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A Stochastic-IGDT model for Energy Management in Isolated Microgrids considering Failures and Demand Response

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Abstract. In power systems, contingencies and outages are more frequent nowadays due to climate changing effects. This circumstance along equipment aging may lead to unexpected failures and outages in power and energy systems. This issue is especially critical in isolated microgrids, which must be supplied by means of own resources and onsite assets. In these systems, unexpected failures may notably provoke a detriment of the economy and users' satisfaction. In order to minimize the impact of these incidents, this paper proposes a novel energy management tool for isolated microgrids that are robust against failures. To this end, a novel stochastic-IGDT formulation is developed, by which typical uncertainties are comfortably modelled via scenarios while components' failures are treated in a robust fashion using IGDT. A solution procedure is proposed in which the operation cost is also considered in order to reproduce useful results and limit the cost of reliability. A variety of simulations are conducted in order to validate the developed model and discuss the particularities derived from considering failures in the energy management task. Moreover, the role of demand response programs is also foregrounded. In particular, the demand response programs allow reducing the operation costs by 3 % while the scheduling result admits up to 13 hours more of accumulated failures, thus confirming a positive effect of such initiatives in both economy and robustness against failures.

Keywords. Microgrid; Stochastic programming; Reliability; Information gap decision theory; Demand response.

Nomenclature

Set (indexes)	
$s(\mathbb{S})$	Scenario
$r(\mathbb{R})$	Representative scenario
$t(\mathbb{T})$	Time
$j(\mathbb{J})$	Curtailable consumer
Ω_r	Cluster of the rth representative scenario
Superscripts	
DEG	Diesel engine generator
PV	Photovoltaic
WG	Wind generator
$BES, ch/dch$	Battery energy storage in charging/discharging mode
IF	Inflexible
$O\&M$	Operation & maintenance
DR	Demand response
$\overline{(*)}/\underline{(*)}$	Maximum/minimum value
$\widehat{(*)}$	Uncertain parameter
Constants & parameters	
R	Ramping limit (kW)
ϑ	Solar irradiance (kW/m^2)
θ	Ambient temperature (ºC)
η	Efficiency (pu)
γ	Wind speed (m/s)
α^{WG}, β^{WG}	Constants of the wind-power curve (kW·(m/s)$^{-3}$, -)
e2P	Energy-to-power ratio (h)
$\Delta\tau$	Time step (h)
DOD	Depth of discharge (%)
π	Probability (pu)
κ	Capital costs ($/kW or $/kWh)
T	Number of life hours (h)
$\omega_1^{DEG}, \omega_2^{DEG}, \omega_3^{DEG}$	Cost coefficients of the DEG ($, $/kWh, S/kW^2)
μ	Operation and maintenance costs ($/kWh or $/kWh^2)
λ	Cost of unserved energy ($/kWh)
*Decision variables (**Φ**)*	
p	Power (kW)
u	Commitment status (Binary)
ε	Energy (kWh)

1 - Introduction

1.1 - Context & motivation

Even nowadays, around 725 million people worldwide do not have access to electricity [1]. These consumers typically dwell in remote rural areas, where the extension of upscale infrastructures suppose unaffordable efforts [2]. On the face of this situation, deployment of onsite generation and storage assets frequently suppose the unique alternative for electricity supplying [3]. Local devices that are deployed near to consumers are usually controlled in a centralized way and organized within an upscale structure called microgrid (MG) [4].

Isolated MGs typically encompass renewable generators, storage systems and backup conventional generation e.g. diesel engine generators (DEGs) [5]. Such components are subjected to unexpected failures due to equipment aging or contingencies [6]. In isolated MGs, these events have a huge impact on consumers because the impossibility of accessing to an upscale grid or the high economic cost of backup generators. In this regard, operational tools devoted on energy management and scheduling tasks of the grid should consider this kind of failures, with the aim of avoiding or limiting their impact on the consumers' satisfaction and monetary expenditures. This paper is devoted on this issue.

1.2 - Literature review

Marzband et al [7] proposed a bio-inspired solver for optimal scheduling of standalone MGs, with the objective of minimizing the energy cost in a local energy market. In [8], a day-ahead Mixed-Integer-Linear programming (MILP) scheduling model for multi-energy MGs is combined with the receding horizon technique for real-time operations. A scheduling model for off-grid MGs under uncertainties in the presence of battery energy storage (BES) is developed in [9]. The developed optimization problem is solved using dynamic programming, while the uncertainties are modelled using probabilistic scenarios. The paper [10] proposes a stochastic-based day-ahead scheduling model based on Mixed-Integer nonlinear programming (MINLP) formulation for isolated MGs. In the considered formulation, pumped-hydro storage units and demand response (DR) are considered and analysed.

Morsali and Kowalczyk [11] developed a scheduling-planning tool for residential isolated areas. The proposed MINLP model is focused on scheduling a set of controllable appliances, with the aim of reducing generation costs and emissions. In [12], a bi-level optimization framework is developed for the optimal coordination of a battery swapping station and an isolated MG. This methodology minimizes the system operation cost in the upper-level, while the lower sub-problem is devoted on maximizing the net profit of the battery station. Likewise, a bi-level optimization framework is proposed in [13] for renewable-based isolated MGs with charging stations. Yan et al [14] proposed a real-time energy management tool for battery swapping stations integrated in smart communities. The objective of this model is to extract the maximum flexibility from stations.

The ref. [15] presents a robust scheduling model for DEG-based isolated MGs. With the aim of being immune against uncertainties from photovoltaic (PV) generators, the mathematical formulation is based on the information gap decision theory (IGDT). The authors in [16] use a heuristic technique to schedule a MG considering self-healing actions under unpredictable failures and outages. In [17] a MILP model is developed for unit commitment of multi-energy MGs and systems. An adjustable robust formulation is incorporated into this model to manage with uncertainties. The ref. [18] presents a bi-level optimization approach for energy management of multi-MGs. The outer level is devoted on optimizing the system on a whole, while the inner level considers the eventual disconnection of some MGs from the networked system. A deterministic energy management model for renewable-based MGs considering DR is presented in [19].

A bi-level day ahead scheduling model for networked MGs is presented in [20]. This approach considers self-healing actions in case of faults in the networks. A robust-oriented approach for energy management in integrated electricity-heat MGs is presented in [21]. In this model, various energy storage technologies are considered to boost up the flexibility of the grid. The ref. [22] explores the use of metaheuristic algorithms for energy management in multi-energy MGs with integrated DR and storage units. Moazeni and Khazaei [23] developed a MILP energy management model for integrated water-energy networks. A resilient-oriented scheduling tool for grid-connected MGs is presented in [24]. This tool incorporates a stochastic-robust formulation to consider eventual upstream network failures and other uncertainties. The ref. [25] presents a MINLP for energy management of isolated rig platforms, via optimal scheduling of DEGs and BESs. In [5], the optimal electrification of isolated residential communities is addressed. In the developed MILP model, DR and vehicle-to-home capabilities are effectively incorporated and analysed. Jordehi [26] proposed a MILP unit commitment formulation for multi-energy hubs. Likewise, the same author incorporated IGDT formulation in [27] to consider uncertainties from renewable generation and demand. In [28], a control strategy for isolated MGs is developed for peak load shaving.

A master-slave optimization problem for networked MGs is developed in [29]. This algorithm incorporates a real-time management sub-problem which detects possible islanding mode and operates the isolated MG consequently. Li et al [30] developed an optimal scheduling model using reinforcement learning for improving forecasting accuracy. In [31], an energy management strategy for PV-based plants with integrated energy storage is developed. The objective of this model is to keep stable the voltage at the connection point. An interval-based formulation for isolated MGs with green-hydrogen storage and DR is developed in [32]. This model uses an innovative interval-based MILP formulation to efficiently cope with the uncertainties in renewable generation and local demand.

1.3 - Contributions

This paper addresses the issue of optimal scheduling of isolated MGs considering components' failures. As commented previously, these incidents may cause consumers' dissatisfaction and economic detriment. Consequently, it is useful to prevent their consequences in order to minimize their impact. To this end, a novel stochastic-IGDT formulation is proposed incorporating DR programs. As seen in Table 1, the present paper supposes the first attempt to use a hybrid Stochastic-IGDT approach for optimal scheduling of isolated MGs considering failures and DR. For the sake of simplicity, the main contributions of this paper are listed below:

- Developing a MILP model for optimal scheduling of isolated MGs considering components' failures and DR programs. Due to its structure, the developed formulation is modular and versatile, being possible to adapt it to any MG layout easily. In addition, the developed problem can be efficiently solved using a standard solver and the reachability of the global optimum is ensured [33].
- Proposing a multi-stage methodology for solving the developed optimization model.
- Analysing the role of DR programs in increasing the robustness of the scheduling program. To this end, curtailable consumers are incorporated, which may be encouraged to reduce their expected consumption on the basis of price-based signals.

- Presenting and discussing a case study, in order to validate the developed model and analyse the effect of considering reliability in the scheduling result and economic indexes.

Table 1. A summary of the relevant literature

Reference	Formulation	Uncertainties modelling	Components failure	DR	Renewables	
					PV	Wind
[5]	MILP	Stochastic	No	Yes	Yes	No
[7]	Metaheuristic	No	No	Yes	Yes	Yes
[8, 19, 29]	MILP	No	No	Yes	Yes	Yes
[9]	Dyn. Prog.	Stochastic	No	No	Yes	Yes
[10]	MINLP	Stochastic	No	Yes	Yes	Yes
[11]	MINLP	No	No	Yes	Yes	No
[12, 13]	Metaheuristic	Stochastic	No	No	Yes	Yes
[14]	Lyapunov	No	No	No	Yes	Yes
[15]	MINLP	IGDT	No	No	Yes	No
[16]	Heuristic	No	Yes	Yes	Yes	Yes
[17]	MILP	Adjustable robust	No	No	Yes	Yes
[18]	MILP	Stochastic	No	Yes	Yes	Yes
[20]	MILP	No	Yes	Yes	Yes	Yes
[21]	MILP	Robust	No	Yes	Yes	No
[22]	Metaheuristic	Stochastic	No	Yes	Yes	Yes
[23, 26, 30]	MILP	No	No	No	Yes	Yes
[24]	MILP	Stochastic-Robust	Yes	Yes	Yes	Yes
[25]	MINLP	No	No	Yes	Yes	Yes
[27]	MILP	IGDT	No	Yes	No	Yes
[28]	Heuristic	No	No	No	Yes	No
[31]	Metaheuristic	No	No	Yes	Yes	No
[32]	MILP	Interval-based	No	Yes	Yes	Yes
Present	MILP	Stochastic-IGDT	Yes	Yes	Yes	Yes

In the rest of this paper, Section 2 overviews the study system layout. Section 3 presents the MILP mathematical model. Section 4 develops the different uncertainties modelling and solution procedure. Section 5 presents a case study and discusses the results. Lastly, Section 6 concludes the paper.

2 - Overview of the isolated system

This work focuses on isolated MGs with various conventional onsite assets and DR programs. For simplicity, the studied system is pictorially represented in Fig. 1. It is assumed that there is no possibility of connection with any upstream network. Consequently, the considered system must be fully supplied by on-site assets. In this sense, renewable and backup generators are deployed. On the one hand, PV and Wind-based generators are considered. However, these generators are assumed to have a limited generation capacity (small-scale) [34]. In addition, their intermittent behaviour makes them non-dispatchable and therefore their generation may be interrupted in some periods throughout the day due to low availability of wind or solar irradiance. To solve this issue, along the backup generation (which is dispatchable), a BES is deployed to store eventual surplus renewable energy and also enable a more efficient energy management [35].

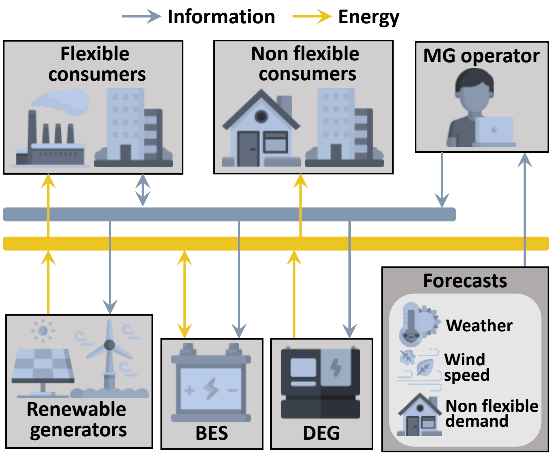

Fig. 1. Pictorial representation of the isolated system under study

Local encompasses inflexible and flexible consumers. The formers are considered inelastic and therefore their instantaneous demand cannot be neither curtailed nor deferred [36]. On the other hand, flexible consumers may accept a curtailment in their predicted demand if a monetary revenue is obtained as a counterpart. In this regard, these consumers establish contractual agreements with the local service entity, by which the operator can reduce the energy supplying to these consumers subjected to price-based DR programs [37].

The coordination of the different local agents and assets is managed in a centralized way. The role of scheduler is assumed in this case by the MG operator, who receives forecast information and performs the day-ahead scheduling program with the aim of reducing the operational cost. To establish an effective communication among the different agents and components, unidirectional and bidirectional communication channels have to be enabled. Communications in MGs is not a trivial question that encompasses a variety of topics such as privacy protection or energy analytics. This issue is far away of the scope of this paper, which is intimately linked to energy management tools. For more information about communication in MGs the reader is referred to [38] and the references therein.

3 - Mathematical models

This section presents the mathematical modelling of the different components and agents involved in the operation of the MG explained in Section 2. The developed formulation is MILP. This kind of problems have several advantages over MINLP and metaheuristic-based tools. For example, they are modular, converge to the global optimum and can be easily formulated and solved in standard software [33]. The formulation is presented in two parts, for simplicity. Firstly, all the models are described without considering components' failures. Next, the developed formulation considering eventual failures is developed and explained.

3.1 - Formulation without failures

3.1.1 - DEG modelling

In the MG under study, it is assumed that the DEG will act as backup generator. In this sense, a medium, large-scale device is assumed to be deployed. This kind of generators are characterized by a minimum and maximum dispatchable powers [39], as said the constraint (1). On the other hand, the constraint (2) imposes ramp limits.

$$\underline{p}^{DEG} \cdot u_t^{DEG} \leq p_{r|t}^{DEG} \leq \overline{p}^{DEG} \cdot u_t^{DEG};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{1}$$

$$p_{r|t-1}^{DEG} - R^{DEG} \leq p_{r|t}^{DEG} \leq p_{r|t-1}^{DEG} + R^{DEG};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \backslash t > 1 \tag{2}$$

3.1.2 - Renewable generators modelling

Renewable generation is strongly influenced by weather parameters (e.g. wind speed and solar irradiance). In the literature, a variety of models have been developed to convert such parameters in potential power generation [40]. For PV arrays, the following model, which depends on the ambient temperature and solar irradiance, is used in this paper [41].

$$\hat{p}_{r|t}^{PV} = \bar{p}^{PV} \cdot \left[0.25 \cdot \hat{\vartheta}_{r|t} + 0.03 \cdot \hat{\vartheta}_{r|t} \cdot \hat{\theta}_{r|t} + (1.01 - 1.13 \cdot \eta^{PV}) \cdot \hat{\vartheta}_{r|t}^{2}\right];\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \qquad (3)$$

As commented in some references (e.g. see [35]), the model above might be unsuitable since it does not consider the peak power of PV panels. In this regard, it is suitable to impose the constraint (4), which limits the maximum PV generation by 10 % over the rated peak power.

$$\hat{p}_{r|t}^{PV} = \begin{cases} \hat{p}_{r|t}^{PV}, \text{if } \hat{p}_{r|t}^{PV} \leq 1.1 \cdot \bar{p}^{PV} \\ 1.1 \cdot \bar{p}^{PV}, \text{o.w.} \end{cases};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \qquad (4)$$

Wind turbines are normally characterized by the so-called wind-speed curve [42], similar to that plotted in Fig. 2. These curves relate the wind speed with the power generated by turbines. Mathematically, the curve in Fig. 2 can be expressed as follows [32]

$$\hat{p}_{r|t}^{WG} = \eta^{WG} \cdot \begin{cases} 0, \text{if } \hat{\gamma}_{r|t} < \underline{\gamma}^{WG} \\ \alpha^{WG} \cdot \hat{\gamma}_{r|t}^{3} - \beta^{WG} \cdot \bar{p}^{WG}, \text{if } \underline{\gamma}^{WG} \leq \hat{\gamma}_{r|t} \leq \gamma^{WG,*} \\ \bar{p}^{WG}, \text{if } \gamma^{WG,*} \leq \hat{\gamma}_{r|t} \leq \bar{\gamma}^{WG} \\ 0, \text{if } \hat{\gamma}_{r|t} > \bar{\gamma}^{WG} \end{cases};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \qquad (5)$$

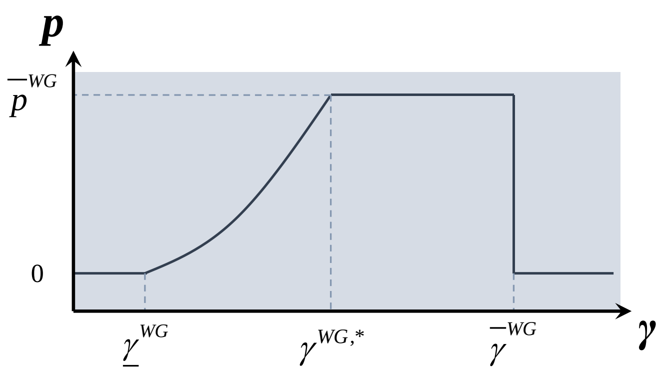

Fig. 2. Wind-power curve of a wind turbine

where $\gamma^{WG,*}$ is the nominal wind speed, that denotes the value beyond which the turbine generates its nominal power. The expressions (3)-(5) yield therefore potential renewable generation based on weather parameters. Thus, the instantaneous power supplied by renewable generators is limited to those values by (6).

$$p_{r|t}^{i} \leq \hat{p}_{r|t}^{i};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge i \in \{PV; WG\} \tag{6}$$

It is noteworthy that the models (3)-(5) are function of uncertain weather parameters. Consequently, the potential renewable generation is considered uncertain and modelled using stochastic programming, as detailed in Section 4.

3.1.3 - BES modelling

A conventional BES model based on exchanging power with the grid is considered in this paper [35]. Firstly, the rated power of a battery is determined by its nominal capacity and the energy-to-power ratio [43], as said the constraint (7). On the other hand, the constraint (8) makes the charging and discharging processes complementary.

$$p_{r|t}^{BES,i} \leq u_{t}^{BES,i} \cdot \frac{\overline{\varepsilon}^{BES}}{\mathrm{e2P}};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge i \in \{ch; dch\} \tag{7}$$

$$\sum_{i \in \{ch;dch\}} \left\{u_{t}^{BES,i}\right\} \leq 1;\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{8}$$

The equation (9) models the instantaneous energy stored in the battery bank as a function of the exchanging power with the system [44]. The state-of-charge (SOC) must be limited by the nominal capacity of the BES and the depth-of-discharge (DOD) settings, as expresses the constraint (10).

$$\varepsilon_{r|t}^{BES} = \varepsilon_{r|t-1}^{BES} + \Delta\tau \cdot \left[\eta^{BES,ch} \cdot p_{r|t}^{BES,ch} - \frac{p_{r|t}^{BES,dch}}{\eta^{BES,dch}}\right];\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \backslash t > 1 \tag{9}$$

$$\left(1 - \frac{\mathrm{DOD}}{100}\right) \cdot \overline{\varepsilon}^{BES} \leq \varepsilon_{r|t}^{BES} \leq \overline{\varepsilon}^{BES};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{10}$$

Lastly, since the model (9) is not defined at $\mathbb{T}(1)$, it is necessary to impose the constraint (11), which fixes the SOC at the first and last time slots to keep the coherency of the model [35].

$$\varepsilon_{r|\mathbb{T}(1)}^{BES} = \varepsilon_{r|\mathbb{T}(\text{end})}^{BES} = \overline{\varepsilon}^{BES};\ \forall r \in \mathbb{R} \tag{11}$$

3.1.4 - Flexible consumers modelling

This paper considers curtailable (flexible) consumers, who are willing to reduce their expected demand on the basis of price-based DR programs [45]. It means that they would receive a compensatory payment (\$/kWh) if they are not fully served by the operator. However, it is reasonable to assume a lower limit below which the consumers are not willing to reduce their consumption. Therefore, curtailable consumers are modelled according to (12).

$$\underline{p}_t^j \leq p_{r|t}^j \leq \overline{p}_t^j;\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge j \in \mathbb{J} \tag{12}$$

3.1.5 - System balance

It is necessary to impose the power balance in the grid by (13). It is worth noting that the inflexible demand has been considered here an uncertain parameter, and therefore modelled via scenarios as explained in Section 4.

$$p_{r|t}^{DEG} + \sum_{i\in\{PV;WG\}}\left\{p_{r|t}^{i}\right\} + p_{r|t}^{BES,dch} = \hat{p}_{r|t}^{IF} + p_{r|t}^{BES,ch} + \sum_{j\in\mathbb{J}}\left\{p_{r|t}^{j}\right\};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{13}$$

3.1.6 - Operation cost

The operation cost referred to the system under study encompasses various terms, as said in (14).

$$F = F^{DEG} + F^{O\&M} + F^{DR} \tag{14}$$

In (14), the first term stands for the costs associated to the DEG, which encompasses fuel and maintenance costs, as defined in (15).

$$F^{DEG} = \sum_{r\in\mathbb{R}}\left\{\pi_r \cdot \sum_{t\in\mathbb{T}}\left\{\Delta\tau \cdot \left[u_t^{DEG} \cdot \left(\frac{\kappa^{DEG}\cdot\overline{p}^{DEG}}{T^{DEG}} + \omega_1^{DEG}\right) + p_{r|t}^{DEG} \cdot \omega_2^{DEG} + \left(p_{r|t}^{DEG}\right)^2 \cdot \omega_3^{DEG}\right]\right\}\right\} \tag{15}$$

As seen above, the DEG costs are formed by maintenance expenditures related to the total operating hours [32] and the fuel cost, which is a quadratic function of the generated power [46]. The quadratic terms in (15) introduce nonlinearities that can be linearized using piecewise representations [47], and thus preserving the MILP structure of the model (see Appendix A).

On the other hand, the second term in (14) stands for the operation and maintenance (O&M) costs of the rest of components (i.e. PV, wind turbines and BES). For the renewable generators, these costs can be considered proportional to the energy generated, while in the case of the batteries, they can be considered a quadratic function of the energy exchanged by the storage bank [48]. With these premises, the second term in (14) is given by

$$F^{O\&M} = \sum_{r\in\mathbb{R}} \left\{\pi_r \cdot \sum_{t\in\mathbb{T}} \left\{\Delta\tau \cdot \left[\sum_{i\in\{PV;WG\}} \left\{\mu^i \cdot p^i_{r|t}\right\} + \mu^{BES} \cdot \sum_{i\in\{ch;dch\}} \left\{\left(p^{BES,i}_{r|t}\right)^2\right\}\right]\right\}\right\} \tag{16}$$

As in (15), the quadratic terms in (16) can be linearized using piecewise representations (see Appendix A). Finally, the last term in (14) stands for the costs of applying DR programs. As commented, the operator must face compensatory payments for each kWh that it is not served to the flexible consumers. Hence, the last term in (14) can be written as follows

$$F^{DR} = \sum_{r\in\mathbb{R}} \left\{\pi_r \cdot \sum_{t\in\mathbb{T}} \left\{\Delta\tau \cdot \sum_{j\in\mathbb{J}} \left\{\lambda^j \cdot \left(\overline{p}^j_t - p^j_{r|t}\right)\right\}\right\}\right\} \tag{17}$$

3.2 - Formulation with failures

The day-ahead scheduling model developed in this paper considers possible failure events of components. As commented, these unexpected events may be caused by equipment aging or contingencies, and might have a significant impact on the operation cost or users' satisfaction. Backup generators may be out of service due to faults in their mechanic or electric components, but also to possible failures of electronic interfaces or communication channels [49].

To consider possible failure of components, the artificial binary variable y^i is introduced, which is equal to 0 if the i^{th} component is damaged and 1 otherwise. This variable allows to modify some of the constraints described above. For the DEG, the constraint (1) is replaced by (18).

$$\underline{p}^{DEG} \cdot u_t^{DEG} \cdot y_t^{DEG} \leq p_{r|t}^{DEG} \leq \overline{p}^{DEG} \cdot u_t^{DEG} \cdot y_t^{DEG};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{18}$$

As seen, the constraint (18) inhibits the DEG commitment at time t if $y_t^{DEG} = 0$. Likewise, the constraints (19) and (20) model the failures on PV, wind turbines and BES by replacing (6) and (7), respectively.

$$p_{r|t}^{i} \leq y_t^i \cdot \hat{p}_{r|t}^{i};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge i \in \{PV; WG\} \tag{19}$$

$$p_{r|t}^{BES,i} \leq u_t^{BES,i} \cdot y_t^{BES} \cdot \frac{\overline{\varepsilon}^{BES}}{\mathrm{e2P}};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge i \in \{ch; dch\} \tag{20}$$

It is worth to note that the introduction of the variable y^i introduces nonlinearity due to the product of two integer variables in (18) and (20). These terms can be linearized using additional variables and constraints, as detailed in Appendix B.

4 - The proposed solution procedure

The main aim of this paper is to develop a day-ahead scheduling tool for isolated MGs robust against unexpected components' failures. In this regard, the developed model should yield a scheduling plan that minimizes the impact of possible incidents, thus reducing their detrimental effects on the economy and overall welfare of the standalone system. To this end, a novel stochastic-IGDT formulation is developed for uncertainties modelling. By this approach, uncertainties in renewable generation and inflexible demand are modelled via scenarios (stochastic programming), while IGDT is used for modelling the unpredictable failures. In addition, operation cost is also modelled as an artificial uncertainty using IGDT for convenience, being so possible to consider it in the final decision process. This approach is founded on the convenience of stochastic programming to model weather parameters. This kind of uncertainties can be easily modelled using probability distribution functions on either forecast profiles or well-fitted models [50]. Thereby, a large number of scenarios can be generated on the basis of this information. However, equipment failures may be difficult to model using probability distribution functions due to the lack of information or suited models [16]. In this sense, IGDT is considered a better approach since this modelling principle does not require a priori knowledge of the probability behaviour of the parameter [51].

Using the developed stochastic-IGDT formulation, a multi-stage solution procedure is developed for optimal scheduling of the system under study. The proposed solution procedure is summarized in the flowchart of Fig. 3. As seen, each stage is devoted on either determining the maximum/minimum possible operating cost and the maximum admissible failure time of each component. This information is useful for the IGDT formulation of failures and operational cost, since in this case uncertainties are modelled according their uncertain radiuses and bounds (see [27, 51] for details). Subsequent sections focus on explaining and presenting the different stages and their corresponding formulation.

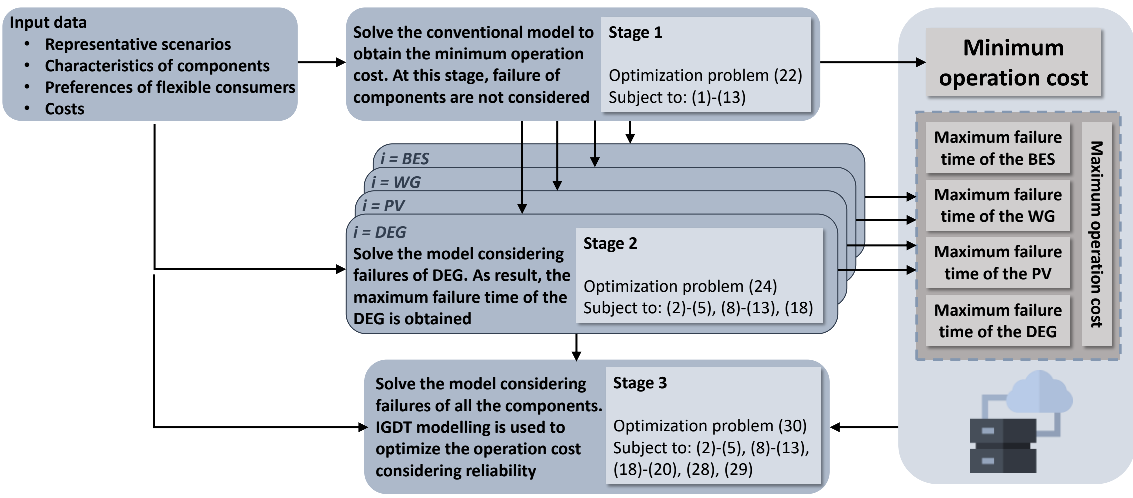

Fig. 3. Flowchart of the proposed solution procedure

4.1 - Stochastic modelling

Conventional stochastic modelling is used in this paper for weather parameters (wind speed, solar irradiance and ambient temperature) as well as inflexible demand. This approach consists on generating a large number of scenarios with the aim of catching the stochastic behaviour of the uncertainty. These scenarios can be constructed using probability distribution functions [50] or assuming forecast errors [52]. In this paper, the second option has been preferred assuming that the concerned uncertainties can be predicted with sufficient accuracy using conventional forecast methods [53]. Nonetheless, well-suited distribution models could be used instead without major modifications. The considered approach assumes that forecast errors follow a Gaussian distribution. Therefore, once the forecast profiles of uncertainties are known, a large number of scenarios (~ 1,000-4,000 [54]) can be easily generated. Due to the large number of required scenarios, the computational cost of the resulting optimization problem may be unaffordable. To circumvent this issue, data reduction or clustering techniques can be used [55]. In this paper, the k-medoids method has been considered due to its good features [56], and the total number of representative scenarios has been set following the ideas in [5]. This way, the scenario space (denoted by $\mathbb{S}$) can be reduced to a minimum representative set (denoted by $\mathbb{R}$). Finally, the probability of each scenario can be calculated according to

$$\pi_r = \frac{\mathrm{size}(\Omega_r)}{\mathrm{size}(\mathbb{S})};\ \forall r \in \mathbb{R} \tag{21}$$

4.2 - Stage 1

This stage is devoted on obtaining the scheduling plan for the isolated system without considering reliability, i.e. assuming no failures over the studied time horizon. Thus, the objective of this stage is minimizing the operating cost subjected to functional constraints, which is expressed in the following optimization problem

$$\underline{F} \rightarrow \min_{\mathbf{\Phi}} F\left(\boldsymbol{Y} == \mathbf{1}_{4\times \mathrm{size}(\mathbb{T})}\right) \tag{22}$$

Subject to: (1)-(13)

where $\mathbf{1}_{m\times n}$ is a matrix of ones and

$$\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{y}^{DEG} \\ \boldsymbol{y}^{PV} \\ \boldsymbol{y}^{WG} \\ \boldsymbol{y}^{BES} \end{bmatrix} = \begin{bmatrix} y^{DEG}_{\mathbb{T}(1)} & \cdots & y^{DEG}_{\mathbb{T}(\mathrm{end})} \\ y^{PV}_{\mathbb{T}(1)} & \cdots & y^{PV}_{\mathbb{T}(\mathrm{end})} \\ y^{WG}_{\mathbb{T}(1)} & \cdots & y^{WG}_{\mathbb{T}(\mathrm{end})} \\ y^{BES}_{\mathbb{T}(1)} & \cdots & y^{BES}_{\mathbb{T}(\mathrm{end})} \end{bmatrix} \tag{23}$$

4.3 - Stage 2

In contrast, this stage does consider possible failure of components. However, each component is analysed individually. In consequence, this stage must be run as many times as components are susceptible to fail. The number of hours that the *i*th component is not working over the studied time horizon is given by

$$\Theta^{i} = \mathrm{size}(\mathbb{T}) - \textstyle\sum_{t\in\mathbb{T}}\left\{y^{i}_{t}\right\};\ \forall i \in \{DEG; PV; WG; BES\} \tag{24}$$

As a result of this stage, the maximum number of hours that the i^{th} component can be out of service is determined, for which the following optimization problem is solved.

$$\left[\overline{\Theta}^{i}; F^{i}\right] \rightarrow \max_{\mathbf{\Phi}, \boldsymbol{y}^{i}} \Theta^{i}\left(\boldsymbol{y}^{m\neq i} == \mathbf{1}_{\mathrm{size}(\mathbb{T})}\right);\ \forall i \in \{DEG; PV; WG; BES\} \tag{25}$$

Subject to: (2)-(5), (8)-(13), (18)∨(19)∨(20)

After carrying out the problem (25) for each component, the maximum operating cost can be calculated as follows

$$\overline{F} = \max\left\{F^{i}\right\};\ \forall i \in \{DEG; PV; WG; BES\} \tag{26}$$

4.4 - Stage 3

The final stage focuses on determining the scheduling plan for the studied system robust against components' failures. To this end, incidents are posed using IGDT. By this approach, the total number of failure hours of each equipment are modelled by their bounds and uncertain radius (ξ's). For convenience in the notation, uncertain radiuses are organized in vector form, as follows

$$\Xi^{Fail} = \begin{bmatrix} \xi^{DEG} \\ \xi^{PV} \\ \xi^{WG} \\ \xi^{BES} \end{bmatrix} \tag{27}$$

Using the uncertain radiuses, the failure time of each component is allowed to vary within their bounds by the following set of constraints.

$$\Theta^i\left(\mathbf{\Phi}, \boldsymbol{Y}, \Xi^{Reliab}, \xi^{Cost}\right) \geq \xi^i \cdot \overline{\Theta}^i;\ \forall i \in \{DEG; PV; WG; BES\} \tag{28}$$

Indeed, as seen above, the failure time of each component is forced to lie within the range [0, $\overline{\Theta}^i$], depending on the value of the corresponding radius, which are declared decision variables. It is worth noting that zero is assumed as the minimum time that each component may be out of service, which is a logic assumption.

Nevertheless, not only the possible failure of components should be considered, since this approach may lead to inadmissible high operating cost. To avoid this unrealistic situation, the operating cost is modelled as an artificial uncertainty and therefore characterized by its bounds (calculated at previous stages), and corresponding uncertain radius, as said (29).

$$F\left(\mathbf{\Phi}, \boldsymbol{Y}, \Xi^{Reliab}, \xi^{Cost}\right) \leq \overline{F} - \xi^{Cost} \cdot \left(\overline{F} - \underline{F}\right) \tag{29}$$

Therefore, this stage consists on maximizing the value of the different radiuses ξ's. Thereby, the failure time of all components is maximized. But also, the operating cost is considered. Indeed, the higher value of ξ^{Cost}, the closer is the operating cost to its optimal value $\underline{F}$. Thus, the Stage 3 can be raised as follows.

$$\max_{\mathbf{\Phi}, \boldsymbol{Y}, \Xi^{Reliab}, \xi^{Cost}} \frac{1}{2} \cdot \left[\frac{1}{4} \cdot \sum\left\{\Xi^{Reliab}\right\} + \xi^{Cost}\right] \tag{30}$$

Subject to: (2)-(5), (8)-(13), (18)-(20), (28), (29) The objective function in (30) has been formulated so that both immunity against failures and economy have similar impacts; thus, both objectives are jointly optimized on a whole.

5 - Case study

This section presents a case study based on the benchmark MG described in Section 2. The developed MILP model has been coded under Matlab R2020b environment and solved using Gurobi [57]. All the simulations were performed over a 24-hours horizon with 30-min ($\Delta\tau = 1/2$) resolution ($\text{size}(\mathbb{T}) = 48$). It is necessary to mention that the case study does not correspond to a particular case. However, the used data have been extracted for different literature in order to create a generic model that contemplates as many potential scenarios as possible. In this regard, the developed formulation encompasses a model of the most common components involved in MG operation. Thereby, this case study serves as a valuable benchmark for application of the developed methodology in real cases. In addition, the modular structure of the mathematical formulation allows to easily tailor the developed procedure to different layouts and situations.

For stochastic modelling of uncertainties, 2,000 scenarios were generated assuming Gaussian distribution of forecast errors on real profiles. This set of data were reduced to only 15 representative scenarios using the k-medoids method and the methodology described in Section 4.1.

Experiments carried out by the authors on an Intel® Core™ i7-10700K CPU 3.80GHz 3.79 GHz personal computer consumed 20-30 minutes by average, which is a reasonable time since the developed tool is conceived to be performed with various hours of margin. Moreover, the developed optimization tool is expected to present a good computational performance even in larger systems, since the scalability of MILP problems has been well-proved in the literature [58].

5.1 - Input data

Weather and inflexible demand forecasts are based on real data and are plotted in Fig. 4 along the representative scenarios considered in simulations. In particular, solar irradiance, temperature and wind speed correspond with real measurements taken at Virgin Islands on May 3, 2016 [59]. On the other hand, inflexible demand has been adapted from real demand observed at La Palma island (Spain) on May 3, 2016 [60]. As seen, peak power reaches ~500 kW at 22:00 h, which is a reasonable peak demand in MGs [61].

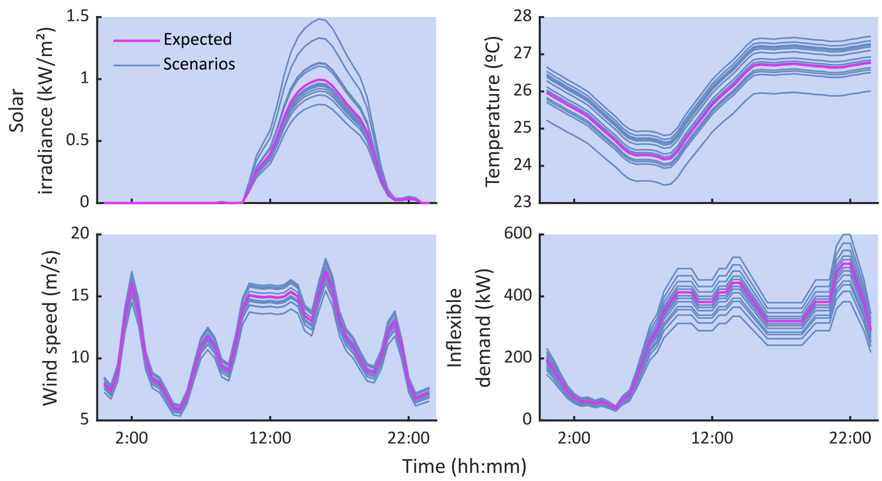

Fig. 4. Expected profiles of uncertainties and representative scenarios

Two flexible consumers are considered, whose expected demand is shown in Fig. 5. As seen, the consumer 1 presents a relatively flat curve demand which spans from early morning to evening. This behaviour is typical of commercial buildings while the consumer 2 presents a higher peak demand and shorter consumption time, which is more common in industries [62]. Thereby, two typical flexible profiles are considered in simulations. The cost of unserved energy is taken equal to 10 $/kWh and 15 $/kWh for the consumer 1 and 2, respectively. Lastly, the data referred to generators and BES are collected in Tables 2-5, and have been extracted from different references.

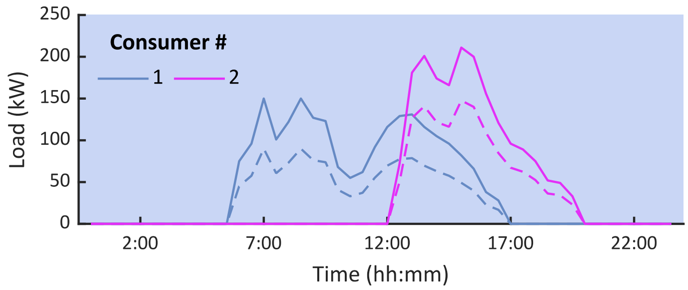

Fig. 5. Expected consumption of flexible consumers (the minimum servable demand is plotted with discontinuous lines)

Table 2. Data of the DEG [32, 46]

Parameter	Value
$\underline{p}^{DEG}$; $\overline{p}^{DEG}$; R^{DEG}	20; 500; 200 kW
ω_1^{DEG}; ω_2^{DEG}; ω_3^{DEG}	0.6 \$/h; 0.05 \$/kWh; 0.02 \$/kWh^2
κ^{DEG}	340 \$/kW
T^{DEG}	30,000 hrs

Table 3. Data of PV panels [39]

Parameter	Value
η^{PV}	0.167 pu
$\overline{p}^{PV}$	150 kW
μ^{PV}	0.24 \$/kWh

Table 4. Data of wind turbines [39]

Parameter	Value
η^{WG}	0.88 pu
$\overline{p}^{WG}$	150 kW
$\underline{\gamma}^{WG}$; $\gamma^{WG,*}$; $\overline{\gamma}^{WG}$	2; 11; 21 m/s
α^{WG}; β^{WG}	0.2268; 0.006 kW/(m/s)$^{-3}$
μ^{WG}	0.19 \$/kWh

Table 5. Data of BES [39, 48]

Parameter	Value
η^{BES}	0.98 pu
ε^{BES}	200 kWh
e2P	2 hrs.
DOD	60 %
μ^{BES}	10^{-6} \$/kWh^2

5.2 - Results & discussion

Next, various results are presented and discussed. Fig. 6 plots the scheduling result without considering failures (Stage 1). In this figure is clearly observed the advantages of implementing DR programs. Indeed, peak demand was reduced by 110 kW after applying DR initiatives. This is due to in the former case the expected demand from flexible consumers is only partially covered by 83%. This strategy entails a notable reduction of the operating cost by 1,000 $ approximately and a lower dependency of the DEG with the consequent reduction of CO_2 emissions [5]. The operational profile of the different assets follows logic principles. Thus, the BES is principally charged during those hours with low demand and high renewable generation (e.g. at noon) while large renewable penetration around 17:00 h serves to notably reduced the diesel generation, which is costly.

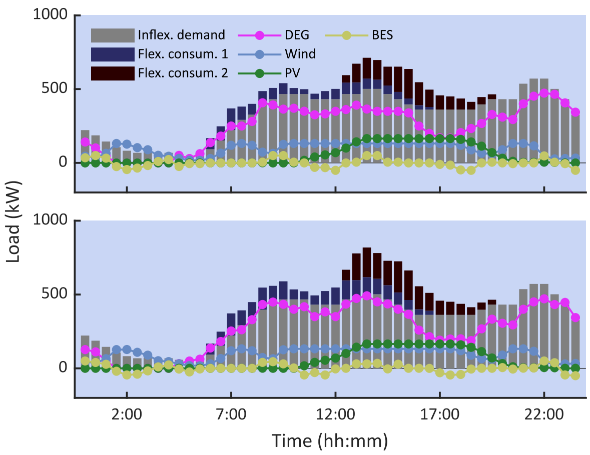

Fig. 6. Scheduling result at Stage 1 with (upper) and without (bottom) DR programs

The Stage 2 of the developed methodology introduces possible failure events in components. Fig. 7 is analogue to Fig. 6 but for the Stage 2 considering failures in the DEG. As observed, in this figure, the optimization tool seeks for the maximum number of failure hours that keep the model feasible. In this case, it was determined that the DEG can be shut down up to 4 hours, being considerably lower than the results observed for the other components (e.g. up to 22 hours in the case of PV panels). This is due to the system layout has been sized so that the DEG results essential to cover the expected inflexible demand, while the other components are mainly devoted on providing flexibility and consequently reducing the operational cost. However, at Stage 2, the optimization problem is run regardless the total expenditures and therefore the importance of renewable generators and storage assets is reduced.

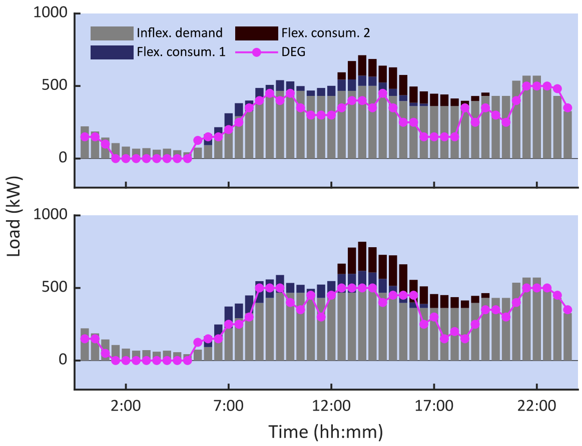

Fig. 7. Scheduling result at Stage 2 considering failures of DEG with (upper) and without (bottom) DR programs (the renewable generation and BES were omitted for simplicity)

The last stage of the developed methodology considers failures in all the components as well as the reduction of the operational cost. In other words, it seeks a compromise solution between reliability and economy. The results obtained at this stage are plotted in Fig. 8. In this figure it is clearly appreciated how the peak demand is notably reduced with the implementation of DR programs (654 kW vs 760 kW). This value is even lower than that obtained at Stage 1 (712 kW). It is also noteworthy that the BES can be out of service during many hours when DR programs are implemented. In this case, flexibility provided by curtailable consumers allows to reduce the dependency of the battery bank. This way, the total number of failure hours is further maximized without notably incrementing the monetary spending. This is however not possible without DR programs, when the system is weaker to components' failures. Indeed, as seen in Fig. 9, where the accumulated failure hours are reported, the considered problem is feasible for 25 failure hours in total under DR programs, while only 12 failure hours are admissible without DR initiatives.

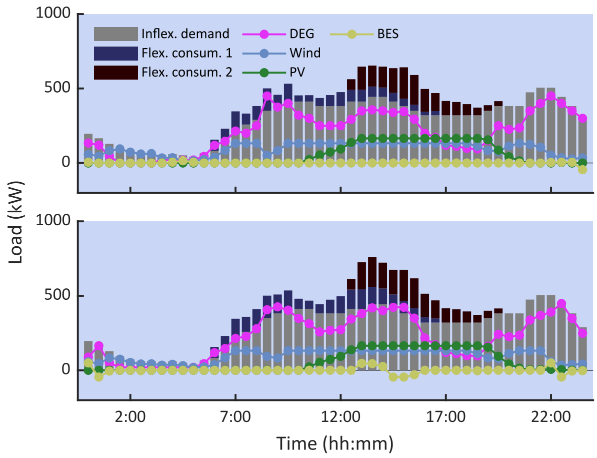

Fig. 8. Scheduling result at Stage 3 with (upper) and without (bottom) DR programs

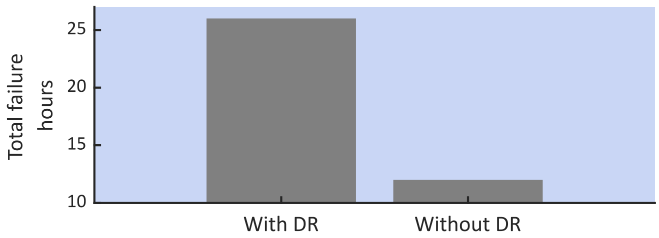

Fig. 9. Total accumulated failure hours

Finally, Table 6 collects valuable inform, which may help to better understand the role of DR programs in the economy and reliability. As expected, the total operation cost was higher when failures are assumed. However, the system always resulted more economic with DR programs. In this case, it results more attractive compensating to flexible consumers for unserved energy than using costly generator units (DEG) to cover this demand. Thus, the total flexible demand was covered by 83 % with and without failures, while without DR programs the operator is forced to satisfy this consumption totally. This result allows to calculate the cost of considering failures. This value indicates the increment of the operating cost that supposes considering possible failures on components. In other words, this indicator stands for the extra monetary expenditures that would suppose making the scheduling plan robust against failures. In this regard, the cost of failures supposes approximately a 4-5 % of the total operation spending. This last result evidences the capability of the scheduling tool to consider failures and economy on a whole, similar to multi-objective problems [63]. Indeed, reliability was considered with only scarce increments of the operational expenditures. In absolute terms, this cost was higher in the case of considering DR programs. This is due to, as seen in Fig. 9, more failure hours are assumable in case of applying DR premises, which redounds in a higher increment of the operation spending.

Table 6. Economic indicators

Indicator	**Without failures (Stage 1)**		**With failures (Stage 3)**	
	With DR	**Without DR**	**With DR**	**Without DR**
Operation cost ($)	34,073	35,231	35,944	36,577
Flexible demand satisfied (%)	83	100	83	100
Cost of failures ($)	--	--	1,871	1,346

5.3 - Comparison with other uncertainties modelling

There exist many other uncertainties modelling approaches in the literature. Monte-Carlo simulation is considered the most common [65]. It relies on generating a large number of scenarios in order to consider all possible information about the uncertainties. This technique usually involves a large computational burden, which has motivated the investigation of other methodologies. This section aims at comparing the developed Stochastic-IGDT approach with other models. More precisely, stochastic programming and robust optimization [66], are considered. The developed approach can be easily adapted to Monte-Carlo or stochastic programming. In this regard, instead of modelling failures via IGDT, they have been modelled using scenarios. To do that, a large number of scenarios have been generated based on the historical outage data at U.S., in a similar way to [67]. These scenarios have been directly used for Monte-Carlo simulation while the data reduction approach described in Subsection 4.1 has been used to generate the representative-set for components' failures. On the other hand, robust optimization can be easily tailored by simply modelling both uncertainties as failures using this approach.

The different uncertainties modelling approaches are compared in Fig. 10. To perform this comparison, two indicators have been used. Regarding the operating cost, it obviously varies depending on the uncertainties modelling. In this regard, both Monte-Carlo and stochastic programming yielded lower operating cost compared with the developed approach. This is due to these two approaches do not consider the most unfavourable values of the failures, in contrast to the developed methodology. Instead, Monte-Carlo and stochastic principles calculate the most probable operating cost on the basis of all the scenarios contemplated, either extreme cases or not. On the other hand, robust optimization reproduced similar results compared with the new proposal. This is because both methodologies are based on similar principles, i.e. implementation of the day-ahead scheduling plan being aware to extreme scenarios for failures.

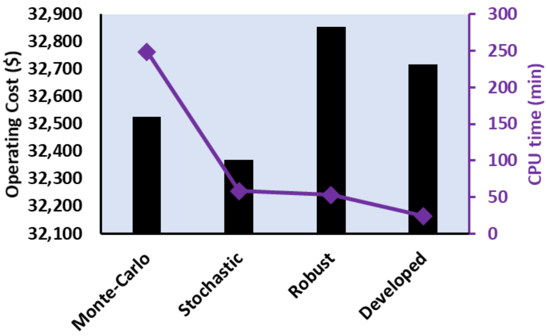

Fig. 10. Comparison of the developed methodology with other uncertainties modelling approaches

Regarding the computational burden, the developed method was clearly more competitive than the other approaches. This is due to not all the uncertainties were modelled using scenarios, as in the case of Monte-Carlo simulation and stochastic programming. This formulation clearly reduces the size of the variable-space. On the other hand, robust optimization was clearly less efficient, since this approach requires the formulation of the dual problem, in which there are as many variables as constraints, which is totally inefficient for the developed model.

6 - Conclusions & future works

In this paper, a novel energy management tool has been developed for isolated microgrids. The main advantage of the proposed tool is the inclusion of components' failures, with the aim of yielding results robust against unexpected failures incidents. To this end, a novel stochastic-IGDT model has been developed and explained, by which typical uncertainties from renewable generation and demand are accommodated using scenarios, while failures are robustly modelled using IGDT. In order to consider such events without disregarding the economy, operational cost has been treated as an artificial uncertainty using IGDT.

A variety of simulations has been performed on a benchmark isolated system and the results obtained served to validate the developed model. It has been highlighted the methodology proposed and how it works, progressively incorporating possible failures on each component individually. The developed model also allows to evaluate the role of DR programs. Thus, it has been detected the capability of such initiatives to reduce the peak demand and operation cost by 14 % and 3 %, respectively. Moreover, versatility offered by flexible consumers allow a higher degree of immunity against failures. Thus, up to a total of 25 accumulated failure hours are assumable when DR programs are launched, while this value is reduced to 12 hours in case of not applying DR initiatives.

Future works will be focused on applying the developed model to other related systems and layouts like smart homes or multi-energy hubs.

Appendix A - Linearization of quadratic terms

Let us consider a quadratic variable namely x^2, it can be drawn by its piecewise representation $\tilde{\psi}$, which is defined by a set of n grid points $\tilde{x}$, as follows

$$\tilde{\psi} = \langle \tilde{x}_i, \psi(\tilde{x}_i) \rangle;\ \forall i \in \{1,2,\dots,n\} \tag{A1}$$

The piecewise representation above allows to replace the nonlinear term x by the dummy linear variable z, which can be calculated as

$$z = \sum_{i=2}^{i=n}\{\delta_i \cdot (K_i \cdot x + L_i)\} \tag{A2}$$

In (A2), the K's and L's stand for the slope and the order at origin of each piecewise section, respectively. These terms are given by

$$K_i = \frac{\psi(\tilde{x}_i)-\psi(\tilde{x}_{i-1})}{\tilde{x}_i-\tilde{x}_{i-1}};\ \forall i \in \{2,3,\dots,n\} \tag{A3}$$

$$L_i = \psi(\tilde{x}_i) - K_i \cdot \tilde{x}_i;\ \forall i \in \{2,3,\dots,n\} \tag{A4}$$

To avoid that more than one piecewise section is activated at once, the constraint (A5) must be imposed and the δ's are declared as SOS1 variables (see [64]).

$$\sum_{i=1}^{i=n-1}\{\delta_i \cdot \tilde{x}_i\} \le x \le \sum_{i=2}^{i=n}\{\delta_{i-1} \cdot \tilde{x}_i\} \tag{A5}$$

A nonlinearity appears in (A2) because the product of the integer variable δ and the continuous one x. To linearize this product, a disjunctive big M approach can be used [35], which is defined by the following set of constraints.

$$x - M \cdot (1-\delta_i) \le w_i \le x + M \cdot (1-\delta_i);\ \forall i \in \{2,3,\dots,n\} \tag{A6}$$

$$-M \cdot \delta_i \le w_i \le M \cdot \delta_i;\ \forall i \in \{2,3,\dots,n\} \tag{A7}$$

where M is a large positive number. The model above allows to replace the nonlinear product $\delta \cdot x$ by the linear variable w.

Appendix B - Linearization of bi-integer terms

Given two integer variables namely a and b, their product can be linearized introducing the dummy variable v and the following constraints [32].

$$v \le a, v \le b \tag{B1}$$

$$v \ge a + b - 1 \tag{B2}$$

$$v \ge 0 \tag{B3}$$

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