating solution. The problem also incorporates an incentive-based DR program, which aims at attracting more participants at peak load hours.

The reference [19] proposed to jointly use energy storage and DR to manage with uncertain in MG operation. To this end, uncertainty associated with demand and market price was treated with point-estimation techniques, while DR programs incorporate both price and incentive-based initiatives. The point-estimation methods are actually a kind of stochastic-based approach; therefore, they require a priori knowledge of distribution function of uncertainties, which is not always available [11]. The reference [20] dealt with optimal day-ahead scheduling of islanded MGs considering frequency regulation. To this end, suitable models of controllable and renewable generators were developed. The main aim of the developed tool is meeting the load in islanded mode, thus reducing the non-satisfied demand and improving the MG economy. However, this reference did not directly tackle the problem of uncertainties modelling as well as the DR programs were not considered. Das and Basu [21] developed an optimal bidding strategy for MGs, which consider the high intermittent nature of renewable sources and DR programs. To this end, chaos maps were used to generate scenarios of renewable generation and also possible outages based on probability functions. Despite the number of scenarios is not excessively large, the resulting procedure is still time-consuming. The risk participation in energy markets was also considered by including the conditional value at risk and penalty costs for incorrect estimations. In [22], an integrated tool for optimal dispatching and power quality improvement of a MG was proposed. The developed model considers the optimal scheduling of both generators and loads, which are encouraged to participate in MG operation through DR initiatives. The optimization is performed in two stages, in the first one, the energy management of the grid is addressed, ensuring the demand satisfaction at minimum cost, while in the second one, it is determined if the scheduling result meets some well-established power quality requirements. The reference [23] analysed the effect of DR programs in MG operation, highlighting their ability to shift the peak load to low-price periods and thus enabling the minimization of storage system size. However, these last two references were not focused on uncertainties modelling and therefore failed to analyse the jointly negative effect of DR programs and unknown parameters.

In [24], a two-stage approach for optimal energy management of interconnected MGs was proposed. In the outer level, the information and energy exchange among MGs is attained, while on the inner level, each MG deals with its own scheduling problem in case of being isolated from the rest of the system. A price-based DR program was considered for each MG while a marginal price mechanism was proposed for energy exchange among sub-systems. The uncertainties are treated via stochastic optimization combined with backward scenario reduction techniques, which aims at alleviating the computational cost that is still higher and suffers from the mentioned disadvantages of stochastic programming. The reference [25] proposed an energy management system for MGs considering responsible loads, which are considered to be useful for cost minimization and reliability improvement. The optimization problem is treated as a combinatorial approach using knapsack models and the effect of uncertainties was not studied. A two-stage coordination scheme for MGs was proposed in [26], by which the price-based responsible loads are firstly scheduled with the aim at reducing the operating cost by maximizing the use of renewable sources, then, in the second stage of the approach, energy storage resources are hourly scheduled within previously calculated state-of-charge (SOC) limits. To manage with uncertainties, the problem is formulated using interval optimization. This uncertainties modelling is computationally cheaper than stochastic programming and do not require knowledge about distribution functions of uncertainties, however, interval-based arithmetic may result in redundant constraints and larger variable-spaces, reducing the efficiency of the procedure.

To manage with uncertainty in MG operation, the reference [27] developed an optimization model which combines the elasticity of price-based responsible loads and risk indexes in the optimization procedure. However, the developed formulation does not directly model the uncertain parameters, hence the robustness is simply ensured by overestimating the effect of such variables. In this case, to efficiently deal with nonlinearities of the problem, the authors used metaheuristic techniques to solve the optimization model. Qiu, et al [28] considered adaptive sets to manage with uncertainties in MG operation under DR programs. The uncertainty sets are achieved by the long short-term memory network and modified fuzzy information granulation. To manage with nonlinearities, a master-slave solution procedure was developed, which takes advantage of the column and constraint generation algorithm and strong duality theory to formulate the problem in form of Mixed-Integer Lineal Programming (MILP). Although the developed formulation effectively coordinates DR programs with uncertainties, undesirable effects like response fatigue are not considered. In addition, the resulting problem is complex and nonlinear, thus forcing to use heuristic techniques that are frequently less efficient and suffers of local-optimum problems [29]. The reference [30] developed a stochastic approach for optimal energy management of MGs. By this methodology, the scenario space is generated using discretized probability functions, to be posteriorly reduced to a representative set using differential clustering. To solve the problem, a metaheuristic-like solver based on Gaussian regularized particle swarm optimization was considered. Similar to other stochastic-based approaches, this model requires a priori knowledge about distribution functions of the uncertain parameters and presents a high computational burden.

The authors in [31] focused on optimal design of MGs using leveraging blockchain technology. The planning methodology developed in this reference considers the real-time price-based DR programs to achieve a cost-effective solution. Other concerns such as environmental and social premises are also considered, utilizing heuristic-based approaches to solve the optimization model. In [32], DR capabilities of electrical and gas consumers are jointly considered taking into account users’ satisfaction. The benchmark

MG model considers high wind power penetration in coordination with gas units and linking technologies such as Power-to-Gas facilities. In this reference, a theory-based risk measure is presented for assessing the randomness and fuzziness characteristics of uncertain wind power. However, the references above do not deal with the necessary robustness of the scheduling algorithm, thus ignoring the negative effects of over-estimated uncertainties.

The reference [33] proposed a robust optimal scheduling model for a coupled wind-solar-thermal-hydro isolated MG in presence of DR programs. A conditional value at credibility index is introduced to manage with uncertainties of renewable generation while a time-of-use pricing scheme is used for encouraging consumers to shift their consumption to valley hours. In [34], a stochastic multi-objective energy management tool for MGs is considered. The uncertain behaviour of renewable generators is modelled via Montecarlo simulation and the multi-objective function is solved using the augmented epsilon-constraint technique. The references [33] and [34] require generating sufficient scenarios to effectively catch the effect of uncertainties. Also, in the case of [34], the epsilon-constraint algorithm may result computationally prohibitive as the optimization problem has to be solved many times to properly explore the Pareto front. The authors in [35] developed a robust scheduling tool for MGs which exploits chance-constrained programming and sample average approximation to solve multi-criteria optimization problems under uncertainty and DR initiatives. By taking advantage of these techniques, the multi-objective model is converted to a linear simple-objective problem, in which the weight of each objective is optimally tuned. This reference is very sensitive to the value of each individual weight, which however has to be tuned on the basis of heuristic criteria or by the trial and error method. On the other hand, the effects of uncertainties are not properly modelled, assuming perfect forecast information.

1.3 - Contributions

The implantation and influence of DR programs in MG operation has been widely studied in the literature, as reflected the review above. However, there is still a need of considering important factors like the response fatigue in energy management tools. The literature review evidences this gap. In addition, there are other important issues that have motivated this work and are listed below:

- The majority of the related literature is focused on price-based DR programs, while only a few references consider other types of schemes. In addition, the considered DR mechanisms are mainly focused on shifting part of the load to low-price periods using well-known time-of-use pricing schemes, while other possible capabilities have not been well-studied yet.
- In some occasions, uncertain behaviour of renewable generators, load and energy pricing are not well treated or directly ignored. On the other hand, many references consider stochastic optimization, which may be computationally costly even using scenario reduction techniques.
- Important factors like users' satisfaction or response fatigue are not considered in most of the studied literature. As explained before, these issues should be properly considered in MG operation, in order to ensure the successful implantation of DR initiatives.
- Most of the references recur to model simplifications to treat with nonlinearities, while others use heuristic-based approaches, which present various drawbacks compared with analytic techniques (see [29]).

To solve the issues above, this paper develops a novel solution procedure for optimal day-ahead scheduling of grid-connected MGs under uncertainties and DR programs. The major contribution of the new proposal is the inclusion of limitations in DR signals, with the aim of bounding the effects of response fatigue. An original two-stage solution procedure based on Information Gap Decision Theory (IGDT) is established to this end. The proposed solution scheme is able to find a robust scheduling solution of MGs, reducing the impact of uncertainties introduced by renewable generation, load and energy pricing, while some premises like duration of DR signals and operating cost are taking into account. Thereby, both uncertainties and response fatigue are jointly tackled, thus posing an effective energy management tool for MGs in which the importance of DR programs is high. To highlight the contributions of this paper, Table 1 reports a comparison among the present paper and other selected references. which are listed for simplicity below:

- The developed optimization model effectively addresses nonlinearities by introducing additional variables and constraints. This way, the new proposal is formulated as a MILP problem, without needing further simplifications or the use of heuristic-based solvers.
- The developed solution procedure is computationally tractable even by average machines, since it does not require the generation of a large number of scenarios like the stochastic approaches. In this sense, only one scenario needs to be solved in each stage to calculate a robust scheduling plan including a notable number of uncertainties.
- Further capabilities of DR loads are modelled and explored. Thereby, the new proposal is not only focused on the classic price-based DR signals, which aims at simply shifting part of the load to low-price periods. In this sense, the present paper models and studies sheddable and curtailable loads, as advanced forms of DR initiatives.

- Because its MILP structure, the developed solution procedure presents a modular structure, being thereby adaptable to any MG layout. In addition, it can be formulated and solved by conventional free-license solvers.

Table 1 - A comparison of the present paper with other selected references

Reference	Uncertainties modelling	Types of DR programs	Solution procedure	Considers response fatigue
[13]	Stochastic	Incentive-based	MILP	No
[14]	Stochastic	Price-based	MILP	No
[15]	Stochastic	Incentive-based	Heuristic	No
[18]	--	Incentive-based	Heuristic	No
[19]	Point estimation	Price-based Incentive-based	MILP	No
[21]	Stochastic	Price-based	MILP	No
[24]	Stochastic	Price-based	MILP	No
[26]	Interval	Price-based	MILP	No
[28]	Uncertain set	Price-based	MILP	No
[30]	Stochastic	Price-based	Heuristic	No
[33]	Robust index	Price-based	MILP	No
[34]	Stochastic	Price-based	MILP	No
Present	**Information Gap decission theory**	**Price-based Incentive-based**	**MILP**	**Yes**

To check the effectiveness of the developed methodology, extensive simulations are performed on a benchmark grid-connected MG, which encompasses PV generators, wind turbines (WTs), various types of responsible loads and battery energy storage (BES) facilities. Various scenarios are considered to show the implications of DR initiatives in MG operation.

In the rest of this paper, Section 2 describes the MG layout considered in this study. Section 3 presents the mathematical models of the components and participants involved in MG operation. Section 4 develops the two-stage solution procedure based on IGDT. Section 5 presents a case study and various numerical experiments. Finally, this paper is concluded with Section 6.

2 - Description of the MG under study

This paper is focused on grid-connected MGs, which can exchange energy with an upscale network. Fig. 1 shows a schematic representation of the agents and components involved in the MG under study, along the main interactions among them. The considered layout counts with a set of on-site assets comprising BES and renewable generators based on PV arrays and WTs. By exploiting these assets and energy exchanging with the grid, the local demand must be met. In this case, various types of consumers are considered, whose characteristics are summarized below:

- Inflexible consumers: these users do not respond to DR signals and therefore their consumption can be considered inflexible. This way, their demand must be instantaneously satisfied completely.
- Curtailable consumers: the expected demand of these users may be only partially satisfied. In such a case, these customers receive a compensation for each kWh that it is not actually covered ($/kWh).
- Sheddable consumers: this kind of users can be in fact dispatched by MG operator, it means that they can be eventually disconnected from the grid. In such a case, they receive a compensation for each hour they are shut down ($/h).

For the proper operation of the MG under study, communication channels among the generators, consumers and the MG operator must be enabled [36]. Thereby, the operator can send commitment and set-point signals to responsible consumers, generators and storage facilities. As seen in Fig. 1, the operator can send commitment signals to the BES and sheddable consumers. The MG can be also virtually disconnected from the upscale grid in case of no exchanging energy with it, which has been identified by commitment signals in Fig. 1. On the other hand, renewable generators cannot be actually dispatched because their availability is function of uncertain parameters [37], but their power output can be controlled via set-point signals, similar to curtailable consumers. Also, forecast information should be provided to the operator with the aim of properly performing a day-ahead scheduling plan for the different assets.

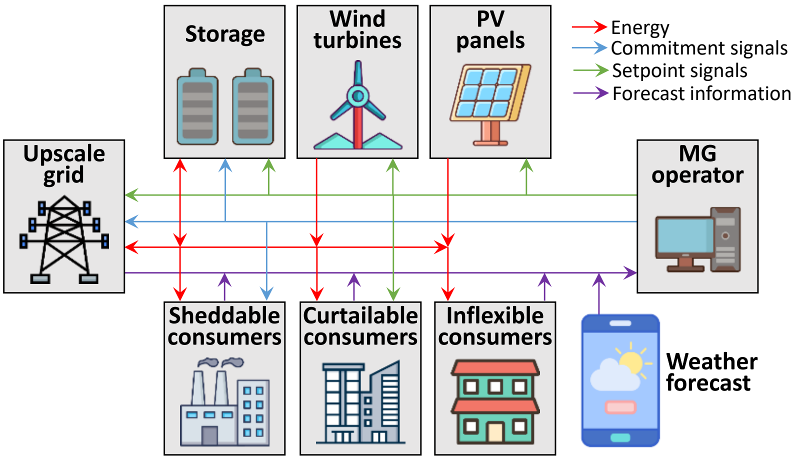

Figure 1 - Schematic view of the MG under study and the main relationships among the different agents and components involved in its operation

Fig. 2 explains the timeline followed to schedule the operation of the considered MG. For simplicity, the axis scale has been taken equal to 1 hour, but this is irrelevant for the explanation. It is assumed that forecast information about energy pricing (from upscale grid), energy demand and weather parameters are available with sufficient accuracy in some moment of the previous day for which the scheduling plan is realised (called 'previous day' in Fig. 2), for which, some suitable forecast tools or historical databases can be employed. This information can be used for the MG operator to calculate, for example, the PV and wind potential generation throughout the day. With this knowledge, the scheduling plan for the generators, consumers and storage systems can be calculated and transferred to these agents through commitment, set-point and DR signals during the so-called previous day. Now, the different agents assume the scheduling plan transferred from the operator and prepare the realization of such program until the realisation day (actual day for which the scheduling plan is calculated). Finally, the scheduling plan calculated in the previous day will be valid until the first hour of the actual day, when it is checked if the forecast conditions are far away to the actual parameters observed (wait and see). To this end, real time energy management tools can be used to adjust the plan calculated to the actual conditions [38], which are not covered in this paper.

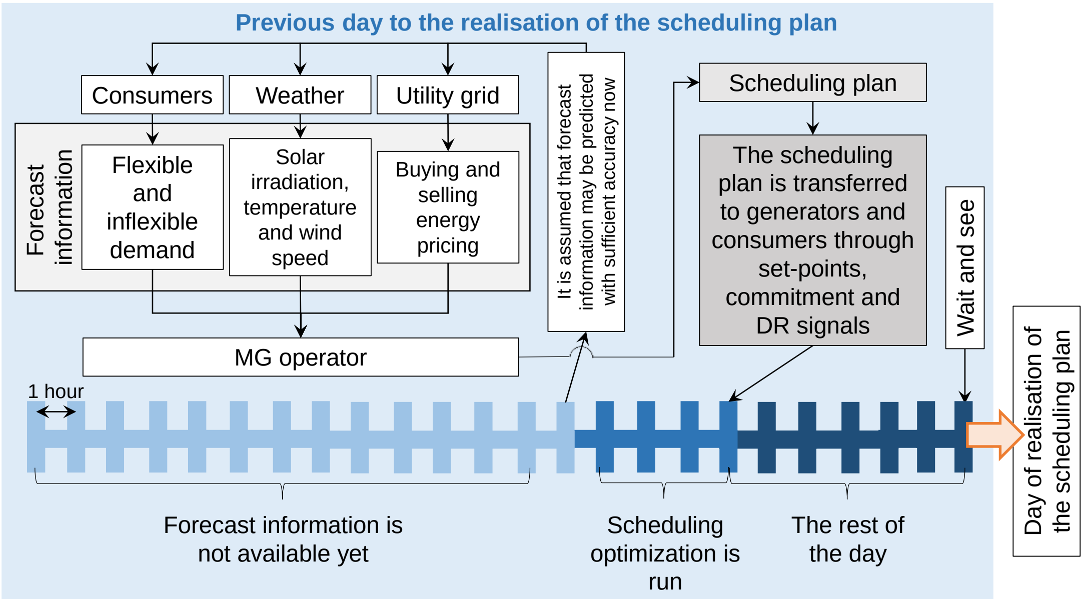

Figure 2 - Scheduling timeline for the MG under study

3 - Mathematical models

The day-ahead scheduling plan performed by the MG operator is frequently formulated as an optimization problem, in which some objectives (typically operating cost) are minimized [37]. This section presents the mathematical models of the different components involved in the MG layout described in Section 2.

3.1 - Operating cost

Mathematically, the daily operating cost of the MG described in Section 2 can be calculated as follows:

$$Cost = \Delta\tau \cdot \sum_{\forall t \in \mathcal{T}} \left\{ \underbrace{\left(\tilde{\lambda}_t^{Buy} \cdot p_t^{Buy} - \tilde{\lambda}_t^{Sell} \cdot p_t^{Sell}\right)}_{Energy\ exchanged\ with\ the\ grid} + \left[\underbrace{\sum_{\forall s \in \mathcal{S}} \{\sigma^s \cdot (\mathrm{size}(\mathcal{T}) - u_t^s)\}}_{Cost\ of\ shedded\ load} + \underbrace{\sum_{\forall c \in \mathcal{C}} \{\sigma^c \cdot (\tilde{p}_t^c - p_t^c)\}}_{Cost\ of\ curtailed\ load} \right] \right\} \quad (1)$$

The equation (1) comprises various terms. On the one hand, the cost of energy exchanging with the main grid is considered, contemplating both buying and selling processes. On the other hand, the expression (1) includes the cost of application of DR programs. In this case, both sheddable and curtailable consumers are considered. While the formers are compensated by the total hours they are disconnected, the latter receives a compensation for the total non-served energy. In (1), the buying and selling energy prices along the expected demand of curtailable consumers are considered uncertain parameters.

3.2 - Upscale grid modelling

It is realistic to assume that power exchanged with the upscale grid is upper bounded, as said the equation (2). On the other hand, the constraint (3) is imposed to force the buying and selling processes to be complementary. Finally, it is assumed that the utility grid is mainly formed by the conventional generators, which have slow-response [39]. In this sense, the utility grid model is completed with constraint (4), which includes the ramping rate limitations that are typical of slow-response conventional generators.

$$p_t^i \leq u_t^i \cdot \bar{p}^i;\ \forall t \in \mathcal{T} \wedge i \in \{Buy, Sell\} \quad (2)$$

$$u_t^{Buy} + u_t^{Sell} \leq 1;\ \forall t \in \mathcal{T} \quad (3)$$

$$p_{t-1}^i - R^i \leq p_t^i \leq p_{t-1}^i + R^i;\ \forall t \in \mathcal{T} \backslash t > 1 \wedge i \in \{Buy, Sell\} \quad (4)$$

3.3 - PV generators modelling

Potential renewable generation is a function of different weather parameters. In the case of PV generators, temperature and solar irradiation have a strong influence [40]. These parameters can be normally day-ahead predicted with sufficient accurateness [40, 41], thus allowing to calculate the available PV generation, as follows [40]:

$$\tilde{\phi}_t^{PV} = \overline{p}^{PV} \cdot \left[0.25 \cdot \tilde{\vartheta}_t + 0.03 \cdot \tilde{\vartheta}_t \cdot \tilde{\theta}_t + (1.01 - 1.13 \cdot \eta^{PV}) \cdot \tilde{\vartheta}_t^2\right];\ \forall t \in \mathcal{T} \quad (5)$$

In (5), both solar irradiance and ambient temperature have been considered uncertain parameters. It is worth noting that, Eq. (5) is a simplification of the PV model developed in [40], for which standard test conditions of solar panels have been assumed. By this simplification, the cell temperature is assumed to have a positive effect on the PV generation. However, one should note that this positive influence is minimized by multiplying it by 0.03 in (5), which results in considering both positive and negative effects on a whole. Similar formulations have been used in other related papers like [42] due to its simplicity. This expression, however does not take into account the limitations of PV devices such as inverters [42]. In this sense, the constraint (6) should be imposed.

$$p_t^{PV} \leq \begin{cases} \tilde{\phi}_t^{PV}, if\ \tilde{\phi}_t^{PV} \leq 1.1 \cdot \overline{p}^{PV} \\ 1.1 \cdot \overline{p}^{PV}, \qquad\qquad o.w. \end{cases}; \forall t \in \mathcal{T} \tag{6}$$

The constraint (6) allows 10% overloads above the nominal values of components, which is normally considered an assumable value [42].

3.4 - Wind generators modelling

As in the case of PV generation, wind power can be calculated as a function of weather parameters. In this case, the wind generation is directly influenced by wind speed. Conventionally, wind speed can be converted to power output by using the well-known turbine curves, that are typically represented by four ranges, as follows [37]:

$$\tilde{\phi}_t^{WG} = \begin{cases} 0, & if\ \tilde{\gamma}_t < \underline{\gamma}^{WG} \\ a \cdot \tilde{\gamma}_t^3 - b \cdot \bar{p}^{WG}, & if\ \underline{\gamma}^{WG} \leq \tilde{\gamma}_t < \gamma^{WG,*} \\ \bar{p}^{WG}, & if\ \gamma^{WG,*} \leq \tilde{\gamma}_t < \bar{\gamma}^{WG} \\ 0, & if\ \tilde{\gamma}_t \geq \bar{\gamma}^{WG} \end{cases}; \forall t \in \mathcal{T} \tag{7}$$

In (7), $\gamma^{WG,*}$ represents the nominal wind speed of a WT, whose value indicates the operating point in which the turbine generates its rated power. By (7), the wind power potential as a function of the wind speed (which is considered an uncertain parameter) can be calculated. This value can be converted to available power output including the efficiency of the different components involved (mechanical equipment and electronic interfaces), as follows:

$$p_t^{WG} \leq \eta^{WG} \cdot \tilde{\phi}_t^{WG};\ \forall t \in \mathcal{T} \tag{8}$$

3.5 - BES modelling

The MG layout under study includes a storage facility composed by batteries. The power that BES can exchange with the system is typically limited by rated values [43], as said the constraint (9).

$$p_t^{BES,i} \leq u_t^{BES,i} \cdot \bar{p}^{BES};\ \forall t \in \mathcal{T} \wedge i \in \{ch, dch\} \tag{9}$$

It is realistic to assume that BES cannot be charged and discharged within the same time interval [11, 43]. In other words, the charging and discharging processes of the BES are complementary, which is ensured by imposing the constraint (10).

$$u_t^{BES,ch} + u_t^{BES,dch} \leq 1;\ \forall t \in \mathcal{T} \tag{10}$$

The equation (11) models the instantaneous SOC of BES, whose value is limited by upper and lower bounds, as established by the constraint (12). It is worth noting that the upper bound in (12) is given by the nominal capacity of batteries, while the lower one is fixed by the depth-of-discharge setting, which is normally considered a pre-set parameter [37, 43].

$$\varepsilon_t^{BES} = \varepsilon_{t-1}^{BES} + \Delta\tau \cdot \left(\eta^{BES,ch} \cdot p_t^{BES,ch} - \frac{p_t^{BES,dch}}{\eta^{BES,dch}}\right);\ \forall t \in \mathcal{T} \backslash t > 1 \tag{11}$$

$$\underline{\varepsilon}^{BES} \leq \varepsilon_t^{BES} \leq \overline{\varepsilon}^{BES};\ \forall t \in \mathcal{T} \tag{12}$$

It is necessary to complete the model by setting the initial SOC of BES, since the equation (11) is not defined for $t = 0$. In many related references (e.g. see [37, 44]), it is assumed that batteries are fully charged at the beginning of the time horizon. To keep the model coherent, it is also suitable to ensure that initial and final SOC of BES are equal. To take into account these premises, the constraint (13) must be imposed.

$$\varepsilon_{t=1}^{BES} = \varepsilon_{t=end}^{BES} = \overline{\varepsilon}^{BES} \tag{13}$$

It is worth noting that constraint (13) could be defined in a variety of ways without requiring further modifications in the mathematical modelling.

3.6 - Curtailable consumers modelling

As previously commented, the expected demand from curtailable consumers can be partially or totally served, being so the served energy a decision variable of the problem. However, it is necessary to bound it by the expected demand, since otherwise the third term in (1) might take negative values, which is not realistic. To avoid this issue, the constraint (14) should be imposed.

$$p_t^c \leq \tilde{p}_t^c;\ \forall t \in \mathcal{T} \wedge c \in \mathcal{C} \tag{14}$$

It is also necessary to model the DR signals that the operator sends to curtailable consumers. In this case, it is assumed that a DR signal is received whenever the expected demand is not fully satisfied. In this paper, the total duration of DR signals for curtailable consumers is modelled by artificial commitment variables, as follows:

$$u_t^c = \begin{cases} 1, if\ \tilde{p}_t^c > p_t^c \\ 0, \qquad\quad o.w. \end{cases};\ \forall t \in \mathcal{T} \wedge c \in \mathcal{C} \tag{15}$$

The ‘if’ condition in (15) can be modelled by imposing the following logical constraints:

$$M \cdot u_t^c \geq \tilde{p}_t^c - p_t^c \tag{16}$$

$$M \cdot (1 - u_t^c) \geq p_t^c - \tilde{p}_t^c \tag{17}$$

where M is a large positive number ($\sim 10^6$). One can check that the condition (15) is effectively modelled by the constraints (16) and (17).

3.7 - MG energy balance

Finally, it is necessary to ensure the generation-load balance any time instant of the time horizon by imposing the constraint (18).

$$p_t^{Buy} + p_t^{PV} + p_t^{WG} + p_t^{BES,dch} = \tilde{p}_t^{LD} + p_t^{Sell} + p_t^{BES,ch} + \sum_{\forall s \in \mathcal{S}} \{u_t^s \cdot \tilde{p}_t^s\} + \sum_{\forall c \in \mathcal{C}} \{p_t^c\}; \ \forall t \in \mathcal{T} \quad (18)$$

It is worth noting that load demand of inflexible and sheddable consumers have been considered uncertain parameters in (18). This way, the total demand is in fact considered uncertain.

4 - Developed solution procedure

To manage with uncertainties, this paper proposes an IGDT approach. IGDT is a non-fuzzy and non-probabilistic method that allows to calculate uncertainty-aware results of optimization problems, without requiring any knowledge regarding probability distributions of uncertain parameters [45]. This technique is based on maximizing the so-called uncertain radiuses that define the interval within which the unknown parameters can vary, while other predefined premises are kept within limits [46]. For the particular case of the MG under study, IGDT allows to calculate a robust scheduling plan, but limiting the duration of DR signals, thus lessening the influence of some undesirable effects like the response fatigue. By this reason, IGDT has been considered a suitable option for the MG under study. Fig. 3 shows a descriptive flowchart of the developed solution procedure, which is performed in two stages that are detailed in subsequent sections.

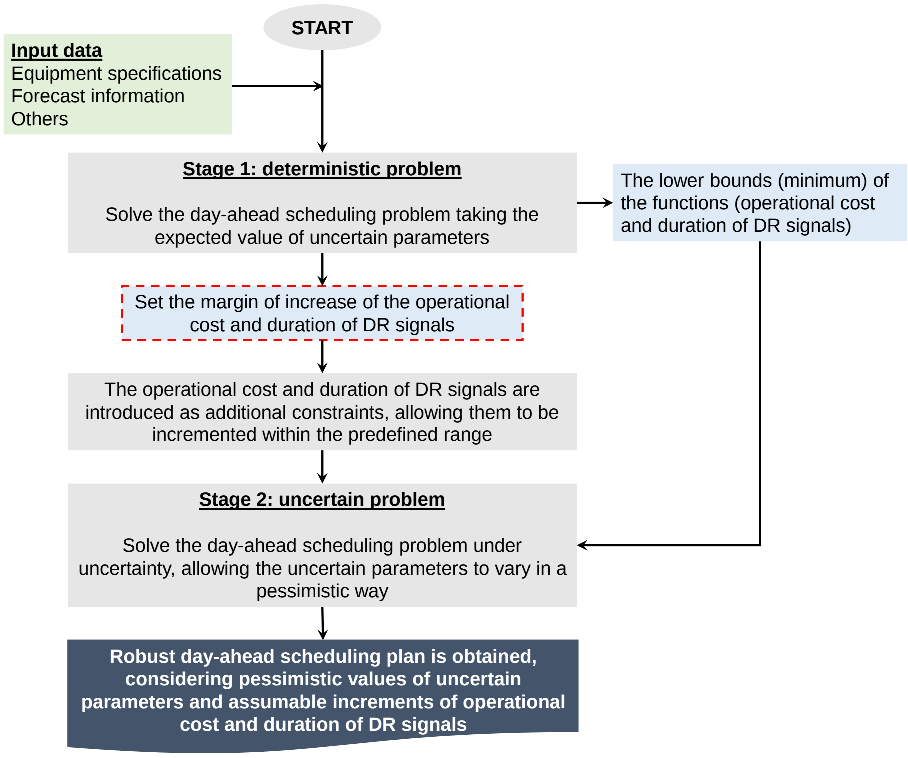

Figure 3 - Descriptive flowchart of the developed solution procedure for day-ahead scheduling of the MG under study

4.1 - Stage 1: deterministic problem

In the first stage, the day-ahead optimal scheduling is solved from a deterministic point of view, taking expected values of uncertain parameters. In this case, the total operating cost is minimized subject to the constraints described in Section 3. Hence, the stage 1 of the developed solution procedure can be mathematically stated as follows:

$$\boldsymbol{F}\big(\mathrm{E}(\Omega)\big) \leftarrow \arg\min_{\boldsymbol{v},\boldsymbol{u}} Cost\big(\mathrm{E}(\Omega)\big) \tag{19}$$

Subject to: (2)-(18)

where:

$$\boldsymbol{F} = \left[Cost;\ f^{s}_{Shedding}, \forall s \in \mathcal{S};\ f^{c}_{Curtail}, \forall c \in \mathcal{C}\ \right] \tag{20}$$

$$f^{s}_{Shedding} = \Delta\tau \cdot \textstyle\sum_{\forall t \in \mathcal{T}} \{\mathrm{size}(\mathcal{T}) - u^{s}_{t}\}\,; \forall s \in \mathcal{S} \tag{21}$$

$$f^{c}_{Curtail} = \Delta\tau \cdot \textstyle\sum_{\forall t \in \mathcal{T}} \{u^{c}_{t}\}\,;\ \forall c \in \mathcal{C} \tag{22}$$

Therefore, as a result of the Stage 1, one obtains the value of the operating cost and duration of DR signals for the expected values of uncertain parameters. These values have been considered optimal ones and thus taking as lower bounds on the concerned functions, since they have been obtained from the minimization of the operating cost.

4.2 - Stage 2: uncertain-aware problem

In the first stage it has been considered that uncertain parameters take their expected (forecast) values. However, this strategy does not consider possible deviations of unknown values from their expected profiles. To take this issue into consideration, the Stage 2 poses an uncertainty-aware solution of the problem based on IGDT. To this end, it is considered that uncertain parameters could deviate a certain radius with respect to their predicted values. This way, the matrix of uncertain radiuses, which collects the hourly deviation of each uncertain parameter with respect to its predicted value, can be constructed as follows:

$$\mathbf{A} = \begin{bmatrix} \alpha_{\Omega(1)|1} & \cdots & \alpha_{\Omega(1)|t=end} \\ \vdots & \ddots & \vdots \\ \alpha_{\Omega(end)|1} & \cdots & \alpha_{\Omega(end)|t=end} \end{bmatrix} \in \mathbb{R}_{+}^{size(\Omega)\times size(\mathcal{T})} \qquad (23)$$

In this sense, it is important to distinguish two kinds of uncertainties. On the one hand, the favourable uncertainties would presumably reduce the operating cost if their values are incremented. In contrast, the unfavourable uncertainties would likely increment the operating cost if their values are incremented. Table 2 collects the different uncertain parameters involved in the day-ahead operation of the study MG, classifying them into favourable or unfavourable. As observed, the favourable parameters increment the potential renewable generation and selling pricing. On the other hand, the unfavourable parameters are the demand and the energy buying price, which would make more expensive the operation of the system.

Table 2 - Uncertain parameters considered in the day-ahead operation of the MG under study

Favourable (Ω^{-})	**Unfavourable (Ω^{+})**
Energy selling price (λ^{Sell})	Energy buying price (λ^{Buy})
Solar irradiance (ϑ)	Inflexible demand (p^{LD})
Temperature (θ)	Sheddable demand (p^{s})
Wind speed (γ)	Curtailable demand (p^{c})

The second stage should be stated in a pessimistic way, in order to obtain a robust solution against uncertainties. In this regard, the most pessimistic situation happens when the favourable uncertainties are reduced and the unfavourable ones are incremented. This situation is depicted in Fig. 4. As observed in this figure, assuming pessimistic conditions, the favourable parameter is reduced a certain radius while the opposite trend is observed for the unfavourable parameter. To better explain this approach, let us consider the solar irradiation as example. This parameter affects positively the PV production and therefore contributes to reducing the total operational cost. Therefore, a pessimistic variation of this parameter supposes its reduction, since it directly affects reducing the PV generation as well and, consequently, the operational cost will likely grow. To let the uncertain parameters vary, they are taken as decision variables and the following associated constraints are imposed.

$$\widetilde{\omega}_t \leq \mathrm{E}(\widetilde{\omega}_t) \cdot \left(1 - \alpha_{\widetilde{\omega}|t}\right);\ \forall t \in \mathcal{T} \wedge \widetilde{\omega} \in \Omega^{-} \tag{24}$$

$$\widetilde{\omega}_t \geq \mathrm{E}(\widetilde{\omega}_t) \cdot \left(1 + \alpha_{\widetilde{\omega}|t}\right);\ \forall t \in \mathcal{T} \wedge \widetilde{\omega} \in \Omega^{+} \tag{25}$$

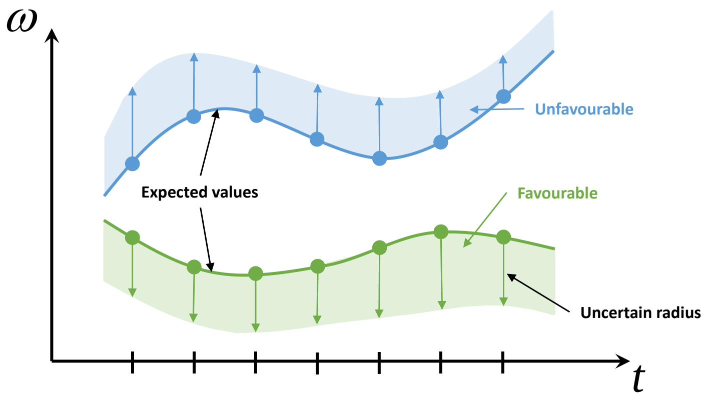

Figure 4 - Illustrative example of pessimistic situation for uncertain parameters. As observed, while the favourable parameter is reduced, the unfavourable one is incremented.

One can check that the constraints (24) and (25) allow the uncertain parameters to vary a certain radius (α), but only in a pessimistic manner. Thereby, the solution found in the second stage can be considered uncertainty-aware.

Typically, the MG operator is willing to accept the robust scheduling plan if this does not entail a notable increment of the operating cost. Otherwise, the operator could choose the deterministic solution and assume the risk of this option. To avoid this situation, it is realistic to limit the operating cost by imposing additional constraints. This idea also allows to lessen the influence of response fatigue, since the total duration of DR signals can be additionally bounded. In this sense, the solution obtained in the first stage is assumed to be the lower bound of the operating cost and duration of DR signals, which allows to impose the following constraint.

$$\boldsymbol{F} \leq \boldsymbol{F}\big(\mathrm{E}(\Omega)\big) \circ (1 + \boldsymbol{\Delta}) \tag{26}$$

where:

$$\boldsymbol{\Delta} = \left[\Delta_{Cost};\ \Delta^{s}_{Shedding}, \forall s \in \mathcal{S};\ \Delta^{c}_{Curtail}, \forall c \in \mathcal{C}\ \right] \tag{27}$$

where Δ_{Cost}, $\Delta_{Shedding}$ and $\Delta_{Curtail}$ are the margin of increase of the operating cost and duration of DR signals for sheddable and curtailable consumers, respectively. By (26), the robust solution calculated in the second stage is obtained without incrementing the operating cost and duration of DR signals beyond an acceptable margin, defined by Δ's.

Considering the constraints (24)-(26), the Stage 2 of the developed solution procedure can be stated as follows:

$$\max_{\boldsymbol{v},\boldsymbol{u},\Omega,\mathbf{A}} \frac{1}{size(\Omega)\cdot size(\mathcal{T})} \cdot \sum_{\forall t\in\mathcal{T}} \sum_{\forall i\in\Omega} \left\{\alpha_{i|t}\right\} \tag{28}$$

Subject to: (2)-(18), (24)-(26)

As seen, the stage 2 aims at maximizing the average value of the uncertain radiuses over the time horizon, thus obtaining an uncertainty-aware solution. To this end, along the decision variables of the first stage, the uncertain parameters and radiuses are also considered variables. However, the robust solution is subjected to acceptable increments of the operating cost and duration of DR signals, as established by the constraint (26).

4.3 - Linearization of variables

When declaring the uncertain parameters as decision variables in the second stage, the optimization problem becomes nonlinear. Normally, solution of nonlinear optimization problems is a challenge [47]. To avoid this issue and keep the solution procedure tractable and solvable with standard software, it is proposed to use different linearization techniques to retain the linearity of the problem. The approaches commented below introduce additional variables and constraints. However, this extra effort is by far compensated by the possibility of using conventional solvers, widely available for MILP formulations. In addition, this kind of model ensures the reachability of the global optimum. As a result of these clear advantages, linear models are preferred in this work instead of nonlinear ones, which require the use of metaheuristic or self-developed solvers that limits the versatility and usability of the model in standard and conventional software [29]. The different techniques considered to linearize the nonlinear variables involved are described in subsequent points.

Linearization of quadratic and cubic terms

Quadratic and cubic terms appear in (5) and (7) when solar irradiance and wind speed are declared variables. To linearize this term, it is proposed to use efficient piecewise representations of the nonlinear functions [3]. This approach is depicted in Fig. 5 and consists of discretizing the nonlinear function ψ in n_1 points that define $n_1 - 1$ segments, as follows:

$$\hat{\psi} = \langle \hat{q}_i, \psi(\hat{q}_i) \rangle; \forall i \in \{1,2, \dots, n_1\} \tag{29}$$

where $\hat{q}$'s are the points within the range of the nonlinear function for which its piecewise representation is defined. Thereby, the nonlinear term can be replaced by the auxiliary variable r which can be calculated as follows:

$$r = \sum_{i=2}^{i=n_1} \{\xi_i \cdot (K_i \cdot q + L_i)\} \tag{30}$$

where ξ is a special ordered set 1 (SOS1) binary variable (see [48]) and K and L are calculated as follows:

$$K_i = \frac{\psi(\hat{q}_i) - \psi(\hat{q}_{i-1})}{\hat{q}_i - \hat{q}_{i-1}}; \ \forall i \in \{2,3, \dots, n_1\} \tag{31}$$

$$L_i = \psi(\hat{q}_i) - K_i \cdot \hat{q}_i; \ \forall i \in \{2,3, \dots, n_1\} \tag{32}$$

Finally, to ensure that only one segment is activated at once, the constraint (33) must be imposed.

$$\sum_{i=1}^{i=n_1-1} \{\xi_i \cdot \hat{q}_i\} \leq q \leq \sum_{i=2}^{i=n_1} \{\xi_{i-1} \cdot \hat{q}_i\} \tag{33}$$

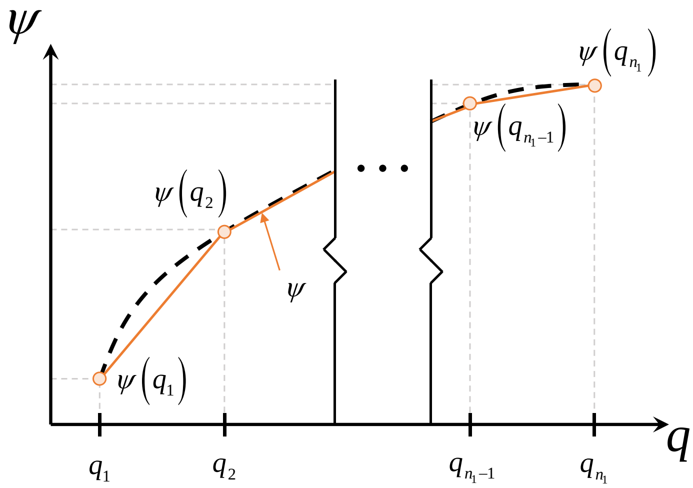

Figure 5 - Sketch of the piecewise linear representation of a nonlinear function ψ

In (30), the product of the integer variable ξ and the continuous one q, yields a nonlinear term which can be linearized by the procedure described below.

Linearization of the product of integer and continuous variables

As commented, a product of continuous and integer variables appears in (30), which should be linearized. To linearize it, let us assume a continuous variable s and an integer one ϱ, whose product can be replaced by the dummy linear variable s and imposing the following constraints [44]:

$$s - M \cdot (1 - \varrho) \leq \beta \leq s + M \cdot (1 - \varrho) \tag{34}$$

$$-M \cdot \varrho \leq \beta \leq M \cdot \varrho \tag{35}$$

Linearization of bilinear terms

When both solar irradiance and temperature are declared variables, a bilinear term appears in (5) because the product of these two continuous variables. To linearize this term, it is proposed to use advanced piecewise representations of the nonlinear function. More precisely, the scheme labelled as 'nf4l' in [48] has been used in this paper because it's a good trade-off between accuracy and efficiency. Let us consider the product of two continuous variables namely x and y, In this case, the domain of one of the involved variables is partitioned into n_2 points, as follows:

$$x \approx \langle \hat{x}_i \rangle; \forall i \in \{0,1, \dots, n_2\} \tag{36}$$

It is worth noting that the partitioning of the domain of x may be non-uniform, therefore, the interval lengths have to be calculated by (37).

$$m_i = \hat{x}_i - \hat{x}_{i-1}; \forall i \in \{1,2,\dots,n_2\} \tag{37}$$

This way, the variable x can be represented using the information of its partitioning and introducing the continuous variable $\delta_{\hat{x}_i}$, which measures the deviation of x from the grid point $\hat{x}_{i-1}$, as follows:

$$x = \sum_{i=1}^{i=n_2} \{\zeta_i \cdot \hat{x}_{i-1} + \delta_{\hat{x}_i}\} \tag{38}$$

$$0 \leq \delta_{\hat{x}_i} \leq m_i \cdot \zeta_i;\ \forall i \in \{1,2,\dots,n_2\} \tag{39}$$

where ζ is a SOS1 binary variable. Similarly, the continuous variable δ_{y_i} is defined to represent the deviation of the variable y and the lower bound of its domain $\underline{y}$, therefore:

$$y = \underline{y} + \sum_{i=1}^{i=n_2} \{\delta_{y_i}\} \tag{40}$$

$$0 \leq \delta_{y_i} \leq \left(\overline{y} - \underline{y}\right) \cdot \zeta_i;\ \forall i \in \{0,1,\dots,n_2\} \tag{41}$$

where $\overline{y}$ is the upper bound of the domain of y. Now, the dummy variable z, which replaces the bilinear term wherever it appears in formulation, can be defined as follows:

$$z = \underline{y} \cdot x + \sum_{i=1}^{i=n_2} \{\hat{x}_{i-1} \cdot \delta_{y_i}\} + \delta_z \tag{42}$$

where δ_z is a continuous variable which needs to impose the following constraints over its bounds:

$$\delta_z \geq \sum_{i=1}^{i=n_2} \{m_i \cdot \delta_{y_i}\} + \left(\overline{y} - \underline{y}\right) \cdot \sum_{i=1}^{i=n_2} \{\delta_{\hat{x}_i} - m_i \cdot \zeta_i\} \tag{43}$$

$$\delta_z \leq \left(\overline{y} - \underline{y}\right) \cdot \sum_{i=1}^{i=n_2} \{\delta_{\hat{x}_i}\} \tag{44}$$

$$\delta_z \leq \sum_{i=1}^{i=n_2} \{m_i \cdot \zeta_i\} \tag{45}$$

Linearization of the power curve of WTs

Finally, the power curve of WTs (7) must be linearized. In this case, since the curve has been piecewise declared in five intervals, the wind speed domain can be similarly partitioned as:

$$\langle \hat{\gamma}_i \rangle = \left| \begin{array}{l} \hat{\gamma}_1 = 0 \\ \hat{\gamma}_2 = \underline{\gamma}^{WG} \\ \hat{\gamma}_3 = \gamma^{WG,*} \\ \hat{\gamma}_4 = \overline{\gamma}^{WG} \\ \hat{\gamma}_5 = M \end{array} \right. \tag{46}$$

As seen in (46), the five grid points that define the partitioning of γ are equal to those that define the intervals of (7). This way, the curve can be treated as a piecewise representation of a nonlinear function, similar to the quadratic and cubic terms, as follows:

$$\sum_{i=1}^{i=4} \{ \varsigma_{i|t} \cdot \hat{\gamma}_i \} \leq \tilde{\gamma}_t \leq \sum_{i=2}^{i=5} \{ \varsigma_{i-1|t} \cdot \hat{\gamma}_i \}; \ \forall t \in \mathcal{T} \tag{47}$$

$$\tilde{\phi}_t^{WG} = \varsigma_{1|t} \cdot 0 + \varsigma_{2|t} \cdot \left(a \cdot \tilde{\gamma}_t^3 - b \cdot \overline{p}^{WG} \right) + \varsigma_{3|t} \cdot \overline{p}^{WG} + \varsigma_{4|t} \cdot 0; \ \forall t \in \mathcal{T} \tag{48}$$

where ς is a SOS1 binary variable. There are still nonlinearities in (48), for which suitable linearization strategies have been previously described.

5 - Case study

In this section, a case study is presented with the aim of validating the developed methodology. To this end, a benchmark MG such as that described in Section 2 is considered. All the simulations are performed on an Intel® Core™ i7-10700K CPU @3.80GHz (32 GB RAM). The developed MILP optimization model is coded under Matlab R2019a environment and solved using Gurobi [49], over a 24-h time horizon with 30-min resolution.

5.1 - Data

For simulations, various real-life profiles available in public databases have been considered for the expected profile of uncertain parameters. In this regard, Fig. 6 plots the buying and selling energy pricing, which is the real-time energy pricing observed on the PJM FE Ohio on July 9, 2019 [50].

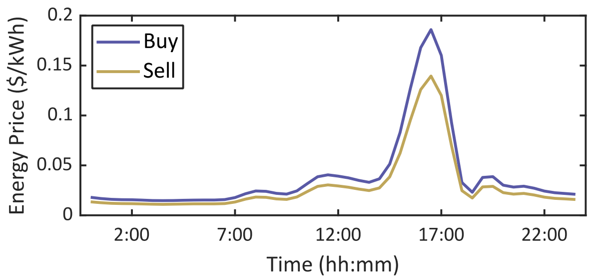

Figure 6 - Expected buying/selling energy pricing considered in the simulations

Fig. 7 shows the profiles of expected values of weather parameters, which have been taken from [51], and correspond with real values measured at Virgin Islands on May 3, 2016. On the other hand, the expected inflexible demand is depicted in Fig. 8, and has been constructed by scaling down the real demand at La Palma Island on May 3, 2016 [52]. Lastly, the expected flexible demand (sheddable and curtailable) considered for simulations is plotted in Fig. 9.

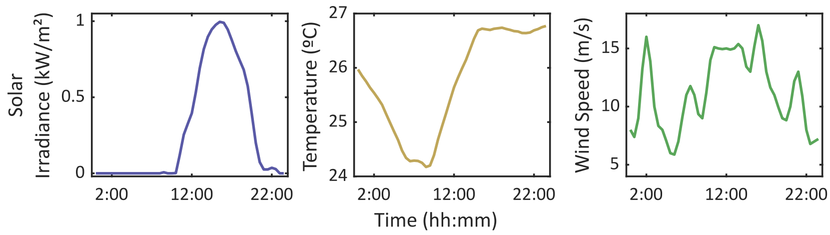

Figure 7 - Expected values of weather uncertainties

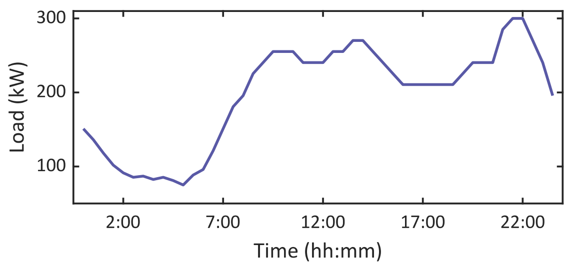

Figure 8 - Expected inflexible demand considered for simulations

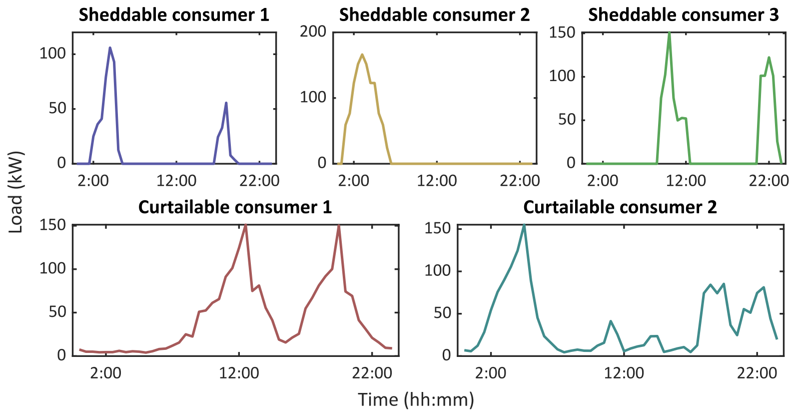

Figure 9 - Expected flexible demand considered in the simulations

The power that can be exchanged with the grid is limited to 500 kW for both buying and selling process, while the ramping rate is fixed at 200 kW. Table 3 summarizes the cost of DR programs and increasing margin of response signals for flexible consumers; whereas the margin for the operating cost has been taken variable with illustrative aims. The remaining necessary parameters are collected in Table 4, which have been taken from various references [37, 40-42].

Table 3 - Data about flexible consumers

Consumer		**Cost (σ)**	**$\Delta_{Shedding}$ or $\Delta_{Curtail}$**
Sheddable	1	2.5 \$/h	0.5 p.u.
	2	2.4 \$/h	2.0 p.u.
	3	3.5 \$/h	2.0 p.u.
Curtailable	1	0.04 \$/kWh	0.5 p.u.
	2	0.06 \$/kWh	1.0 p.u.

Table 4 - Parameters used in simulations

Parameter	**Value**
$\overline{p}^{PV/WG/BES}$	100/100/150 kW
$\eta^{PV/WG/BES,ch/dch}$	0.167/0.45/0.95/0.9 p.u.
$\underline{\gamma}^{WG}/\gamma^{WG,*}/\overline{\gamma}^{WG}$	2/11/20 m/s
a/b	0.0756 kW/(m/s)^3/0.006
$\overline{\varepsilon}^{BES}/\underline{\varepsilon}^{BES}$	300/90 kWh

5.2 - Results

Now, a variety of numerical results are presented and commented, with the aim of checking the performance of the developed solution procedure and its ability to manage with uncertainties while the effect of response fatigue is kept harmless. To this end, the results are reported for various values of Δ_{Cost}, this way, one can check how the different indicators vary as the economic requirements are relaxed. Firstly, let us study how the operating cost varies with the increasing of Δ_{Cost}, which is shown in Fig. 10. As expected, the total operating cost almost equals the allowable margin in all cases. It means that the developed algorithm considers pessimistic values of uncertain parameters at the expense of making more expensive the operation of the system. In this regard, the developed algorithm seeks for the value of the uncertain parameters that maximizes the operational cost. This fact is more easily observable in Fig. 11, where the expected energy potential of PV and WTs is plotted. As seen in this figure, as more margin is allowed to increment the operating cost, less energy is expected to be extracted from renewable sources. This result is redundant with previous conclusions and highlight the capability of the developed methodology to be able to consider low renewable penetration values. Thereby, although the cost of operating the grid is higher, the scheduling result is more robust since lower renewable potential is considered. This way, the scheduling result is able to predict forecast errors that may result in over-optimistic predictions and thus being able to impose countermeasures on the scheduling program. In fact, the total expected renewable energy considered with $\Delta_{Cost} = 0.35$ p.u. is almost 50% lower than that expected with $\Delta_{Cost} = 0.05$ p.u.

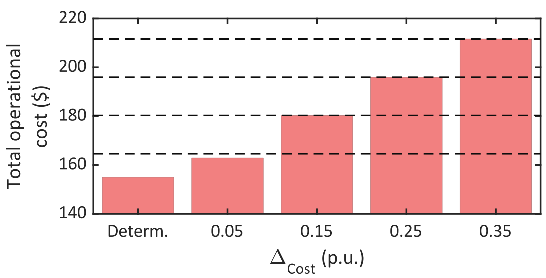

Figure 10 - Total operating cost for various values of Δ_{Cost}. Horizontal discontinuous lines show the allowable margin in each case

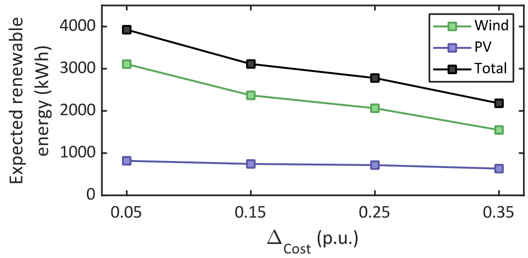

Figure 11 - Expected renewable energy potential for various values of Δ_{Cost}

The effect of incrementing the cost margin can be also noted in DR programs. Fig. 12 plots the duration of DR signals and the cost of DR programs. As seen, both indexes are normally increased as the allowable margin also increases, however, the duration of DR signals does not surpass the imposed upper threshold in any case. This means that, despite the operation of the grid is performed under pessimistic conditions, the effect of the response fatigue is bounded within acceptable limits. In this regard, the new proposal is capable of determining a scheduling program immune against the negative effect of uncertainties, but considering the negative impact of DR signals in the users' satisfaction. Thereby, successful implantation of DR programs is ensured or, at least, the grid operation is prevented against users' discouragement. It is worth commenting the case of the curtailable consumer 2. For this customer, the duration of DR signals is always at limit regardless the allowable margin of increase in the operating cost. However, the cost of its DR scheme increases, which means that, despite no more DR signals can be sent to avoid response fatigue, less energy is expected to be served under pessimistic conditions. In this regard, the operator incurs in more penalizations due to unserved energy.

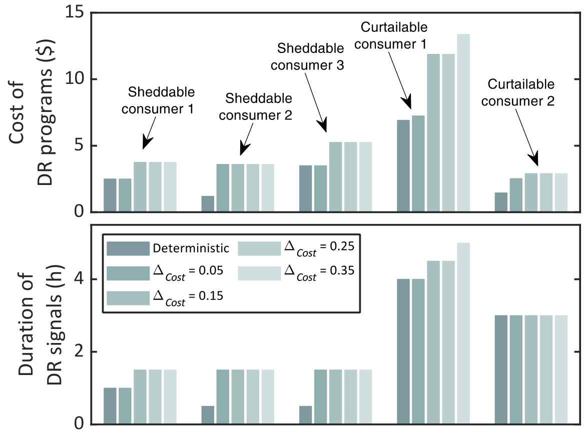

Figure 12 - Cost of DR programs and duration of response signals for various values of Δ_{Cost}

To better show how the developed solution procedure works, Table 5 reports various indicative results regarding favourable and unfavourable uncertainties. As seen in this Table, the indicators referred to unfavourable uncertainties, such as the demand and buying prices, are increased for higher allowable margins of the operating cost, while the opposite behaviour is observed for the favourable uncertainties. This evidences the uncertainty-aware orientation of the proposed methodology, since the result of the optimization problem is found in the most unfavourable conditions. For example, one can analyse the average buying and selling prices, determining that while the former increases with the cost margin, the opposite trend is observed for the latter, which means that higher monetary expenditures are devoted to purchase energy from the utility grid. Other relevant results can be appreciated for the demand of the different consumers (flexible or not), which clearly increase with the margin cost, supposing a more unfavourable landscape for self-generation and, therefore, may provoke a higher dependency of the energy purchased from the utility grid. In this regard, the total demand is overestimated to contribute to the worst-case perspective. In this sense, total flexible and non-flexible loads were incremented by ~20% at the stage 2. This feature of the developed methodology is also illustrated in Figs. 13 and 14, where the expected profiles of various uncertainties are plotted. In the case of the energy pricing, it can be observed how the peak price about 16:00h increases when more margin is allowed. In contrast, the selling price is zero for most of the day, being so only profitable selling energy to the grid during a short period at evening. This profile clearly hinders the profitability of selling energy to the grid, which in addition should be devoted on supplying the increasing local demand, as previously commented. Similarly, renewable forecast is also minimized by increasing Δ_{Cost}. As observed in Fig. 14, when the allowable increasing margin is 0.35, the expected renewable potential during most of the day is considered null, which supposes a challenge scenario for the grid operation, incrementing its dependency from the utility network and consequently incrementing the energy purchasing from it. These results, of course, provoke a much lower renewable penetration, as shown in Fig. 11.

Table 5 - The value of several indicative indexes for various values of Δ_{Cost}

Indicator	Δ_{Cost} (p.u.) 0.05	0.15	0.25	0.35
Average buying price ($/kWh)	0.040	0.042	0.044	0.054
Average selling price ($/kWh)	0.015	0.008	0.006	0.006
Total inflexible demand (kWh)	4727.20	4750.70	5113.20	5164.10
Total demand of sheddable consumer 1 (kWh)	332.27	377.40	416.90	463.40
Total demand of sheddable consumer 2 (kWh)	813.70	858.50	949.50	949.50
Total demand of sheddable consumer 3 (kWh)	703.43	705.45	705.45	742.34
Total demand of curtailable consumer 1 (kWh)	1113.10	1169.30	1235.90	1285.20
Total demand of curtailable consumer 2 (kWh)	1038.70	1147.10	1294.50	1411.00

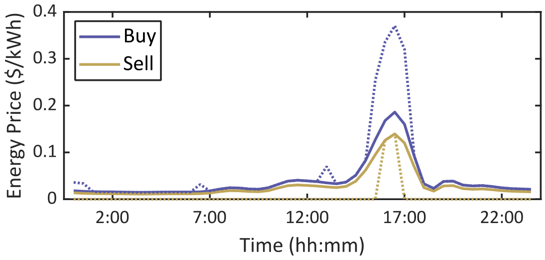

Figure 13 - Buying and selling energy pricing under deterministic conditions (solid lines) and with $\Delta_{Cost} = 0.35$ (discontinuous lines)

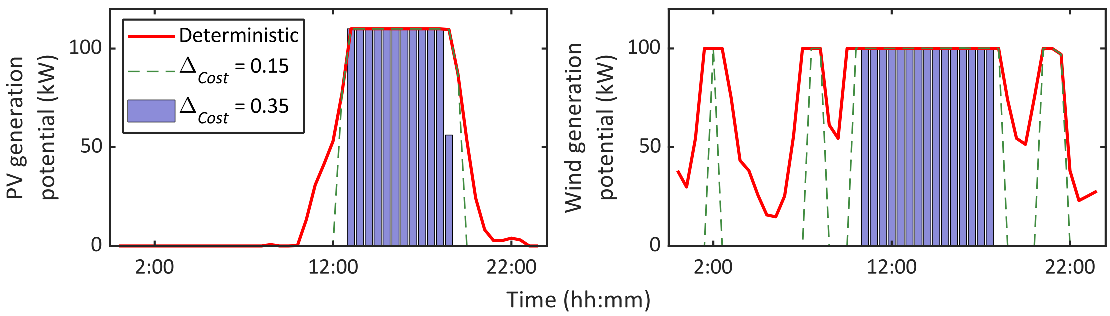

Figure 14 - Expected renewable potential for various values of Δ_{Cost}

Now, let us analyse the effect of uncertainties in the scheduling of BES. This is relevant since storage systems in MGs are principally devoted to storing surplus renewable energy, to be posteriorly consumed during periods of low renewable generation [41]. Fig. 15 shows the SOC of BES for the deterministic case and $\Delta_{Cost} = 0.35$. As observed, in the case of considering uncertainties the batteries are more frequently charged-discharged. This is due to unavailability of renewable energy during most of the day. In this regard, the scheduling result with $\Delta_{Cost} = 0.35$ tries to also exploit low energy price periods (noon) for charging the batteries from the upscale grid. This explains why their SOC is recovered later at morning than in the deterministic case. In contrast, the storage can use the wind penetration during the noon to rapidly recover its SOC in the deterministic case. During the evening, behaviour of BES is similar in both cases, since, as shown in Fig. 14, PV and wind penetration are high during those time slots even under pessimistic conditions.

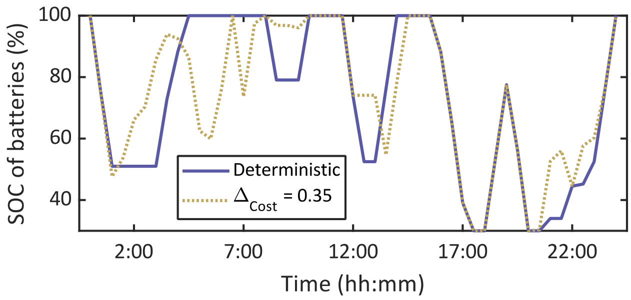

Figure 15 - SOC of BES for the deterministic case and $\Delta_{Cost} = 0.35$

5.3 - Comparison with other approaches

In this subsection, the developed solution procedure is numerically compared with MonteCarlo simulation [53], stochastic programming [13] and robust approaches [54]. In the case of MonteCarlo and stochastic approaches, it is considered that all the uncertainties are modelled via scenarios, considering that forecast errors follow a Gaussian distribution [55]. Then, the second stage of the developed procedure is converted into a maximization problem in which the total operational cost is taken as an objective function. Thereby, stochastic programming is converted to a robust methodology, simulating pessimistic conditions. For these approaches, up to 1000 scenarios were generated, which is considered an acceptable number [56]. However, in the case of stochastic programming, this number was reduced to 15 using the clustering procedure described in [42]. For the robust approach, a conventional min-max problem has been considered [54], by which the operational cost is minimized subjected to maximize the negative effect of uncertainties.

Fig. 16 reports the total operational cost for the different considered approaches. As seen, when the increasing margin is below 0.35 p.u, all the methods yield the same objective function. This is due to scenario-based approaches determine a pessimistic scheduling result in which the objective function is maximized to the upper bound, which is fixed by the value of Δ_{Cost} (except for the case $\Delta_{Cost} = 0.05\ p.u,$ whose maximum is not reachable as commented before). However, when the increasing margin is fixed at 0.35 p.u, the scenario-based techniques did not hit the maximum allowable value for the total operational cost. This is due to these approaches did not consider the worst-case scenario. Instead, they calculate the average value over the scenario-space and therefore the result obtained is not as robust as in the case of the developed methodology. On the other hand, the robust and developed methodologies always yielded the same result, demonstrating the capability of the developed method to determine the worst-case operational conditions.

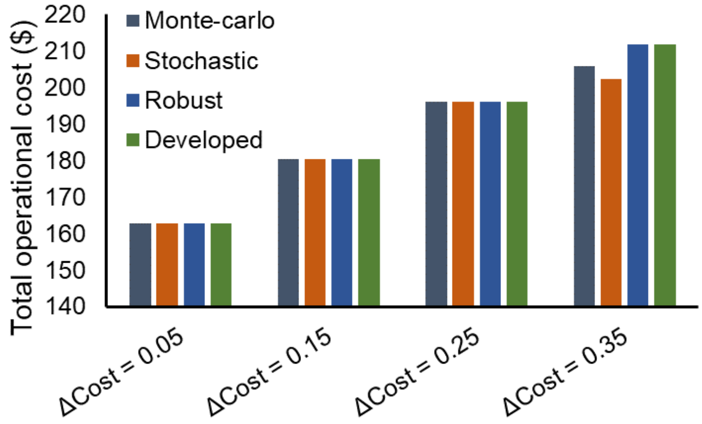

Fig. 16 - Total operational cost calculated with various uncertainties modelling

Finally, the computational efficiency of the developed methods is compared. For which, the average time of various experiments have been determined. All the compared techniques were run on the same computer using the same base code and the results are shown in Fig. 17. As observed, the developed method was considerably cheaper than the other studied methods. These results were logic since in the case of scenario-based approaches, despite they do not require to use linearization techniques, all the variables have the same size that the scenario-space, considerably incrementing the size of the problem. For the case of the robust approach, although it is not based on scenarios, it requires to formulate the dual problem to convert the min-max problem into a single minimization problem. This way, the variable-space is incremented and, therefore, the computational performance is affected.

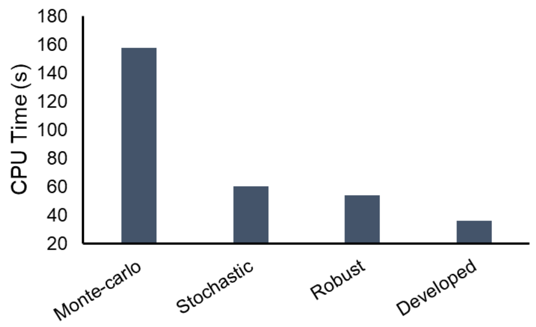

Fig. 17 - Total CPU time consumed with various uncertainties modelling

6 - Conclusions and future trends

A novel uncertainty-aware scheduling tool for grid-connected MGs has been developed. The new proposal is based on IGDT and allows to impose additional constraints to minimize the duration of DR signals. This way, the robust scheduling is found taking into account the harmful consequences of response fatigue. Moreover, the developed solution methodology presents a modular structure, being so easily adaptable to different MG layouts with implication of various uncertainties from either renewable generation, demand or energy pricing. In addition, various linearization techniques have been applied to avoid the nonlinearities introduced in the formulation when some uncertain parameters are taken as decision variables, this way, the problem is formulated as a MILP, being solvable with standard software and average machines.

A benchmark case study has served to validate the developed procedure and analysing the effect of uncertainties in both operating cost and DR programs. It has been checked that more pessimistic conditions are considered at the expense of making more expensive the operation of the grid. For the sake of example, the developed methodology was able to determine a scheduling plan with a total renewable generation 50% lower compared with the deterministic case while the total demand was overestimated by ~20%. This evidences the ability of the developed methodology to find an uncertainty-aware scheduling result for the studied MG, while the duration of DR signals is maintained within acceptable bounds. This way, the negative effects of response fatigue can be lessened. The developed methodology was also compared with other uncertainties modelling, demonstrating its accurateness and efficiency. In this sense, it was proved that the new proposal is able to effectively detect the worst-case scenario, in contrast to stochastic-based programming, which is only limited to consider a set of predefined scenarios.

Ongoing works are devoted to applying similar optimization frameworks to other related problems such as home energy management systems. The developed methodology could also offer good results in planning tools and therefore this possibility should be explored in future works.

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