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ORIGINAL RESEARCH

A four-stage framework for optimal scheduling strategy of smart prosumers with vehicle-to-home capability under real time pricing based on interval optimization

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Abstract

With the emergence of the Smart Grid concept, utility companies require more active participation of home users in the power sector. This changing paradigm is enabled by the wide deployment of multiple home assets such as small renewable-based generators or storage facilities. In this context, consumers are no longer conceived as pure loads but also active agents that can exchange energy with the grid. To promote this active participation, utility companies promote different price-based demand response programs to change the consumer patterns on pursuing a more efficient and economic system operation. In this regard, home energy management programs are becoming an essential tool for efficiently managing the different home users while addressing multiple demand response goals at minimum cost. In essence, a home energy management system is a computational optimization tool, which has to handle multiple uncertainties brought by weather forecast or energy pricing. This paper tackles this issue by developing a novel robust home energy management program based on interval optimization. In contrast to other related approaches, the proposal avoids the explicit use of interval arithmetic. Instead, the different uncertain parameters are sequentially incorporated into the scheduling task through different stages and interval-based formulation. The developed methodology incorporates weather, load, energy pricing and plug-in electric vehicle related uncertainties. A benchmark case study in a smart prosumer layout serves to prove the effectiveness of the new approach.

1 | INTRODUCTION

1.1 | Context and motivation

The increasing demand for electricity and environmental concerns are among the most important crises of modern power system [1]. In this context, residential sector supposes a large percentage of overall electricity consumption [2]. Hence, optimizing domestic consumption patterns supposes a formidable opportunity to reduce electricity consumption worldwide. To this end, home energy management (HEM) tools are gaining increasing importance because their capability to optimally coordinate the operation of domestic appliances as well as onsite generation assets such as photovoltaic (PV) generators and storage technologies. In fact, a recent study points out that nearly 15–40% of domestic demand can be reduced using HEM systems [3].

The emergence of controllable and smart appliances enables a further optimization of residential consumption patterns. In this sense, thermostatically controlled appliances can play a crucial role on reducing energy consumption from domestic users [4], but also new capabilities like vehicle-to-home (V2H) [5] increases the flexibility of residential installations. However, the effective coordination of such smart capabilities increases the complexity of HEM programs, being so necessary further developments in these computers tools to effectively model smart appliances and devices, but also to consider uncertainties from renewable generation, demand and electric vehicle (EV) behaviour.

The complexity of the HEM programs is further increased by the inclusion of demand response (DR) programs [6]. Such initiatives are launched by utility companies in order to encourage users to actively partake in grid operation, thus promoting the adoption of beneficious strategies such as valley filling and peak clipping through ambitious pricing schemes like time-of-use or real time pricing (RTP) tariffs [7]. In the latter case, the energy purchasing price becomes non-deterministic, thus being determined by hourly local marginal prices from distribution network. This way, further uncertainties are introduced into the HEM program, which are forced to work under strong uncertainties environments.

1.2 | Literature review

As commented, HEM systems are gaining importance nowadays. This circumstance has motivated extraordinary research efforts recently. However, not many references have addressed the HEM problem considering V2H capabilities and advanced uncertainties modelling. A stochastic dynamic control was proposed in [8], for improving the economy of a smart home considering PV arrays and V2H capability, showing up that the developed control architecture brings considerable advantages compared to conventional controllers. The authors in [9] developed an approximate dynamic programming framework to optimize the energy consumption of a grid-connected smart home considering various DR scenarios. The HEM problem for a smart prosumer is solved in [10] using a cooperative particle swarm optimizer, considering RTP and V2H capabilities.

Shafie-khah and Siano developed in [11] a stochastic-based Mixed Integer-Lineal programming (MILP) HEM tool considering response fatigue in order to reduce the discouragement effect of repetitive response signals. The reference [12] proposed a hybrid genetic algorithm-constrained integer algorithm for optimizing the energy consumption and maximizing renewable utilisation of a grid-connected smart home. The optimization problem formulated in [13] also contemplates the possibility of reactive compensation for utility network from smart homes, for which smart appliances and EVs coordination turned out to be essential. The authors in [14] developed a MILP optimization model for HEM, which acts in coordination with a developed control mechanism for effective coordination of V2H capability with onsite battery systems. In [15], a developed index is integrated into a novel HEM tool for avoiding the load congestion during peak hours, resulting in an optimization model that is solved using metaheuristic methods.

Various stochastic models for domestic components are discussed in ref. [16], involving PV generation and appliances demand. Alfaverh et al. [17] developed a control strategy for a grid-connected smart home based on Reinforcement Learning and Fuzzy Membership, considering V2H and onsite renewable generation and storage assets. In [18] a hybrid model is developed by which day-ahead renewable generation is modelled via scenarios while purchasing energy price is managed using robust optimization, however, V2H capability and uncertainties associated with EV were not considered. The ref. [19] proposed a risk-averse HEM system in which the different stochastic scenarios for PV generation are treated in a risk-averse manner using the conditional value at risk (CVaR). Javadi et al. developed in [20] a stochastic-based self-scheduling model for smart homes considering various pricing mechanisms and the presence of PV panels and battery banks. A two-stage nonlinear stochastic HEM model was developed in [21], considering V2H and RTP models in which the different scenarios for domestic demand and renewable generation are generated using an improved neural network approach.

In [22], a stochastic-based energy management tool is developed for multi-homes smart grids with high PV and EV penetration. The ref. [23] uses a stochastic Model Predictive Control (MPC) for a prosumer environment with enabled V2H and heat pump. The importance of properly controlling the thermostatically controlled appliances like heating-ventilation-air conditioner (HVAC) systems is highlighted in [4] taking an isolated smart home as example. Furthermore, in [24] a simplified HVAC model considering inverter-based air conditioner devices is incorporated into the conventional HEM model. The ref. [25] proposed a control strategy for optimally coordinating the charging-discharging profile of the EV considering daily multi-trips. In [26], and advanced HEM tool is developed incorporating sophisticated thermostat models based on fuzzy membership functions. The article [11] describes a planning process for domestic layout in isolated homes considering flexibility from smart appliances and V2H capability.

Koltsaklis et al. developed in [27] a MILP optimization model for smart homes based on various forecast techniques that allow to model different uncertain parameters. The authors in [28] developed a stochastic multi-objective HEM system using the epsilon-constraint method and VIKOR decision making process. Slama [29] proposed a heuristic control mechanism for grid-connected smart homes, that allows to analyse the impact of V2H capability and EV daily trips characteristics in improving the economy and sustainability of the installation. In [30], a stochastic many-objective HEM framework is developed, which combines lexicographic optimization and scalarizing functions to achieve a compromise solution among a variety of conflictive objective functions.

1.3 | Research gaps and contributions

Table 1 summarizes the main characteristics of the studied references. As result of the literature review above, the following research gaps have been detected, which this paper aims to overcome:

- Many references recur to nonlinear models or other approaches instead of MILP formulations. Such models are

TABLE 1 Summary of the studied references.

Ref.	Formulation	V2H	RTP	Uncertainties	EV uncertainties	Prosumer
[4]	MILP	No	No	Stochastic	No	No
[5]	MILP	Yes	No	Stochastic	Stochastic	No
[8]	Dynamic programming	Yes	No	Stochastic	Stochastic	Yes
[9]	Dynamic programming	Yes	Yes	No	No	No
[10]	Metaheuristic	Yes	Yes	No	No	Yes
[11]	MILP	Yes	Yes	Stochastic	Stochastic	Yes
[12]	Metaheuristic	No	Yes	No	No	No
[13]	MILP	Yes	Yes	No	No	Yes
[14]	MILP	Yes	Yes	No	No	Yes
[15]	Metaheuristic	Yes	No	No	No	Yes
[16]	MILP	Yes	No	Stochastic	Stochastic	Yes
[17]	Fuzzy	Yes	No	No	No	No
[18]	MILP	No	Yes	Robust-Stochastic	No	Yes
[19]	Metaheuristic	Yes	No	CVaR	No	Yes
[20]	MILP	No	Yes	Stochastic	No	No
[21]	Nonlinear	Yes	Yes	Stochastic	No	Yes
[22]	Metaheuristic	Yes	No	Stochastic	Stochastic	Yes
[23]	MPC	Yes	No	Stochastic	No	Yes
[24]	MILP	No	No	Stochastic	No	Yes
[25]	Heuristic	Yes	Yes	No	No	No
[26]	MILP	Yes	Yes	No	No	Yes
[27]	MILP	Yes	Yes	No	No	Yes
[28]	MILP	No	Yes	Stochastic	No	Yes
[29]	Heuristic	Yes	No	No	No	Yes
[30]	MILP	No	No	Stochastic	Stochastic	No
Present	MILP	Yes	Yes	Interval	Interval	Yes

frequently non-modular and may be complex to solve or lead to non-global optimum. In this sense, MILP formulations are by far preferred [30].

- Some modern characteristics of smart homes are normally not jointly considered such as the possibility of exporting energy to the grid (prosumer) or V2H capability of the EV.
- Most of studied references use simple pricing mechanism based on Time-of-use tariffs. This way, uncertain behaviour associated with RTP is not contemplated at all.
- While some references do not contemplate the uncertain behaviour of renewable generation or demand, other approaches consider stochastic programming to that end. This approach requires to generate a large number of scenarios which leads to time-consuming optimization procedures [30]. Moreover, this uncertainties modelling needs a priori knowledge about the distribution functions of the uncertain parameters. On the other hand, uncertain behaviour of EV is not considered in many references, assuming deterministic profiles.

As seen in Table 1, the present work overcomes the limitations of other HEM models available in the literature. For the sake of simplicity, the main contributions of this paper are numerated below:

- Developing a HEM model for prosumer environments considering V2H and RTP. The proposed formulation is MILP, thus presenting a modular structure that allows it to be adapted to different layouts and situations [31]. In addition, reachability of the global optimum is ensured using standard solvers in reasonable computational times [30].
- A novel interval-based formulation is used for uncertainties modelling. This way, instead of conventional models based on scenarios, uncertainties from renewable generation, home demand and energy price are modelled using interval numbers. This approach reduces considerably the complexity of stochastic programming and does not require to use distribution functions or historical data.

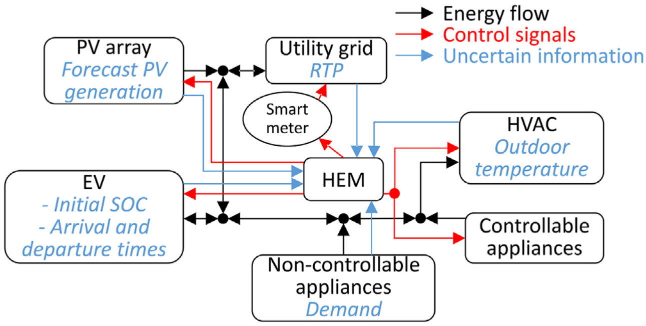

FIGURE 1 Scheme of the home system under study.

- A four-stage methodology is developed for incorporating the uncertainties brought by the unpredictable behaviour of the EV. Thereby, arrival and departure times as well as EV initial state-of-charge (SOC) are modelled using interval numbers.
- A case study is performed on a benchmark prosumer environment with the aim of validating the novel optimization procedure.

The remainder of this paper is organized as follows. Section 2 overviews the home system under study, describing the different components and their role in the HEM system. Section 3 presents the mathematical modelling of the different home assets, which is based on interval formulation. The developed four-stage solution procedure is developed in Section 4. A case study with numerical results is presented in Section 5. The paper is concluded with Section 6.

2 | PRELIMINARIES

2.1 | Overview of the home system

This paper is focused on a home system such as that depicted in Figure 1. This installation is connected to a utility grid through a smart meter, from which can purchase energy. The system comprises onsite renewable generation based on PV arrays, which allow to partially cover the home demand and even produce surplus energy that can be sold to the grid to obtain monetary revenues. A bidirectional charging point is installed with sufficient capacity for a plug-in EV which provides V2H capability, being so possible to exploit the onboard battery bank as a storage asset. The home demand is therefore formed by the charging requirements of the EV and also a group of appliances, that can be classified as follows:

- Non-controllable appliances: this kind of devices is controlled on the basis of human decisions and therefore their operation cannot be scheduled.
- Controllable appliances: the operation of these devices can be controlled, thus deferring their duty cycle to appropriate time slots. However, these appliances could not be scheduled out of predefined time windows, that are specified by users' preferences. These appliances are in turn classified into interruptible and non-interruptible. The former can be interrupted once their operation has started while the latter not.
- HVAC system: this system is devoted on keeping the indoor temperature within comfortable bounds [32]. To this end, it is continuously controlled through a smart thermostat. In this sense, the power set-point of the HVAC system can be controlled.

2.2 | Scheduling principle

The scheduling program of the different controllable appliances and PV array is day-ahead calculated by a HEM system. The principle of operation of this program is sketched in Figure 2. The users' preferences like appliances time windows or temperature set-points serve as inputs of the tool, while necessary forecast parameters are assumed to be day-ahead forecasted. These parameters correspond to those uncertain values of different variables like renewable generation, non-controllable appliances demand, RTP or EV behaviour. On the basis of these inputs, the HEM program is able to determine the scheduling routine of the different controllable assets, which is transferred to the devices through smart controllers like plugins or inverters. Internally, the HEM program aims to minimize the overall energy cost under uncertain environment, for which a novel interval formulation is used in this paper (see Section 3).

2.3 | Uncertainty modelling

As commented previously, this paper focuses on uncertainty modelling in HEM systems. Currently, a number of uncertainty models are available in the literature. Broadly, these models can be classified into probabilistic and robust methodologies [33]. On the one hand, probabilistic methodologies model the possible realization of uncertainties via scenarios, which are normally generated on the basis of well-suited probabilistic functions or data-driven approaches. Probabilistic methodologies then optimize the system over the considered scenario-space, giving the optimum point for the most probable realization of uncertainties. In this regard, probabilistic approaches cannot be considered robust and their application in risk-averse or risk-seeker methodologies is limited.

On the other hand, robust approaches seek for the worst-case realization of uncertainties and optimize the system in consequence. This way, robust methodologies are distinguished to reproduce pessimistic situations and therefore the results obtained can be considered robust against uncertainties. Among the most popular robust approaches one can find interval optimization [34], information gap decision theory [35] and robust max-min frameworks [36]. In particular, interval notation has been considered in this paper. The foundations and advantages of this methodology are discussed in Section 3.

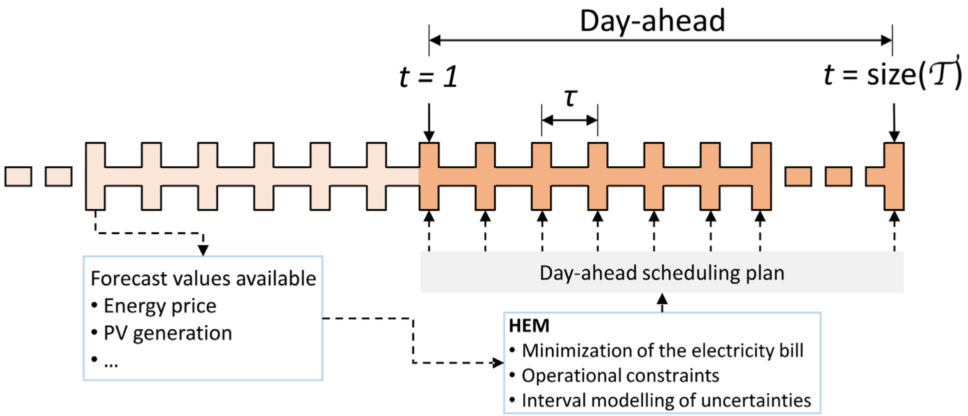

FIGURE 2 Sketch of the day-ahead scheduling performs of the HEM.

3 | MATHEMATICAL MODELS

Throughout this section, the mathematical formulation of the developed methodology is presented. First, we briefly introduce the concept of interval numbers and the notation used in this paper. Mathematical models are developed for a conventional smart prosumer paradigm with V2H capability, onsite PV generators and RTP tariff, as schematically shown in Figure 1.

3.1 | Vectors notation

In this section, various variables are grouped in vectors, for simplicity. The notation of these vectors is given below:

- Vector of continuous decision variables (i.e. power, energy and temperature) $\rightarrow \mathbf{x}$
- Vector of commitment status of the grid $\rightarrow \mathbf{y}^{grid} = [y_t^{grid,b}, y_t^{grid,s}]$; $\forall t \in \mathcal{T}$
- Vector of commitment status of the controllable appliances $\rightarrow \mathbf{y}^{c,app} = [y_t^k, y_t^{HVAC,i}]$; $\forall t \in \mathcal{T} \wedge k \in \mathcal{K}^{\mathrm{NI}} \cup \mathcal{K}^{\mathrm{I}} \wedge i \in \{h, c\}$
- Vector of commitment status of the plug-in EV $\rightarrow \mathbf{y}^{EV} = [y_t^{EV,c}, y_t^{EV,d}]$; $\forall t \in \mathcal{T}$
- Vector of parking status of the plug-in EV $\rightarrow \mathbf{z}^{EV} = [\hat{z}_{t=1}^{EV}, \ldots, \hat{z}_{t=\mathrm{size}(\mathcal{T})}^{EV}]$; $\forall t \in \mathcal{T}$
- Vector of uncertain parameters $\rightarrow \mathbf{u} = [\hat{p}_t^{nc,app}, \hat{p}_t^{PV}, \hat{\theta}_t^{out}, \hat{\lambda}_t]$; $\forall t \in \mathcal{T}$

3.2 | Interval numbers

Interval analysis to address uncertainties was first proposed by Moore [37]. Let us consider an inexact or uncertain parameter denoted by a. Normally, its exact value cannot be predicted with total accuracy but a good approximation is accessible using conventional forecast techniques. Assuming that this parameter can be predicted with sufficient accurateness, its exact value will lie within a box around the predicted value. Such limits define a box within which the exact value of the uncertainty will lie with high probability. Interval optimization takes advantage of this principle, thus the inexact parameters are modelled by their minimum and maximum values, as follows:

$$[\hat{a}] = \left[\bar{a}, \underline{a}\right], \tag{1a}$$

$$[\hat{a}] = \left\{ \hat{a} \middle| \underline{a} \leq \hat{a} \leq \bar{a} \right\}. \tag{1b}$$

Note that the model (1) aligns with frequent knowledge of uncertain parameters in HEM problems. Indeed, taking weather parameters as example, such uncertainties can be predicted using conventional techniques or even freely available tools. Nevertheless, their exact value is inexact yet, but restricted within predefined limits.

It is noteworthy that conventional forecast techniques give a good approximation of the exact value of uncertainties and a confidence interval associated to it [38], so that interval notation can be considered a natural model of most of the uncertainties arisen in HEM. On the basis of the reasons above, we consider interval modelling of uncertainties in this paper. Thus, the following interval notation is used:

$$[\hat{a}] = \langle E\left[\hat{a}\right], \overline{\Delta a}, \underline{\Delta a} \rangle, \tag{2a}$$

$$\bar{a} = E\left[\hat{a}\right] + \overline{\Delta a}, \tag{2b}$$

$$\underline{a} = E\left[\hat{a}\right] - \underline{\Delta a}, \tag{2c}$$

where the function $E[*]$ yields the expected value of an uncertain parameter. As seen, the notation (2) models the uncertain parameter a as an interval number using its expected value and upper/lower bounds. This approach is illustrated in Figure 3.

3.3 | Objective function

Conventionally, HEM programs aim at minimizing the electricity bill subject to different operational or convenience

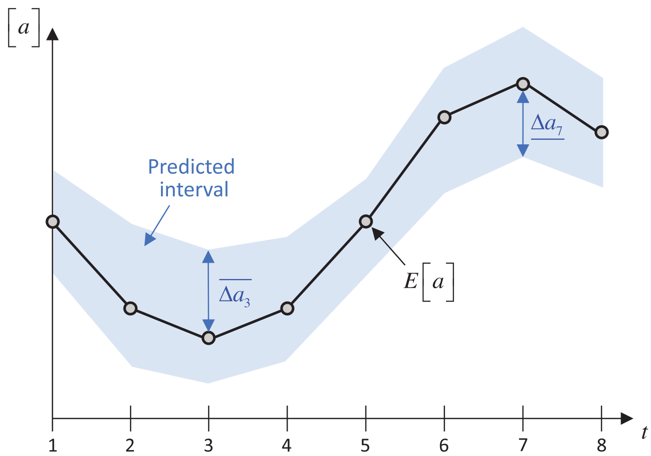

FIGURE 3 Illustration of the interval approach used in this paper for modelling of uncertain parameters.

constraints [39]. Therefore, considering an RTP tariff, the objective function for the HEM system can be formulated as follows:

$$f = \sum_{t\in\mathcal{T}} \left\{ \tau \cdot [\hat{\lambda}_t] \cdot \left(p_t^{grid,b} - \mu \cdot p_t^{grid,s} \right) \right\}. \tag{3}$$

As customary, it is assumed the energy selling price is a fraction of the purchasing pricing [40]. This fraction is modelled by the scalar parameter $\mu \in \mathbb{R}^+$, which is taken fixed for simplicity. Nevertheless, different price schemes could be easily considered by declaring additional variables/parameters. It is noteworthy that the energy price is considered unknown and therefore modelled as an interval number.

3.4 | Utility grid modelling

It is realistic to assume that the power that can be purchased/sold from/to the utility grid would be upper bounded by either contractual conditions or physical limitations [39]. This condition is expressed by the constraint (4), while the expression (5) forces the buying and selling processes to be complementary.

$$0 \leq p_t^{grid,i} \leq y_t^{grid,i} \cdot \overline{p}^{grid}; \; \forall t \in \mathcal{T} \wedge i \in \{b, s\}, \tag{4}$$

$$y_t^{grid,b} + y_t^{grid,s} \leq 1; \; \forall t \in \mathcal{T}. \tag{5}$$

Note that commitment statuses (variables y) are introduced in (4) and (5) to remain the optimization model linear. Indeed, by making use of binary commitment statuses (indicating activation of a scheduling process when equalling to 1), complementarity of buying and selling processes can be easily modelled by (5) instead of using complementarity nonlinear operations. In this regard, it is easy to see that the model (4) and (5) avoids simultaneous imports and exports as well as limits the power that can be exchanged with the grid. Note that similar models are used for other elements throughout this paper.

3.5 | PV array modelling

In this paper, potential PV generation is considered an uncertain parameter and therefore is modelled as an interval number according to (1) and (2). Thereby, the PV array is simply modelling by (6), which bounds the instantaneous PV generation to predicted values.

$$0 \leq p_t^{PV} \leq \left[\hat{p}_t^{PV}\right]; \; \forall t \in \mathcal{T}. \tag{6}$$

3.6 | Controllable appliances modelling

As commented, the controllable appliances are classified into interruptible and non-interruptible [30]. In the latter case, the operation must be continuous, which is ensured by the constraint (7) while the expression (8) ensures that the non-interruptible appliances are scheduled only once over the time horizon.

$$y_t^k - y_{t-1}^k = on_t^k - off_t^k; \; \forall t \in \mathcal{T} \backslash t > 1 \wedge k \in \mathcal{K}^{NI}, \tag{7}$$

$$\sum_{t\in\Psi^k} on_t^k = 1; \; \forall t \in \mathcal{T} \wedge k \in \mathcal{K}^{NI}. \tag{8}$$

The continuity in operation of non-interruptible appliances is ensured by (7). This expression establishes logic among commitment statuses of these appliances (denoted by the binary commitment variables y, which are equal to 1 when the appliance is scheduled) and their on/off statuses. In this regard, the binary variables on/off are equal to 1 when a controllable appliance activates/deactivates. This way, by the logic established in (7), the non-interruptible appliances cannot be deactivated once their duty cycle has started. On the other hand, (8) establishes that on variables are only equal to 1 once throughout the optimization time window, thus ensuring that the duty cycle of non-interruptible appliances is completed once. This last point is necessary when the minimization of energy cost is not the objective of the problem, as occurred in our developed methodology (see Section 4), since in this case the appliances could be scheduled repeatedly, which is not realistic.

On the other hand, all the controllable appliances must complete their duty cycles within the predefined time windows, which is ensured by imposing the constraint (9).

$$\sum_{t\in\Psi^k} y_t^k = \delta^k; \; \forall t \in \mathcal{T} \wedge k \in \left\{\mathcal{K}^{NI} \cup \mathcal{K}^{I}\right\}. \tag{9}$$

3.7 | HVAC modelling

For the HVAC system, the indoor temperature is modelled using differential equations [41], which can be linearized under plausible assumptions [31], resulting in the model (10) that determines the indoor temperature as a function of the outdoor temperature (which is considered uncertain), the actual indoor temperature and the thermal resistance of the building.

On the other hand, the model (11) ensures the thermal comfort of home inhabitants forcing the indoor temperature to lie inside acceptable dead-bands.

$$\theta_{t+1}^{in} = \left(1 - \frac{\tau}{10^3 \cdot M^{in} \cdot C^{air} \cdot R}\right) \cdot \theta_t^{in} + \frac{\tau}{10^3 \cdot M^{in} \cdot C^{air} \cdot R} \cdot [\hat{\theta}_t^{out}] + \frac{\tau \cdot \left(p_t^{HVAC,h} - p_t^{HVAC,c}\right)}{0.000277 \cdot M^{in} \cdot C^{air}} \cdot COP; \; \forall t \in \mathcal{T} \backslash t > 1, \tag{10}$$

$$\theta^{HVAC,sp} - \theta^{HVAC,db} \leq \theta_t^{in} \leq \theta^{HVAC,sp} + \theta^{HVAC,db}; \; \forall t \in \mathcal{T}. \tag{11}$$

It is worth noting that the model (10) is not defined for $t = 1$. Hence, the value of the initial temperature must be fixed [30]. In this paper, it is assumed that the initial indoor temperature is equal to the HVAC set-point. To keep the model coherent, the final temperature is forced to be equal to the initial one by the constraint (12).

$$\theta_{t=1}^{in} = \theta_{t=\mathrm{size}(\mathcal{T})}^{in} = \theta^{HVAC,sp}. \tag{12}$$

The HVAC modelling is completed by including coherent limitations on the device. Thus, the constraint (13) upper bounds the consumption of the system to rated values while the expression (14) makes the heating and cooling modes complementary.

$$0 \leq p_t^{HVAC,j} \leq y_t^{HVAC,i} \cdot \bar{p}^{HVAC}; \; \forall t \in \mathcal{T} \wedge i \in \{h, c\}, \tag{13}$$

$$y_t^{HVAC,h} + y_t^{HVAC,c} \leq 1; \; \forall t \in \mathcal{T}. \tag{14}$$

3.8 | EV modelling

The instantaneous SOC of the onboard battery bank is determined by the model (15), which is a function of the previous SOC and the exchanged power [42]. On the other hand, the energy stored in the batteries must be limited by their nominal capacity and depth-of-discharge settings, as said the constraint (16) while the constraint (17) makes complementary the charging and discharging processes of the EV.

$$\varepsilon_t^{EV} = \varepsilon_{t-1}^{EV} + \tau \cdot \left(\eta^{EV} \cdot p_t^{EV,c} - \frac{p_t^{EV,d}}{\eta^{EV}}\right); \; \forall t \in \mathcal{T} \backslash t > 1, \tag{15}$$

$$(1 - d) \cdot \bar{\varepsilon}^{EV} \leq \varepsilon_t^{EV} \leq \bar{\varepsilon}^{EV}; \; \forall t \in \mathcal{T}, \tag{16}$$

$$y_t^{EV,c} + y_t^{EV,d} \leq 1; \; \forall t \in \mathcal{T}. \tag{17}$$

It is worth noting that the model (15) contemplates both charging and discharging processes thus enabling the V2H capability of the vehicle.

One of the main novelties of this work is considering the EV behaviour unknown. It means that arrival and departure times are considered uncertain parameters. To model the availability of the EV, the binary variable $\hat{z}_t^{EV}$ is introduced. This variable is equal to 1 only when the EV is parked at home. Making use of this variable, the constraint (18) ensures that the EV can be only scheduled when it is parked at home.

$$0 \leq p_t^{EV,i} \leq \hat{z}_t^{EV} \cdot y_t^{EV,i} \cdot \bar{p}^{EV}; \; \forall t \in \mathcal{T} \wedge i \in \{c, d\}. \tag{18}$$

As seen, the variable $\hat{z}_t^{EV}$ is considered uncertain since the arrival and departure times are unknown. However, in contrast to other uncertain parameters, this variable is not actually modelled as an interval number. Instead, the EV time window is modelled as an interval number keeping it linked with the variable $\hat{z}_t^{EV}$ by the model (19).

$$\left[\Psi^{EV}\right] = \left\{\mathbf{z}^{EV} \in \mathbb{B}^{\mathrm{size}(\mathcal{T})} : \hat{z}_t^{EV} = 1\right\}. \tag{19}$$

Indeed, the expression (19) says that the EV time windows is determined by those time slots for which $\hat{z}_t^{EV}$ is equal to 1.

The initial SOC of the EV is also considered an uncertain parameter. In this paper, it is modelled as an interval number similar to other uncertain parameters introducing the variable $\hat{\varepsilon}_0^{EV}$, which indicates the SOC of the EV at the arrival time. Therefore, the constraint (20) can be now imposed. On the other hand, it is assumed that the home users desire to get the EV fully charged at the departure time, which is ensured by imposing the constraint (21).

$$\varepsilon_{t=[\Psi^{EV}(1)]}^{EV} = \left[\hat{\varepsilon}_0^{EV}\right], \tag{20}$$

$$\varepsilon_{t=[\Psi^{EV}(\mathrm{end})]}^{EV} = \bar{\varepsilon}^{EV}. \tag{21}$$

Indeed, the initial SOC of the EV is considered uncertain and modelled as an interval number in (21). In this equation, it is noteworthy that the plugging time window is modelled by the set Ψ^{EV}, so that $\Psi^{EV}(1)$ corresponds with the arrival time of the vehicle (i.e. the firs time slot in which the EV is plugged and therefore available for scheduling). Likewise, (21) forces the vehicle to be fully charged at the departure time, which is denoted by $\Psi^{EV}(\mathrm{end})$.

Finally, it must be noted that the expression (18) is nonlinear because the product of two integer variables. In this paper, the HEM model is linearized in order to keep it solvable by standard solvers. Also, modularity of the model is preserved and the reachability of the global optimum is ensured [31]. To this end, the following dummy variables must be introduced.

$$\omega_t^{EV,i} = \hat{z}_t^{EV} \cdot y_t^{EV,i}; \; \forall t \in \mathcal{T} \wedge i \in \{c, d\}. \tag{22}$$

The linear variables above can replace the bi-integer terms in (18) and preserve the linearity of the formulation, for which the following constraints must be introduced.

$$\omega_t^{EV,i} \leq \hat{z}_t^{EV}, \omega_t^{EV,i} \leq y_t^{EV,i}; \; \forall t \in \mathcal{T} \wedge i \in \{c, d\}, \tag{23}$$

$$\omega_t^{EV,i} \geq \hat{z}_t^{EV} + y_t^{EV,i} - 1;\ \forall t \in \mathcal{T} \wedge i \in \{c,d\}, \tag{24}$$

$$\omega_t^{EV,i} \geq 0;\ \forall t \in \mathcal{T} \wedge i \in \{c,d\}. \tag{25}$$

3.9 | Power balance

The HEM model is completed imposing the power balance (26). It is noteworthy that non-controllable appliances demand has been considered an uncertain parameter and modelled as an interval number in this equation.

$$p_t^{grid,b} + p_t^{EV,d} + p_t^{PV} = p_t^{grid,s} + [p_t^{nc,app}] + p_t^{EV,c} + \sum_{k\in\{\mathcal{K}^{NI}\cup\mathcal{K}^{I}\}} \{y_t^k \cdot p^k\} + \sum_{i\in\{h,c\}} \{p^{HVAC,i}\};\ \forall t \in \mathcal{T}. \tag{26}$$

4 | THE DEVELOPED FOUR-STAGE SOLUTION PROCEDURE

To solve the HEM model described in Section 3 using the interval notation described in Section 3.2, a four-stage methodology has been designed, which is described by the flowchart in Figure 4. In the proposed solution procedure, optimistic or pessimistic strategies can be adopted. In the former, it is assumed that the uncertain parameters take favourable values in the sense of reducing the electricity bill, while the opposite trend is assumed under pessimistic point of views. In this regard, the optimistic and pessimistic perspectives can be conceived as the risk-seeker and risk-averse strategies in [43], respectively. Each stage of the developed methodology is summarized in Figure 4 and fully explained and formulated in subsequent sections.

4.1 | Stage 1: Deterministic problem

The stage 1 of the developed methodology corresponds with the deterministic problem. Therefore, at this stage, the uncertain parameters take expected values. As a result of this problem, the optimal scheduling plan for controllable appliances, HVAC and energy exchanging with the grid is obtained. Therefore, the mathematical model of stage 1 is fully described as follows

$$\mathbf{y}_1^{grid}, \mathbf{y}_1^{c,app} \rightarrow \underset{\mathbf{x},\mathbf{y}^{c,app},\mathbf{y}^{grid},\mathbf{y}^{EV}}{\arg\min}\ f\left(E\left[\mathbf{z}^{EV}\right], E\left[\varepsilon_0^{EV}\right], E\left[\mathbf{u}\right]\right). \tag{27}$$

Subject to: (4)-(26).

Note that (27) is performed taking expected values of uncertainties, which concern for EV-related uncertainties as well as appliances demand, weather parameters and energy prices. In this sense, those uncertainties that are not related with the EV are collected into the vector $\mathbf{u}$ for convenience in the notation, so that $E[\mathbf{u}]$ refers to the expected weather parameters, energy pricing and appliances demand.

4.2 | Stage 2: EV-related problem

At this stage, the EV-related uncertainties are concerned and therefore they are modelled as interval numbers. The initial SOC of the EV depends on the daily mileage [44]. Typically, this aspect is determined by users' daily and repetitive routines and, therefore, it can be easily predicted with an acceptable degree of accurateness [11]. These features allow to model the initial SOC of the EV as an interval variable, allowing it varies between its predicted intervals, as said in the constraint (28).

$$E\left[\varepsilon_0^{EV}\right] - \xi \cdot \underline{\Delta\varepsilon}_0^{EV} \leq \varepsilon_{t=[\Psi^{EV}(1)]}^{EV} \leq E\left[\varepsilon_0^{EV}\right] + \xi \cdot \overline{\Delta\varepsilon}_0^{EV}, \tag{28}$$

where $\xi \in [0,1]$ is the so-called uncertain level. This factor is introduced in the developed model to allow setting the degree in which the predicted intervals are considered. Thereby, if this parameter is set equal to 1, the entire interval is taken to model the corresponding variable; in contrast, if the uncertain level takes 0, the whole problem becomes deterministic as the predicted intervals are totally ignored and the uncertain parameters take their expected values.

On the other hand, the other EV-related uncertainty (i.e. the hours in which the EV is parked at home) could be also modelled as an interval number. This uncertain variable determines the EV time window, which is intimately linked with the vector $\mathbf{z}^{EV}$ as said the Equation (19). This vector avoids scheduling the EV when it is not parked at home by the constraint (18). Hence, it indirectly allows to model the hours in which the EV is parked at home including it as a variable of the problem. To model the parking timetable, the problem considers the total number of time slots in which the EV is parked at home (α^{EV}) as an interval number. This variable is linked with $\mathbf{z}^{EV}$ by the constraint (29) and modelled as an interval number with (30).

$$\sum_{t\in\mathcal{T}} \left\{\hat{z}_t^{EV}\right\} = [\alpha^{EV}], \tag{29}$$

$$E[\alpha^{EV}] - \xi \cdot \underline{\Delta\alpha}^{EV} \leq [\alpha^{EV}] \leq E[\alpha^{EV}] + \xi \cdot \overline{\Delta\alpha}^{EV}. \tag{30}$$

By the constraints (29) and (30), the EV time window is indirectly treated as an interval set by first considering $\mathbf{z}^{EV}$ as a variable and second treating α^{EV} as an interval number.

In conclusion, the model above allows to consider the EV-related uncertainties as interval numbers and consequently the HEM problem becomes immune against the unpredictable behaviour of the EV. Thus, depending on the point of view (optimistic or pessimistic) the stage 2 can be stated as follows

$$\mathbf{z}_{2,pes}^{EV}, \varepsilon_{0,2,pes}^{EV} \rightarrow \underset{\mathbf{x},\mathbf{y}^{EV},\mathbf{z}^{EV},\varepsilon_0^{EV}}{\arg\max}\ f\left(\mathbf{y}_1^{grid}, \mathbf{y}_1^{c,app}, E\left[\mathbf{u}\right]\right), \tag{31a}$$

$$\mathbf{z}_{2,opt}^{EV}, \varepsilon_{0,2,opt}^{EV} \rightarrow \underset{\mathbf{x},\mathbf{y}^{EV},\mathbf{z}^{EV},\varepsilon_0^{EV}}{\arg\min}\ f\left(\mathbf{y}_1^{grid}, \mathbf{y}_1^{c,app}, E\left[\mathbf{u}\right]\right). \tag{31b}$$

Subject to: (4)–(26), (28)–(30)

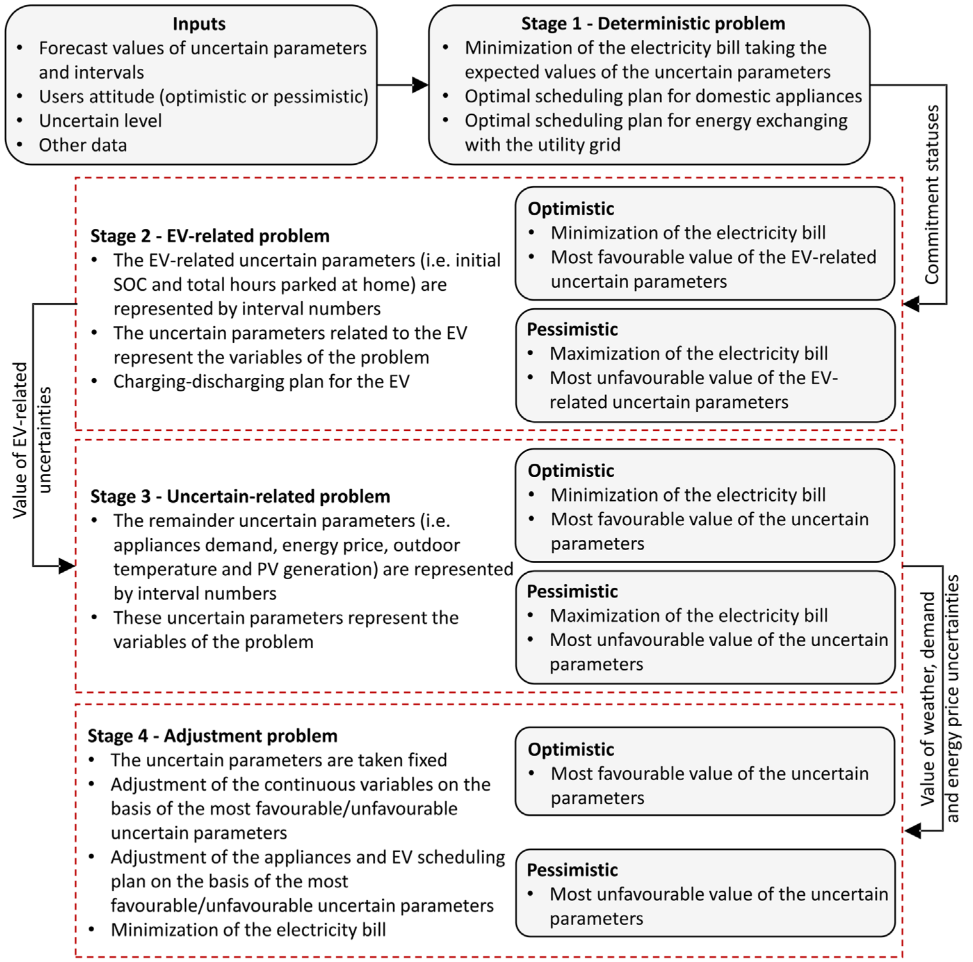

FIGURE 4 Flowchart of the developed methodology.

It is important to note that the problem (31) is solved regardless the impact remainder uncertainties (i.e. PV generation, outdoor temperature, non-controllable appliances demand and energy price), which take expected values. As result of this problem, the most favourable or unfavourable value of the EV-related uncertainties are obtained, taking the scheduling plan yielded at stage 1 as input.

4.3 | Stage 3: Uncertain-related problem

Similar to the stage 2, the stage 3 is focused on those uncertainties that are not related with the EV, which are modelled as interval numbers by the constraint (32).

$$E\left[\hat{a}_t\right] - \xi \cdot \underline{\Delta a}_t \leq \left[\hat{a}_t\right] \leq E\left[\hat{a}_t\right] + \xi \cdot \overline{\Delta a}_t;\ \forall t \in \mathcal{T} \wedge a \in \mathbf{u}. \tag{32}$$

As result of this problem, the most favourable or unfavourable value of the uncertainties comprised in the vector **u** are obtained, for which the results of previous stages are taken as inputs. Thus, the stage 3 can be mathematically expressed as follows

$$\mathbf{u}_{3,pes} \rightarrow \underset{\mathbf{x},\mathbf{y}^{EV},\mathbf{u}}{\arg\max}\, f\left(\mathbf{y}_1^{grid}, \mathbf{y}_1^{c,app}, \mathbf{z}_{2,pes}^{EV}, \boldsymbol{\varepsilon}_{0,2,pes}^{EV}\right), \tag{33a}$$

$$\mathbf{u}_{3,opt} \rightarrow \underset{\mathbf{x},\mathbf{y}^{EV},\mathbf{u}}{\arg\min}\, f\left(\mathbf{y}_1^{grid}, \mathbf{y}_1^{c,app}, \mathbf{z}_{2,opt}^{EV}, \boldsymbol{\varepsilon}_{0,2,opt}^{EV}\right). \tag{33b}$$

Subject to: (4)-(26), (32)

4.4 | Stage 4: Adjustment problem

Lastly, the continuous variables besides the controllable appliances, HVAC and energy exchanging schedules, are adjusted on the basis of the uncertain values calculated in the previous steps. Therefore, this problem is mathematically stated as follows

$$\min_{\mathbf{x},\mathbf{y}^{grid},\mathbf{y}^{c,app},\mathbf{y}^{EV}} f\left(\mathbf{z}_{2,i}^{EV}, \boldsymbol{\varepsilon}_{0,2,i}^{EV}, \mathbf{u}_{3,i}\right);\ i = opt \vee pes. \tag{34}$$

Subject to: (4)-(26)

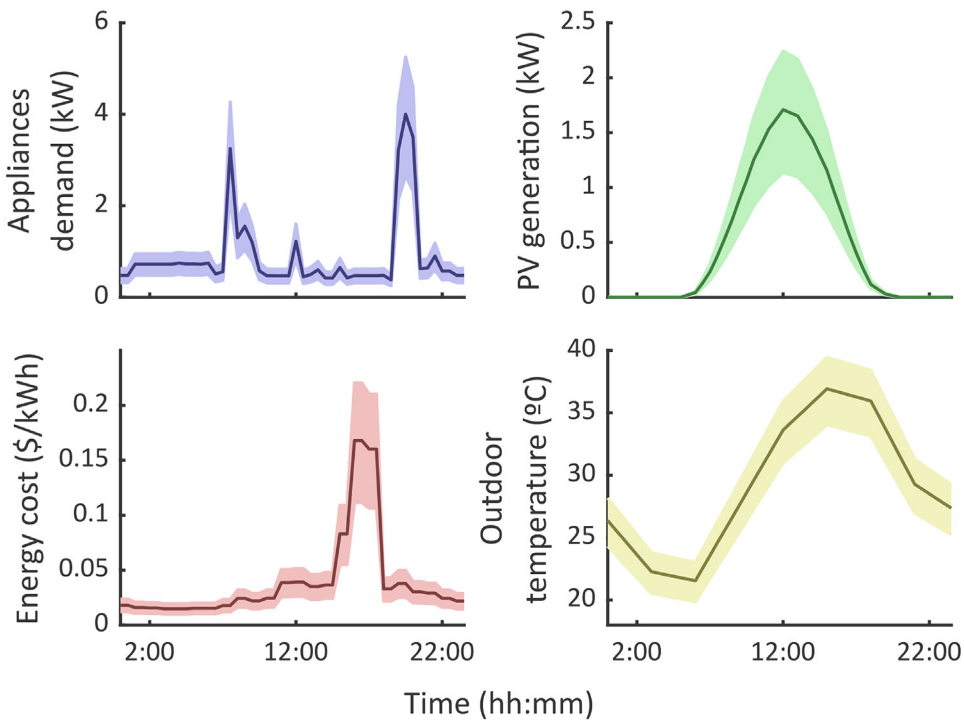

FIGURE 5 Expected values of the uncertain parameters and their corresponding predicted intervals.

5 | CASE STUDY

5.1 | Input data

In this case study, the developed four-stage HEM strategy is applied to a benchmark prosumer environment such as that showed in Figure 1. The home system under study is connected to a utility grid, from which can purchase/sell up to 10 kW. Figure 5 plots the expected value of the uncertain parameters and their predicted intervals. Such profiles have been built on the basis of some real datasets. Thus, the demand of non-controllable appliances has been extracted from [45], the PV generation and outdoor temperature are characteristic days observed at the city of Madrid during 2016 [46], whereas the energy cost corresponds with the real-time pricing observed in the PJM FE Ohio at July 9, 2019 [47]. Last, the selling price has been taken 0.9 times the purchasing rate [40].

A 22-kWh Renault Zoe with a 3-kW charging/discharging power limitation is considered. The initial SOC of the EV ranges from 50 to 95% of its total capacity (with expected value equal to 80%). On the other hand, the total hours the EV may be parked at home ranges from 6 to 13 h (with an expected value of 8 h), while assuming a storage efficiency of 98% and a depth-of-discharge of 80%. The data of the controllable appliances are summarized in Table 2 and are based on [48], while the thermal parameters of the building and the HVAC system are reported in Table 3 and are the same as in [4].

TABLE 2 Data of the controllable appliances.

	Controllable appliance		
Parameter	**Washing machine**	**Dishwasher**	**Clothes dryer**
Rated power (kW)	3	2.5	3
Time window	1:00-12:00	1:00-18:00	13:00-21:00
Length of the duty cycle (h)	3	2	2.5
Type	Non-interruptible	Interruptible	Interruptible

TABLE 3 HVAC parameters.

Parameter	Value	Parameter	Value
M^{in}	1778,4 kg	Rated power	2 kW
C^{air}	1.01 kJ/kg°C	COP	1.2
R	$3.2 \cdot 10^{-6}$ J/°C	$\theta^{HVAC,sp/db}$	23/0.5°C

5.2 | Results

Next, various numerical results are presented and discussed. The developed methodology has been coded under Matlab R2019a environment and solved with Gurobi [49], on an Intel® Core™ i7-10700K (32 GB RAM) personal computer. A 24 h day ahead time horizon with 30-min resolution ($\tau = 0.5\ h$) has been taken for simulations.

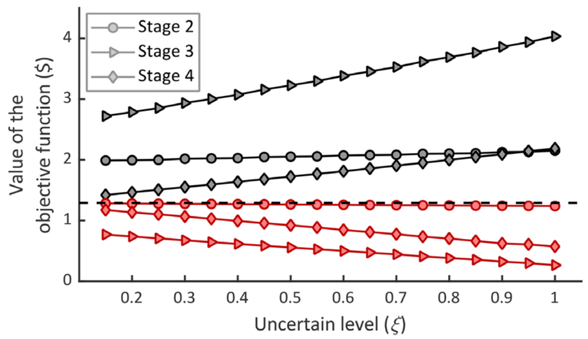

FIGURE 6 The value of the objective function yielded by the different stages of the developed methodology taking pessimistic (black) or optimistic (red) perspectives and different uncertain levels. The value of the objective function for the deterministic case (stage 1) is plotted with black discontinuous line.

TABLE 4 Expected PV generation (kWh) under different conditions.

Uncertain level	Optimistic	Pessimistic
0 (determ.)	11.7	11.7
0.25	12.7	11.0
0.50	12.7	10.4
0.75	12.7	9.7
1.00	12.7	9.0

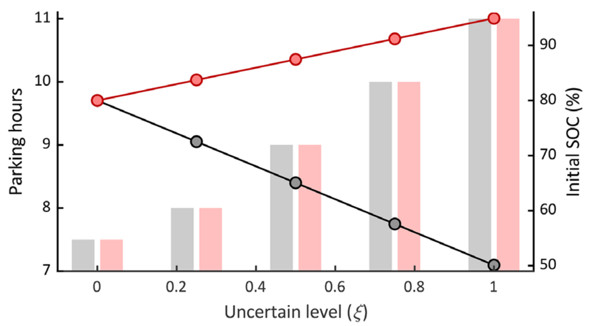

FIGURE 7 Value of the EV-related uncertainties under pessimistic (black) and optimistic (red) points of view. In this figure, the total parking hours is plotted with bars while the initial SOC is plotted with lines.

Figure 6 plots the value of the objective function yielded by the different stages involved in the developed methodology taking optimistic or pessimistic perspectives. As observed, depending on the attitude of the users, the objective function follows different trends by varying the value of the uncertain level. Thus, under a pessimistic point of view, the objective function grows with the value of ξ. In contrast, the objective function follows the opposite trend with optimistic conditions. This result is logic since the developed methodology lets the uncertain parameters vary over a wider range as the uncertain level grows. For the sake of exemplify, Table 4 reports the expected PV generation for different uncertain levels. As seen, the PV generation decreases with the value of ξ under a pessimistic attitude.

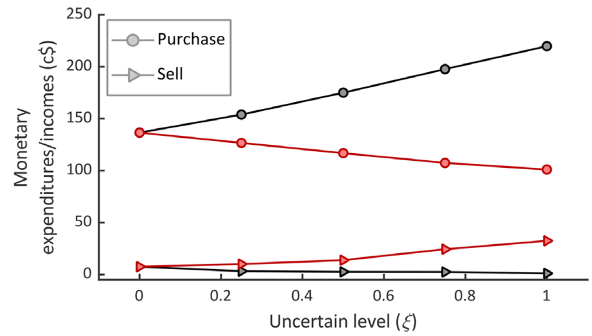

FIGURE 8 Monetary balance due to energy exchanging with the grid with pessimistic (black) and optimistic (red) conditions.

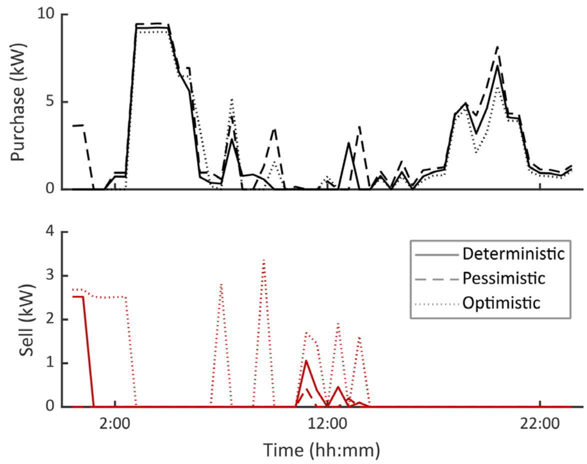

FIGURE 9 Purchased (top) and sold (bottom) power with the grid for the deterministic, pessimistic and optimistic cases with $\xi = 1$.

The value of the uncertain level besides the users' attitude also determines the value of the EV-related uncertainties. Figure 7 shows the initial SOC and the total parking hours for different values of ξ. In this case, the initial SOC decreases with the uncertain level under pessimistic conditions, while the opposite trend is followed with an optimistic attitude. In contrast, the total parking hours simply grows with the uncertain level regardless the users' point of view. This result indicates that the worst conditions for the EV-related uncertainties are principally determined by the initial SOC, while the parking timetable is simply adjusted to make the problem feasible.

Figure 8 summarizes the expected monetary balance due to energy exchanging with the grid with different perspectives and uncertain levels. As seen, the results showed in this figure follow logic trends. Indeed, the monetary expenditures because energy purchasing grow or decrease with the uncertain level under pessimistic or optimistic perspectives, respectively. In contrast, the incomes obtained from energy selling follow the opposite trend. These results are in accordance with the pattern follows by the other uncertainties, as explained throughout this section. To get a better overview, Figure 9 shows the energy exchanging with the utility grid for the deterministic, optimistic and pessimistic cases (for illustrative purposes only results with

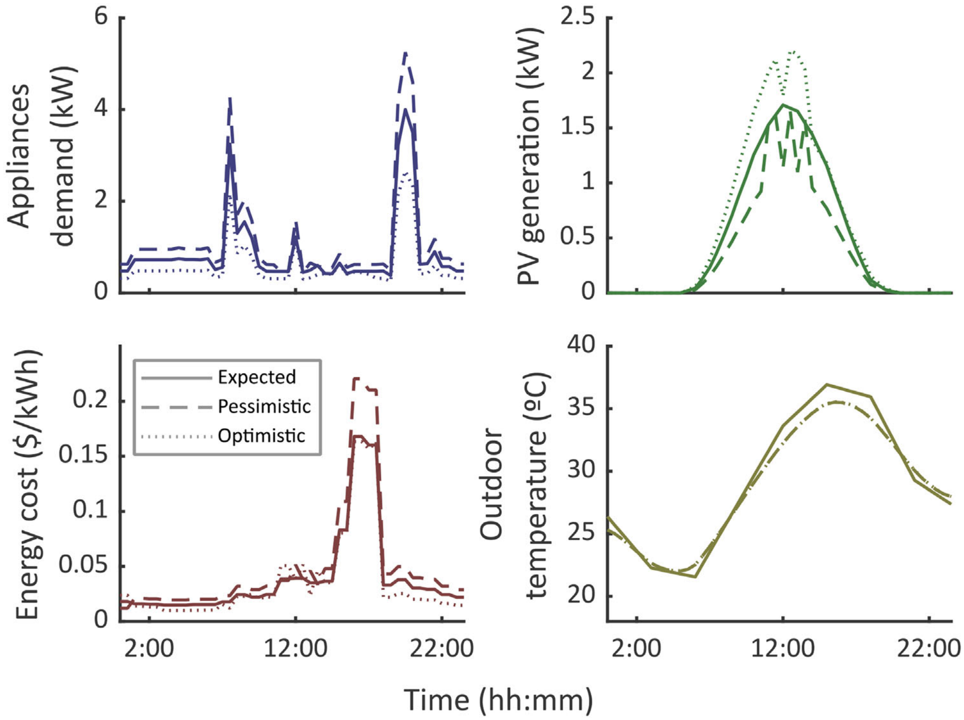

FIGURE 10 Expected value of some uncertain parameters besides the calculated profiles under pessimistic and optimistic points of view with $\xi = 1$.

$\xi = 1$ are plotted). As observed in this figure, more energy is normally purchased under pessimistic conditions, actually, peak consumptions are observed during morning and midday, which are avoided in the optimistic case due to more favourable PV conditions. Contrarily, the home system is capable of only selling a small amount of energy under pessimistic conditions, while this aspect is clearly enhanced in the optimistic case.

Likewise, the value of the non-controllable appliances demand, PV generation, RTP and outdoor temperature are plotted in Figure 10 for various cases. As expected, the uncertain parameters took unfavourable or favourable values depending under which point of view the developed HEM program is performed. Thus, PV generation is normally observed below its expected profile for the pessimistic case whereas the energy price and non-controllable appliances demand frequently present higher values than their expected profiles. In contrast, opposite trends are typically observed under optimistic conditions. On the other hand, the outdoor temperature fell near to the expected profile regardless the conditions under which the developed methodology is carried out.

5.3 | Computational burden

The developed tool is devoted on day-ahead scheduling of domestic assets, so that it is expected to be performed with various hours of margin before the scheduling realization. In this sense, the computational burden of our tool is not critic for its implantation.

Nevertheless, the experiments performed by the authors reveal that the computational performance of the developed tool is acceptable, taking 10–20 s by average in completing the four stages involved.

In this sense, the developed tool overcomes the problems of probabilistic-based approaches, which need to optimize the system over a large set of scenarios. Thus, these approaches need to enlarge the number of variables according to the number of scenarios analysed, which may be eventually large. In this sense, preliminary experiments performed in stochastic approaches showed that the total computational time was normally 2–5 times the computational burden of our methodology.

In addition, it is expected that the reported computational burden keeps for a variety of layouts and situations. Note that the computational cost of our methodology just depends on the size of the time interval ($\Delta\tau$), whose value can be coarsely fixed at 0.25-1 h. In addition, the MILP character of the developed methodology ensures its good scalability to systems with more appliances or vehicles [50].

6 | CONCLUSIONS

In this paper, a novel four-stage interval-based HEM program has been presented. The novel proposal is suitable for smart prosumers with RTP tariff, V2H capability and PV-based onsite generation. The developed HEM system considers uncertainties on PV generation, EV behaviour, energy prices, non-controllable appliances demand and outdoor temperature. The different uncertain processes are incorporated into the scheduling task progressively through different stages and modelled by interval numbers. This approach allows performing the scheduling plan of the home assets from different perspectives from pessimistic to optimistic point of views. Under the former perspective, the home users aim at finding the scheduling plan, which minimizes the electricity bill under the most unfavourable value of the uncertain parameters within the predicted intervals. Contrarily, if the users adopt an optimistic perspective, the developed HEM program assumes that the uncertainties take favourable values.

The novel HEM system has been validated on a benchmark prosumer environment with RTP tariff and V2H capability. Results obtained were coherent thus validating our proposal and proving its effectiveness. The influence of the users' attitude and the uncertain level on the results obtained has been extensively analysed. In addition, it has been reported that the developed solution framework is computationally light and tractable by standard solvers and average machines.

Ongoing works are being conducted on extending the novel proposal to cooperative game-oriented scheduling mechanisms on virtual power plant schemes. Studying the applicability of the developed interval-based scheduling tool for renewable-based isolated microgrids might suppose a promising future research line as well.

NOMENCLATURE

Indexes (Sets)

- Ψ Time window of the electric vehicle and controllable appliances
- $k\ (\mathcal{K}^{NI}/\mathcal{K}^{I})$ Non-interruptible/interruptible appliances
- $t\ (\mathcal{T})$ Time slots forming the optimization horizon (i.e. $t \in \{1, 2, \ldots, \mathcal{T}\}$)

Superscripts

- $\hat{*}$ Uncertain parameter
- $\bar{*}/\underline{*}$ Maximum/minimum value
- $EV, c/d$ Electric vehicle in charging/discharging mode
- $HVAC, h/c$ Heating-ventilation-air conditioner system in heating/cooling mode
- PV Photovoltaic
- $c/nc, app$ Controllable/non-controllable appliances
- $grid, b/s$ Buying/selling from/to the utility grid
- in/out Indoor/outdoor
- sp/db Set-point/dead-band

Subscripts

- C^{air} Heat capacity of the air (kJ/(kg·°C))
- M^{in} Mass of air inside the building (kg)
- ε_0^{EV} Initial state of charge of the electric vehicle (kWh)

Parameters

- COP Coefficient of performance (pu)
- R Equivalent thermal resistance of the building (J/°C)
- d Depth-of-discharge (pu)
- opt/pes Optimistic/pessimistic
- δ Length of the duty cycle of a controllable appliance
- η Efficiency (pu)
- τ Size of time slots (hrs)

Variables

- $\hat{z}_t^{EV}$ Binary variable that takes 1 if the electric vehicle is parked at home at time t and 0 otherwise
- on_t/off_t Pair of binary variables that take 1 if a controllable appliance is activated/deactivated at time t, and 0 otherwise
- p Power (kW)
- y Commitment status (binary)
- ε Energy (kWh)
- θ Temperature (°C)
- λ Energy price ($/kWh)

AUTHOR CONTRIBUTIONS

Marcos Tostado-Véliz: Conceptualization, data curation, investigation, methodology, validation, writing-original draft. **Ali Asghar Ghadimi**: Data curation, formal analysis, funding acquisition, investigation, methodology, validation, writing-original draft. **Mohammad Reza Miveh**: Formal analysis, funding acquisition, project administration, supervision, validation, writing-review and editing. **Ra'ed Nahar Myyas**: Investigation, project administration, resources, supervision, visualization, writing-review and editing. **Francisco Jurado**: Formal analysis, funding acquisition, project administration, resources, supervision, validation, writing-review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest that could have appeared to influence the work reported in this paper.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES

None.

DATA AVAILABILITY STATEMENT

The data used in this study is available upon request from the corresponding author.

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