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Optimal Home Energy Management including Batteries and Heterogenous Uncertainties

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Abstract. Energy storage will play a vital role in the decarbonization of the electricity sector, especially in domestic installations. In such kind of systems, home energy management applications are becoming essential. These kinds of tools enable active control of domestic appliances and storage systems to pursue a more efficient use of energy in household installations. However, the emergence of renewable generators and electric vehicles makes the operation of residential assets more difficult, as multiple uncertainties should be managed on a whole. These unknowns have a different character, in fact, some of them can be easily predicted while others are subject to a high level of randomness. This paper addresses this issue by developing a novel home energy management tool that accounts for the different levels of the randomness of the uncertainties involved in home operation. To this end, a novel Lexicographic-Interval formulation of the home energy management problem is presented, by which the uncertainties can be easily modelled using interval notation. Unlike conventional tools, the new proposal sorts the uncertainties according to their level of randomness. Then, the energy management mechanism performs the scheduling plan according to the predefined classification so that the more random parameters rule the impact of others, thus giving more importance to those uncertainties that are hardly predictable. A benchmark case study is performed to validate the new proposal and illustrate its capabilities. Different tariffs are compared, showing that the Time-of-Use mechanism is normally more expensive than Real-Time-Pricing tariffs, increasing the electricity bill by 12% in some cases. However, the level of robustness achieved with Time-of-Use tariffs seems higher, allowing to assume an abruptly unexpected reduction of photovoltaic generation.

Keywords. Battery energy storage; Home energy management; Renewable energy; Robust optimization; Uncertainty.

Nomenclature

Indexes (Sets)	
$t(T)$	Time
$a(A^{I}/A^{NI})$	Interruptible/non-interruptible controllable appliances
Θ	Time window
$\boldsymbol{\Omega}$	Uncertainties

Superscripts	
$Grid, buy/sell$	Buying/selling processes of the utility grid
Air, in, out	Indoor/outdoor air
PV	Photovoltaic panels
$BES, ch/dch$	Battery energy storage in charging/discharging mode
EV	Electric vehicle
$HVAC, h/c$	Heating-ventilation-air conditioner system in heating/cooling mode
sp/db	Setpoint/deadband
NC	Non-controllable
$\underline{(*)}/\overline{(*)}$	Minimum/maximum value
$\widehat{(*)}$	Uncertain parameter

Functions	
$\mathrm{E}(*)$	Expected value
$\mathrm{size}(*)$	Number of elements within a set

Parameters & constants	
ϑ	Solar irradiance (W/m²)
θ	Temperature (ºC)
η	Efficiency (%)
e2P	Energy-to-power ratio (h)
DOD	Depth-of-discharge (%)
D	Duty cycle (h)
m	Mass (kg)
C	Heat or thermal capacity (kJ/(kg·ºC) or kWh/ºC)]
R	Equivalent thermal resistance of the building (kW/ºC)
COP	Coefficient of performance (-)
λ	Energy price ($/kWh)

Variables	
p	Power (kW)
u	Commitment status (binary)
ε	Energy (kWh)
on/off	On/off status (binary)

1 - Introduction

1.1 - Context & motivation

Decarbonization of the electricity sector should be accompanied by a notable reduction in electricity consumption. Although the worldwide electricity demand fell by 1% in 2020 because of the effects of the COVID-19 pandemic, it is expected to recover in 2021 levels by 2019 and continue to increase in 2022 [1]. This trend compromises the objectives imposed by European countries to be nearly carbon neutral by 2050 [2]. In this regard, the residential sector accounts for nearly two-thirds of total primary energy use in Europe [3], being responsible of 35-40% related CO2 emissions [4]. Hence, domestic installations suppose a great opportunity to achieve the imposed environmental goals. However, this is not a simple task as most of resident users are still inelastic and therefore do not have the capability to respond to the external demand response (DR) signals. In this sense, home energy management (HEM) systems become an essential tool to enable users to actively partake in grid operation and propitiate a more efficient use of domestic energy. In fact, a recent study pointed out that nearly 15-40% of domestic demand could be reduced using HEM systems [5].

HEM systems exploit smart appliances to maximize the energy efficiency of dwellings. To this end, controllable appliances (CAs) can be optimally scheduled together with on-site generators and plug-in electric vehicles (EVs) [6]. Usually, domestic users are encouraged to actively partake in grid operation through price-based DR initiatives. Although it is not typical, residential buildings may install on-site storage systems, mainly formed by batteries, which help to improve the energy utilization in this kind of systems. To provide an incentive on the use of storage systems at home, time-of-use (TOU) tariffs have been widely employed worldwide [7], by which low prices during valley hours animate to shift part of the consumption at noon. This way, home inhabitants can improve their economy as well as increase the efficiency of the building.

The presence of storage systems and other smart devices make the energy management in dwellings complex, especially when uncertainties from e.g. renewable generation or demand are considered. In this regard, HEM systems usually perform under strong uncertain environments provoked by unpredictable renewable behaviour, non-controllable demand [8] or departure of EV. This paper focuses on this issue.

1.2 - Literature review

The literature related to HEM systems was rich, especially throughout the last 10 years. Proposed HEM tools range from simple heuristic algorithms to sophisticated mechanisms which account for different premises and models. In [9], a HEM tool incorporating load-shaping DR strategies is developed. With the proposed tool, the HEM algorithm seeks to minimize the electricity bill while some DR premises are considered, however, the effect of uncertainties is neglected. Likewise, [10] incorporates priority in appliances' operation, following the perspective of users, which is made by incorporating the value of lost load for each appliance into the objective function. These two references are based on Mixed-Integer Linear Programming (MILP) formulation, while [11] uses heuristic principles for appliances scheduling. In this reference, the authors consider different metaheuristic algorithms and propose a new one for minimization of electricity bill and peak-to-average ratio.

Huang, et al [12] developed a chance-constrained HEM system, which accounts for possible forecast errors in solar irradiance. To determine the probability distribution of uncertainties, a point-estimate method was used, so that only the expected values and standard deviations are necessary. Then, the optimization problem is solved using a metaheuristic algorithm. On the other hand, [13] focuses on maximizing the support from smart homes in microgrid operation. To this end, a multi-objective framework is developed in which the electricity bill is minimized while the demand curve is flattened. Shafie-Khah and Siano [14] developed a stochastic-based HEM tool accounting for weather and EV-related uncertainties. The developed model also considers the minimization of response fatigue, thus reducing the risk of DR failures caused by repetitive response signals. Similarly, [15] takes into account possible annoyances experienced by the users when appliances are scheduled only attending to energy saving. In this regard, a two-stage methodology is developed by which the appliances are scheduled considering both, users' perception and possible surplus renewable energy. Thus, it is demonstrated that the annoyance perceived by the users is reduced at the expenses of only a limited reduction in energy saving.

Killian, et al [16] developed a model predictive control for smart buildings, based on a Mixed-Integer Quadratic programming (MIQP) approach. The considered mechanism is especially devoted to keeping the thermal comfort of home inhabitants, as well as exploiting the storage capacity of the building in order to reduce the overall electrical requirements. A two-stage stochastic-based HEM model is developed in [17]. This tool accounts for battery degradation, for which an equivalent cost model is developed based on a Lagrangian relaxation of the problem. However, the resulting mathematical formulation becomes nonlinear which calls for a need to use the metaheuristic optimization approaches. Lokeshgupta and Sivasubramani [18] proposed a multi-objective HEM tool that aims at minimizing the peak demand and electricity bill simultaneously. This way, the users and the utility's objectives are met as they depend on each other. However, this study assumes perfect forecasts and therefore the effect of uncertainties and forecast errors is diminished. In [19], the authors consider the demand charge tariff in HEM calculation, by which the users are penalized for the maximum demand throughout a billing cycle. With this premise, a HEM tool is developed, which considers interdependencies among appliances, in order to model the user lifestyle.

A two-stage approach is proposed in [20] for optimal day-ahead of a grid with multiple smart homes. In this case, the first step is devoted on individual HEM thus aiming at maximizing the household profit. Then the utility performs a profit reduction in the second stage with the objective of reducing the peak demand and flattening the power curve at the substation level. In [21], a HEM tool is proposed which takes into account task classification to decide the scheduling plan for domestic appliances. In this regard, quadratic utility functions are proposed for each appliance, from which the monetary equivalent value is derived. Then, this indicator can be used to determine the allocation of appliances on the basis of human's preferences. Javadi, et al [22] developed a HEM tool that accounts for uncertainties from photovoltaic (PV) generation using a stochastic-based approach. With this methodology, a large number of scenarios are generated based on historical data or fitted probability functions. Posteriorly, the scenario-space is reduced using a clustering technique in order to keep the model tractable. Likewise, the authors of [23] propose a hybrid approach to manage uncertainties in PV generation and energy price. In this regard, a stochastic approach is used to model the renewable generation, whereas the energy price is handled using a robust formulation.

Ref. [24] compares two HEM strategies namely timetable and tree-based approaches. A multi-objective optimization framework is developed, which comprises economy and environmental factors. The resulting optimization problem is solved using genetic algorithms. Kong, et al [25] uses a risk-cost approach to manage with uncertainties from non-controllable demand and EV trips. To this end, a two-stage optimization approach is developed which optimizes the electricity bill at first stage while the second step focuses on calculating the so-called conditional value-at-risk (CVaR). A hierarchical controller for smart homes is proposed in [26]. This methodology poses a two-level scheme for domestic appliances, by which the upper level optimal schedule performs the non-thermal appliances centrally, while the thermal devices are locally controlled attending to the corresponding thermal zones. In this reference, uncertainties are treated using a robust model, that considers the Wassertein metric to account for deviations between the theoretical and empirical distribution functions derived from historical data.

In [27], a self-scheduling model for prosumers encompassing two objective functions is presented. On the one hand, the electricity bill is minimized, as customary. On the other hand, a suited discomfort index is proposed that accounts for deviations in scheduling plan for appliances with respect to an ideal timetable. The multi-objective model is solved using the epsilon-constraint approach and VIKOR decision making is considered to select the compromise solution. In [28], a MILP framework is developed for optimal sizing domestic components considering possible grid outages. To this end, failures are modelled using probability functions and scenarios, derived from historical data. Similarly, the HEM model in [29] allows to choose the best tariff program for a benchmark prosumer, including a module for optimally deciding the best hours to be hired in a ‘happy hours’ tariff scheme. Nezhad, et al [30] developed a HEM tool that incorporates inverter-based air conditioning modelling, with the aim of capturing with accuracy the thermal performance of the building. This model is performed considering various scenarios for PV generation and considers different tariffs together a developed discomfort index to account for satisfaction of home users.

Ref. [31] focuses on optimal electrification of off-grid smart homes. Flexible demand and vehicle-to-home capabilities are considered in order to demonstrate the impact of these two factors in sizing the domestic assets. The results demonstrate that vehicle-to-home contributes to diminish the rated power of the backup generation, while flexible appliances allow reducing storage necessities. In this reference, uncertainties of demand, renewable generation and EV are treated via scenarios using historical databases. Ebrahimi, et al [32] pointed out that some uncertainties in HEM problems are correlated. In this regard, a Copula-based HEM framework was developed, by which correlations were considered for modelling the scenarios under a stochastic programming approach. The correlation among uncertainties is highlighted through real data of a home located in Austin, Texas. However, as the authors pointed out, a large number of scenarios and optimizations must be evaluated in order to faithfully capture the correlated character of uncertainties, which leads to a computational costly problem. In [33], a many-objective HEM problem is developed involving up to six different objective functions, for which a simple yet efficient algorithm is proposed.

1.3 - Research gap & contributions

As mentioned, this paper focuses on uncertainties modelling in HEM systems. Such tools normally perform under the influence of a variety of uncertain parameters like outdoor temperature, solar irradiance, non-controllable demand or EV daily mileage. However, as seen in Table 1, this topic has not been profusely studied yet. Most of the related literature poses simple stochastic-based approaches, that are normally based on historical data or probability distributions. However, this information is not always available, especially in domestic installations [34]. Therefore, stochastic programming, although simple, may be unpractical in HEM tools. Moreover, as pointed out in some references [23, 32], uncertainties in HEM problems have different features. This heterogeneity relies on the model, but also in the difficulty of predicting such uncertainties. Indeed, one can intuitively think that the departure time of EVs is more easily predictable than the home demand. It is clear that the former is determined by repetitive daily routines, while the latter is highly subjected to unpredictable human behaviour, as can be deduced from the historical data in [28]. These evidences lead one to think that some uncertainties are harder predictable than others. This feature depends on the level of randomness of the parameter, which can be defined by its stochastic nature. Thus, a particular parameter is said to have a higher level of randomness if it is more difficult to predict with the available techniques. The level of randomness is very different depending on the uncertainty considered, however, to the best of the authors knowledge, this topic has not yet been studied. This paper aims at filling this gap. For simplicity, the main contributions of the present work are enumerated below:

- Developing a MILP interval-based formulation of the HEM problem. Most existing works consider the problem deterministic, which is inexact given the amount of uncertainties involved in domestic installations. In this regard, most related papers recur to simple stochastic approaches (see Table 1). Thus, to the best of our knowledge, this paper is the first attempt to apply interval notation to HEM problems. This new proposal models the inherent uncertainties in HEM problems as interval numbers. This way, confidence intervals are considered to account for possible forecast errors [35]. In contrast to other interval formulations proposed in other related problems, the developed framework avoids using interval operations and arithmetic, resulting in a more straightforward procedure that can be efficiently coded and executed in average machines.
- While the existing works consider all the uncertainties homogeneity, thus giving all of them the same importance, our proposal ranks the uncertain parameters according to their level of randomness, benign, and, more important, those uncertainties that are hardly predictable. To do this, a novel Lexicographic-based methodology is developed. In contrast to traditional uses of Lexicographic optimization [36], typically employed for multi-objective optimization problems,

this technique is applied novelty, giving different importance to each uncertain parameter involved in the issue.

Table 1. Taxonomy of the related literature

Ref.	Model	Uncertainties			Uncertainties modelling	Randomness considered?
		Weather	Demand	EV		
[9, 10, 13, 18]	MILP	No	No	No	--	--
[11, 15, 19, 24]	Heuristic	No	No	No	--	--
[12]	Heuristic	Irradiance	No	No	Point-estimate	No
[14]	MILP	Irradiance	No	Yes	Stochastic	No
[16, 20]	MIQP	No	No	No	--	--
[17]	Heuristic	Irradiance	Yes	No	Stochastic	No
[21]	MINLP	No	No	No	--	--
[22, 27, 30]	MILP	Irradiance	No	No	Stochastic	No
[23]	MILP	Irradiance	No	No	Hybrid	No*
[25]	Heuristic	No	Yes	Yes	CVaR	No
[26]	MILP	Yes	No	No	Wassertein-based	No
[28, 29, 32, 33]	MILP	Yes	Yes	No	Stochastic	No
[31]	MILP	Yes	Yes	Yes	Stochastic	No
Present	**MILP**	**Yes**	**Yes**	**Yes**	**Interval**	**Yes**

* It considers different models for uncertainties, but they are not specifically referred to the randomness of the uncertain source.

In the rest of this paper, Section 2 describes the necessary background. Section 3 presents the mathematical models used in this paper. Section 4 develops the solution methodology proposed for HEM tools. Section 5 describes a case study and presents numerical results. The paper is concluded with Section 6.

2 - Background

2.1 - HEM system

This paper focuses on HEM problems such as that pictorially represented in Fig. 1. The dwelling is assumed to be connected to an upscale grid managed by a local utility, from which can purchase or sell energy under a TOU tariff, as usual. Energy is delivered to the home through a smart meter, with the aim of continuously controlling the amount of energy that is acquired or sold. Moreover, the home can be supplied through on-site assets encompassing a battery energy storage (BES) system and PV panels. The scheduling plan for the home assets is centrally performed by a HEM system. This tool daily forecasts information about uncertainties, namely weather parameters, non-controllable demand and EV behaviour. On the basis of this information, the day-ahead scheduling plan for the CAs, EV, batteries and PV units is performed. The set of CAs is formed by interruptible, non-interruptible and a heating-ventilation-air conditioner (HVAC) system, which is devoted to keeping the indoor temperature within comfortable bounds. All these appliances can be controlled by the HEM unit. In contrast, it is assumed that non-controllable appliances are managed on the basis of human decisions and therefore cannot be scheduled by the central controller (e.g. TV, lighting, cooker, etc [33]).

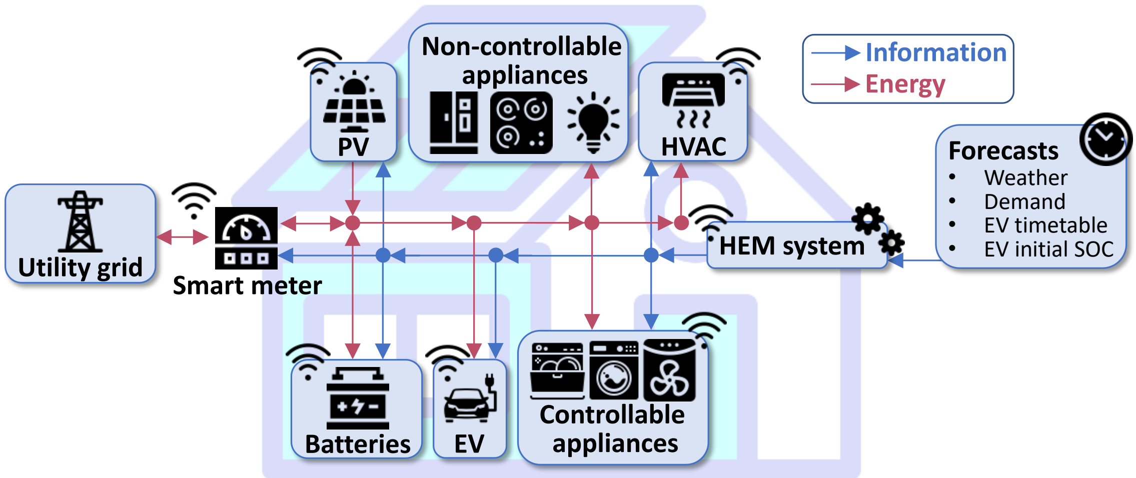

Fig. 1. Pictorial representation of the home system under study.

Note that modern paradigms such as cloud energy storage allows to share storage resources within a group of prosumers [37, 38]. However, as this paper is focused on HEM tools for individual peers, we considered only individual storage systems in order to easily interpret the results obtained. This way, the inclusion of cloud energy storage will imply the consideration of other neighbours in the mathematical problem, thus complexing the problem unjustifiably. Thereby, this kind of paradigms has not been included and its impact on domestic operation will be considered in future papers. For the same reasons, we do not consider communal parking lots as in [39].

2.2 - Lexicographic optimization

In the field of mathematical optimization, multi-objective frameworks are, in general, more difficult to solve than single-objective problems [40, 41]. This is due to the different objectives are typically contradictory, which implies that one target cannot be achieved without deteriorating the rest. However, many real problems are actually multi-objective paradigms. This issue motivated the development of a variety of solution methods for multi-objective optimization problems. In this paper, one of these techniques called Lexicographic optimization is used [36]. However, contrary to its typical use, this method is considered here to handle uncertainties, as detailed in Section 4. Nevertheless, this section presents the Lexicographic optimization concisely, focusing on its more usual finality. To this end, let us consider a multi-objective problem that aims at optimizing a set of N^P generic objective functions, denoting by f_i the ith objective function. Then, the Lexicographic scheme allows us to rank the objectives correlativity, according to their importance. This way, the solution methodology gives more significance to one objective with respect to others (e.g. the electricity bill was assumed to be the most important target in [33]). Then, assuming that $i = 1$ is the most important objective and minimization problems, the following iterative procedure is carried out.

$$\begin{cases} \min f_i \\ \text{s.t.}\, f_j = \underline{f_j}; \forall j \in \{1,2,\ldots,i-1\} \end{cases}; \forall i \in \{1,2,\ldots,N^P\} \qquad (1)$$

As seen, the methodology (1) optimizes the ith objective while forcing the problem to equal the remainder objectives to their optimum, which is assumed to be calculated in previous steps. A major disadvantage of this method is that it tends to favour certain objectives, making the Pareto front converges to a particular region [42]. However, this issue does not suppose a problem in the developed methodology, as discussed later.

3 - Mathematical model of the HEM system

This section presents the mathematical modelling of the HEM system. The formulation hereinafter is properly adapted from other references [33], and it is posed in its deterministic version, without expressly modelling uncertainties. Nevertheless, the uncertainties involved have been highlighted in order to simplify the readability of the paper.

3.1 - Utility grid modelling

Normally, the electrical energy received by home users is supplied by the utility. This imposes a limit in the power capability that can be purchased/sold from/to the network. Moreover, this bound can be imposed by the physical limitations of equipment. This restriction is given by constraint (2), while (3) avoids the simultaneous purchases and sales.

$$p_t^{Grid,i} \leq u_t^{Grid,i} \cdot \overline{p}^{Grid}; \forall t \in T \wedge i \in \{buy, sell\} \tag{2}$$

$$u_t^{Grid,buy} + u_t^{Grid,sell} \leq 1; \forall t \in T \tag{3}$$

3.2 - PV modelling

The home system under study can be self-supplied through a rooftop PV unit. Potential PV generation is strongly determined by weather conditions such as temperature or solar irradiance [43], although other models exist that consider other weather parameters [24]. Hence, the model used in this paper was derived from [44] and is given by:

$$\phi_t^{PV} = \overline{p}^{PV} \cdot \left[0.25 \cdot \hat{\vartheta}_t + 0.03 \cdot \hat{\vartheta}_t \cdot \hat{\theta}_t^{Air,out} + \left(1.01 - 1.13 \cdot \frac{\eta^{PV}}{100}\right) \cdot \hat{\vartheta}_t^2\right];\ \forall t \in T \tag{4}$$

It is noteworthy that weather parameters in (4) have been considered uncertain. As pointed out in [29], the constraint (5) is necessary to keep the model coherent and realistic.

$$p_t^{PV} \leq \begin{cases} \phi_t^{PV}, \text{if } \phi_t^{PV} \leq \overline{p}^{PV} \\ \overline{p}^{PV}, \qquad\qquad \text{o.w.} \end{cases};\ \forall t \in T \tag{5}$$

When considering the solar irradiance is a variable of the problem (see Section 4), the quadratic term in (4) must be linearized using piecewise representations [45, 46].

3.3 - BES modelling

The maximum power that batteries can exchange with the dwelling is limited by their capacity and energy-to-power ratio [47], as said (6), whereas (7) imposes complementarity in the charging and discharging processes. The model (8) defines the dynamics of the storage system and (9) limits the energy stored to nominal values and depth-of-discharge settings. Lastly, the constraint (10) fixes the initial and final state-of-charge (SOC) of the BES unit.

$$p_t^{BES,i} \leq u_t^{BES,i} \cdot \frac{\overline{\varepsilon}^{BES}}{\mathrm{e2P}}; \forall t \in T \wedge i \in \{ch, dch\} \tag{6}$$

$$u_t^{BES,ch} + u_t^{BES,dch} \leq 1; \forall t \in T \tag{7}$$

$$\varepsilon_t^{BES} = \varepsilon_{t-1}^{BES} + \Delta\tau \cdot \left[\frac{\eta^{BES}}{100} \cdot p_t^{BES,ch} - \frac{100 \cdot p_t^{BES,dch}}{\eta^{BES}}\right]; \forall t \in T \backslash t > 1 \tag{8}$$

$$\left(1 - \frac{\mathrm{DOD}}{100}\right) \cdot \overline{\varepsilon}^{BES} \leq \varepsilon_t^{BES} \leq \overline{\varepsilon}^{BES}; \forall t \in T \tag{9}$$

$$\varepsilon_{T(1)}^{BES} = \varepsilon_{T(\mathrm{end})}^{BES} = \overline{\varepsilon}^{BES} \tag{10}$$

3.4 - EV modelling

The EV is modelled similar to the BES. Thus, the constraints (11) and (12) are analogue to (6) and (8).

$$p_t^{EV} \leq \overline{p}^{EV}; \forall t \in T \tag{11}$$

$$\varepsilon_t^{EV} = \varepsilon_{t-1}^{EV} + \Delta\tau \cdot \frac{\eta^{EV}}{100} \cdot p_t^{EV}; \forall t \in T \backslash t > 1 \tag{12}$$

However, there are two main differences with respect to the stationary BES. On the one hand, the EV cannot be scheduled when the vehicle is not plugged at home, which is ensured by the constraint (13). On the other hand, the initial SOC of the on-board batteries is unknown, as said (14), since it depends on the daily mileage [48]. However, it is assumed that the EV cannot be scheduled before 0:00 h, as usual in domestic installations where the controller seeks to exploit the valley hours to charge the batteries [49]. Thus, in this paper, it is supposed that the beginning of the EV time window coincides with the beginning of the time horizon. Nevertheless, the departure time is considered unknown. Thereby, the EV time window has been modelled as an uncertain parameter, describing in the Appendix the modifications introduced in the EV modelling when the departure time is declared as a variable. Finally, it is assumed that the users are keen to get the vehicle fully charged at the departure time, as imposed by the constraint (15).

$$p_t^{EV} = 0; \forall t \notin \widehat{\Theta}^{EV} \tag{13}$$

$$\varepsilon_{\widehat{\Theta}^{EV}(1)}^{EV} = \hat{\varepsilon}_0^{EV} \tag{14}$$

$$\varepsilon_{\widehat{\Theta}^{EV}(\mathrm{end})}^{EV} = \overline{\varepsilon}^{EV} \tag{15}$$

3.5 - CAs modelling

In this paper, two types of CAs are considered. On the one hand, the non-interruptible appliances cannot be interrupted once they have been scheduled, in contrast to interruptible devices, whose work cycle can be freely adapted. In any case, the appliances must complete their duty cycles within allowable time windows, as imposed by (16), while the constraints (17) and (18) ensure the continuous operation of non-interruptible appliances.

$$\sum_{t \in \Theta^a} \{u_t^a\} = \frac{\mathrm{D}^a}{\Delta\tau}; \forall a \in A^I \cup A^{NI} \tag{16}$$

$$u_t^a - u_{t-1}^a = \mathrm{on}_t^a - \mathrm{off}_t^a; \forall t \in T \backslash t > 1 \wedge a \in A^{NI} \tag{17}$$

$$\sum_{t \in \Theta^a} \{\mathrm{on}_t^a\} = 1; \forall a \in A^{NI} \tag{18}$$

3.6 - HVAC modelling

The HVAC system is devoted to controlling the indoor temperature. As such, the temperature has to be declared as a decision variable and modelled using (19), that defines the indoor temperature as a function of weather conditions and the action of the HVAC system [50]. In this regard, the HVAC devices are assumed to be installed inside the building [9]. On the other hand, (20) limits the power consumed by the HVAC system and (21) imposes complementarity on the heating and cooling processes. The HVAC model is completed by (22), that limits the indoor temperature to comfortable bounds, taking into account temperature dead-bands, and (23) that keeps the model coherent.

$$\theta_t^{air,in} = \left(1 - \frac{\Delta\tau}{10^3 \cdot m^{Air,in} \cdot C^{Air,in} \cdot R}\right) \cdot \theta_{t-1}^{air,in} + \frac{1}{10^3 \cdot m^{Air,in} \cdot C^{Air,in} \cdot R} \cdot \hat{\theta}_{t-1}^{air,out} + \frac{p_t^{HVAC,h} - p_t^{HVAC,c}}{0.000277 \cdot m^{Air,in} \cdot C^{Air,in}} \cdot \mathrm{COP};\ \forall\, t \in T \backslash t > 1 \quad (19)$$

$$p_t^{HVAC,i} \leq u_t^{HVAC,i} \cdot \overline{p}^{HVAC};\ \forall\, t \in T \wedge i \in \{h, c\} \quad (20)$$

$$u_t^{HVAC,h} + u_t^{HVAC,c} \leq 1;\ \forall\, t \in T \quad (21)$$

$$\theta^{HVAC,sp} - \theta^{HVAC,db} \leq \theta_t^{air,in} \leq \theta^{HVAC,sp} + \theta^{HVAC,db};\ \forall\, t \in T \quad (22)$$

$$\theta_{T(1)}^{air,in} = \theta_{T(\mathrm{end})}^{air,in} = \theta^{HVAC,sp} \quad (23)$$

It is worth commenting that other HVAC modelling exist in the literature [30, 51]. However, we preferred that presented above as this model is temperature-focused rather than device-focused. In this regard, the indoor temperature is explicitly modelled by (19) and declared a variable, which is especially suitable for the methodology developed in Section 4, which requires to declare the outdoor temperature a decision variable of the problem.

3.7 - Home balance

The generation-load balance must be matched any time instantly, considering the energy delivered to the grid together the power discharged from batteries. Under these premises, (24) defines the power balance in the home installation.

$$p_t^{Grid,buy} + p_t^{PV} + p_t^{BES,dch} = \hat{p}_t^{NC} + p_t^{Grid,sell} + p_t^{BES,ch} + p_t^{EV} + \sum_{a \in A^I \cup A^{NI}} \{u_t^a \cdot \overline{p}^a\};\ \forall\, t \in T \quad (24)$$

The non-controllable demand in (24) encompasses the power consumption of those appliances that cannot be managed by the HEM scheduler, as commented in Section 2. As such, this parameter has been considered unknown as they depend on unpredictable human behaviour.

3.8 - Energy cost

The electricity bill would depend on the purchased energy, which is performed under a dynamic pricing tariff. However, the monetary balance should consider the energy exported as well, by which inhabitants can get a monetary revenue. With these assumptions, the energy cost can be defined by (25).

$$Cost = \sum_{\forall t \in T} \left\{ \lambda_t^{Grid,buy} \cdot p_t^{Grid,buy} - \lambda_t^{Grid,sell} \cdot p_t^{Grid,sell} \right\} \quad (25)$$

Note that some references account for multi-objective paradigms [18, 32], in which the electricity bill is optimized together with other indicators. For this kind of problems, specific solvers have been developed in the literature (see [52, 53]). However, we used a single-objective function in this paper due to most of existing tools are only focused on minimizing the electricity bill and, in addition, the inclusion of different objectives may difficult the interpretation of the role of uncertainties in the results, which is the main focus of the present work. Nevertheless, it is worth noting that the new proposal is versatile enough to incorporate multi-objective functions easily.

It is also worth noting that lifecycle cost of batteries has not been included in (25). This is due to fixed and capital costs are assumed to be counted in sizing tools, while HEM tools are more focused on daily scheduling. Moreover, variable maintenance costs of batteries are normally marginal in comparison with energy prices [54].

4 - The developed solution procedure

The HEM problems are subjected to various sources of uncertainties. In particular, weather, non-controllable demand and EV behaviour have been assumed to be unknown in this paper. Nevertheless, some uncertainties are more easily predictable than others. In other words, the level of randomness of some profiles is notably higher than others. For instance, the departure time of the EV may be easily predicted in case of repetitive routines, while the non-controllable demand might be highly unpredictable. On the other hand, some weather parameters can be forecasted with accuracy (e.g. temperature) even consulting websites or applications, while the solar irradiance may be subjected to high variations due to temporal cloudy periods [55]. In this regard, each uncertainty parameter should be particularly treated according to how easily its expected value can be predicted. To this end, a novel solution methodology for the HEM problem has been developed, which is, in essence, based on ranking the uncertainties according to their level of randomness, as represented in Fig. 2.

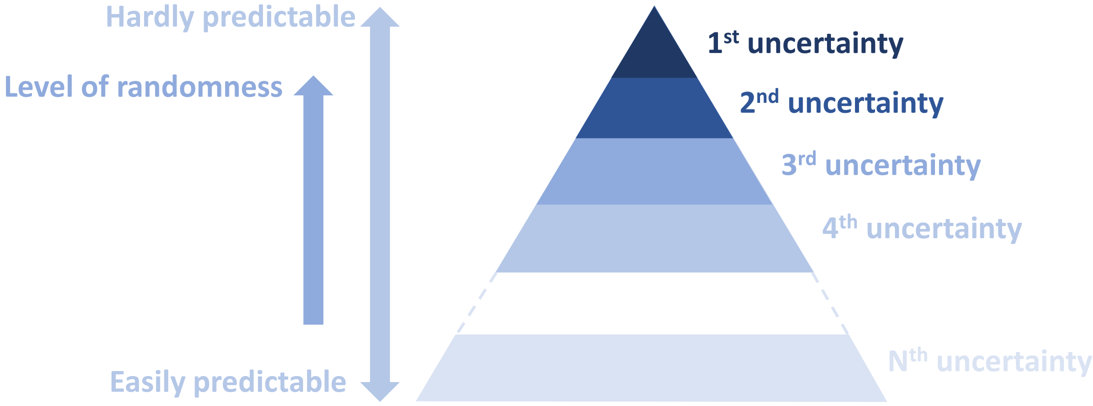

Fig. 2. Representation of the essential foundations of the developed methodology.

Therefore, the developed methodology aims to rank the involved uncertainties according to their level of randomness, giving more importance to those hardly predictable parameters as sketched in Fig. 2. This particular idea is very similar to the foundation of the Lexicographic method described in Section 2.2. Indeed, Lexicographic optimization is based on ranking the different objectives according to their level of importance. This same principle can be applied to uncertainties, but, in this case, the significance of each uncertainty is inherent to its randomness level, the most important one being the uncertainty with the highest randomness level. There is no formal way to classify the uncertainties according to this criterion, so we assume that personal experience or preferences are needed to establish a classification of uncertainties for each particular case.

Based on the idea commented above, the Lexicographic method looks pretty suitable for this paper. To apply this methodology to HEM problems under uncertainties, we develop a multi-stage methodology described hereinafter. Firstly, the minimum cost must be calculated, for which the conventional HEM problem, that aims at minimizing the electricity bill [33], is performed, as follows:

$$\boldsymbol{u}^{det}, \underline{Cost} \rightarrow \underset{\boldsymbol{x},\boldsymbol{u}}{\operatorname{argmin}}\, Cost\big(\mathrm{E}(\boldsymbol{\Omega})\big) \tag{26}$$

s.t. (2)-(24)

where $\boldsymbol{x}$ and $\boldsymbol{u}$ are the vectors of continuous and binary decision variables, respectively. Once the problem (26) has been solved, the uncertainties are ranked according their level of randomness, being the first one the most difficult predictable and the last one (the Nth uncertainty) the easiest one. Then, for each uncertainty the user can establish a confidence interval, within which the actual value of the uncertainty may lie with total accuracy, as depicted in Fig. 3.

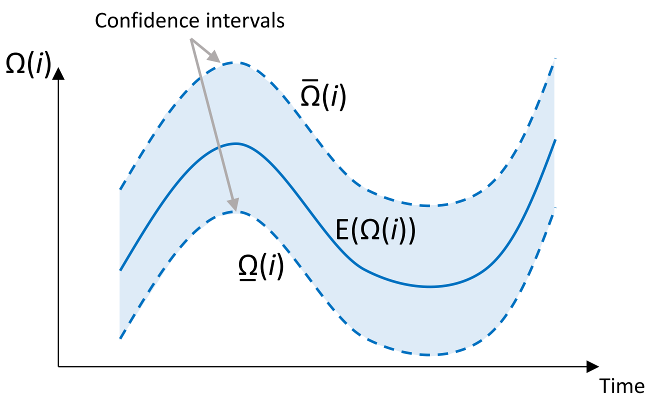

Fig. 3. Interval modelling adopted in this paper for uncertainties

The next step consists off iteratively solving a series of optimization problems, starting from $i = 1$ for the most random uncertainty and finalizing with $i = N$ for the most easily predictable. Each of these problems aims at seeking the most unfavourable profile of each uncertainty (denoted by $\widetilde{\boldsymbol{\Omega}}$). The concerned uncertainty is declared a variable of the problem, thus allowing to vary its value within the predicted limits, as pointed out in Fig. 3. Mathematically, this iterative algorithm can be established, as follows:

$$\widetilde{\mathbf{\Omega}}(i) \rightarrow \underset{x,\mathbf{\Omega}(i)}{\operatorname{argmax}}\, Cost\big(\mathrm{E}\big(\mathbf{\Omega}(j)\big), \widetilde{\mathbf{\Omega}}(k), \boldsymbol{u}^{det}\big)\,; \forall i \in \mathbf{\Omega} \wedge j \in \{i+1, i+2, \dots, \mathrm{size}(\mathbf{\Omega})\} \wedge k \in \{1,2,\dots,i-1\} \tag{27}$$

s.t. (2)-(24)

$$Cost(\mathrm{E}(\mathbf{\Omega}), \boldsymbol{u}^{det}) \leq \underline{Cost} \cdot \left[1 + \frac{i \cdot (\Delta_{Cost} - 1)}{\mathrm{size}(\mathbf{\Omega})}\right] \tag{28}$$

$$\underline{\mathbf{\Omega}}(i) \leq \mathbf{\Omega}(i) \leq \overline{\mathbf{\Omega}}(i) \tag{29}$$

For simplicity, the iterative procedure above is summarized with the flowchart in Fig. 4. As seen, the new proposal and the Lexicographic optimization follow the same principle. For $i = 1$, the problem is run, assuming the expected value of the remainder uncertainties. As a result of this problem, the most pessimistic profile of the highest ranked uncertainty is obtained. To avoid an increase in the electrical bill beyond a pre-established threshold (i.e. Δ_{Cost}), the constraint (28) is imposed, whereas (29) limits the value of the ith uncertainty to be within the established lower and upper intervals. The remaining steps assume the most pessimistic profile of the previous uncertainties. Thereby, the algorithm takes into account the capability of the system to predict the different unknowns. Thus, the HEM system is more robust against the highly random parameters, at the expense of diminishing the impact of the more easily predictable ones. To illustrate this idea, let us assume that a home user has no reliable capability to predict the non-controllable demand, while the departure time of the EV can be foreseen with almost total accuracy. In this situation, the departure time can be assumed to be more deterministic. Hence, the developed algorithm assumes this principle and would seek the most pessimistic departure time, but under the pre-calculated unfavourable profile for the non-controllable demand.

The idea above is automatically integrated within the Lexicographic-based structure of the developed method. Since each stage is devoted to seeking the most pessimistic profile of each uncertain parameter, the highest-ranked uncertainties (i.e., the hardiest predictable ones) will vary over a wide interval. In contrast, the easily predictable profiles scarcely deviate from their expected values since the sub-problems associated with them are upper bounded by the pessimistic profiles obtained in previous stages.

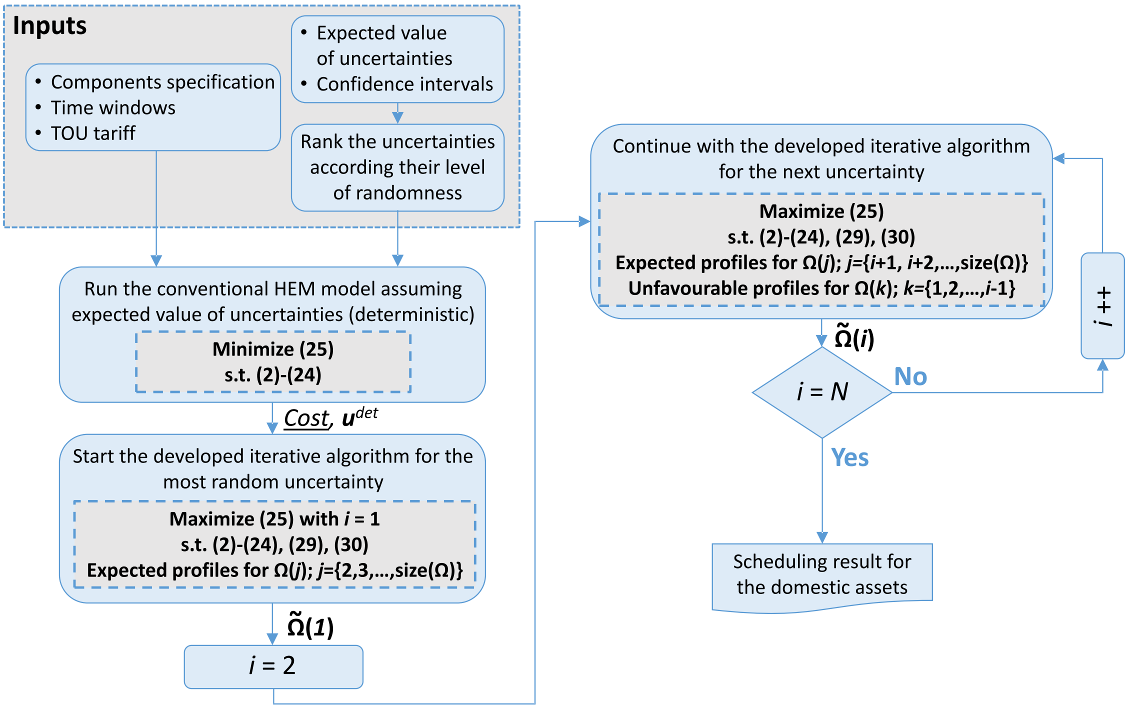

Fig. 4. Flowchart of the developed solution procedure

5 - Case study

This section presents a case study aiming to validate and illustrate the new HEM tool. A benchmark household installation has been considered, as described in Section 2. The MILP formulation presented in previous sections has been coded under MATLAB R2020a and solved using Gurobi [56]. The simulations were run on an Intel® CoreTM i5-9400F, 2.90 GHz, 8.00 GB RAM personal computer over a 24 hours horizon with 30 minutes resolution. Preliminary simulations performed by the authors were completed in 15 minutes on average, which results reasonably for HEM problems. In addition, the computational cost of the mathematical problem is expected to grow polynomially with the problem's size, being efficient and scalable to more significant issues [57].

The developed procedure requires sorting the uncertainties involved according to their level of randomness. In domestic applications, these uncertainties usually involve weather parameters and non-controllable demand. In this case, the EV's initial SOC and departure time have also been considered uncertainties. The different uncertainties have been ranked based on their usual level of randomness. Thus, the non-controllable demand has been placed first, followed by the solar radiation, initial SOC of the EV, departure time, and outdoor temperature. This order follows logical ideas as the temperature can be easily predictable, and the departure time is normally repetitive and subjected to daily routines. In contrast, the non-controllable demand may be highly unpredictable because it is strongly influenced by random human behaviour, and partial shadows in cloudy environments can easily perturb solar irradiance.

5.1 - Input data

Fig. 5 plots the expected weather parameters and non-controllable demand, together with their associated confidence intervals. The solar irradiance and outdoor temperature correspond to the real data observed in Madrid (Spain) on July 19, 2016 [58], whereas the non-controllable profile has been constructed based on real measures in [59] and well-known consumption patterns reported in [22]. A small-scale rooftop PV array is installed, formed by three panels of 0.5 kW rating power with 16.7% efficiency [27], resulting in a total installed capacity of 1.5 kW.

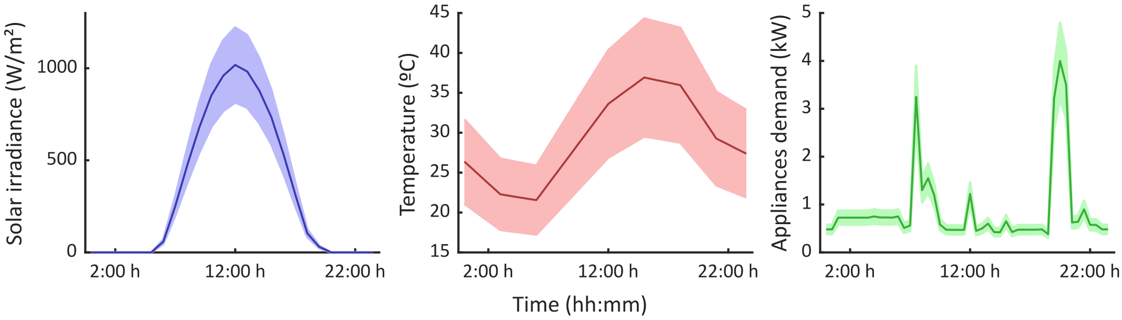

Fig. 5. Expected solar irradiance (left), outdoor temperature (middle), and non-controllable demand (right) together with their respective confidence intervals

Two pricing schemes are compared, shown in Fig. 6. On the one hand, a typical TOU tariff is similar to those offered by Spanish retailers [60]. On the other hand, an RTP pricing mechanism based on that used in [22] has also been included. It is worth noting that the RTP tariff has been suitably adapted (scaled up) to be fairly compared with the considered TOU tariff. The considered RTP pricing is normally lower than the TOU scheme. However, the former presents a higher peak price at about 17:00 h. To avoid incoherent behavior of the installation, the selling price has been taken 0.9 times the purchasing price [61]. On the other hand, it is assumed that the home can exchange up to 5 kW with the utility grid.

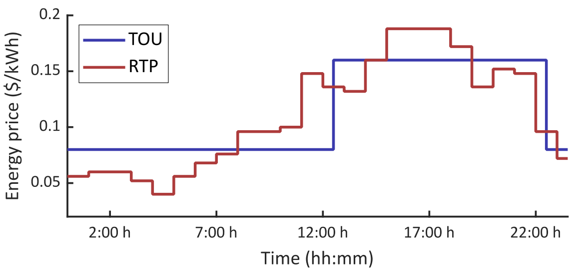

Fig. 6. Tariff schemes used in simulations

The domestic BES system is assumed to be formed by Li-ion batteries with 95% of efficiency in charging and discharging processes, providing 5 kWh of storage capacity in total. The energy-to-power ratio is equal to 2 hours [47], and to avoid a fast degradation of batteries, they cannot be discharged beyond 60% of their total capacity. On the other hand, a 22 kWh Renault Zoe equipped with a 3 kW charger has been considered, which supposes one of the most extended models in many countries [62]. The Li-ion onboard batteries have an efficiency of 95%, are expected to be initially charged with 60%, and cannot be discharged beyond 80% of their nominal capacity. A simple control mechanism avoids charging the vehicle before 0:00 h, and it is expected to leave home at 9:00 h. Table 2 collects the data regarding CAs, which encompasses a washing machine, a dishwasher and a spin dryer. Although some references consider these appliances non-interruptible, we assumed that the dishwasher and spin dryer are interruptible devices as in other papers [33, 63]. Nevertheless, these settings can be easily modified by users without introducing major modifications in the methodology.

Furthermore, time windows corresponding to the washing machine and dryer are not overlapped, thus respecting logical constraints between appliances. On the other hand, a domestic-scale HVAC system is considered, whose data are summarized in Table 3 [9]. Finally, the thermal data of the building can be found in [9].

Table 2. CAs data [33]

Appliance	Duty cycle (h)	Power (kW)	Time window	Type
Washing machine	3	3	7:30-11:00 h	Non-interruptible
Dishwasher	4	2.5	7:00-16:00 h	Interruptible
Spin dryer	2	2.5	12:00-17:00 h	Interruptible

Table 3. HVAC data [9]

Parameter	Value
Power (kW)	2
Coeff. of performance	1.2
Set-point (ºC)	23
Dead-band (ºC)	0.5

5.2 - Simulation results

Taking the order described at the beginning of this section for the uncertainties, the developed model was performed for different values of the parameter Δ_{Cost}. This parameter determines the increment of the electricity bill that the users are willing to assume on pursuing more uncertainty-aware scheduling of the home assets. Fig. 7 plots the value of the electricity bill for different incrementing costs, as expected, the total energy cost grows with this parameter until hitting the limit imposed by the constraint (28). In this regard, the optimization model finds the optimal solution that is given at the point where the cost equals its maximum. Thus, the difference with the expected cost under deterministic conditions supposes the available margin to consider the most unfavourable conditions. It means that the scheduling tool is performed under pessimistic values of uncertainties (within the predicted intervals) at expenses on incrementing the expected electricity bill. In this regard, the parameter Δ_{Cost} plays a crucial role in determining how much the users are willing to pay for robustness.

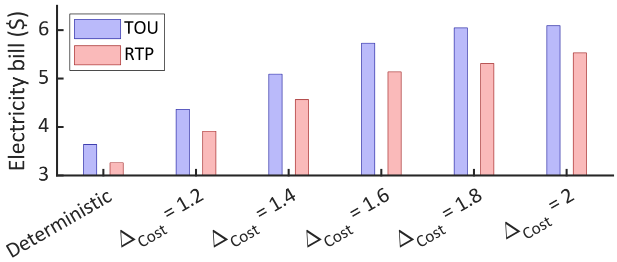

Fig. 7. The value of the electricity bill for different Δ_{Cost}

A different view in Fig. 7 allows us to compare the bill price under other pricing mechanisms. In all cases, the electricity bill was cheaper in case of considering an RTP tariff, being reduced the total cost by 9-12%, depending on the value of Δ_{Cost}. This result is explained by the fact that the considered RTP tariff presents a lower valley price, especially during noon. At these time intervals, the home imports energy from the grid to charge the EV. This energy is eventually purchased at a low cost. In addition, this energy can be stored in batteries to be used later, thus reducing the imported energy during peak hours. With this strategy, the home reduces the impact of higher peak prices drawn by the assumed RTP tariff.

As discussed, incrementing the parameter Δ_{Cost} allows the scheduling tool to be further from the expected profiles from uncertainties. This way, the scheduling plan is more risk-averse, and therefore the possible impact of uncertainties is minimized. This fact is clearly illustrated in Fig. 8, where the actual PV generation in two extreme cases (deterministic and $\Delta_{Cost}= 2$) is shown. As seen, under deterministic conditions, the scheduling tool aims to extract as PV generation as possible, propitiated by high solar irradiance and only limited by the rated power of panels. In contrast, if the users are keen to obtain an uncertainty-aware scheduling result, the PV generation is notably reduced with the aim of accounting for possible deviations from expected values. In this sense, the result shown in Fig. 8 may correspond to actual PV generation during intense cloudy days, observing intermittent clear periods followed by large shadows that limit the production of the PV array.

Some notable differences can be observed in Fig. 8 when comparing TOU and RTP tariffs. The most remarkable is the reduced PV generation under an RTP tariff at midday. In contrast to the case of a TOU mechanism, the installation can assume that PV is unable at 12:00 h. This comparison is better illustrated in Table 3, where the total PV generation is reported for various cases. From this table, we can extract two conclusions. On the one hand, as expected, PV generation is further reduced with the parameter Δ_{Cost} as reported in Table 4. In this case, solar generation reaches the minimum allowable when $\Delta_{Cost}=$ 1.6, which means that scheduling is not feasible if PV generation is reduced beyond this limit. On the other hand, more energy has to be generated by PV panels under an RTP tariff (+25% with $\Delta_{Cost}= 1.4$). It means that more favourable conditions are assumed in this case, leading to less uncertainty-aware conditions. Indeed, although some peak periods can be neglected, as observed in Fig. 8, actual PV generation must be higher in some periods, especially in the early morning and evening.

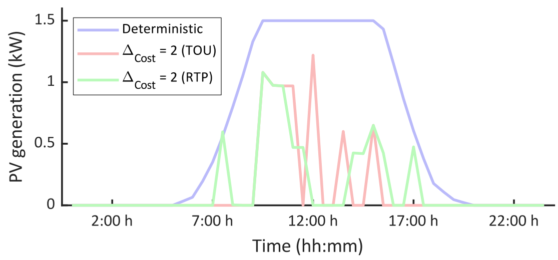

Fig. 8. Actual PV generation with deterministic assumptions and $\Delta_{Cost}= 2$

Table 4. Total PV generation in various cases

Tariff	Δ_{Cost}					
	Deterministic	**1.2**	**1.4**	**1.6**	**1.8**	**2**
TOU	13.59 kWh	10.12 kWh	5.53 kWh	3.23 kWh		
RTP	13.59 kWh	11.82 kWh	7.33 kWh	3.48 kWh		

Although the ability of the developed methodology to consider adverse PV conditions has been clearly evidenced by the results above, the other uncertainties may have a direct impact on the scheduling plan calculated by the proposed HEM tool. In this regard, the other unknowns may directly increase domestic appliance consumption. One clear example is the outdoor temperature and its clear impact on HVAC consumption. To illustrate this fact, Fig. 9 shows the total consumption of different appliances under deterministic assumptions and $\Delta_{Cost}= 2$. As seen, both HVAC and EV are expected to consume much more energy in case of assuming unfavourable values of uncertainties. This is clearly due to pessimistic profiles of outdoor temperature and initial SOC and departure time. The former affects the HVAC while the latter directly impacts the EV performance.

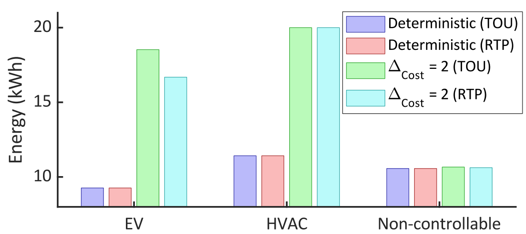

Fig. 9. Total energy consumed by different appliances with deterministic assumptions and $\Delta_{Cost}= 2$

It is worth mentioning the apparent few effects of Δ_{Cost} in the non-controllable appliances demand. As seen in Fig. 9, this parameter seems to have few effects on this consumption, despite the uncertain behaviour of these appliances being placed first on the uncertainties list. Therefore, it is assumed that the non-controllable demand is the most difficult predictable uncertainty among the involved profiles. However, the result reported gives a clear evidence that this uncertainty has a reduced impact on the scheduling performance. In other words, the home installation is able to easily absorb large variations of the non-controllable demand at least within the predicted intervals. In this sense, the HEM tool disregards the effect of this uncertainty while focusing on the higher harmful effect induced by others. This result shows the capability of the developed tool to filter the impact of uncertainties, focusing on them that have a higher potential to increase the electricity bill. Note that few differences are observed in Fig. 9 between TOU and RTP tariffs. Only in the case of EV energy, when the home demanded 10% less energy than in the case of TOU mechanism. This situation is illustrated in Fig. 10, where the SOC of the EV is plotted. Firstly, it is worth noting that the initial SOC is notably lower in the case of TOU tariff (4.4 kWh vs 6.15 kWh) when pessimistic conditions are considered. It clearly forces to purchase of more energy to the grid for charging the onboard batteries, which explains the results in Fig. 9.

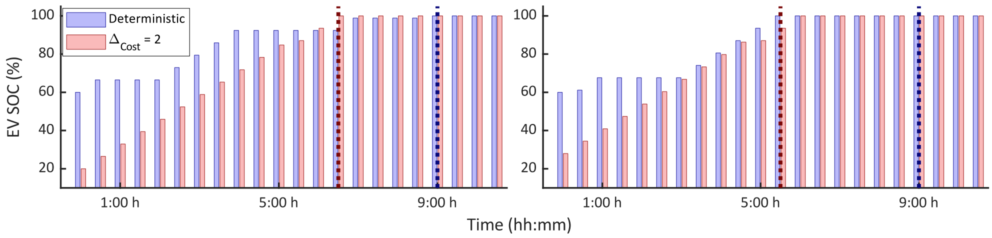

Fig. 10. EV SOC with deterministic assumptions and Δ_{Cost}= 2 under a TOU (left) or RTP tariff (right). The departure time in each case is plotted with dotted vertical lines

Fig. 10 allows us to extract more conclusions. Indeed, when taking Δ_{Cost}= 2 a lower initial SOC and an earlier departure time are assumed. These unfavourable conditions force the onboard batteries to charge rapidly, allowing the vehicle to be fully charged at the expected departure time. Moreover, since it is assumed that batteries are not charged sufficiently at the beginning of the time horizon, the energy necessary to fully charge them is much higher, as clearly shown in Fig. 11, where the scheduling result is plotted for the two extreme cases. As seen in this figure, the energy demanded by the EV during noon is much higher in case of taking $\Delta_{Cost} = 2$. Also, it is noteworthy the low PV potential in the pessimistic case. When comparing both pricing schemes in Fig. 11, few differences are appreciated. Nevertheless, it is worth observing how the stationary batteries are more profusely exploited during noon in case of adopting an RTP tariff, which is explained by the fact that this tariff presents lower energy prices during this period.

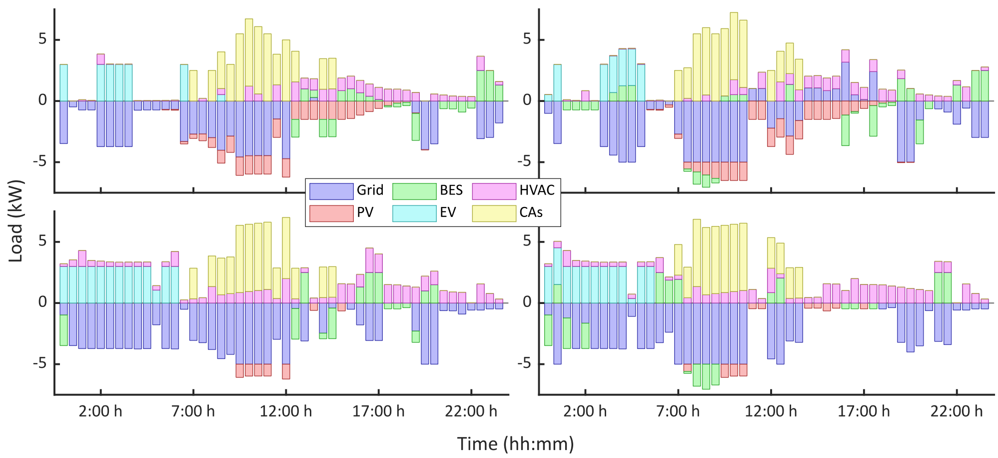

Fig. 11. Scheduling comparison under deterministic assumptions (upper) and $\Delta_{Cost} = 2$ (bottom) with TOU (left) and RTP (right) tariffs

5.3 - Analysing the effect of uncertainties sorting

As discussed throughout this paper, the main novelty of the developed HEM tool is its ability to sort the different uncertainties involved according to their level of randomness. This way, those uncertainties that are hardly predictable have more importance than others that can be, a priori, easily forecasted. To illustrate this capability, the predefined classification has been altered. More specifically, the initial SOC of the EV is now placed after the departure time of the vehicle. This assumption draws the situation where the users are more confident about the SOC of batteries at the beginning of the time horizon, while the hour at which the vehicle leaves home is subjected to a high level of uncertainty. With this premise, the developed tool was run taking $\Delta_{Cost} = 2$ and the results were compared with the case studied in the previous subsection (for the sake of brevity, only results with TOU tariff are compared since similar conclusions can be drawn for the RTP case). To avoid misleading, the previous situation is denoted as 'Case 1', while the new problem is denoted as 'Case 2'.

Fig. 12 shows the value of the uncertainties involved in the two studied cases. As observed, the initial SOC is lower for Case 1, while the number of parking hours follows a different trend. These results illustrate the performance of the developed tool. In Case 1, the HEM system was more aware of the initial SOC, which is likely more random than the departure time. In this regard, the HEM tool is performed under a more pessimistic value of the initial SOC, influencing the departure hour. In other words, the HEM tool first finds the most pessimistic value of the initial SOC; then, the departure time is adapted to the pre-calculated energy stored in batteries. As expected, Case 2 drew the opposite situation, in which the departure time is firstly managed, and then the initial SOC is adapted. To get a better overview, Fig. 13 plots the instantaneous SOC of the EV in the two analysed cases. As seen in Case 2, the EV must be rapidly charged since it leaves home earlier. However, the initial SOC is notably higher than in Case 1. These results demonstrated the capability of the developed HEM system to sort the different uncertainties according to their level of randomness. Thereby, those uncertainties that are hardly predictable rule the value of the others, thus obtaining a more robust scheduling plan.

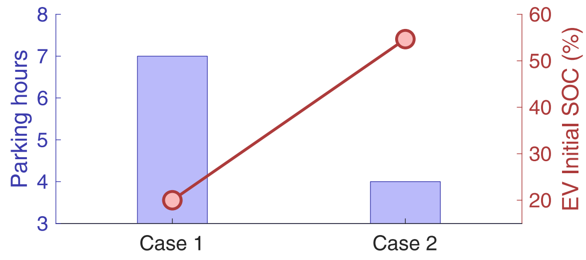

Fig. 12. Total parking hours and initial SOC of the EV for the different cases analyzed

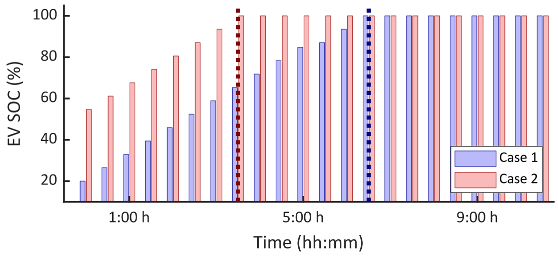

Fig. 13. EV SOC for the analysed cases. The departure time in each case is plotted with dotted vertical lines

5.4 - Discussion

The results reported above validate the new method, whose capability to schedule home assets attending to the level of randomness of uncertainties has been proved. However, some differences between the new proposal and other benchmark HEM methodologies are worth commenting. In this regard, stochastic-based methods may be the most widely used in the field because of their simplicity [14, 22]. Fairly, the new proposal cannot be directly compared with stochastic methods since the latter does not allow, a priori, to classify the uncertainties according to their level of randomness. In this regard, our methodology is considered more advanced than simple stochastic approaches.

On the other hand, the interval-based formulation presented in this paper can be considered novel in HEM-based problems. This principle has been used in different fields like microgrids [64]. Regarding the ability to deal with uncertainties, interval-based approaches can be more useful in some conditions. Note that stochastic-based approaches require a well-suited model to generate scenarios normally derived from well-known probability functions or historical data. While these models are widely available for weather parameters, few attempts have been made regarding other related uncertainties, like the EV timetable or initial SOC [31]. In addition, stochastic-based approaches are not actually robust, since they do not yield the worst-case scenario and other additional modules like CVaR have to be incorporated to reproduce the risk-averse or seeker character of users [65].

Stochastic-based approaches generate a set of feasible scenarios for uncertainties, evaluating them on the whole to obtain the most economical result. This approach increases the variable space by the number of scenarios considered, for which space reduction techniques can be used [22]. Although our methodology encompasses various stages, its computational burden is comparable to conventional stochastic processes. The computational cost inferred by the optimization problems that must be solved at each stage is compensated by the increasing variable space in stochastic-based methodologies.

Thus, our method is robust and versatile in managing with different uncertainties. Its computational burden is not comparable with simple deterministic approaches, which are more efficient. In this sense, the computational cost of the new proposal is proportional to the number of uncertainties involved. Thus, although less efficient than conventional deterministic formulations, the computational burden of our method is perfectly affordable by average machines in most cases, especially if few uncertainties are involved (note that in most real cases, users are concerned about weather and consumption parameters only).

6 - Conclusions and future works

A novel HEM tool has been presented in this paper. In contrast to other related approaches, which rely on deterministic or simply stochastic foundations, the new proposal is based on interval formulation. It allows sorting of the uncertainties according to their level of randomness, thus giving more importance to those parameters that are hardly predictable while minimizing the significance of others. To this end, a novel Lexicographic-Interval formulation of the HEM problem has been presented.

A benchmark case study has been presented in a prosumer environment with EV and rooftop PV panels. Various simulations are performed to illustrate the capabilities of the developed tool. It has been evidenced by the results of its ability to reproduce robust scheduling plans, considering multiple uncertainties on the whole. An example has also been presented to illustrate how the developed HEM tool can sort the different uncertainties so that knowing the more complex parameters to predict determines the importance of other uncertainties. In this way, those easily predictable uncertainties had less impact on the HEM performance, while the more random parameters clearly influenced the final result more notably. The results also allowed us to compare the new method's performance under TOU or RTP tariffs. It is concluded that while the considered RTP tariff results are more economical (-12% in daily electricity bill), the level of robustness achieved is lower, assuming a higher PV consumption (+25%) and initial SOC of the EV (+32%).

The mathematical framework presented here can be adapted to various engineering problems involving multiple uncertainties. Future works will study the adaptability of the developed tool to other applications.

Appendix - Modelling the EV time window as a decision variable

When considering the EV departure time uncertain, the mathematical model presented in Section 3 should be modified in order to consider the EV time window a decision variable. To this end, the binary variable u_t^{EV} is declared, which is equal to 1 when the vehicle is plugged at home and 0 otherwise. Then, the constraint (11) must be replaced by (A1).

$$p_t^{EV} \leq u_t^{EV} \cdot \overline{p}^{EV}; \forall t \in T \quad \text{(A1)}$$

In addition, the constraint (A2) must be imposed, which avoids charging the on-board batteries when the vehicle is not parked at home. Additional constraints could be imposed to impose continuity in the EV time window, for which the vehicle could be modelled similar to the non-interruptible appliances.

$$u_t^{EV} = 0; \forall t \notin \Theta^{EV} \tag{A2}$$

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