Published in Energy with doi: 10.1016/j.energy.2022.124146

A Novel Hybrid Lexicographic-IGDT Methodology for Robust Multi-Objective Solution of Home Energy Management Systems

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Abstract - With the emergence of smart appliances and communication infrastructures, Home Energy Management Systems have gained importance to help home users to reduce their electricity bills. A Home Energy Management System is a tool able to optimally coordinate the different home assets such as controllable appliances, onsite generators and storage facilities, among others. Such kind of tools has become more complex with the appearance of dynamic pricing tariffs and novel appliances such as electric vehicles. In this context, scheduling tools must attain a high level of robustness against uncertainties as well as being able to consider the particular behaviour of unpredictable energy pricing and vehicle routines, while some complementary objectives like thermal comfort are not ignored. This paper addresses this issue by developing a novel hybrid robust-multi objective home energy management approach. The novel proposal is based on information gap decision theory and lexicographic optimization, which are combined in an original way to attain a scheduling plan immune against the negative effect of uncertainties, while the economy and comfort of the building are jointly considered. The developed mathematical formulation is Mixed Integer Linear Programming, employing advanced linearization techniques to overcome the problems arisen from nonlinear models. Its particular integer-linear structure makes the developed optimization problem easily tractable by conventional solvers and average machines. Also, further capabilities are explored such as the possibility of selling energy to the grid and the vehicle-to-home ability of electric vehicles. Extensive simulations are performed on a benchmark prosumer environment considering real time pricing and time-of-use tariffs. The result serves to prove that the developed methodology is able to deal with uncertainties whereas different objective functions are jointly accounted.

Keywords: home energy management; information gap decision theory; multi-objective optimization; vehicle-to-home; prosumer; smart home.

Nomenclature

Indexes(Sets)	
$t(\mathbb{T})$	Time
Φ	Time window in which the electric vehicle is parked at home
$a(\mathbb{A}^{\mathrm{I}}/\mathbb{A}^{\mathrm{NI}})$	Interruptible/non-interruptible appliance
Ψ	Allowable time window of a controllable appliance
$\Omega^{-/+}$	Set of favourable/unfavourable uncertainties ($\Omega = \Omega^{-} \cup \Omega^{+}$)
Superscripts	
$Grid, buy/sell$	Buy/sell energy from/to the utility grid
$PEV, ch/dch$	Plug-in electric vehicle in charging/discharging mode
PV	Photovoltaic
$Air, in/out$	Indoor/outdoor air
$HVAC, h/c$	Heating-ventilation-air conditioner system in heating/cooling mode
sp/db	Set-point/dead-band
NC	Non-controllable appliance
$\overline{(\cdot)}/\underline{(\cdot)}$	Maximum/minimum value of a variable or parameter
$\widehat{(\cdot)}$	Uncertain parameter
U/SN	Utopia/pseudo-Nadir point
Constants & Parameters	
$\Delta\tau$	Time step (h)
η	Efficiency (p.u.)
d	Depth-of-discharge (p.u.)
ε_0^{PEV}	Initial energy stored in the electric vehicle (kWh)
ϑ	Solar irradiance (kW/m²)
θ	Temperature (ºC)
φ	Duty cycle of a controllable appliance (h)
m	Mass (kg)
Q	Heat or thermal capacity (kJ/(kg · °C) or kWh/ºC)
R	Equivalent thermal resistance of the building (kW/ºC)
C	Coefficient of performance (pu)
λ	Energy price ($/kWh)
α	Uncertain radius (p.u.)
Decision variables (deterministic, $\boldsymbol{\beta}$)	
p	Power (kW)
ε	Energy stored (kWh)
u	Scheduling status (binary)
on/off	Activation/deactivation status (binary)

1 - Introduction

1.1 - Context & motivation

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 of 2019 and continue to increase by 2022 [1]. This trend implies a major concern because of the dependency of pollutant fossil fuels for electricity generation. In this context, the residential sector supposes a large sharing of total worldwide electricity consumption. For example, domestic users consumed nearly 21% of the total energy consumption in Hong Kong in 2016, being over 70% of this demand attributable to electrical loads [2]. In this regard, the residential sector presents a great opportunity to reduce overall energy consumption. Actually, a recent study shows that nearly 15-40% of domestic demand can be reduced using home energy management systems (HEMSs) [3].

A HEMS can improve the residential energy usage by scheduling the operation of domestic appliances. The proliferation of dynamic energy tariffs as well as the increasing utilization of on-site renewable generators and storage facilities has increased the complexity of HEMSs, which are frequently performed under uncertain environments caused by unpredictable weather parameters and pricing behaviour. In this regard, there is a need of tackling this issue by exploring uncertainty-aware energy management tools capable to deal with multiple uncertainties, besides considering different user-defined objectives and emerging appliances such as electric vehicles (EVs) [4]. This paper addresses this issue.

1.2 - Literature review

A HEMS for smart consumers under real time pricing (RTP) was developed in [5]. In that study, uncertainties from unpredictable energy pricing are treated via scenarios. Lin and Tsai developed in [6] a multi-objective home energy management (HEM) paradigm which is solved using metaheuristic techniques. This methodology incorporates a module to identify load patterns of major appliances based on historical data. Ref. [7] deals with the optimal coordination of a plug-in electric vehicle (PEV) and photovoltaic (PV) panels considering stochastic behaviour of household demand, renewable generation and EV journeys. Hemmati developed in [8] a Montecarlo-based simulation of a HEMS which considers optimal capacity of battery energy storage (BES). The developed model contemplates nonlinearities, for which the author used nature-inspired optimizer. The model developed in [8] was enhanced in [9] by incorporating uncertainties from PV generators.

A chance-constrained model for HEMS has been developed in [10]. This method employs point estimation methods (PEMs) to extract statistical information of uncertain parameters such as RTP and PV generation. The problem of response fatigue was contemplated by Shafie-Khah and Siano in [11]. In this reference, a stochastic HEMS model that bounds the number of demand response (DR) signals received by home inhabitants was proposed. A stochastic HEMS was proposed in [12], in which the degradation of BES is incorporated as a secondary objective function. The resulting problem is nonlinear, being necessary the use of heuristic optimizers to solve it. A multi-objective HEMS has been developed in [13], by which the electricity bill and peak load are jointly minimized. In this model, uncertainty of home demand is treated by probability functions and scenarios. The reference [14] discusses the influence of wholesale electricity markets in household appliances scheduling. To this end, a stochastic bi-objective HEM model was developed in which overall cost of the home system and payoff of the PV-BES facility are optimized.

In [15], a robust multi-objective HEMS model that considers the worst distribution of PV generation was developed. The resulting problem is formulated as a second order conic programming (SOCP) model and solved using commercial solvers (such as CPLEX [16]). In [17], the possible effect of forecast errors has been addressed by developing a HEMS with real-time rescheduling capability. This model performs a day-ahead optimal scheduling plan, which can be readjusted to tackle deviations from forecast values of uncertain parameters. The reference [18] proposes a cooperative two-stage optimization mechanism, by which the distribution system operator seeks the flexibility of HEMSs through local marginal prices. The authors of [19] developed a multi-agent approach for appliances scheduling under hour-ahead price-based DR. Artificial neural networks (ANNs) are considered to predict the energy price over a 1-h time horizon. Hosseinnezhad et al., [20] developed a home system model with day-ahead and real-time regulation capability. In the day-ahead problem, uncertainties are taken equal to forecast values, whereas possible errors are taken into account in real-time management through adaptive neuro-fuzzy inference system.

Ref. [21] deals with the appliances scheduling problem under uncertainties. To this end, a hybrid risk-averse Metaheuristic-mixed integer linear programming (MILP) model was developed considering different types of appliances and vehicle-to-home (V2H) capability of PEVs. The authors in [22] and [23] developed an approximate dynamic programming approach for HEMS, which aims to find a near optimal solution circumventing the computational burden derived of conventional dynamic programming algorithms. In [24], a multi-objective HEMS immune against cyber-attacks has been developed. The proposed methodology incorporates the battery degradation into the objective function whereas the uncertainties are modelled via scenarios. In [25], a stochastic model for the optimal appliances scheduling problem in a smart consumer has been proposed. This study analyzes the effect of three pricing schemes in the scheduling result for controllable appliances. Similarly, Kong, et al., [26] considered the HEMS problem under stochastic environment incorporating chance-constrained formulation and inhabitants comfort aims.

The reference [27] proposes a three-level strategy for coordination of distributed HEMSs and volt/var optimization in unbalanced distribution networks. Each level of this framework focuses on the different agents involved; thus, the lower level is devoted on the HEMS which is performed in a stochastic paradigm incorporating chance-constrained formulation. A risk-averse HEMS was proposed in [28]. The optimization model minimizes two objective functions regarding energy cost and peak-to-average ratio. Power and time risk indexes are incorporated as constraints for nullifying the effect of uncertainties. Saberi et al., proposed in [29] a distributed HEMS based on dynamic programming. The central controller is devoted on scheduling the non-thermal loads, while the thermostatically-controlled appliances are programmed in real-time, counting for deviations of forecast values of uncertain weather parameters. Ref. [30] proposed a stochastic multi-layer HEMS model. This paradigm comprises various stages that are coordinated in a pyramidal fashion. Thereby, the appliances scheduling problem is considered the third level of the structure and posed as a nonconvex optimization model. In [31], Nezhad et al., developed a multi-objective HEMS with comprehensive inverter-based air conditioner model. The optimization problem is performed considering uncertainties from PV generation, which are modelled via scenarios.

1.3 - Contributions & paper organization

Table 1 presents a summary of the analysed references, comparing some of them. On the view of this report, the following gaps have been detected:

- Many references use stochastic approaches for uncertainties modelling. This approach presents two important drawbacks. On the one hand, it requires a priori knowledge of the probability functions of uncertain parameters. On the other hand, a large number of scenarios should be considered (~1000 [32]) which entails a significant computational burden.
- Various references state the HEMS model as a nonlinear optimization problem, which must be solved using metaheuristic of advanced commercial solvers. In this regard, MILP formulations are preferable because its modular structure, computational cost and availability of suitable optimizers [33].
- Frequently, the model considered is quite simplistic, ignoring some kind of appliances or functionalities (e.g. V2H capability of PEVs [34]). Moreover, most of references consider the home system a passive load, neglecting its capacity to sell energy to the grid (prosumer [35]).
- Although the energy cost is undoubtedly the primary objective of a HEMS, other objective functions should be considered (e.g. thermal comfort [31]). However, there are no many approaches that raise the HEM problem as a multi-objective optimization procedure.

This work is motivated in the aforementioned gaps. In this sense, this paper develops an original multi-objective HEMS based on information gap decision theory (IGDT) and lexicographic optimization, supposing so far, to the best of our knowledge, the first reference that combines these two approaches in HEMS. In this way, the developed methodology is capable to contemplate two or more objective functions in a lexicographic fashion, in which the electricity bill is considered the most important aim of home inhabitants, as customary. On the other hand, various intrinsic uncertainties are modelled using IGDT, resulting in a robust paradigm. Other salient features of the new proposal are numerated below:

- Intrinsic nonlinearities in some component models are not neglected. Instead, sophisticated linearization techniques are used to preserve the MILP structure of the problem.
- A variety of controllable appliances are considered, seeking to represent the wide casuistry offered by smart domestic appliances.
- The possibility of selling energy to the grid by exploiting onsite generators is not ignored, furthermore, V2H capability is also contemplated. In this sense, uncertainties related to PEV behaviour and energy pricing are properly modelled and treated.

As seen in Table 1, the present work supposes the most advanced approach among the all literature revised. To validate the developed approach, a case study on a benchmark smart prosumer environment is presented, analysing various results.

In the rest of this paper, Section 2 overviews the studied prosumer architecture. Section 3 presents the mathematical models of home components. Section 4 introduces the developed solution methodology for HEMS. Section 5 presents a case study and various numerical results. This paper is concluded with Section 6.

Table 1 - Summary of the reviewed references

Ref.	Uncertainties modelling	Formulation	Controllable appliances	Multi-objective	V2H	Prosumer
[6]	Historical data	Metaheuristic	Interruptible	Weighted sum.	No	No
[8, 9]	Stochastic	Metaheuristic	No	No	No	Yes
[10]	PEM	Metaheuristic	Interruptible Non-interruptible Temp. Controlled	No	No	Yes
[11]	Stochastic	MILP	Non-interruptible Temp. Controlled	No	Yes	Yes
[12]	Stochastic	Metaheuristic	Temp. Controlled	Weighted sum.	No	No
[13]	Stochastic	MILP	Non-interruptible	Weighted sum.	No	No
[14]	Stochastic	Heuristic	Non-interruptible Temp. Controlled	Weighted sum.	No	Yes
[15]	Chance-constrained	SOCP	Non-interruptible Temp. Controlled	Weighted sum.	No	No
[17]	Rescheduling	Metaheuristic	Interruptible Non-interruptible	No	No	No
[19]	ANN	Decision-making	Non-interruptible	Weighted sum.	No	No
[21]	Stochastic	Metaheuristic/ MILP	Non-interruptible Temp. Controlled	No	Yes	No
[24]	Stochastic	MILP	Non-interruptible Temp. Controlled	Weighted sum.	No	No
[25]	Stochastic	MILP	Interruptible Temp. Controlled	No	Yes	Yes
[26]	Stochastic	Metaheuristic	Interruptible Temp. Controlled	Weighted sum.	No	No
[27]	Stochastic	Nonlinear	Non-interruptible Temp. Controlled	No	Yes	Yes
[28]	Risk-averse	Metaheuristic	Interruptible Non-interruptible Temp. Controlled	Lexicographic	No	No
[29]	Stochastic	MILP	Temp. Controlled	No	No	No
[30]	Stochastic	Nonlinear	Non-interruptible	No	No	Yes
[31]	Stochastic	MILP	Non-interruptible Temp. Controlled	Weighted sum.	No	Yes
Present	IGDT	MILP	Interruptible Non-interruptible Temp. Controlled	Lexicographic	Yes	Yes

2 - Description of the home system under study

This research is focused on smart prosumers, whose benchmark architecture is schematically described in Fig. 1. The home is connected to a utility grid, from which can purchase or sell energy considering pre-established energy tariffs (flat, TOU or RTP). Energy supplying of the building can be also attained by means of onsite PV generation, being therefore capable of exporting eventual surplus renewable energy to the utility network, thus obtaining a monetary revenue. Energy management of the home system is daily performed by a HEMS in a centralized fashion. In this sense, not only energy exchanging with the main grid can be scheduled, but also a series of appliances can be controlled on pursuing a more efficient energy management of the system. In contrast, it is assumed that some appliances cannot be controlled by the centralized scheduler and their consumption responds to inhabitants' decisions and routines such as fridge, TV or computers [11]. Thermal comfort of the users is ensured by controlling a central heating-ventilation-air conditioner (HVAC) system, which is devoted on maintaining the indoor temperature within acceptable bounds, taking advantage of heating and cooling operational modes. On-board batteries of PEVs can be operated in charging and discharging modes when the vehicle is parked at home. This way, PEVs can be exploited as storage facilities through bi-directional chargers [34]. In this regard, charging-discharging cycles of PEVs can be also managed by the HEMS, taking into account users' preferences and requirements.

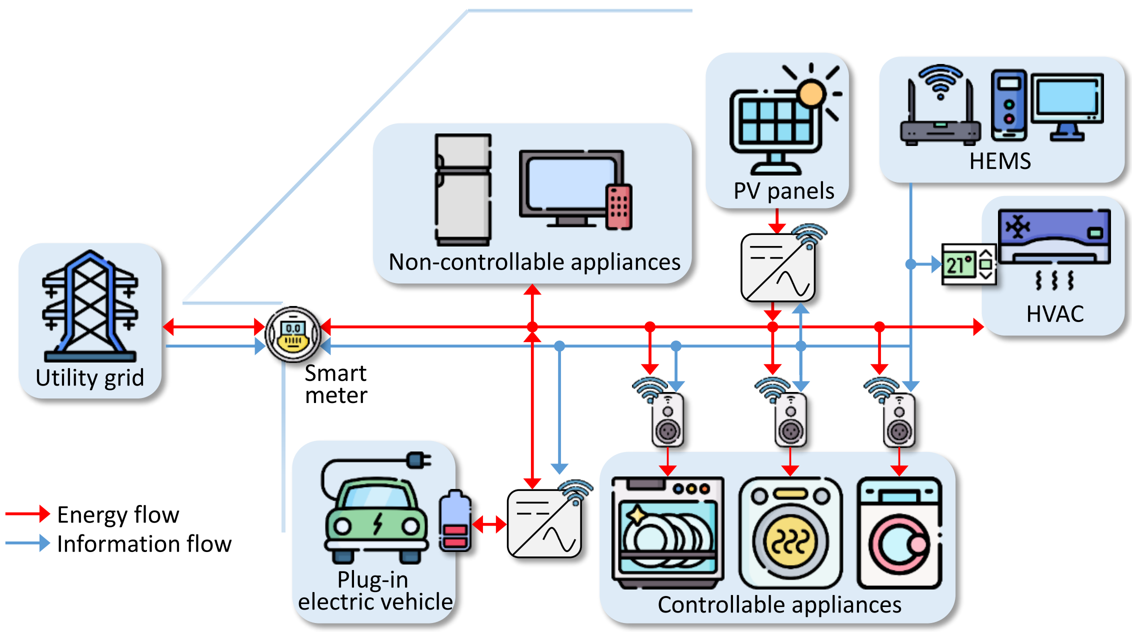

Figure 1 - Schematic diagram of the home system under study

Various kind of controllable appliances with different premises and characteristics are considered in this work. Firstly, the non-interruptible appliances have to be operated continuously, it means that once they have been scheduled, their operation cannot be interrupted until completing their duty cycle (φ). Contrarily, the interruptible appliances can be scheduled in different time intervals, interrupting their operating cycles if necessary. In both cases, the appliances must complete their duty cycles within allowable time windows (Ψ). On the other hand, the HVAC is operated so that the indoor temperature is maintained within acceptable limits. In this sense, home inhabitants set up a temperature set-point and, on the basis of this value, a hysteresis interval is established to avoid the continuous operation of the appliance. For the sake of clarity, Fig. 2 shows the operational foundations of each type of controllable appliance.

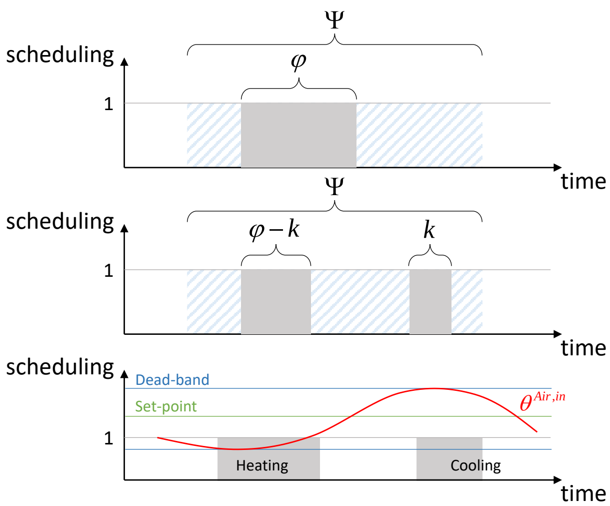

Figure 2 - Examples of scheduling plans for non-interruptible appliances (top), interruptible appliances (middle) and HVAC system (bottom)

3 - Mathematical models

In this section, the mathematical models of the home components are formulated. Herein, the different expressions are linear involving binary and continuous variables. In this section, all the parameters and variables are considered known, discussing later how the different uncertainties brought by load demand, renewable generation and energy pricing are treated.

3.1 - Grid modelling

It is realistic to assume that power exchanging with the grid is upper bounded [35], as said the expression (1). On the other hand, the constraint (2) needs to be imposed to avoid buying and selling energy at the same time.

$$p_t^{Grid,i} \leq u_t^{Grid,i} \cdot \bar{p}^{Grid};\ \forall t \in \mathbb{T} \wedge i \in \{buy, sell\} \tag{1}$$

$$\sum_{i \in \{buy,sell\}} \left\{u_t^{Grid,i}\right\} \leq 1;\ \forall t \in \mathbb{T} \tag{2}$$

3.2 - PEV modelling

As mentioned earlier, the PEV is treated in this work as a storage facility, enabling charging and discharging modes of its on-board BES [34]. The constraint (3) is imposed to limit the power that the PEV can exchange with the home [36]. Similar to the grid modelling, the constraint (4) is necessary to make the charging and discharging processes complementary.

$$p_t^{PEV,i} \leq u_t^{PEV,i} \cdot \bar{p}^{PEV};\ \forall t \in \mathbb{T} \wedge i \in \{ch, dch\} \tag{3}$$

$$\sum_{i \in \{ch,dch\}} \left\{u_t^{PEV,i}\right\} \leq 1;\ \forall t \in \mathbb{T} \tag{4}$$

The expression (5) models the state-of-charge (SOC) of the on-board storage system [34], as a function of the SOC at $t-1$ and the energy exchanging with the home. The energy stored in the PEV is upper and lower bounded by nominal capacity of batteries and depth-of-discharge (DOD) settings [36], as given by (6).

$$\varepsilon_t^{PEV} = \varepsilon_{t-1}^{PEV} + \Delta\tau \cdot \left(\eta^{PEV} \cdot p_t^{PEV,ch} - p_t^{PEV,dch} / \eta^{PEV}\right);\ \forall t \in \mathbb{T} \backslash t > 1 \tag{5}$$

$$(1 - d^{PEV}) \cdot \bar{\varepsilon}^{PEV} \leq \varepsilon_t^{PEV} \leq \bar{\varepsilon}^{PEV};\ \forall t \in \mathbb{T} \tag{6}$$

As pointed out in [37], the initial SOC of storage facilities must be imposed, since the expression (5) is not defined at $t = 1$. In this particular case, it is assumed that the PEV is parked at home at the beginning of the time horizon. In this regard, the initial SOC is considered a parameter in (7), which would depend on the daily trip mileage [38].

$$\varepsilon_{t=1}^{PEV} = \hat{\varepsilon}_0^{PEV} \tag{7}$$

While the PEV is parked at home, it can exchange energy with the home through bidirectional chargers. However, this capability is not enabled when the vehicle leaves the home, which is ensured by imposing the constraint (8).

$$\sum_{i \in \{ch,dch\}} \left\{ u_t^{PEV,i} \right\} = 0;\ \forall t \notin \widehat{\Phi} \tag{8}$$

At the departure time, the SOC of the vehicle has to be sufficient to cover the upcoming trips. Similar to other works [34], the batteries must be fully charged when the PEV leaves the home, as ensured the constraint (9).

$$\varepsilon_{\widehat{\Phi}(end)}^{PEV} = \overline{\varepsilon}^{PEV} \tag{9}$$

3.3 - PV modelling

Potential PV generation depends on weather parameters such as solar irradiation and temperature [37]. These parameters can be converted to power units using (10) [39]. The PV array model is completed by including the constraint (11), which considers the rated power of PV panels [34].

$$\hat{p}_t^{PV} = \overline{p}^{PV} \cdot \left[0.25 \cdot \hat{\vartheta}_t + 0.03 \cdot \hat{\vartheta}_t \cdot \hat{\theta}_t^{Air,out} + (1.01 - 1.13 \cdot \eta^{PV}) \cdot \hat{\vartheta}_t^2 \right];\ \forall t \in \mathbb{T} \tag{10}$$

$$p_t^{PV} \leq \begin{cases} \hat{p}_t^{PV}, \text{if } \hat{p}_t^{PV} \leq 1.1 \cdot \overline{p}^{PV} \\ \overline{p}^{PV}, \quad \text{otherwise} \end{cases};\ \forall t \in \mathbb{T} \tag{11}$$

3.4 - Controllable appliances modelling

As commented in Section 2, interruptible and non-interruptible appliances are considered. In both cases, duty cycles must be completed within allowable time windows, as said the expression (12).

$$\sum_{t\in\Psi^a}\{u_t^a\} = \varphi^a; \forall a \in \{\mathbb{A}^{\mathrm{I}} \cup \mathbb{A}^{\mathrm{NI}}\} \tag{12}$$

In the case of non-interruptible appliances, the constraints (13) and (14) must be imposed. The first expression ensures that these appliances are not interrupted, while the second one ensures that non-interruptible devices are only scheduled once.

$$u_t^a - u_{t-1}^a = on_t^a - off_t^a;\ \forall t \in \mathbb{T}\backslash t > 1 \wedge a \in \mathbb{A}^{\mathrm{NI}} \tag{13}$$

$$\sum_{t\in\Psi^a}\{on_t^a\} = 1; \forall a \in \mathbb{A}^{\mathrm{NI}} \tag{14}$$

3.5 - HVAC system modelling

For the HVAC system, a temperature-dependent model is adopted [40], for which the indoor temperature is taken as a variable and defined by the expression (15).

$$\theta_t^{Air,in} = \left(1 - \frac{\Delta\tau}{10^3 \cdot m^{Air,in} \cdot Q^{Air,in} \cdot R}\right) \cdot \theta_{t-1}^{Air,in} + \frac{1}{10^3 \cdot m^{Air,in} \cdot Q^{Air,in} \cdot R} \cdot \theta_{t-1}^{Air,out} + \frac{\left(p_{t-1}^{HVAC,h} - p_{t-1}^{HVAC,c}\right)}{0.000277 \cdot m^{Air,in} \cdot Q^{Air,in}} \cdot C^{HVAC};\ \forall t \in \mathbb{T}\backslash t > 1 \tag{15}$$

As seen in (15), the indoor temperature not only depends on the outdoor temperature, but also on the action of heating and cooling modes of the HVAC system. Similar to the SOC of batteries, the model (15) is not defined at $t = 1$. Therefore, this value has to be taken as a parameter. As in other similar works [34], the initial indoor temperature is taken equal to the HVAC system set-point. Also, to keep the model coherent, the constraint (16) ensures that the initial and final temperatures are equal.

$$\theta_{\mathbb{T}(1)}^{Air,in} = \theta_{\mathbb{T}(end)}^{Air,in} = \theta^{HVAC,sp} \tag{16}$$

The power consumption of the HVAC system should be limited by rating power of devices, as said the constraint (17). It is also realistic to assume that heating and cooling modes of the HVAC system are complementary [41], as said the equation (18). The HVAC system model is completed by the expression (19), which limits the variation of the indoor temperature to acceptable bounds.

$$0 \le p_t^{HVAC,i} \le u_t^{HVAC,i} \cdot \overline{p}^{HVAC};\ \forall t \in \mathbb{T}, i \in \{h,c\} \tag{17}$$

$$\sum_{i\in\{h,c\}} \left\{u_t^{HVAC,i}\right\} \le 1;\ \forall t \in \mathbb{T} \tag{18}$$

$$\theta^{HVAC,sp} - \theta^{HVAC,db} \le \theta_t^{Air,in} \le \theta^{HVAC,sp} + \theta^{HVAC,db}; \forall t \in \mathcal{T} \tag{19}$$

It is worth noting that the model above allows to easily incorporate modern climatization systems. For example, those that incorporate nanofluids with superior thermal characteristics [42]. In this regard, it would be sufficient modifying the thermal properties of the air and the building in consequence.

3.6 - Home energy balance

The equality constraint (20) ensures the energetic balance in the home at any time (generation = load).

$$p_t^{Grid,buy} + p_t^{PEV,dch} + p_t^{PV} = \hat{p}_t^{NC} + p_t^{Grid,sell} + p_t^{PEV,ch} + \sum_{i\in\{h,c\}} \left\{p_t^{HVAC,i}\right\} + \sum_{a\in\{\mathbb{A}^{\mathrm{I}} \cup \mathbb{A}^{\mathrm{NI}}\}} \left\{u_t^a \cdot \overline{p}^a\right\};\ \forall t \in \mathbb{T} \tag{20}$$

In (20), the non-controllable demand refers to the consumption drawn by those appliances which are managed on the basis of human decisions. In this regard, the HEMS is inhibited of scheduling such appliances, since it is assumed that the home inhabitants are not willing to subordinate the governance of these devices to a central controller. Typical examples of non-controllable appliances are TV, computers, kettles, etc [11]. Nevertheless, the developed mathematical model allows to consider other appliances as controllable on the basis of users' preferences. Intuitively, this demand is unpredictable due to the unknown behaviour of home inhabitants and, in consequence, it has been considered uncertain in (20).

4 - The developed solution procedure

To solve the HEMS problem under uncertainty while multiple objectives are jointly tackled, a novel hybrid lexicographic-IGDT methodology is developed, which is summarized in Fig. 3. Lexicographic optimization is a well-known multi-objective procedure that allows ordering the different objective functions according their importance [43]. This feature is particularly attractive in HEMS problems, for which the minimization of the electricity bill is normally the major concern [35]. On the other hand, IGDT is a robust optimization technique that does not require a priori knowledge about probability distribution of uncertain parameters [44]. Instead, IGDT uses immunity functions to inform the decision-maker about the positive and negative effects that may be caused by uncertainties and, on the basis of this information, being able to take logical decisions which may be safe or risky [45]. Thereby, the scheduling result is immune against the effect of uncertainties, ensuring that unknown parameters do not affect notably to the main goal of the HEMS. For example, considering IGDT, the HEMS may take care of possible deviations of PV generation with respect to the expected profile and take decisions in consequence, ensuring that the electricity bill is not critically incremented compared with the expected case. As seen in Fig. 3, the combination of these two approaches leads to a three-stage methodology, which is further explained in subsequent sections.

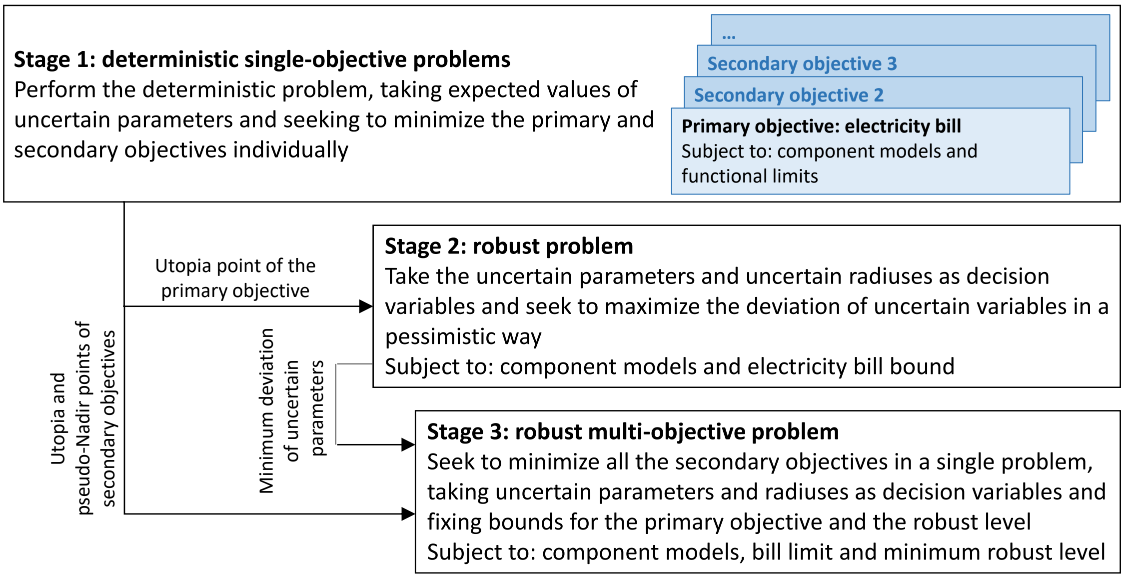

Figure 3 - Flowchart of the developed methodology

4.1 - Stage 1: deterministic single-objective problems

In the stage 1 of the developed methodology, all the considered objectives are separately optimized. As commented, one of the objectives must be distinguished as the primary one. As customary in HEM problems, the energy cost will be taken as the most important target for home inhabitants. Eq. (21) expresses the daily energy cost as a function of energy exchanging with the utility grid.

$$f_1 = \Delta\tau \cdot \textstyle\sum_{t\in\mathbb{T}}\left\{\hat{\lambda}_t^{Grid,buy} \cdot p_t^{Grid,buy} - \hat{\lambda}_t^{Grid,sell} \cdot p_t^{Grid,sell}\right\} \qquad (21)$$

As a sake of example, thermal comfort will be considered as secondary objective. This premise is typically tackled in multi-objective HEM problems (e.g. see [31]) and refers to the preference of households to maintain the indoor temperature as close as possible to a preset set-point. In this paper, the function (22) measures the thermal comfort degree achieved in the home scheduling plan.

$$f_2 = \textstyle\sum_{t\in\mathbb{T}}\left\{\underbrace{\left|\theta^{HVAC,sp} - \theta_t^{Air,in}\right|}_{\varsigma_t}\right\} \qquad (22)$$

It is worth noting that the higher value of (22), the lower thermal comfort. Indeed, the function (22) would be equal to zero if the indoor temperature is kept equal to the HVAC system set-point at any time. The function (22) involves an absolute value that must be linearized by declaring the dummy variables ω and ς, and imposing the constraints (23)-(26).

$$M \cdot \omega_t \geq \theta^{HVAC,sp} - \theta_t^{Air,in};\ \forall t \in \mathbb{T} \tag{23}$$

$$M \cdot (1 - \omega_t) \geq \theta_t^{Air,in} - \theta^{HVAC,sp};\ \forall t \in \mathbb{T} \tag{24}$$

$$\varsigma_t \geq \theta^{HVAC,sp} - \theta_t^{Air,in};\ \forall t \in \mathbb{T} \tag{25}$$

$$\varsigma_t \geq \theta_t^{Air,in} - \theta^{HVAC,sp};\ \forall t \in \mathbb{T} \tag{26}$$

where M is a large positive number ($\sim 10^6$).

Therefore, the HEM problem must be performed twice in the stage 1 considering the minimization of each objective individually. Hence, the utopia and pseudo-Nadir points [43], which are necessary for remainder stages, are obtained as follows.

$$f_1^U, f_2^{SN} \rightarrow \arg\min_{\boldsymbol{\beta}} f_1\big(\mathbb{E}(\Omega)\big) \tag{27}$$

Subject to: (1)-(20)

$$f_2^U \rightarrow \arg\min_{\boldsymbol{\beta}} f_2\big(\mathbb{E}(\Omega)\big) \tag{28}$$

Subject to: (1)-(20)

where $\mathbb{E}(\cdot)$ returns the expected value of an uncertain parameter and $\boldsymbol{\beta}$ stands for the vector of decision variables.

4.2 - Stage 2: robust problem

The stage 2 of the developed methodology seeks the uncertainty-aware solution of the HEM optimization problem. To this end, robust immunity functions are used with the aim of finding a solution immune against the negative effects of uncertain parameters. In this sense, the unknown parameters are taken as decision variables, allowing them to vary a certain radius α from their expected value. For convenience, the matrix of uncertain radiuses can be defined as follows:

$$\mathbf{A} = \begin{bmatrix} \alpha_{\mathbb{T}(1)}^{\Omega(1)} & \cdots & \alpha_{\mathbb{T}(end)}^{\Omega(1)} \\ \vdots & \ddots & \vdots \\ \alpha_{\mathbb{T}(1)}^{\Omega(end)} & \cdots & \alpha_{\mathbb{T}(end)}^{\Omega(end)} \end{bmatrix} \in \mathbb{R}_{+}^{\mathrm{size}(\Omega)\times\mathrm{size}(\mathbb{T})} \tag{29}$$

The effect of uncertainties may be different depending on the parameter considered. For example, if the buying price increases, its effect on the electricity bill is clearly negative. On the other hand, some parameters have a clear positive effect, like the solar irradiance that increases the availability of PV generation. Since the developed procedure seeks for the worst-case scenario in which the solution encountered is robust against uncertainties, the unknown parameters are allowed to vary only in a pessimistic way, as said the constraints (30) and (31).

$$\hat{b}_t^i \leq \mathbb{E}\left(\hat{b}_t^i\right) \cdot \left(1 - \alpha_t^i\right);\ \forall t \in \mathbb{T} \wedge i \in \Omega^- \tag{30}$$

$$\hat{b}_t^i \geq \mathbb{E}\left(\hat{b}_t^i\right) \cdot \left(1 + \alpha_t^i\right);\ \forall t \in \mathbb{T} \wedge i \in \Omega^+ \tag{31}$$

where b is a generic unknown parameter. It is noteworthy that a quadratic term appears in (10) when solar irradiance is considered a decision variable. To linearize this term, its piecewise representation is considered including the following additional constraints and variables [46].

$$w_{i|t} = \sum_{i=2}^{i=n}\left\{\delta_{i|t} \cdot \left(K_i \cdot \hat{\vartheta}_t + L_i\right)\right\};\ \forall t \in \mathbb{T} \tag{32}$$

$$K_i = \frac{\tilde{\vartheta}_i^2 - \tilde{\vartheta}_{i-1}^2}{\tilde{\vartheta}_i - \tilde{\vartheta}_{i-1}};\ \forall i \in \{2,3,\dots,n\} \tag{33}$$

$$L_i = \tilde{\vartheta}_i^2 - K_i \cdot \tilde{\vartheta}_i;\ \forall i \in \{2,3,\dots,n\} \tag{34}$$

$$\sum_{i=1}^{i=n-1}\left\{\delta_{i|t} \cdot \tilde{\vartheta}_i\right\} \leq \hat{\vartheta}_t \leq \sum_{i=2}^{i=n}\left\{\delta_{i-1|t} \cdot \tilde{\vartheta}_i\right\};\ \forall t \in \mathbb{T} \tag{35}$$

$$\hat{\vartheta}_t - M \cdot \left(1 - \delta_{i|t}\right) \leq v \leq \hat{\vartheta}_t + M \cdot \left(1 - \delta_{i|t}\right);\ \forall t \in \mathbb{T} \wedge i \in \{1,2,\dots,n\} \tag{36}$$

$$-M \cdot \delta_{i|t} \leq v \leq M \cdot \delta_{i|t};\ \forall t \in \mathbb{T} \wedge i \in \{1,2,\dots,n\} \tag{37}$$

where $\tilde{\vartheta}$'s are the n grid points taken for piecewise representation, δ is a special ordered set 1 binary variable [47] and v is a dummy variable to replace the product of integer and continuous variables [36]. To deal with the bi-linear terms that appear in (10) and (21) when the temperature, solar irradiance and energy price are taken as variables, advanced piecewise representations have been considered, more precisely, the approach denoted by 'nf4l' in [47], has been properly adapted.

For the PEV, both the initial SOC and departure times have been considered unknown parameters. To properly model the time slots in which the PEV is not parked at home, the following constraint has to be considered.

$$p_t^{PEV,i} \leq \underbrace{\hat{\zeta}_t^{PEV} \cdot u_t^{PEV,i}}_{\chi_t^{PEV,i}} \cdot \bar{p}^{PEV};\ \forall t \in \mathbb{T} \wedge i \in \{ch, dch\} \tag{38}$$

In (38), the dummy variable ζ is equal to 1 if the PEV is parked at home and 0 otherwise. In this way, the time window associated with the PEV (Φ) can be modelled as an uncertain parameter, as follows:

$$\widehat{\Phi} = \left\{\hat{\boldsymbol{\zeta}}^{PEV} \in \mathbb{B}^{\mathrm{size}(\mathbb{T})}: \hat{\zeta}_t^{PEV} = 1\right\} \tag{39}$$

The model (39) allows to declare $\widehat{\Phi}$ as an unknow parameter, whose associated variable would be the length of $\hat{\boldsymbol{\zeta}}^{PEV}$. It remains to linearize the product of binary variables in (38), which is attained by declaring the dummy variable χ and imposing the following set of constraints.

$$\chi_t^{PEV,i} \leq u_t^{PEV,i};\ \forall t \in \mathbb{T} \wedge i \in \{ch, dch\} \tag{40}$$

$$\chi_t^{PEV,i} \leq \hat{\zeta}_t^{PEV};\ \forall t \in \mathbb{T} \tag{41}$$

$$\chi_t^{PEV,i} \geq u_t^{PEV,i} + \hat{\zeta}_t^{PEV} - 1;\ \forall t \in \mathbb{T} \wedge i \in \{ch, dch\} \tag{42}$$

It is realistic to assume that home users are allowed to consider the effect of uncertainties only if this strategy does not entail a significance detriment of the primary objective (i.e. the electricity bill). It means that uncertain parameters are allowed to vary until a level in which the energy cost is not increased beyond a predefined threshold, which is achieved by imposing the constraint (43).

$$f_1(\boldsymbol{\beta}, \Omega, \mathbf{A}) \leq q \cdot f_1^U \tag{43}$$

where $q > 1$. To attain the maximum level of robustness, the objective of this stage is maximizing the value of the uncertain radiuses, which is expressed by the problem (44).

$$f_3^U \rightarrow \underset{\boldsymbol{\beta}, \Omega, \mathbf{A}}{\arg\max} f_3 \tag{44}$$

Subject to: (1), (2), (4)-(20), (30)-(43)

where

$$f_3 = \frac{1}{\mathrm{size}(\mathbb{T}) \cdot \mathrm{size}(\Omega)} \sum_{t \in \mathbb{T}} \left\{ \sum_{i \in \Omega} \left\{ \alpha_t^i \right\} \right\} \tag{45}$$

4.3 - Multi-objective problem

The last stage is devoted on seeking a compromise solution between the secondary objective and robustness. To this end, the minimum threshold for uncertain radiuses is fixed by the constraint (46).

$$f_3(\boldsymbol{\beta}, \Omega, \mathbf{A}) \geq f_3^U \tag{46}$$

As seen, the constraint (46) avoids the uncertain radiuses be lower than the value calculated at stage 2, in which the robustness is the primary focus. This way, one ensures that the solution calculated in this stage is at least as robust at that calculated in the stage 2, while the primary objective can be considered by including the constrain (43) in the problem. Thereby, the thermal comfort is the target and the optimization problem to be solved at this stage is given by [43]:

$$\min_{\boldsymbol{\beta},\Omega,\mathbf{A}} \frac{f_2(\boldsymbol{\beta},\Omega,\mathbf{A})-f_2^U}{f_2^{SN}-f_2^U} \quad (47)$$

Subject to: (1), (2), (4)-(20), (30)-(43), (46)

Indeed, the optimization problem (47) maximizes the thermal comfort but taking into consideration the limitation in the energy cost imposed by the constraint (43). Furthermore, the constraint (46) ensures that the solution calculated in stage 3 is still immune against uncertainties. It is also worth noting that the developed solution procedure is a MILP whose computational burden grows polynomically with its size.

5 - Case study

This section presents various experiments with the aim of validating the developed HEMS solution procedure described in Section 4. To this end, a benchmark prosumer architecture such as that described in Section 2 is considered. The HEM optimization problem is coded under Matlab R2019a environment and solved using Gurobi [48] over a 24 h time horizon with 30 min resolution. All simulations are run on an Intel® Core™ i7-10700K (32 GB RAM).

5.1 - Input data

In simulations, RTP and TOU tariffs are assumed for purchasing pricing, which are shown in Fig. 4. The considered RTP tariff corresponds with the energy price observed on the PJM FE Ohio on July 9, 2019 [49]. On the other hand, the TOU tariff has been adapted from [50], in order to be comparable to the considered RTP pricing scheme. For simplicity, it is assumed that the expected selling energy is 0.8 times the purchasing price [51]. Fig. 5 plots the expected profiles of weather uncertainties and daily demand attributable to non-controllable loads. The expected temperature and solar irradiance correspond to real profiles measured at Virgin Islands on May 3, 2016 [52]. As commented, the non-controllable demand refers to those appliances which are assumed to be operate manually by users, such as TV, computers or kettles. For this parameter, typical well-reported data have been considered to construct the expected profile [34, 53]. Nevertheless, other reported demand could be considered in case of installing modern appliances, such as coke ovens that use high-performance flue [54].

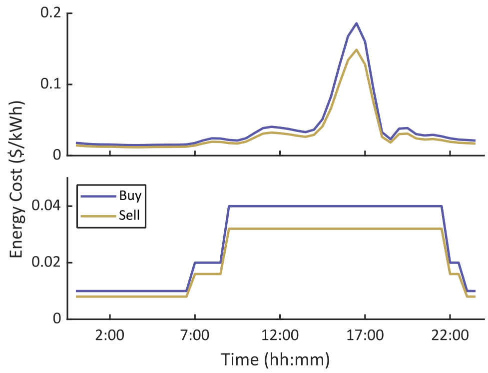

Figure 4 - Expected RTP (top) and TOU (bottom) energy pricing used in simulations

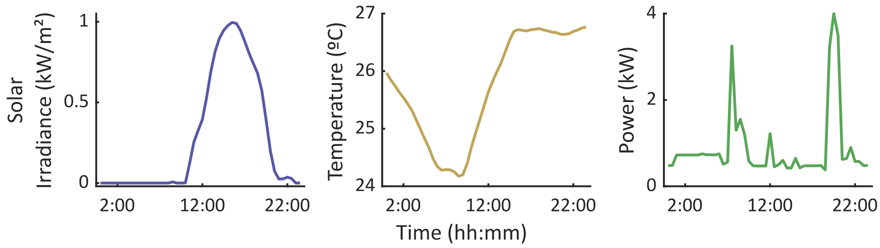

Figure 5 - Expected values of weather parameters and non-controllable appliances demand

An electric plug-in 22 kWh Renault Zoe with 3 kW power limitation is considered as benchmark PEV [11]. The PEV is expected to leave the home at 9:30 h, for its expected initial SOC, an optimistic scenario has been adopted, taking 80% of its fully capacity at the arrival time ($t = 1$) [11, 34]. Nevertheless, these aspects are not much relevant since the developed methodology will seek for the most unfavourable scenario. The Li-ion on-board batteries achieve an efficiency of 98% [36] with DOD settings at 80%. Table 2 shows the characterization of the controllable appliances. As seen, consecutive time windows ensure that the operating cycle of the washing machine has to be completed before scheduling the spin dryer. Table 3 collects the data regarding the HVAC system [33] whereas the rest of necessary parameters are reported in Table 4.

Table 2 - Data of the controllable appliances

Appliance	**Power (kW)**	**φ (hrs.)**	**Ψ**	**Type**
Dishwasher	2.5	2	1:00-18:00	Interruptible
Washing machine	3	3	1:00-12:00	Non-interruptible
Spin dryer	3	3	13:00-21:00	Interruptible

Table 3 - Data of the HVAC system

Parameter	**Value**
Rated power	2 kW
Coefficient of performance	1.20
Temperature set-point	23 ºC
Temperature dead-band	0.50 ºC
Equivalent thermal resistance	$3.20 \cdot 10^{-6}$ (J/ºC)
Heat capacity of the air	1.01 (kJ/(kg · ºC))
Mass of air	1,778.40 kg

Table 4 - Parameters used in simulations

Parameter	**Value**
Rated power of PV panels	1 kW
Efficiency of PV panels	0.167 p.u.
Max. Grid power	10 kW
q	1.25 p.u.

5.2 - Robustness of the developed methodology

The first test is devoted on checking the robustness of the solution calculated by the developed methodology. To this end, Fig. 6 compares the expected profiles of uncertain parameters and those resulted after performing the stages 2 and 3 of the developed procedure. As observed in this figure, under both RTP and TOU pricing schemes the uncertainties took pessimistic values when the IGDT technique was performed to model unknown variables. Thus, solar irradiance notably decreased, especially during evening when PV generation is expected to be high. On the other hand, non-controllable demand grows at noon, when low PV generation is available and therefore the home must be supplied from the grid. The ambient temperature was considerably lower than the expected profile, thus supposing a negative effect for PV generation and thermal comfort.

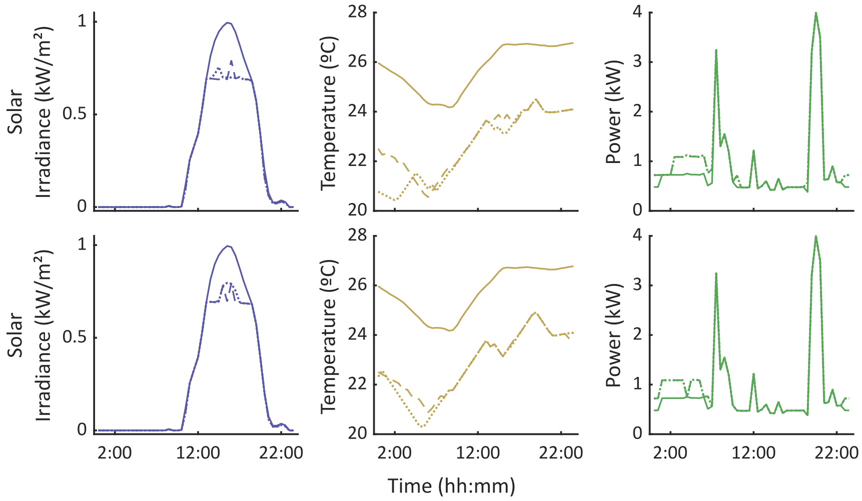

Figure 6 - Comparison of the expected values of uncertain parameters and those profiles calculated at stages 2 (dashed lines) and 3 (discontinuous lines) with RTP (top) and TOU (bottom) pricing schemes

The effect of robust optimization can be also appreciated on the scheduling plan for the PEV. In this sense, there are two uncertainties associated with the vehicle namely the initial SOC and departure time. The SOC of the PEV for different scenarios is plotted in Fig. 7. As observed, the worst case assumes that the vehicle leaves the home earlier compared with the deterministic case. Also, the initial SOC is comparatively lower. Indeed, it is considered that the PEV is half charged at the beginning of the time horizon in case of robust optimization with RTP. It is also worth noting that V2H capability of the EV was less exploited at stages 2 and 3. This is because the negative effect of uncertainties forces to devote almost all the parking time to charge the on-board batteries, in order to be fully charged at the departure time.

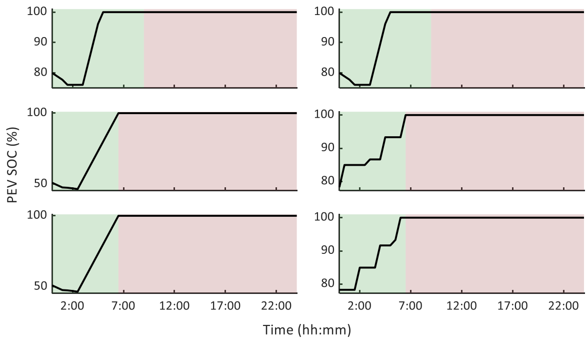

Figure 7 - SOC of the PEV at stages 1 (top), 2 (middle) and 3 (bottom) with RTP (left) and TOU (right) pricing schemes. In this figure, green areas indicate the hours when the EV is parked at home

Fig. 8 depicts the energy exchanging with the utility grid for different cases. As observed, under robust optimization the home needs to purchase more energy during noon, because the PEV demands more energy to charge its on-board system earlier. In the case of TOU tariff, the peak load is actually shifted from approximately 3:00 h to 2:00 h in order to meet this requirement before the vehicle leaves the home. It is also worth noting that the building generally demands more energy from the network at evening, due to lower PV generation. The negative effect of uncertainties is even more notable when observing the selling energy. As seen, the home is barely capable to sell a minimum amount of energy during evening with TOU tariff. This is clearly due to a low availability of PV generation, hindering the possibility of generating a surplus energy.

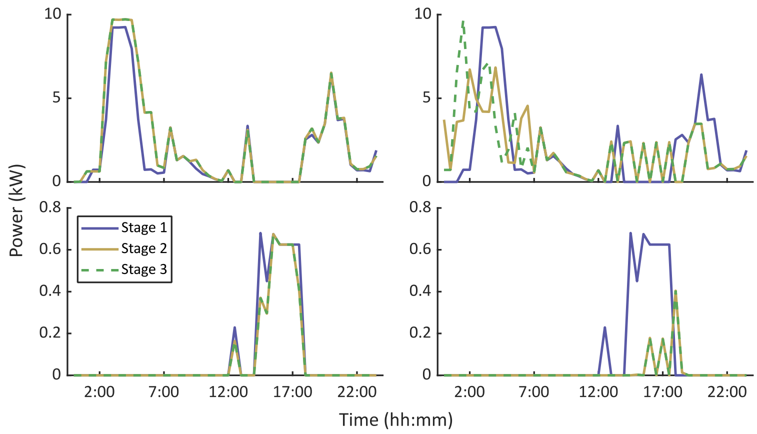

Figure 8 - Energy purchasing (top) and selling (bottom) from/to the utility grid with RTP (left) and TOU (right) pricing schemes

5.3 - Multi-objective optimization

Next, the ability of the developed methodology to find a compromise solution among the different objectives is analysed. In this sense, the proposed optimization framework should be able to optimize the thermal comfort under robust conditions and without incrementing the energy cost beyond a predefined threshold. To validate that, the multi-objective optimization result should lie among the utopia and pseudo nadir points, calculated in the stage 1 of the developed methodology [55]. Table 5 reports the value of the different objective functions (f_1, f_2 and f_3) at each stage of the developed methodology. It is worth remembering that stage yields the utopia and pseudo Nadir points of f_2. It means that thermal comfort level calculated at stage 3 should take a value among these points, since it is calculated taking into consideration the energy cost and minimum deviation of uncertainties. As observed, these premises were met in simulations. As expected, the energy cost takes its maximum allowable value at stages 2 and 3, whereas the minimum robust level was respected at stage 3. With these results, it is proved that the developed methodology was able to find a compromise solution among economy, comfort and immunity against uncertainties.

Table 5 - The value of the objective functions at each stage

Obj. Function	**Stage 1**	**Stage 1 (f_2)**	**Stage 2**	**Stage 3**
f_1 (RTP)	0.76 $	1.39 $	0.95 $	0.95 $
f_2 (RTP)	54.23 ºC	0 ºC	31.25 ºC	27.94 ºC
f_3 (RTP)	--	--	0.155 p.u.	0.155 p.u.
f_1 (TOU)	0.76 $	1.56 $	0.95 $	0.95 $
f_2 (TOU)	54.23 ºC	0 ºC	32.28 ºC	27.67 ºC
f_3 (TOU)	--	--	0.132 p.u.	0.132 p.u.

To get a better overview about how the developed methodology works, Figs. 9 and 10 plot the indoor temperature and HVAC scheduling plan for different cases, respectively. As expected, the indoor temperature was always equal to the HVAC set-point when f_2 is minimized at stage 1. This fact was also appreciated in Table 5, since this function takes zero at stage 1, which means that indoor temperature does not vary over the time horizon. Under these circumstances, the HVAC system must be continuously operated to keep stable the indoor temperature, as seen in Fig. 10. At stage 3, the indoor temperature occasionally deviates from the set-point temperature, but it varies over a narrower region compared with the stage 1, which indicates that a higher level of thermal comfort is reached, thus proving the ability of the developed methodology to attain a compromise solution among objectives. Logically, the HVAC must be more profusely operated at stage 3 in order to attain high comfort conditions.

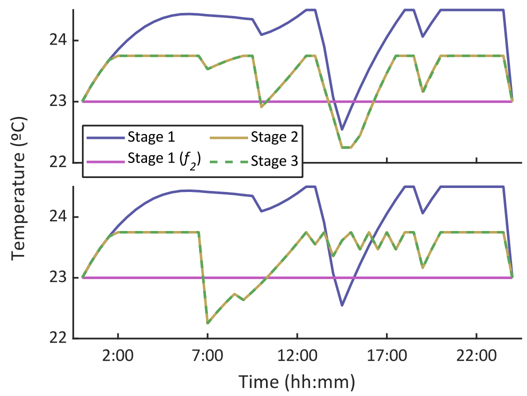

Figure 9 - Evolution of the indoor temperature with RTP (top) and TOU (bottom) tariffs

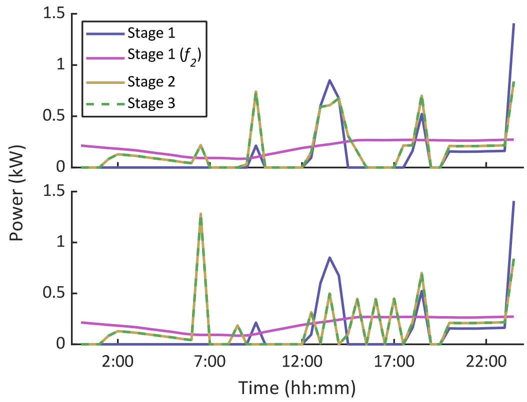

Figure 10 - HVAC scheduling plan with RTP (top) and TOU (bottom) tariffs

6 - Conclusions

In this paper, a novel robust multi-objective HEMS model has been developed. The new proposal combines IGDT and lexicographic optimization to attain a compromise solution among objectives, while the negative effect of uncertainties is also tackled. The developed mathematical model incorporates a variety of controllable appliances, besides dynamic energy pricing and PEV with V2H capability. In this sense, uncertainties associated with energy price and vehicle routines have been properly modelled. The nonlinearities that appear when some uncertain parameters are declared as decision variables have been removed, therefore, the resulting optimization problem is a MILP, which can be managed by average machines and conventional solvers.

Extensive simulations have been performed on a benchmark prosumer environment. As a sake of example, energy cost and thermal comfort have been considered the optimization objectives. It has been proved that the developed procedure is able to consider the variation of uncertainties until reach an assumable worst-case scenario, for which the energy cost does not surpass a preset threshold. Assuming this robustness level, the developed approach was able to find a compromise solution between energy cost and thermal comfort, resulting in a scheduling plan for which all the objectives were satisfactorily optimized. The features of the new proposal have been highlighted by reporting various relevant results. This way, the effect of uncertainties in PEV behaviour or weather parameters was analysed.

Future works should be focused on applying similar approaches in other problems such as microgrid energy management or optimal design of power systems. Furthermore, laboratory testbeds will be developed to validate the new proposals on real equipment.

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