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Research paper

Home energy management system considering effective demand response strategies and uncertainties

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ABSTRACT

Nowadays, load serving entities require more active participation from consumers. In this context, demand response programs and home energy management systems play a crucial role in achieving multiple goals such as peak clipping. However, the adoption of demand response initiatives typically has a negative impact on the monetary expenditures of the users. This way, a demand response program should be as effective as possible to make the different goals more easily achievable without compromising the financial requirements of the users. This paper develops a home energy management system that incorporates three novel effective demand response strategies. The effectiveness of the adopted demand response strategies is checked through extensive simulations in a benchmark prosumer environment. To this end, a novel scenario-based approach is developed in order to manage uncertainties. The introduced strategies are compared with other well-known demand response mechanisms. To that end, a novel comparative index, which serves to evaluate the compromise between demand response achievements and energy bills, is introduced. Results obtained demonstrate that the developed strategies are more effective than other approaches. In fact, through the use of the proposed mechanisms, different indicators can be improved until ∼70%, while the electricity bill is only scarcely increased (∼0.11€). Other relevant aspects like the influence of the storage capacity and computational performance of the introduced optimization framework are also analysed.

1. Introduction

1.1. Context and motivation

The Smart Grid vision requires active end-user participation in system operation and electricity markets (Kilkki et al., 2015). In this context, households play a crucial role as they suppose a notable percentage of the total electricity consumption (Eurostat, 2018). In this context, home energy management (HEM) programs gain great importance (Bradac et al., 2015), being necessary to optimize household consumption by properly appliances scheduling (Shafie-Khah and Siano, 2017). Active end-user participation is enabled via demand response (DR) programs launched by the load serving entities (Safdarian et al., 2014). Customarily, DR programs are classified as price-based or incentive-based (Sarker et al., 2020). Within the first category, dynamic pricing tariffs such as Time-of-use (TOU) or real-time pricing (RTP) have gained popularity because of their effectiveness to achieve multiple goals (He et al., 2020). Typically, the load serving entities aim at reducing peak demand (peak clipping) (Awais et al., 2018) or improving the peak-to-average ratio (PAR) (Vardakas et al., 2015).

Nowadays, deployment of new types of home devices such as battery energy storages (BES) (Lu et al., 2020), photovoltaic (PV) generation (Fakhraian et al., 2021), heating-ventilation-air conditioning (HVAC) systems or plug-in electric vehicles (PEV); enables a great degree of flexibility from household users to participate in DR programs (Shakeri et al., 2020). However, this kind of device makes it difficult for residential customers to manage home appliances manually on their own (Rastegar et al., 2012). In this context, the use of HEM systems (HEMSs) has become essential for the efficient and effective operation of all electrical aspects of the household under DR initiatives, as recently manifested by comprehensive reviews in Guelpa and Verda (2021) and Shewale et al. (2020).

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Nomenclature

Superscripts

G2H/H2G	Grid-to-home/Home-to-grid
PV	Photovoltaic
BES, d/c	Battery energy storage in discharging/charging mode
EV, d/c	Electric vehicle in charging/discharging mode
HVAC, h/c	Heating-ventilation-air conditioner system in heating/cooling mode
in/out	Indoor/outdoor
sp/db	Set-point/dead-band
$\overline{(\cdot)}/\underline{(\cdot)}$	Maximum/minimum value of a variable
$\widehat{(\cdot)}$	Forecasted value of an uncertain parameter

Index(Set)

s ($\mathcal{S}$)	Scenario
r ($\mathcal{R}$)	Representative scenario
t ($\mathcal{T}$)	Time
k ($\mathcal{K}$)	Controllable appliance
Ω_r	Cluster of the representative scenario r

Functions

size $(\cdot)$	Returns the number of elements within a cluster or set
avg $(\cdot)$	Returns the average value
$\breve{\mathfrak{N}}(\mu, \sigma, a, b)$	Yields a random number with truncated Gaussian probability function with mean μ, standard deviation σ and limits a and b

Parameters and Constants

ω	Probability (pu)
$\Delta\tau$	Time step (h)
λ	Electricity price ($/kWh)
ρ	Penalty cost
D	Non-controllable appliances demand (kW)
P	Rated power of a controllable appliance (kW)
I	Solar irradiance (kW/m^2)
η	Efficiency (pu)
e2P	Energy-to-power ratio (h)
DOD	Depth of discharge (pu)
E	Initial energy stored (kWh)
Ψ	Allowable time window Ψ = [LB, . . . , UB]
δ	Time slots of the duty cycle of a controllable appliance
M	Mass of air (kg)
C_p	Thermal capacity of air (kJ/kg °C)
R	Equivalent thermal resistance of the home (h °C/J)
COP	Coefficient of performance (pu)
L	Large positive number
K	Integer arbitrary number
x	Uncertain parameter

Decision Variables

p	Power (kW)
α, β, γ	Variables for demand response-based strategies
e	Energy stored (kWh)
θ	Temperature (°C)
u	Commitment status (1 = on, 0 = off) (binary)
on/ off	If equal to 1, indicates the activation/deactivation of a controllable appliance (binary)
y	Dummy variable

Traditionally, HEM programs aim at minimizing the electricity bill by considering dynamic pricing tariffs (Tostado-Véliz et al., 2021c), while other aspects such as the concept of 'waiting time' (Rahim et al., 2016); scheduling preferences (Javadi et al., 2020a); DR fatigue (Bradac et al., 2015) and thermal comfort (Tostado-Véliz et al., 2022a); have also been taken into account in some works. However, the lonely consideration of the energy cost in the objective function of the HEMS may unwittingly provoke undesirable effects. Rightly, Ref. Mohsenian-Rad and Leon-Garcia (2010) reported that dynamic pricing tariffs might be unsuitable since peak demand is actually shifted rather than reduced, which was further confirmed in Zhao et al. (2013). This phenomenon is known as 'load synchronization' and is illustrated in Fig. 1. Let us assume that a HEMS can schedule the operation of three appliances (namely A, B and C in Fig. 1). These appliances can be operated, for simplicity, within the same time window. The three loads would be scheduled under user decisions and preferences without an energy management control, as exemplified in Fig. 1.

In contrast, if the management program aims to minimize the electricity bill under a TOU tariff scheme, scheduling planning is only restricted by the allowable time windows, within which the different appliances would be scheduled at off-peak hours when the energy price is reduced low. As seen in Fig. 1, most of the demand would be shifted to dawn, provoking a very high peak consumption during these hours. In this regard, the aims of DR programs such as peak clipping or PAR reduction may not be achieved.

1.2. Literature review

Recently, HEM has been a very hot topic because of its importance in the future smart grid paradigm. A clear evidence is the increasing number of works developed in recent years. Current trends include uncertainties modelling. In HEM problems, stochastic optimization has been widely adopted to model unpredictable weather parameters (Beraldi et al., 2020). However, other authors have explored more sophisticated schemes, like the Ref. Akbari-Dibavar et al. (2020), where a HEMS with a hybrid robust-stochastic model was developed to jointly handle weather and price uncertainties under the RTP mechanism. In Javadi et al. (2021), the authors dealt with multi-objective solution of HEM problems. To that end, the epsilon-constraint method was applied to explore the Pareto front, while the VIKOR decision-maker was considered to select the most suitable solution. A similar multi-objective formulation was considered (Mansouri et al., 2021), but in this case the interaction of multiple smart homes with microgrid was studied. Other recent references have

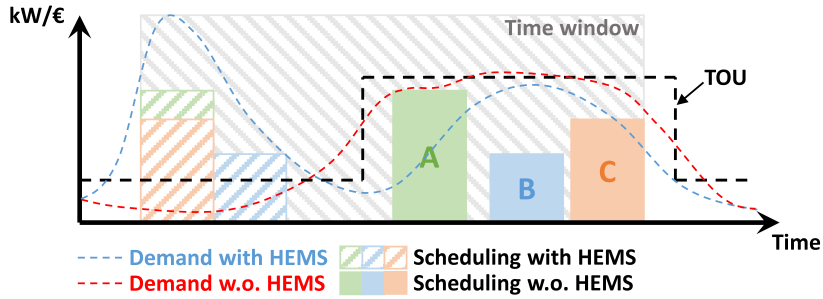

Fig. 1. Illustration of the 'load synchronization' phenomenon.

focused on appliances modelling, like (Nezhad et al., 2021), where an inverter-based air conditioner model was developed for HEM software.

However, this paper is focused on DR programs. As commented before, the application of DR initiatives may provoke extra monetary expenditures for the users or even provoke undesirable effects, which may lead to unsuccessful implantation of DR programs. To avoid such kind of issues, complementary pricing mechanisms have been successfully put into practice by load serving entities. Two of the most popular are the inclining block rate (IBR) and peak load pricing (Rasheed et al., 2015). Some works have showed the effectiveness of these mechanisms to improve the performance of HEMSs. In Mohsenian-Rad and Leon-Garcia (2010), the authors proposed a pricing mechanism with IBR in combination with RTP tariff; reported results evidence that PAR can be notably reduced by applying an IBR penalty mechanism. Similar conclusions with the same pricing mechanism are extracted in He et al. (2020), where, in addition, it is shown that total energy consumption is reduced with respect to the base case with TOU tariff. The authors in Javadi et al. (2020a) adopted a combined pricing mechanism with TOU tariff and IBR, proving that this approach can significantly reduce overloads along providing incentives to self-generation investments.

However, the tariff schemes referenced above make the energy bill inevitably overpriced since IBR is devoted to penalizing rather than incentivizing. This fact may discourage end users from voluntary adopting these mechanisms. This way, some authors have explored other alternatives, which consist of modifying the HEM routine to adopt DR initiatives without supposing an explicit monetary penalization for the user. This kind of initiative is known as DR programs based on decision variables (Vardakas et al., 2015) and mainly consists of modifying the scheduling task of HEMSs to accomplish some DR premises. Such is the case of the HEM program proposed in Paterakis et al. (2015), where two power-limiting strategies are applied.

On the one hand, a simple limit is imposed over the power demand so that the users cannot demand more power than that imposed by the entity. On the other hand, a soft limit is adopted by which overconsumption is allowed but penalized. Other examples are the Refs. Soares et al. (2017) and Lokeshgupta and Sivasubramani (2019), where multi-objective approaches are adopted to jointly reduce energy cost and peak demand.

1.3. Research gaps & contributions

Apparently, home users may be more encouraged to adopt a DR strategy such as those proposed in Paterakis et al. (2015), Soares et al. (2017) and Lokeshgupta and Sivasubramani (2019), rather than other mechanisms based on prices such as the IBR. This way, the inclusion of DR strategies within HEM programs may suppose an effective way to achieve DR goals. Obviously, home users may not voluntarily adopt such DR strategies if they suppose an increment in their electricity bills. Thereby, load serving entities may encourage end users to adopt these initiatives by adopting incentives or other kinds of promoting programs (Vardakas et al., 2015). For example, an electricity retailer could apply a discount rate over the energy price if an end user adopts some kind of DR premises. This paper does not discuss how a company may encourage or force the adoption of any DR program. However, it seems clear that such DR strategies should be as effective as possible. It means that an end user should meet the DR premises without seeing how its bill is notably incremented. Thus, load serving entities could successfully apply such DR initiatives as consumers are not considerably harmed; thereby, the presumably increment observed in the electricity bill due to DR strategies' adoption may be easily compensated with incentive initiatives. In addition, the company would obtain the benefits of the DR premises, which may directly impact the economic operation of electricity systems (Rastegar et al., 2012). This way, both agents would obtain a benefit. Otherwise, if a load serving entity establishes penalty costs or even force the adoption of DR strategies, the users will be interested in achieving the imposed DR goals at minimum cost.

In the light of the reflections above, it seems clear that the effectiveness of a DR strategy or program is a critical point that presumably determines its successful implantation. However, there are still some research gaps in the existing literature that should be addressed, which are numerated below:

- So far, very few DR strategies based on decision variables have been developed and explored. Only few works (Paterakis et al., 2015; Soares et al., 2017; Lokeshgupta and Sivasubramani, 2019) have covered this topic. However, as commented above, this kind of strategies seems to be very promising, as they do not suppose a direct negative effect on home economy.
- Some specific problems like the load synchronization phenomenon have not been addressed. In this sense, most of the existing literature is focused on either reducing peak demand or improving PAR (see Table 1).
- From a quantitative point of view, it is very difficult to compare different DR strategies. This is due to a proper index has not been established yet. In this sense, effectiveness of a DR programs should not be only evaluated from its effects on system operation, but also on the monetary expenditures caused to home inhabitants. In this sense, a DR initiative would be effective if its implantation achieve the predefined goals without notably incrementing the monetary expenditures of the users.

This paper tackles the issues above by proposing a novel HEMS that incorporates three novel DR strategies. As seen in Table 1, the developed HEM model supposes the most complete approach proposed so far, to the best of our knowledge. For the sake of clarity, the major contributions of this work are listed below:

Table 1
A summary of the studied references compared with the actual paper.

Reference	Model	Prosumer	DR goal		
			Peak clipping	Improve PAR	Reduce load synchronization
He et al. (2020)	Nonlinear	No	Yes	No	No
Javadi et al. (2020a)	MILP	Yes	Yes	No	No
Mohsenian-Rad and Leon-Garcia (2010)	MILP	No	No	Yes	No
Rasheed et al. (2015)	Metaheuristic	Yes	Yes	No	No
Paterakis et al. (2015)	MILP	Yes	Yes	No	No
Soares et al. (2017)	Metaheuristic	Yes	Yes	No	No
Lokeshgupta and Sivasubramani (2019)	MILP	Yes	Yes	No	No
Present	MILP	Yes	Yes	Yes	Yes

- Developing three novel DR strategies to be incorporated within a HEM program for smart prosumers. In contrast to conventional initiatives based on tarification, the developed schemes are based on decision variables. Unlike tariff schemes, the developed approaches are focused on specific issues such as the load synchronization phenomenon described above. More specifically, the three novel strategies are briefly described below
  - A peak clipping strategy is developed which, unlike other similar approaches, presents linear formulation, being so more easily adaptable to standard software.
  - A load allocation DR strategy is developed which supposes, to the best of our knowledge, the first attempt to directly tackle the load synchronization phenomenon.
  - Unlike to other DR strategies that are not directly focused on plattening the load demand, a novel mechanism is developed which directly takes this issue.
- Renewable-based generators such as PV arrays have become a very common self-consumption approach in smart homes. However, this kind of generator brings some difficulties for the HEM programs, mainly due to unpredictable and intermittent behaviour. In this regard, this paper develops an original scenario-based approach for managing uncertainties.
- In the literature, there does not exist a clear index to compare DR strategies. In this regard, this paper proposes a novel index to measure the effectiveness of a DR program. This way, different DR initiatives can be compared and their effectiveness can be assessed.
- Although the developed DR strategies present some nonlinearities, some tricks are used to linearize the formulation. Thereby, the developed formulation is Mixed-Integer Lineal Programming (MILP), being so modular and computationally tractable by conventional solvers (Paterakis et al., 2015).
- The effectiveness of the developed DR strategies is checked on a benchmark prosumer environment by comparing them with other conventional price-based DR schemes. To that end, the developed comparative index is profusely used, thus proving its effectiveness. This index aims to compare the different DR premises fairly, pointing attention to their impact on the electricity bill. This way, the introduced index may be used to discern the degree of successful implanting different DR strategies. In addition, it is demonstrated the superiority of the developed DR strategies over traditional price-based programs.

The rest of this paper is organized as follows. Section 2 overviews the studied smart prosumer environment. Section 3 develops the mathematical formulation of the proposed HEM program, which incorporates three novel DR strategies. Section 4 presents various conventional indexes for comparing DR strategies and introduces a novel indicator for assessing the monetary cost of achieving DR goals. Section 5 introduces a scenario-based approach for managing uncertainties. Section 6 presents and discusses various numerical results. Finally, this paper is concluded with Section 7.

2. Overview of the analysed prosumer environment

A benchmark prosumer environment is considered in this paper, which is described through this section and schematically represented in Fig. 2.

The main proposal of the considered HEMS is controlling a series of home devices with the aim of complying with some DR goals at minimum cost for the users. To that end, the proposed HEM environment is able to send operating set-points to a PV array and a BES for convenience. A scheduler and a local data acquisition system compose the considered HEM framework. Both components are usually part of an average computer machine, which is normally sufficient for HEM purposes (Paterakis et al., 2015). The local data acquisition system stores necessary information normally provided by the users based on some prior knowledge such as the depth of discharge (DOD) of the BES, the duty cycle of controllable appliances, etc. This information is transferred to the HEM optimization program in the form of parameters, which the home inhabitants can predefine for convenience. Although the developed HEM framework does not require real-time data, the scheme of Fig. 2 can be straightforwardly adapted to this concept by using advanced metring infrastructures (Javadi et al., 2020a).

It is assumed that some appliances can be scheduled on the basis of control signals (controllable appliances), while the energy management software cannot govern others and, consequently, are operated based on user decisions. Thermal comfort of home users is maintained within acceptable limits by sending set-points signals to an HVAC system, which can be operated on either heating or cooling modes. The studied system encompasses a PEV that counts vehicle-to-home and home-to-vehicle capabilities (Paterakis et al., 2015). Energy can be purchased or delivered from/to the utility grid for convenience. Communication with the main grid is established via a smart metre, which can receive information from the HEMS in order to determine the amount of energy to exchange with the grid at any moment.

The scheduling plan of the analysed prosumer framework is carried out over a day-ahead time horizon similar to other HEM models proposed in the literature (Shafie-Khah and Siano, 2017; Javadi et al., 2020a). To this task, the system requires various forecasted profiles (i.e. solar irradiation, outdoor temperature, and non-controllable appliances demand), which are assumed to be obtained by a well-known forecasting technique (Singh et al., 2019) and stored on the local data acquisition system. This information is transferred to the HEM program for carrying out the scheduling planning.

As commented, load serving entities can encourage the end users to adopt DR premises through price-based mechanisms.

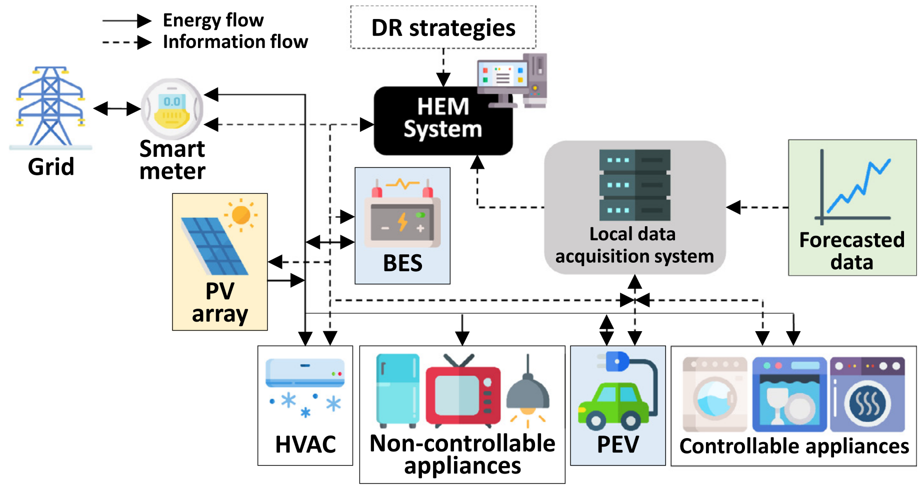

Fig. 2. Schematic representation of the analysed prosumer environment.

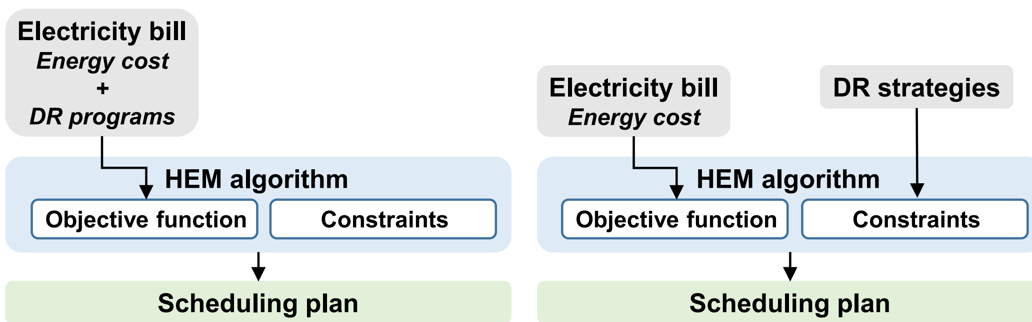

Fig. 3. Integration of DR premises within HEM programs. Left: by the inclusion of additional costs in the electricity bill, this is the principle of price-based DR mechanisms such as IBR. Right: through including DR strategies, which is the principle considered in this paper.

This is the principle considered on IBR and peak load pricing rates. Thereby, HEM programs indirectly achieve those DR endings by reducing the electricity bill. This paradigm is shown in Fig. 3. As seen, since the electricity bill reflects both energy consumption and DR impositions, the HEM program self-imposes DR premises over the scheduling program on pursuing a reduction of the electricity bill. However, the developed DR strategies follow a different principle. In this sense, it is assumed that the electricity bill only contemplates the energy cost (possible incentive or penalty programs are not contemplated); therefore, DR requirements are achieved by modifying the scheduling plan rather than reducing the electricity bill. In this regard, the developed DR strategies are implemented within the HEM model through constraints, as shown in Fig. 3. Thus, the HEMS should also receive information from load serving entities such as price or incentive signals, in order to adopt the most favourable control strategy. In this sense, the developed DR strategies may be classified into the DR programs based on decision variables, as it is defined in Vardakas et al. (2015). As pointed out in this reference, such kinds of DR programs are based on controlling the activation time of the different loads; in other words, they are implemented within the HEM program.

3. Mathematical formulation of the developed HEMS

The mathematical formulation of the developed HEMS is described in this section.

3.1. Assumptions

Firstly, the degradation of the PEV batteries has been neglected since it is assumed the household participates in a battery rental business program offered by manufacturers (see Paterakis et al., 2015; Anon, 2021). This kind of program offers a change of vehicle batteries when these degrade to a level that requires a replacement. In return, manufacturers demand a monthly paid regular rental fee.

Secondly, operation and maintenance costs of BES and PV array have been neglected due to the small size of this kind of system at the home level. In such cases, the associated costs with the degradation of these devices can be considered negligible compared to electricity rates (Shafie-Khah and Siano, 2017; Paterakis et al., 2015).

Thirdly, the required forecasted profiles are assumed to be known in this research, as this topic is out of the scope of this paper. The wide variety of forecasting tools existing in the literature (see Singh et al., 2019 and references therein) could be straightforwardly integrated within the developed HEMS without requiring a further explanation in this work.

3.2. Objective function

The objective function formulated in (1) aims to minimize the energy cost plus a penalty term which is included to address some DR goals (see Section 3.9).

$$\min_{\Phi} \sum_{\forall r \in \mathcal{R}} \left\{ \omega_r \left[\underbrace{\sum_{\forall t \in T} \left\{ \Delta\tau \left(\lambda_t^{\mathrm{G2H}} p_{r,t}^{\mathrm{G2H}} - \lambda_t^{\mathrm{H2G}} p_{r,t}^{\mathrm{H2G}} \right) \right\}}_{\text{Energy cost}} \right. \right.$$
$$\left. \left. + \underbrace{\rho \left(\alpha_r + \frac{\beta_r}{K} + \gamma_r \right)}_{\substack{\text{Penalty term for} \\ \text{DR strategies}}} \right] \right\} \tag{1}$$

Some aspects of the objective function (1) are further explained below:

- To take into account the influence of some uncertain parameters, a scenario-based model is adopted in this work (see Section 5). As customary in such approaches (Shafie-Khah and Siano, 2017; Guelpa and Verda, 2021); the objective function (1) aims at minimizing the average value over the scenario-space.
- The variable β appears in (1) divided by the parameter K, since this parameter represents the upper bound of the concerned variable. Thus, all the elements involved in the penalty term are ranged between 0 and 1.
- The parameter ρ is introduced in (1) to weight the importance of the DR premises in the objective function. Therefore, the higher value of ρ, the more DR-oriented the control scheme.

As it seems, the objective function only considers the energy cost as monetary expenditure since the penalty term is not defined in terms of monetary cost. However, the inclusion of the penalty term in (1) may undoubtedly affect the energy cost term, so that the energy cost may be increased if different DR strategies are adopted, such as explained in Section 1. In that sense, it is assumed that users are encouraged to adopt such kinds of premises by means of incentive (or penalties) programs. Further analysis about these kinds of initiatives is out of the scope of this paper, and the reader is referred to the excellent reviews (Guelpa and Verda, 2021; Shewale et al., 2020) for further information.

The developed HEM problem involves typical variables of such kinds of applications (e.g. see Shafie-Khah and Siano, 2017). Thus the vector Φ in (1) encompasses power, stored energy, commitment status and temperature variables. Nevertheless, the introduced model also incorporates the DR-related variables α, β, γ. Therefore, the vector of decision variables is given by:

$$\Phi = \left\{ \begin{array}{l} p_{r,t}^{\mathrm{G2H}}, p_{r,t}^{\mathrm{H2G}}, p_{r,t}^{\mathrm{PV}}, p_{r,t}^{\mathrm{BES,d}}, p_{r,t}^{\mathrm{BES,c}}, p_{r,t}^{\mathrm{EV,d}}, p_{r,t}^{\mathrm{EV,c}}, \\ p_{r,t}^{\mathrm{HVAC,h}}, p_{r,t}^{\mathrm{HVAC,c}}, e_{r,t}^{\mathrm{BES}}, e_{r,t}^{\mathrm{EV}}, u_{r,t}^{\mathrm{G2H}}, u_{r,t}^{\mathrm{H2G}}, \\ u_{r,t}^{\mathrm{BES,d}}, u_{r,t}^{\mathrm{BES,c}}, u_{r,t}^{\mathrm{EV,d}}, u_{r,t}^{\mathrm{EV,c}}, u_{r,t}^{k}, u_{r,t}^{\mathrm{HVAC,h}}, \\ u_{r,t}^{\mathrm{HVAC,c}}, \mathrm{on}_{r,t}^{k}, \mathrm{off}_{r,t}^{k}, \theta_{r,t}^{\mathrm{in}}, \alpha_r, \beta_r, \gamma_r, y_{r,t} \end{array} \right\}; \quad \forall r \in \mathcal{R}, \forall t \in \mathcal{T}, \forall k \in \mathcal{K} \tag{2}$$

3.3. Grid modelling

Under the prosumer environment, energy can be either purchased or delivered to the grid. However, these two processes are upper bounded either by physical restrictions or limits imposed by utility companies. In this work, it is assumed that the total amount of power that can be exchanged with the grid is limited by a constant limit $\overline{p}^{\sim}$, which may reflect either physical or contractual restrictions. In order to ensure these bounds, constraints (3) and (4) are considered in the model.

$$0 \le p_{r,t}^{\mathrm{G2H}} \le u_{r,t}^{\mathrm{G2H}} \overline{p}^{\mathrm{G2H}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{3}$$

$$0 \le p_{r,t}^{\mathrm{H2G}} \le u_{r,t}^{\mathrm{H2G}} \overline{p}^{\mathrm{H2G}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{4}$$

In addition, it is assumed that both purchasing and selling processes are complementary, which is ensured by imposing the constraint (5).

$$0 \le u_{r,t}^{\mathrm{G2H}} + u_{r,t}^{\mathrm{H2G}} \le 1; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{5}$$

3.4. PV array modelling

The PV generation depends on some stochastic parameters such as temperature and solar irradiation. Once these parameters have been determined (by using some forecasting technique for instance), the instantaneous power that can be generated by a PV array can be calculated using some device model. In this work, the PV array model developed in Mandal et al. (2018) has been used, which can calculate the instantaneous power that a PV array can generate for given values of temperature and solar irradiation, as follows:

$$\phi_{r,t}^{\mathrm{PV}} = \overline{p}^{\mathrm{PV}} I_{r,t} \left\{ 0.8 + 0.024 \left(\theta_{r,t}^{\mathrm{in}} + I_{r,t} \left[33.8 - 37.5\eta^{\mathrm{PV}} \right] - 25 \right) \right\}; \quad \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{6}$$

However, no limits are considered in (6). In this way, the value of $\phi_{r,t}^{\mathrm{PV}}$ may be higher than $\overline{p}^{\mathrm{PV}}$, which is unreal since solar inverters impose functional limits in practice. In order to reflect this restriction, the upper bound on the PV generation is actually limited by the constraint (7).

$$0 \le p_{r,t}^{\mathrm{PV}} \le \begin{cases} \phi_{r,t}^{\mathrm{PV}}, \text{ if} \phi_{r,t}^{\mathrm{PV}} \le \overline{p}^{\mathrm{PV}} \\ \overline{p}^{\mathrm{PV}}, \quad \text{o.w.} \end{cases}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{7}$$

3.5. BES modelling

The developed HEM program includes a BES, which can exchange energy with the home. In practice, instantaneous power that a battery bank can either absorb or deliver is upper bounded by its total capacity and the energy-to-power ratio, as follows (Alsaidan et al., 2018).

$$0 \le p_{r,t}^{\mathrm{BES,d}} \le u_{r,t}^{\mathrm{BES,d}} \frac{\overline{e}^{\mathrm{BES}}}{\mathrm{e2P^{BES}}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{8}$$

$$0 \le p_{r,t}^{\mathrm{BES,c}} \le u_{r,t}^{\mathrm{BES,c}} \frac{\overline{e}^{\mathrm{BES}}}{\mathrm{e2P^{BES}}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{9}$$

Since this work is not focused on BES sizing, both nominal capacity and energy-to-power ratio are considered constants. Similar to the grid, constraint (10) ensures that the BES charging and discharging processes are complementary.

$$0 \le u_{r,t}^{\mathrm{BES,d}} + u_{r,t}^{\mathrm{BES,c}} \le 1; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{10}$$

Eq. (11) models the instantaneous energy stored in the BES, which is limited by its nominal capacity and DOD as indicated by the constraint (12).

$$e_{r,t}^{\mathrm{BES}} = e_{r,t-1}^{\mathrm{BES}} + \Delta\tau \left(p_{r,t-1}^{\mathrm{BES,c}} \eta^{\mathrm{BES,c}} - \frac{p_{r,t-1}^{\mathrm{BES,d}}}{\eta^{\mathrm{BES,d}}} \right); \quad \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \backslash t > 1 \tag{11}$$

$$\overline{e}^{\mathrm{BES}}\left(1-\mathrm{DOD}^{\mathrm{BES}}\right) \leq e_{r,t}^{\mathrm{BES}} \leq \overline{e}^{\mathrm{BES}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{12}$$

The DOD of a BES has to be set in order to effectively exploit the battery bank while its lifetime is not dramatically reduced (Alsaidan et al., 2018). For simplicity, the DOD has been taken constant in this work as customary in most related references (e.g. see Shafie-Khah and Siano, 2017). Over the study time horizon, it has to be assumed that the initial state of charge (SOC) of the BES is known (Paterakis et al., 2015). However, a priori difficulty in imposing this premise can be properly assumed by simply imposing that the final SOC of the BES is equal to the initial value. Thereby, it is ensured that each day the initial SOC is fixed and equal to the SOC at the end of the preceding time horizon (Tostado-Véliz et al., 2021a). In order to ensure this operational principle, the initial SOC has been taken as a parameter. Thus, the premises above are achieved by imposing the constraints (13) and (14).

$$e_{r,1}^{\mathrm{BES}} = E^{\mathrm{BES}}; \forall r \in \mathcal{R} \tag{13}$$

$$e_{r,\mathcal{T}}^{\mathrm{BES}} = e_{r,1}^{\mathrm{BES}}; \forall r \in \mathcal{R} \tag{14}$$

3.6. PEV modelling

In this work, vehicle-to-home and home-to-vehicle processes of the PEV are considered in order to fully exploit its capabilities (Shafie-Khah and Siano, 2017; Paterakis et al., 2015). In that sense, the developed mathematical model considers the PEV as a storage system formed by batteries. Hence, the PEV model defined by (15)–(19) is equivalent to that considered for the BES in (8)–(12) (Shafie-Khah and Siano, 2017).

$$0 \leq p_{r,t}^{\mathrm{EV,d}} \leq u_{r,t}^{\mathrm{EV,d}} \overline{p}^{\mathrm{EV}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{15}$$

$$0 \leq p_{r,t}^{\mathrm{EV,c}} \leq u_{r,t}^{\mathrm{EV,c}} \overline{p}^{\mathrm{EV}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{16}$$

$$0 \leq u_{r,t}^{\mathrm{EV,d}} + u_{r,t}^{\mathrm{EV,c}} \leq 1; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{17}$$

$$e_{r,t}^{\mathrm{EV}} = e_{r,t-1}^{\mathrm{EV}} + \Delta\tau\left(p_{r,t-1}^{\mathrm{EV,c}}\eta^{\mathrm{EV,c}} - \frac{p_{r,t-1}^{\mathrm{EV,d}}}{\eta^{\mathrm{EV,d}}}\right); \forall r \in \mathcal{R}, \forall t \in \mathcal{T}\backslash t > 1 \tag{18}$$

$$\overline{e}^{\mathrm{EV}}\left(1-\mathrm{DOD}^{\mathrm{EV}}\right) \leq e_{r,t}^{\mathrm{EV}} \leq \overline{e}^{\mathrm{EV}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{19}$$

The main difference between the PEV and the BES is the availability of the former. While the BES can be scheduled anytime, it is assumed that the PEV leaves home at some hour to come back later (Paterakis et al., 2015). Thereby, the PEV capabilities can only be scheduled when it is parked at home. This model assumes that arriving and departing hours are, a priori, known since they are based on daily inhabitant routines. Therefore, the constraints (20) and (21) are, in fact, equivalent to (13) and (14) but adapted to consider limited PEV availability.

$$e_{r,\mathrm{LB^{EV}}}^{\mathrm{EV}} = E_r^{\mathrm{EV}}; \forall r \in \mathcal{R} \tag{20}$$

$$e_{r,\mathrm{UB^{EV}}}^{\mathrm{EV}} = \overline{e}^{\mathrm{EV}}; \forall r \in \mathcal{R} \tag{21}$$

The initial SOC of PEV batteries depends on daily mileage (Negarestani et al., 2016), which should not be considered constant (Shafie-Khah and Siano, 2017). Thus, in contrast to the BES, the initial SOC of the PEV batteries is considered unknown and treated as an uncertain parameter (see Section 5).

Intuitively, the PEV charging and discharging processes cannot be scheduled when the vehicle is not parked at home, which is ensured by imposing the constraint (22).

$$\sum_{\forall t \notin \Psi^{\mathrm{EV}}} \left\{u_{r,t}^{\mathrm{EV,d}} + u_{r,t}^{\mathrm{EV,c}}\right\} = 0; \forall r \in \mathcal{R} \tag{22}$$

3.7. Controllable appliances modelling

A conventional model for controllable appliances is used in this work, a modified version of that used in Pateraki s et al. (2015). Firstly, the controllable appliances must complete their duty cycle within allowable time windows, which is ensured by imposing the constraint (23).

$$\sum_{\forall t \in \Psi^k} \left\{u_{r,t}^k\right\} = \delta^k; \forall r \in \mathcal{R}, \forall k \in \mathcal{K} \tag{23}$$

By (23), it can be easily checked that the total number of time slots that a controllable appliance is operated within its time window is equal to its corresponding duty cycle defined by the constant δ.

Conventional controllable appliances such as dishwashers or dryers are considered in this research. Conventionally, it is assumed that home inhabitants are required to operate such appliances once over a time horizon. This operating assumption is modelled by the constraint (24).

$$\sum_{\forall t \in \mathcal{T}} \left\{\mathrm{on}_{r,t}^k\right\} = 1; \forall r \in \mathcal{R}, \forall k \in \mathcal{K} \tag{24}$$

Given the characteristics of the controllable appliances considered in this research, they must be continuously operated. In other words, once an appliance has been activated, it cannot be interrupted until its duty cycle has been completed, which is ensured by the constraint (25).

$$u_{r,t}^k - u_{r,t-1}^k = \mathrm{on}_{r,t}^k - \mathrm{off}_{r,t}^k; \forall r \in \mathcal{R}, \forall t \in \mathcal{T}\backslash t > 1, \forall k \in \mathcal{K} \tag{25}$$

Other kinds of controllable appliances allow interrupting their operation (see interruptible appliances in Longe et al. (2017)). This kind of device is not considered in this work. However, its performance can be easily implemented by simply neglecting the constraint (25) in such cases.

3.8. HVAC modelling

In this work, the HVAC system is considered a thermostatically controllable appliance (Pateraki s et al., 2015). Thus, this system is requested to be operated in order to keep the indoor temperature within acceptable limits. It is well-known that the thermal inertia of buildings can be modelled by differential equations (Wang et al., 2013). However, such a model can be linearized under some plausible assumptions (Pateraki s et al., 2015). In this regard, a linearized model of the thermal inertia of buildings is used in this paper. Such model considers the indoor temperature as a variable, which is modelled as a function of the outdoor temperature and power consumption of the HVAC system in both cooling and heating modes, as follows.

$$\begin{aligned}\theta_{r,t}^{\mathrm{in}} = &\left(1-\frac{\Delta\tau}{10^3MC_pR}\right)\theta_{r,t-1}^{\mathrm{in}} + \frac{\Delta\tau}{10^3MC_pR}\theta_{r,t-1}^{\mathrm{out}} \\ &+ \frac{\Delta\tau\left(p_{r,t-1}^{\mathrm{HVAC,h}} - p_{r,t-1}^{\mathrm{HVAC,c}}\right)}{0.000277MC_p}\mathrm{COP}; \forall r \in \mathcal{R}, \\ &\forall t \in \mathcal{T}\backslash t > 1\end{aligned} \tag{26}$$

Similar to other devices, its rated power limits the power consumption of the HVAC system in both heating and cooling modes, which is ensured by the constraints (27) and (28).

$$0 \leq p_{r,t}^{\mathrm{HVAC,h}} \leq u_{r,t}^{\mathrm{HVAC,h}} \overline{p}^{\mathrm{HVAC}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{27}$$

$$0 \leq p_{r,t}^{\mathrm{HVAC,c}} \leq u_{r,t}^{\mathrm{HVAC,c}} \overline{p}^{\mathrm{HVAC}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{28}$$

Typically, heating and cooling modes of the HVAC systems can be provided by different devices (e.g. an air conditioner provides the cooling mode while a stove provides the heating mode). Nevertheless, we assume for simplicity that both modes are enabled by the same component, such as an air conditioner with a heating unit. Under this assumption, the HVAC cannot be operated in both cooling and heating modes at the same time, which is ensured by imposing the constraint (29).

$$0 \le u^{\mathrm{HVAC,h}}_{r,t} + u^{\mathrm{HVAC,c}}_{r,t} \le 1; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{29}$$

The main goal of the HVAC is to keep the indoor temperature within acceptable limits. In this regard, the HEMS sends set point signals to this device in order to control its operation. To avoid the repeated operation of the HVAC system, a hysteresis band is introduced. Under these premises, the constraint (30) must be imposed.

$$\theta^{\mathrm{sp}}_{r,t} - \theta^{\mathrm{db}} \le \theta^{\mathrm{in}}_{r,t} \le \theta^{\mathrm{sp}}_{r,t} + \theta^{\mathrm{db}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{30}$$

Similar to the BES, the developed HEMS requires the initial indoor temperature as an input parameter. In this work, this parameter has been considered equal to the set-point temperature, which is assumable if temperature set points do not notably vary through a year and wide dead bands are not allowed. Keeping this in mind, the HVAC model is completed by the constraint (31).

$$\theta^{\mathrm{in}}_{r,1} = \theta^{\mathrm{sp}}; \forall r \in \mathcal{R} \tag{31}$$

Nevertheless, if the initial indoor temperature is unknown, it can be considered an uncertain parameter using the approach introduced in Section 5.

3.9. Home balance

In the developed model, the home demand must be entirely covered anytime by either home resources or the local grid. Thus, the constraint (32) must be satisfied.

$$\begin{aligned} p^{\mathrm{G2H}}_{r,t} + p^{\mathrm{PV}}_{r,t} + p^{\mathrm{BES,d}}_{r,t} + p^{\mathrm{EV,d}}_{r,t} = p^{\mathrm{H2G}}_{r,t} + D_{r,t} + \sum_{\forall k \in \mathcal{K}} \left\{ u^{k}_{r,t} P^{k} \right\} \\ + p^{\mathrm{HVAC,h}}_{r,t} + p^{\mathrm{HVAC,c}}_{r,t} + p^{\mathrm{BES,c}}_{r,t} + p^{\mathrm{EV,c}}_{r,t}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \end{aligned} \tag{32}$$

3.10. Proposed DR strategies

The major contribution of this paper is to develop novel DR strategies to be implemented in the HEMS described in Section 3. As commented, in contrast to conventional mechanisms that directly affect the monetary expenditures, the new proposals are incorporated into the HEM optimization procedure as constraints. This way, the economy of the users is not directly affected, while the DR goals can still be accomplished. This extreme will be proved in the results section. The developed mechanisms are devoted to reducing the peak demand and flattening the load curve, which are common DR goals (Vardakas et al., 2015).

Peak clipping strategy

This strategy is a further implementation of that introduced (Lokeshgupta and Sivasubramani, 2019). In that reference, total appliances consumption is limited by a penalty parameter. Accordingly, the strategy adopted in Lokeshgupta and Sivasubramani (2019) would be formulated as follows.

$$p^{\mathrm{HVAC,h}}_{r,t} + p^{\mathrm{HVAC,c}}_{r,t} + \sum_{\forall k \in \mathcal{K}} \left\{ u^{k}_{r,t} P^{k} \right\} \le \alpha_r; \forall r \in \mathcal{R}, \forall t \in T \tag{33}$$

However, from our point of view, the strategy (33) has a limited impact on the demand curve since some devices such as BES and PEV, which can eventually act as loads, are not taken into account. In addition, part of the load can be momentarily covered by storage facilities or self-generation; therefore, it does not actually contribute to the demand curve. To solve these issues, it is proposed to replace the constraint (33) with the following one.

$$0 \le p^{\mathrm{G2H}}_{r,t} \le \alpha_r u^{\mathrm{G2H}}_{r,t} \overline{p}^{\mathrm{G2H}}, 0 \le \alpha_r \le 1; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{34}$$

The constraint (34) involves a bilinear term. In order to keep the MILP structure of the developed HEM model, the bilinear term in (34) is converted to a linear one by introducing the dummy variable (35) and imposing the constraints (36) and (37) (Gupte et al., 2013).

$$y_{r,t} = u^{\mathrm{G2H}}_{r,t} \alpha_r; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{35}$$

$$\alpha_r - \mathrm{L}\left(1 - u^{\mathrm{G2H}}_{r,t}\right) \le y_{r,t} \le \alpha_r + \mathrm{L}\left(1 - u^{\mathrm{G2H}}_{r,t}\right); \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{36}$$

$$-\mathrm{L}u^{\mathrm{G2H}}_{r,t} \le y_{r,t} \le \mathrm{L}u^{\mathrm{G2H}}_{r,t}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{37}$$

Hence, the Eq. (34) is converted to the linear constraint (38), which is implemented within the developed HEM model instead of (3).

$$0 \le p^{\mathrm{G2H}}_{r,t} \le y_{r,t} \overline{p}^{\mathrm{G2H}}; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{38}$$

It is worth noting that the proposed peak clipping strategy is based on the same fundamentals that the peak load pricing (see Vardakas et al., 2015). However, the introduced strategy is not based on monetary penalties foundations.

Load allocation strategy

This strategy is devoted to limiting the effect of the 'load synchronization' phenomenon illustrated in Fig. 1. In this regard, the constraint (39) is imposed.

$$u^{\mathrm{BES,c}}_{r,t} + u^{\mathrm{EV,c}}_{r,t} + u^{\mathrm{HVAC,h}}_{r,t} + u^{\mathrm{HVAC,c}}_{r,t} + \sum_{\forall k \in \mathcal{K}} \left\{ u^{k}_{r,t} \right\} \le \beta_r; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{39}$$

By constraint (39), the total number of controllable loads that can be operated at the same time is limited to the variable β. Thus, it is avoided that many devices are scheduled simultaneously, and the load synchronization effect may be reduced. The variable β reflects the total number of controllable loads that are allowed to be operated at the same time. Consequently, it has to be a positive integer number, which is ensured by imposing the constraint (40).

$$\beta_r \in \{0, 1, \ldots, K\}; \forall r \in \mathcal{R} \tag{40}$$

In this case, the variable β is upper bounded by the parameter K, whose value is considered set by user preferences.

Flat demand strategy

Finally, a DR strategy is introduced with the aim of achieving a flattening effect over the demand curve. This is expected to be achieved by imposing the constraint (41).

$$\left| p^{\mathrm{G2H}}_{r,t} - p^{\mathrm{G2H}}_{r,t-1} \right| \le \gamma_r \overline{p}^{\mathrm{G2H}}, 0 \le \gamma_r \le 1; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \backslash t > 1 \tag{41}$$

In (41), it is assumed that the maximum difference between the power purchased from the grid at two consecutive time slots cannot exceed $\overline{p}^{\mathrm{G2H}}$, due to the limits imposed on this variable. By implementing the constraint (41), one expects to limit sharp ramps over the power demand as the variable γ has a penalizing effect on the objective function.

It is worth mentioning that the developed strategies can be similarly adapted for the power delivered to the grid. However, these mechanisms have not been applied so as not to impair the monetary income that the user expects to obtain from selling energy. Also, one should note that α, β, γ are taken as variables in the developed HEM model. By this approach, the optimization framework is able to decide the degree to which the introduced

DR strategies are matched. This is achieved by weighting these three variables by the penalty term σ in (1). Thus, it is expected that the higher the value of ρ, the more DR-oriented the HEMS is. Nevertheless, it is worth noting that ρ is artificially introduced in the objective function as it does not suppose an extra monetary expenditure for home inhabitants. In that sense, the penalty term ρ should be conceived as an input parameter, which is set by home users according to how they are disposed to adopt the different DR strategies.

3.11. Optimization framework

Throughout Section 3, the developed HEM model has been formulated by constraints. The different introduced constraints along with the objective function (1) compose an optimization problem, which is formally established as follows:

Objective Function minimize (1)
Subject to:

- **Inequality constraints:** (3)–(5), (7)–(10), (12), (15)–(17), (19), (27)–(30), (36)–(39), (41).
- **Equality constraints:** (11), (13), (14), (18), (20)–(26), (31), (32).
- **Integrality constraints:** (40) and (42)

$$u_{r,t}^{\mathrm{BES,d}}, u_{r,t}^{\mathrm{BES,c}}, u_{r,t}^{\mathrm{EV,d}}, u_{r,t}^{\mathrm{EV,c}}, u_{r,t}^{k}, u_{r,t}^{\mathrm{HVAC,h}}, u_{r,t}^{\mathrm{HVAC,c}}, \mathrm{on}_{r,t}^{k}, \mathrm{off}_{r,t}^{k} \in \{0,1\}\,; \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{42}$$

4. Comparative indexes for DR strategies

In order to compare different DR strategies and their impact on the load serving entities' objectives, it is helpful to use comparative indexes. Maybe the peak demand is the most obvious and evident, which reflects the peak shaving effect precisely. In this case, this index can be defined as follows.

$$\mathrm{PD}_r = \max_{\forall t \in \mathcal{T}} \left\{ p_{r,t}^{\mathrm{G2H}} \right\}; \forall r \in \mathcal{R} \tag{43}$$

To check the effectiveness of a DR strategy to flatten the demand curve, some authors use the well-known PAR (e.g. see Awais et al., 2018). However, PAR may not be suitable under prosumer environments since this index does not contemplate the energy delivered to the grid. Instead, the LF (44) and average ramping indexes (45) are recognized to be fairer indicatives for prosumer households (Paterakis et al., 2015).

$$\mathrm{LF}_r = \frac{\mathrm{avg}_{\forall t \in \mathcal{T}} \left\{ \left| p_{r,t}^{\mathrm{G2H}} - p_{r,t}^{\mathrm{H2G}} \right| \right\}}{\max_{\forall t \in \mathcal{T}} \left\{ \left| p_{r,t}^{\mathrm{G2H}} - p_{r,t}^{\mathrm{H2G}} \right| \right\}}; \forall r \in \mathcal{R} \tag{44}$$

$$\mathrm{ARI}_r = \frac{1}{\mathrm{size}\,(\mathcal{T}-1)} \sum_{\forall t \in \mathcal{T} \setminus t>1} \left\{ \left(p_{r,t}^{\mathrm{G2H}} - p_{r,t}^{\mathrm{H2G}} \right) - \left(p_{r,t-1}^{\mathrm{G2H}} - p_{r,t-1}^{\mathrm{H2G}} \right) \right\}; \forall r \in \mathcal{R} \tag{45}$$

Indeed, the higher the LF index, the flatter the power curve of the household is. Oppositely, to facilitate regulating the load from the system operator, it is desirable to have low ARI values since sharp load ramps are avoided. It is also worth noting that both PD and ARI indexes are ranged between 0 and $\overline{p}^{\mathrm{G2H}}$ (if $\overline{p}^{\mathrm{G2H}} \geq \overline{p}^{\mathrm{H2G}}$), whereas the LF index spans between 0 and 1.

Under the developed stochastic framework defined through scenarios, it is suitable to describe the above indexes over the $\mathcal{R}$-space. In this regard, the indexes (46)–(48) are introduced, taking into account each scenario's probability.

$$\mathrm{PD} = \sum_{\forall r \mathcal{R}} \{\omega_r \mathrm{PD}_r\} \tag{46}$$

$$\mathrm{LF} = \sum_{\forall r \mathcal{R}} \{\omega_r \mathrm{LF}_r\} \tag{47}$$

$$\mathrm{ARI} = \sum_{\forall r \mathcal{R}} \{\omega_r \mathrm{ARI}_r\} \tag{48}$$

While the indexes described above are good indicators of DR achievements, they do not reflect the impact of DR premises on monetary expenditures for the users. In other words, the indexes described in (46)–(48) do not catch how much money do users invest in complying DR requirements. In order to solve this issue, the so-called DR cost index (DRCI) is introduced, as follows.

$$\mathrm{DRCI} = \frac{\mathrm{Bill}_{\mathrm{DR}}}{\mathrm{Bill}_{\mathrm{Base}}} + \left(\frac{\mathrm{PD} + \mathrm{ARI}}{\overline{p}^{\mathrm{G2H}}} - \mathrm{LF} \right) \tag{49}$$

The first term in (49) reflects the increment on the electricity bill before and after applying for DR programs. Here, $\mathrm{Bill}_{\mathrm{Base}}$ makes mention for the monetary expenditures in some so-considered base cases (e.g. the lonely application of a dynamic pricing tariff), while $\mathrm{Bill}_{\mathrm{DR}}$ is the energy bill that resulted after applying DR strategies. On the other hand, the second term in (49) measures the influence of the comparative indexes described in this section. Consequently, the lower value of (49), the better the trade-off between DR achievements and monetary expenditures.

5. Uncertainties modelling

This paper is not focused on uncertainties modelling, nevertheless, this topic has been widely investigated for HEM problems (e.g. see Tostado-Véliz et al., 2022b). In this sense, simple stochastic modelling has been considered for the developed model in order to approach this paper to the reality as much as possible. Nevertheless, the modular structure of the developed formulation allows tailoring other uncertainties modelling like interval formulation (Tostado-Véliz et al., 2022c) or Information Gap decision theory (Jordehi, 2021).

In the developed HEM model, four parameters have been considered unknown and treated as uncertainties, i.e. outdoor temperature, solar irradiation, non-controllable appliances demand and initial SOC of the PEV. As described in Section 2, the developed model assumes that some of these profiles can be forecasted. Even so, they should be treated as stochastic variables as their behaviour cannot be predicted in a fully accurate way. To handle the uncertain parameters, a scenario-based approach is developed. Let us consider a generic uncertain parameter x, to reflect the variability of its value on the basis of a forecasted profile, as scenarios, as desired, can be generated by using a truncated Gaussian distribution, as follows.

$$x_{s,t} = \breve{\mathfrak{N}}(\mu, \sigma, a, b)\,\hat{x}_t; \forall s \in \mathcal{S}, \forall t \in \mathcal{T} \tag{50}$$

Basically, several scenarios can be constructed by (50) around the forecasted value. This way, possible errors on the forecasted profile are taken into account. It is worth noting that other works consider different probability distribution functions for the different variables (such is the case of the Beta distribution for PV generation Shafie-Khah and Siano, 2017). However, this approach is suitable when forecasted profiles are not available. By (50), it is assumed that one has some knowledge about the value of the day-ahead uncertain parameter x. Thereby, the developed approach aims at exploiting this knowledge.

Nonetheless, the initial SOC of the PEV cannot be a priori predicted. For this parameter, we use the same approach described in Shafie-Khah and Siano (2017). Details of the distribution functions used for the involved uncertain parameters are provided in Section 6.

According to the law of large numbers, variability of the random variable can be faithfully caught by generating a sufficiently

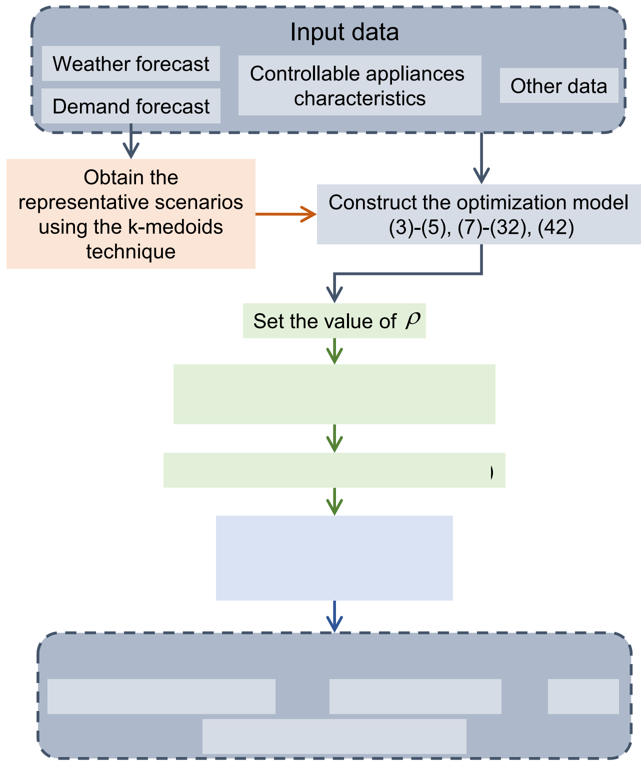

Fig. 4. Flowchart of the proposed HEM solution incorporating DR strategies.

large number of scenarios by (50) (Rashidizadeh-Kermani et al., 2019). Thus, this parameter can be set arbitrarily large as it does not suppose a relevant computational burden for the entire optimization framework. However, this fact provokes a huge amount of data to be managed, which may be difficult in practice. To solve this issue, it is proposed to use the k-medoids technique only to take the most representative profiles. In other words, the scenario-space ($\mathcal{S}$) is reduced to the representative scenario-space ($\mathcal{R}$) in simulations. For further information about the k-medoids technique, the reader is referred to Pinto et al. (2020). The k-medoids technique presents one degree of freedom, namely the total number of clusters. Typically, this parameter should be tuned as a compromise solution between computational performance and accurateness. Intuitively, the more clusters taken, the more accurate and reliable the results would be; however, the computational cost of the HEM model described in Section 3 grows proportionally. In this regard, it is usually taken the lowest number of clusters that yields a reasonable value of some indicators indexes such as the total sum of distances and the Davies Bouldin index (Swaminathan et al., 2020).

One of the salient features of the k-medoids method is that the probability of each scenario can be calculated in a very simple way, as follows.

$$\omega_r = \frac{\text{size}\,(\Omega_r)}{\text{size}\,(\mathcal{S})};\ \forall r \in \mathcal{R} \tag{51}$$

It is worth mentioning that the developed approach for uncertainties modelling presents a modular structure. Thereby, other uncertain parameters can be easily accommodated if necessary. For the sake of summarizing, Fig. 4 shows the flowchart for HEM solution incorporating the developed DR strategies and uncertainties modelling described in this paper.

Table 2
The value of grid, PV array and BES parameters.

Parameter	Value	Parameter	Value
$\bar{p}^{G2H}/\bar{p}^{H2G}$	5/2 kW	e2P^{BES}	4 h
$\bar{p}^{PV}$	500 W	$\eta^{BES,c}/\eta^{BES,d}$	0.98/0.98
η^{PV}	0.167	DOD^{BES}	0.60
$\bar{e}^{BES}$	5 kWh	E^{BES}	5 kWh

Table 3
Details of the PEV.

Parameter	Value
$\bar{p}^{EV}$	3 kW
$\bar{e}^{EV}$	22 kWh
$\eta^{EV,c}/\eta^{EV,d}$	0.98/0.98
DOD^{EV}	0.90
Availability	0:00–6:30 h

Table 4
Data of the controllable appliances.

Appliance	P	δ	Time window
Washing machine	3 kW	3	7:30–11:00 h
Dishwasher	2.5 kW	4	7:00–16:00 h
Spin dryer	2.5 kW	2	12:00–17:00 h
Vacuum cleaner	1.2 kW	1	9:00–16:00 h
Cooker hob	3 kW	1	7:30–8:00 h
Laptop	0.1 kW	4	18:00–23:00 h

Table 5
Data of the HVAC system.

Parameter	Value
Rated power	2 kW
COP	2
θ^{sp}	25 °C; $\forall r \in \mathcal{R}, \forall t \in \mathcal{T}$
θ^{db}	0.50 °C

6. Results

In this section, various numerical results are provided in order to prove the effectiveness of the DR strategies introduced in Section 3.10. To do that, the prosumer framework described in Section 2 has been taken as a benchmark by using the HEMS model described in Section 3. The indexes explained in Section 4 are used for comparing different DR strategies, while the approach introduced in Section 5 is considered for uncertainties modelling.

6.1. Input data

Table 2 collects the value of the grid, PV array and BES parameters. Details of PEV are provided in Table 3 and correspond with a Renault Zoe model (Shafie-Khah and Siano, 2017). Data of controllable appliances and HVAC systems are provided in Tables 4 and 5, respectively (Javadi et al., 2020a; Paterakis et al., 2015). The data of home building have been taken from Paterakis et al. (2015). The considered forecasted profiles are shown in Fig. 5. The solar irradiation and outdoor temperature were taken from European Comission (2021) for the city of Madrid in 2016, while the demand for non-controllable appliances was extracted from Singh (2018).

As commented, the developed scenario-based approach for managing uncertainties is carried out in two stages. Firstly, a large number of scenarios are generated by using (50). It is difficult to set a priori the total number of scenarios to be generated in order to catch the randomness of a stochastic variable; however,

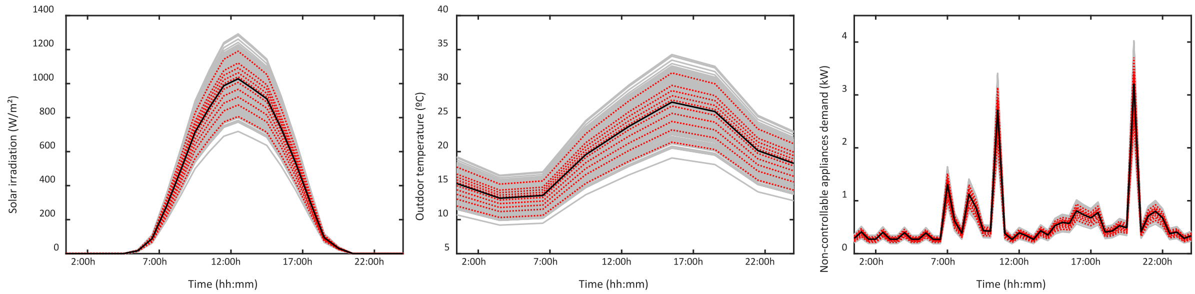

Fig. 5. Forecasted (black line), generated scenarios (grey line) and representative scenarios (red dotted line) of some uncertain parameters. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
Details of the Gaussian distribution functions used for uncertainties modelling.

Variable	μ	σ	a	b
I	1	0.1	0	Inf.
θ^{out}	1	0.1	0	Inf.
D	1	0.1	0	Inf.
E^{EV}	0.5	0.25	0.3	0.95

as commented, this number can be set as large as desired. In this case, 1000 scenarios have been generated. Then, this amount of data is reduced to a manageable number by using the k-medoids technique. The total number of clusters has been selected following the same procedure used in Tostado-Véliz et al. (2021b), which observes the value of the total sum of distances and the Davies Bouldin index.

Further details about this approach are not provided here, referring the reader to the Ref. Tostado-Véliz et al. (2021b) for detailed information. Thus, the generated scenarios have been reduced to 10 representative profiles, which are shown in Fig. 5 with red dotted lines. For the initial SOC of the PEV, also 1000 scenarios are generated by using the Eq. (50). Details of the considered Gaussian distributions are provided in Table 6.

6.2. Comparison of different DR strategies

In this section, the following DR strategies are compared:

- *Strategy 1* lonely application of a dynamic pricing tariff based on a TOU mechanism. The energy price at peak and off-peak hours is shown in Fig. 6 and corresponds with the conventional TOU tariff offered by the company Endesa in Spain (Endesa, 2021). This is considered the base case for the calculation of the DRCI.
- *Strategy 2:* the IBR and TOU pricing schemes shown in Fig. 6 are jointly applied. The considered IBR is based on that used in Javadi et al. (2020a), properly adapted to this case.
- *Strategy 3:* the developed peak clipping strategy is applied along to the TOU tariff shown in Fig. 6. In that sense, the objective function (1) is considered without including the variables β and γ. One should note that this approach presents the same philosophy as peak load pricing and is similar to those strategies introduced in Soares et al. (2017) and Lokeshgupta and Sivasubramani (2019).
- *Strategy 4:* the three developed DR strategies are jointly applied along the TOU tariff plotted in Fig. 5.

In all studied cases, the selling rate has been considered equal to the purchasing pricing, which is generally a reasonable assumption (Javadi et al., 2020b). All simulations have been run under Matlab R2019a on an Intel® Core™ i5-9400F 2.90 GHz 8.00 GB RAM. The HEM optimization problem described in Section 3 was solved over a 24 h time horizon with 30 min resolution using Gurobi (2021).

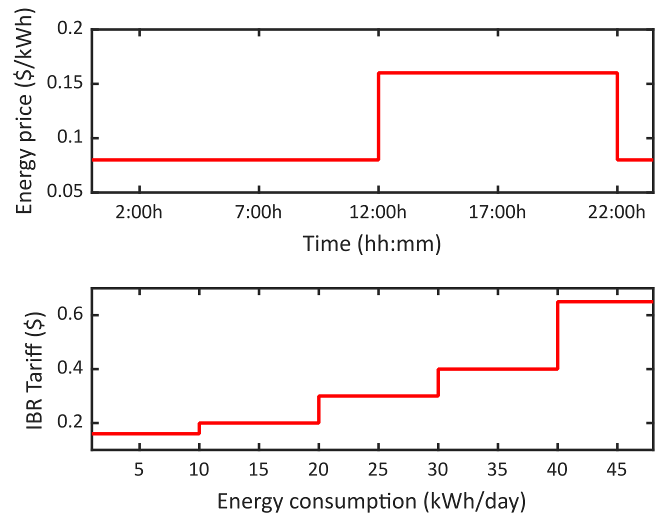

Fig. 6. TOU tariff (upper) and IBR mechanism (bottom) used in simulations.

6.2.1. Base case

Firstly, we analyse the considered base case, which corresponds with the benchmark prosumer paradigm described in Fig. 2. Fig. 7 compares the indexes (43)–(48) for the different considered DR strategies. As seen, both strategies 1 and 2 did not serve to reduce the peak demand. Strategy 2 could not improve the index LF while the index ARI was slightly reduced with strategy 1. With the application of strategies 3 and 4, the indexes PD, LF and ARI were further improved as ρ grows. Comparing strategies 3 and 4, one can clearly check that the latter is more effective as the ARI index was notably improved as the penalty parameter was increased.

Fig. 8 compares the scheduling plan with the strategy 1 and 4 ($\rho = 1$). As observed, it can be clearly appreciated the effect of applying the developed DR strategy. Firstly, the grid peak power is notably reduced in the case of strategy 4. Secondly, the adoption of strategy 4 can reduce the effect of the load synchronization phenomenon; rightly, up to 3 controllable loads are scheduled at the same time with strategy 1 while only two are operated at the same time slot with the developed strategy. Finally, the grid power curve is clearly flattered in the case of strategy 4, as sharp ramps are avoided.

The conclusions drawn can be straightforwardly described through the introduced index (DRCI), which is reported along with the expected electricity bill in Table 7. As observed in this table, strategies 1 and 2 present the highest value of the DRCI. This was expected since, despite those strategies, the monetary expenditures are low, the different DR indexes present bad values, as shown in Fig. 7. On the other hand, the DRCI is notably reduced with the adoption of strategies 3 and 4. In such cases,

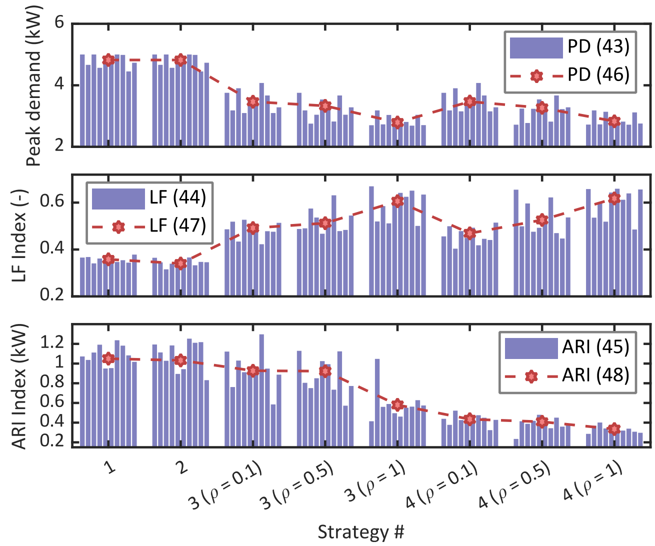

Fig. 7. The value of the indexes (43)–(48) for different DR strategies in the base case.

Table 7
Expected electricity bill and value of the DRCI with different DR strategies with base case conditions.

Index	DR strategy #							
	1	2	3			4		
			$\rho = 0.1$	$\rho = 0.5$	$\rho = 1$	$\rho = 0.1$	$\rho = 0.5$	$\rho = 1$
Bill (€)	3.2875	3.7150	3.2906	3.3027	3.3731	3.3055	3.3413	3.4092
DRCI	1.8162	1.8304	1.3867	1.3382	1.0682	1.3120	1.2093	1.0151

the electricity bill is increased; however, DR goals are more satisfactorily complying. Finally, it is worth noting that strategy 3 achieves a better trade-off between monetary expenditures and DR achievements. As seen in Fig. 7, this is coherent since the introduced mechanism notably enhanced some indexes like ARI, while the electricity bill was just scarcely increased with respect to strategy 1 (∼0.11 €). These results show the coherency and usefulness of the introduced index.

6.2.2. *Assessing the influence of storage capacity*

Although it has been shown that the DR schemes 3 and 4 are more effective than strategies 1 and 2, the formers' application requires further exploitation of the BES, as shown in Fig. 8. This fact may provoke the fast ageing of batteries due to more charging–discharging cycles are completed (Alsaidan et al., 2018). These facts have motivated us to explore further the storage capacity's influence in the developed DR strategies. To do that, extensive experiments have been carried out, and the scenarios below have been analysed:

- *Scenario 1*: it is assumed that the PEV is not able to provide the vehicle-to-home capability. This is a very common situation since vehicle-to-home capacity has to be enabled through bi-directional chargers (Shin and Baldick, 2017), which frequently suppose a monetary investment that home inhabitants are unwilling to undertake. In this sense, storage capacity is only provided by the BES; however, the PEV has to be still fully charged at its departure time as in the base case.
- *Scenario 2*: in this case, it is assumed that the BES is not deployed. In this regard, the unique storage capacity is provided by the PEV and its vehicle-to-home capability.
- *Scenario 3*: under these conditions, it is assumed that the home system under study does not count with any storage capacity. Thus, a BES is not installed, and the PEV is not able to provide vehicle-to-home capacity.

Firstly, scenario 1 is studied. In this regard, Fig. 9 is analogue to Fig. 7 for this scenario. The results are quite similar to the base case, and the same conclusions can be extracted for this scenario. As shown in Fig. 9, these results were expected since storage capacity was entirely provided by the BES in the base case. This circumstance leads us to think that vehicle-to-home capability is irrelevant if a BES is installed. This point is confirmed by observing the scheduling results with the application of strategy 4 in scenario 1 (Fig. 10). As seen, this scheduling plan is practically identical to that shown in Fig. 9.

Results reported for scenario 1 may lead to the conclusion that storage capacity strongly influences the performance of the introduced DR strategies. This idea is further confirmed by observing Fig. 11, which plots the value of the indexes (43)–(48) for scenarios 2 and 3. As observed in this figure, strategies 3 and 4 still outperform strategies 1 and 2. However, in contrast with the base case, all the indexes are only scarcely improved compared to strategy 3. This is mainly due to the flexibility provided by the BES is lost in these scenarios. This fact limits the ability of the developed strategies to achieve DR goals. This conclusion was already outlined with the results obtained in the base case and scenario 1. In such a case, the BES was exploited in-depth to pursue DR achievements. As this capacity vanishes in scenarios 2 and 3, the same level of complying with demand response programs is not expected.

Nevertheless, one can still think that vehicle-to-home capability could provide a certain degree of flexibility and storage capacity to the home system in scenario 2. However, this fact has not been reflected in the results shown in Fig. 11. For the sake of analysing these results in detail, Fig. 12 compares the scheduling results for scenarios 2 and 3 with strategy 4. As seen in this figure, both scheduling plans are quite similar. This is due to, although the PEV has certain storage capability in scenario 2, it is rather restricted due to few availabilities of the PEV. This fact forces the operation of the PEV as a pure load to meet its requirements.

Finally, Fig. 13 provides an overview of the expected electricity bill and DRCI for scenarios 1–3, including the results reported in Table 6 for comparison. As seen, the expected electricity bill notably grows in scenarios 2 and 3, which is expected due to flexibility enabled by the BES is lost in these scenarios. On the other hand, this figure also serves to remark the usefulness of the introduced DRCI. As observed, this index is able to reflect the trade-off between monetary expenditures and DR achievements effectively. Indeed, one can observe that strategies 3 and 4 are clearly more effective than strategies 1 and 2. On the other hand, strategy 4 outperforms strategy 3 in scenarios 1 and 2; however, as commented before, this mechanism is not so competitive in scenarios 3 and 4. In such cases, strategies 3 and 4 yielded similar DRCI values, reflecting a similar performance in both cases.

6.3. *Computational burden*

This section is devoted to providing son insights into the computational performance of the developed HEMS described in Section 3. In that sense, it is worth remarking that this optimization framework is conceived for a 24-h time horizon. It means that it should be usually carried out with some margin hours on the previous day for which the scheduling result is applied. As commented, the introduced HEMS is formulated as a MILP problem. The computational burden of such optimization frameworks directly depends on the size of the problem (Tostado-Véliz et al., 2021b), i.e. the total number of variables

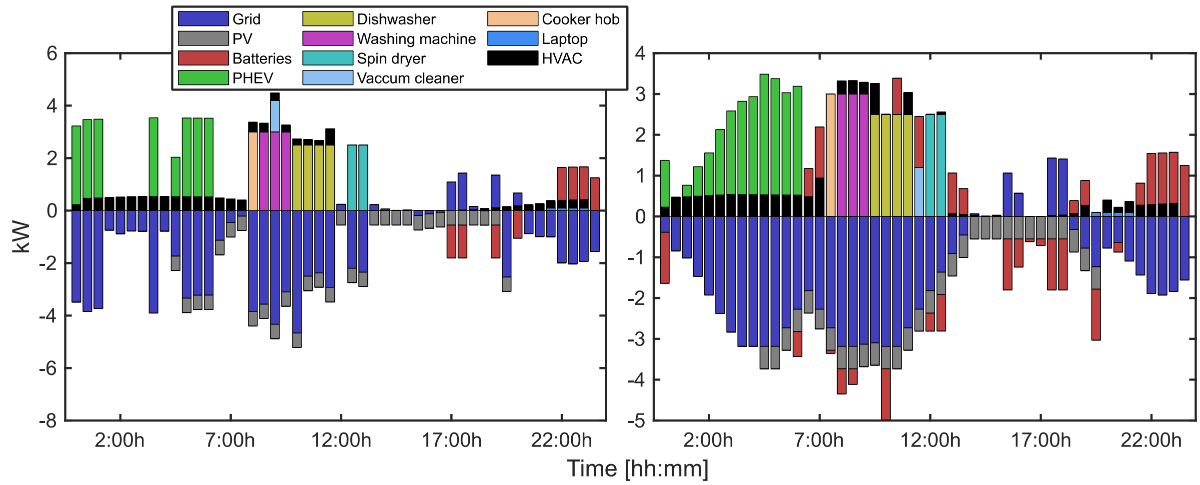

Fig. 8. Scheduling result with the strategies 1 (left) and 4 (right). In this figure, negative power indicates 'to home' direction (generation).

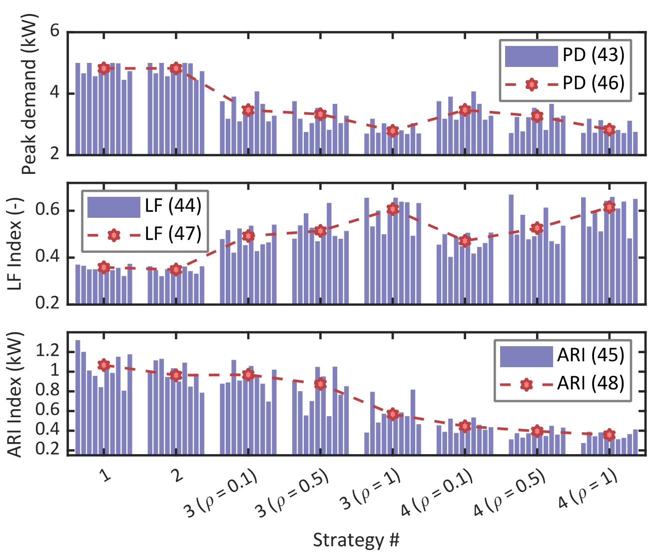

Fig. 9. The value of the indexes (43)–(48) for different DR strategies in scenario 1.

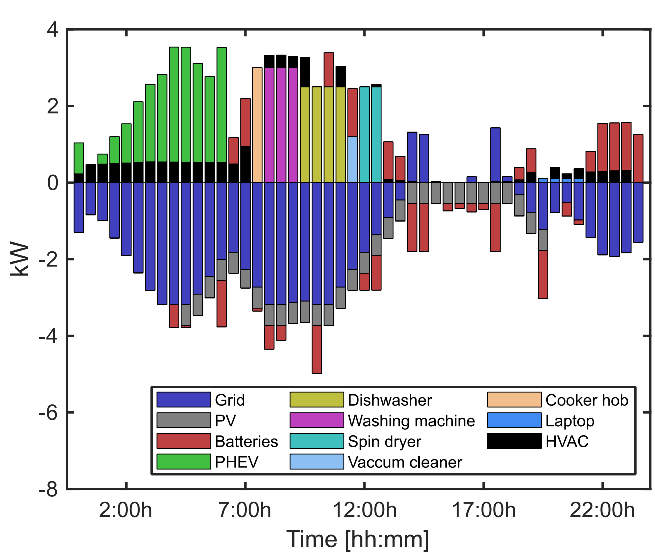

Fig. 10. Scheduling result with strategy 4 ($\rho = 1$) in scenario 1. In this figure, negative power indicates 'to home' direction (generation).

and constraints involved. Keeping this in mind, the computational time to solve the developed HEM problem would depend on both the DR strategy adopted and the scenario studied. Indeed, one could intuitively guess a high computational burden on solving the developed HEMS with strategy 4 than the same situation but with strategy 1, since the constraints (35)–(41) are not applied in the latter case.

Similarly, it seems clear that scenario 1 entails a high computational burden than scenario 4 since some variables related to the BES and PEV are not included in the latter case. These ideas are confirmed by observing Fig. 14, where computational time employed on solving the developed HEM formulation for different strategies and scenarios is depicted. Nevertheless, one can clearly check that exhibited computational times are reasonable for the concerning application.

7. Conclusions

This paper has developed a HEMS that includes three novel DR routines focused on peak clipping and demand flattening strategies. In contrast to other conventional DR initiatives that directly impact the electricity bill, the novel proposals are incorporated into the mathematical formulation of the HEMS. So that they should be categorized as DR strategies based on decision variables. This feature makes them interesting for home's inhabitants since their economy is directly affected by adopting a DR program. In addition, a novel comparative index has been introduced, which aims at assessing the balance between DR achievements and electricity bills. Finally, a scenario-based approach has been developed for uncertainty modelling.

The developed DR strategies have been compared with other well-known DR mechanisms based on pricing signals in a prosumer benchmark environment. Results have shown that the developed DR strategies were more effective in achieving DR goals than the other programs. This result is evidenced in the fact that less monetary expenditures are necessary to achieve different targets. In other words, DR goals are achieved without significant detriment to the economy of users. In fact, compared to the case in which only a TOU tariff is applied, the peak demand was reduced by ∼2 kW, while the ARI and LF indexes were improved by ∼70% and ∼42%, respectively, by using the developed strategies. It has been also analysed the influence of the storage capacity on the performance of the developed strategies. In that sense, it has been shown that a BES's availability strongly influences the effectiveness of such strategies. Finally, the usefulness of the developed index has been illustrated. In all cases, the

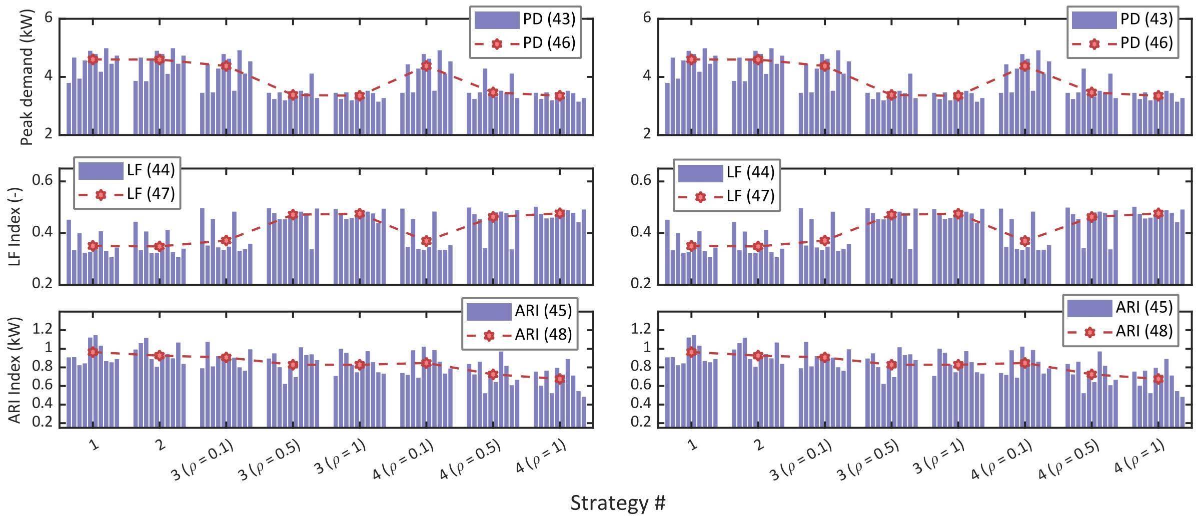

Fig. 11. The value of the indexes (43)–(48) for different DR strategies in the scenario 2 (left) and 3 (right).

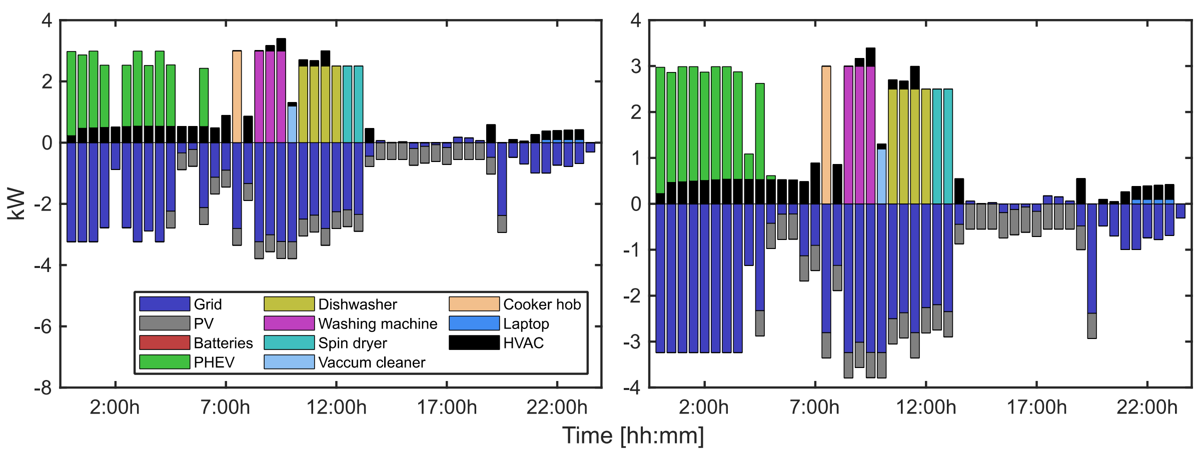

Fig. 12. Scheduling result with the strategy ($\rho = 1$) in scenarios 2 (left) and 3 (right). In this figure, negative power indicates 'to home' direction (generation).

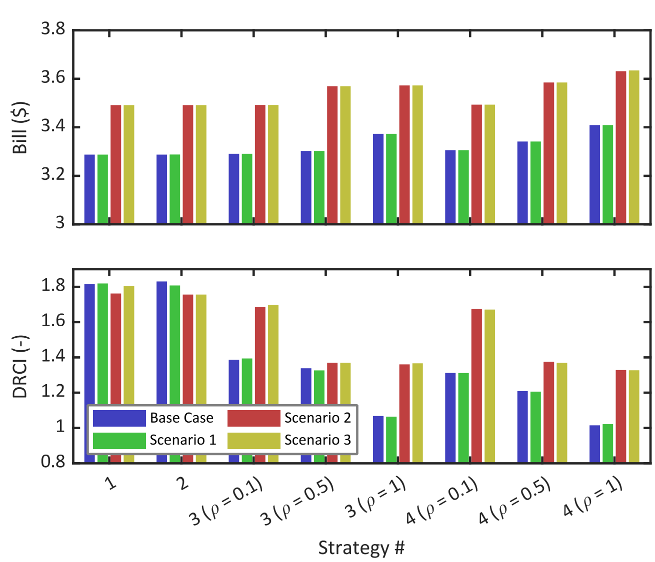

Fig. 13. Expected electricity bill (upper) and DRCI (bottom) with different DR strategies and scenarios.

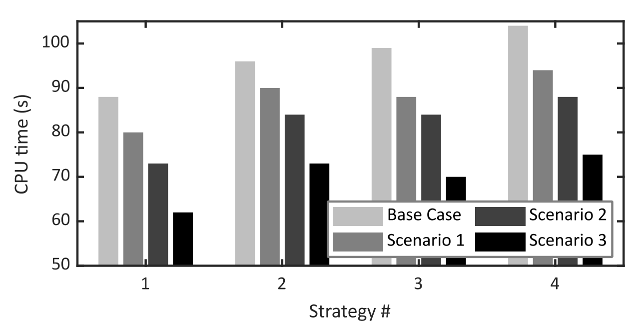

Fig. 14. Computational time employed on solving the developed HEMS for different strategies and scenarios.

introduced indicator was able to clearly reflect the effectiveness of the different DR strategies. Thus, those DR initiatives purely based on prices normally yielded high DRCI values, because of their notable detriment of users' economy. In this sense, the developed strategies resulted very effectively, achieving better results with a very low increment of the electricity bill (∼0.11 € higher in comparison with the base case). This last feature was well catched by the developed index, whose value was clearly lower in the case of the developed DR strategies.

Ongoing works are conducted to confirm the results obtained in this work to other users, like commercial and industrial buildings.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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