

# Optimal participation of prosumers in energy communities through a novel stochastic-robust day-ahead scheduling model

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**Abstract.** With the advent of smart grids, novel businesses like energy communities are becoming more frequent, thus enabling alternative energy transactions for smart prosumers like peer-to-peer mechanisms, that may increment the efficiency of residential installations while reducing the electricity bill. However, the optimal participation in such frameworks is a formidable challenge because the multiple uncertainties involved and energy paths enabled, which increments the number of decision variables and pricing mechanisms. This paper addresses this issue by developing a novel day-ahead scheduling model for prosumers integrated in energy communities based on a stochastic-robust approach. The developed formulation contemplates energy transactions with the utility grid, the community and other peers, besides the intrinsic uncertainties that arise from these processes. The heterogeneity of the unknown parameters is effectively addressed by using different uncertainty models, thus, while the predictable parameters are modelled using robust formulation, the highly volatile uncertainties are treated via scenarios. A case study is presented with the aim of validating the new tool as well as analyse the different energy transactions and their monetary implications. The obtained results evidence the important role of storage assets in reducing the electricity bill by 86 %, which is achieved by incrementing the exportable capacity of the dwelling by 84 %. The impact of uncertainties is also studied, expecting more pessimistic profiles at expenses of incrementing the monetary cost in 0.37-\$.

**Keywords.** Energy community; Peer-to-peer; Prosumer; Smart home; Smart grid.

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## Nomenclature

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### *Indexes (Sets)*

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$s(S)$	Scenario
$r(R)$	Representative scenario
$t(T)$	Time
$c(C^I/NI)$	Interruptible/non-interruptible controllable appliance
$\Theta$	Time window

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### *Superscripts*

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<i>Home</i>	Referred to the smart home under study
<i>Grid</i>	Utility grid
<i>Comm</i>	Community
<i>P2P</i>	Referred to peer-to-peer energy trading
<i>Import/Export</i>	Referred to imported/exported energy
<i>PV</i>	Rooftop photovoltaic panels
<i>Air, in/out</i>	Indoor/outdoor air
<i>BES, ch/dch</i>	Battery energy storage in charging/discharging mode
<i>HVAC, heat/cool</i>	Heating-ventilation-air conditioner in heating/cooling mode
<i>sp/db</i>	Set-point/dead-band
<i>EWH</i>	Electric water heater
<i>W, hot/cold</i>	Hot/cold water
<i>NC</i>	Referred to non-controllable appliances
$\overline{(\cdot)}/\widehat{(\cdot)}$	Maximum/predicted value of a parameter or variable

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### *Constants and parameters*

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$\eta$	Efficiency [%]
$\Delta\tau$	Time step [h]
DOD	Depth-of-discharge [%]
$m$	Mass [kg]
$Q$	Heat or thermal capacity [ $\text{kJ}\cdot\text{kg}^{-1}\cdot\text{°C}^{-1}$ or $\text{°C}\cdot\text{kW}^{-1}$ ]
$\mathcal{R}$	Equivalent thermal resistance [ $\text{J}\cdot\text{°C}^{-1}$ or $\text{°C}\cdot\text{kWh}^{-1}$ ]
COP	Coefficient of performance [pu]
$v$	Volume [gal]
$\delta$	Duty cycle [h]
$\pi$	Probability [%]
$\Gamma$	Robust parameter [pu]

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### *Decision variables*

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$p$	Power [kW]
$u$	Commitment status [binary]
$\varepsilon$	Energy [kWh]
<i>on/off</i>	On/off transition status [binary]
$z, q, y$	Auxiliary variables for robust optimization

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## 1 - Introduction

### 1.1 - Context and motivation

With the advent of the smart grid concept, power networks are evolving to be more flexible, efficient and environmentally friendly [1, 2]. In this context, traditional large-scale centralized generation will cohabit with small-scale distributed generators (usually renewable-based), which may be owned by home users or even public entities [3, 4]. This emerging paradigm calls up for new businesses, by which consumers are progressively evolving towards prosumers, thus being able to actively partake in the system operation [5, 6]. However, this new framework presents formidable challenges. One of the hottest topics nowadays is the optimal participation of domestic prosumers in both system operation and energy markets [7]. In this regard, virtual power plants and energy communities (ECs) have emerged as valuable frameworks, by which a group of prosumers can collaborate on maximizing the collective welfare [8, 9]. Within a community, a prosumer can participate in different energy transactions, as depicted in Fig. 1. Indeed, in addition to energy exchanges with the utility grid under real-time-pricing (RTP), a particular prosumer can trade with the community to which it belongs, but also with other prosumers through peer-to-peer (P2P) mechanisms enabled by bilateral agreements [10].

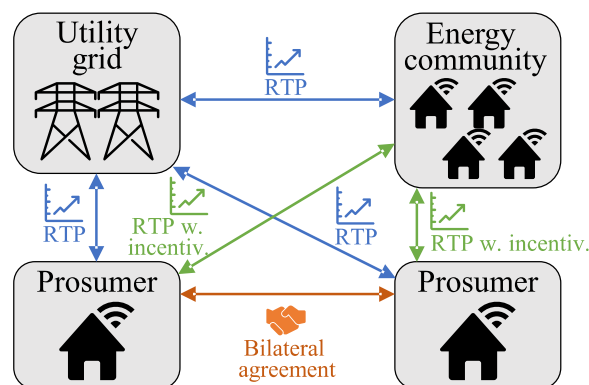


Fig. 1 - Possible energy trading within an EC

The new concepts described above require to further developing existing home energy management (HEM) tools, which are essential for an efficient and economic use of domestic energy [11, 12]. This kind of tools devote on properly coordinating domestic controllable appliances (e.g. thermostatically-controlled devices) and onsite assets like photovoltaic (PV) panels or small-scale batteries. This task is inherently affected by multiple uncertainties that arise from weather parameters or demand. In this sense, HEM systems should evolve to take into account multilateral energy trading within communities, but also the uncertain associated to energy prices as well as importable and exportable energies. Undoubtedly, these aspects will be crucial for a practical and useful development of HEM tools. This paper is focused on this issue.

### *1.2 - Literature review*

The literature regarding HEM systems is rich and contributions have notably increased during the last few years (see the reviews [13, 14]), focusing on different aspects such as amicable formulations or uncertainties modelling, among others. However, most of the available literature is focused on only grid-connected dwellings and HEM problem in integrated ECs has received few attentions so far, especially when different energy trading processes are involved. Liu et al [15] dealt with the deterministic operation of multi-energy ECs, in which various energy carriers interact involving both storage and conversion devices. The optimization problem is mixed integer-nonlinear programming (MINLP), which may be not tractable by average machines and solvers and does not ensure the global optimum reachability. To circumvent this issue, the authors developed a sequential method by which the community is decomposed into smaller subsystems that are more easily manageable. A day-ahead scheduling strategy for cooperative ECs was developed in [16]. The proposed formulation is mixed integer-linear programming (MILP), based on alternating direction method of multipliers, which

preserves the privacy of the users. That reference focuses on cooperative ECs, in which prosumers jointly contribute on maximizing the social welfare without expecting a monetary counterpart. In consequence, P2P transactions among prosumers are not performed on the basis of prices, but to minimize the community operational cost.

High renewable penetration supposes a challenge for optimal operation of ECs. This issue was addressed in [17] by using a Markovian-stochastic approach. By this method, the optimal energy sharing among peers within a community is obtained while treating uncertainties via scenarios. The resulting MILP problem considers thermal and electrical loads and aims at minimizing net demand and CO<sub>2</sub> emissions, for which renewable generators such as PV panels and battery energy storage (BES) banks are profusely exploited on pursuing the community welfare. A two-phase operation-planning model for nearly net-zero ECs was proposed in [18]. The considered community's layout incorporates different energy storages involving electrical, heating and cooling carriers. The model also encompasses electric vehicles (EVs). However, despite the large number of uncertain and unpredictable patterns considered, the model is solved under a deterministic point of view, thus overestimating the economy and environmental results obtained. Furthermore, metaheuristic techniques including heuristic subroutines are employed to solve the optimization problem, which makes the mathematical modelling few versatile and probably sub-optimal [19, 20]. Jo et al [21] proposed a scheduling mechanism for ECs with customer-owned BESs. In this regard, the MILP scheduling model includes a market-oriented sub-module in which the participants bid offers based on their storage capacities. Thus, the users can offer their own storage capability, thus resulting in a non-cooperative structure in which collective welfare is not maximized. Similar to other works, inherent uncertainties are not considered.

Rao et al [22] developed an optimal capacity management strategy for ECs involving an incoming generation of loads such as heat pumps or hydrogen storages. The proposed optimization problem aims to determine the percentage of grid capacity that is assigned to each load, with the objective of keeping stable and safe the operation of the distribution network. To this end, a nonlinear problem involving load flow constraints was developed, as applied to a real case in Austria under deterministic conditions. The inherent nonlinearity of the formulation requires the use of metaheuristic techniques, which may result computationally costly and do not ensure the reachability of the global optimum, limiting the applicability of the developed tool. In [23], an optimal bidding strategy for ECs was developed. As a result, a MILP-based optimization problem is derived in which HEM systems gain importance. Controllable appliances (CAs) as well as onsite generators and storage assets are centrally managed on pursuing the social welfare and launch offers in local energy markets. In this sense, individual interests of users are not considered and the optimization framework takes a community-oriented perspective.

Ref. [24], which supposes an improvement of [18], proposes a heuristic-based optimization routine for optimal planning and operating nearly zero-energy communities based on different kind of smart and efficient buildings, as well as distributed energy resources and multi-energy storage assets. In contrast to [18], Ref. [24] poses a multi-objective problem in which CO<sub>2</sub> emissions are also reduced. Similar to [16], a scheduling strategy for ECs based on alternating direction of multipliers was developed in [25]. In this case, the authors considered the intra-day operation in coordination with day-ahead decisions, including a scenario-based approach to account for uncertainties in renewable generation. In [26], a multi-objective optimization approach was developed, for ECs encompassing multi-energy storage assets. The developed multi-objective routine is based on heuristic algorithms and metaheuristic solvers. This optimization procedure

allows to compare different building configurations, thus extracting different conclusions. This way, the authors concluded that community operation is much beneficial than isolated consideration in residential areas, enabling notable emissions and economic savings. However, the results may be sub-optimal because the strong heuristic principles adopted.

### *1.3 - Gaps and contributions*

Most of the operation strategies developed for ECs are conceived from the community operator point of view. Although this vision is generally valid, the interests of individual users should not be ignored, especially when prosumers can access to different energy trading under a variety of economic or regulatory principles. These particular interests and objectives cannot be properly treated when the management framework is community-oriented, when typically collective welfare prioritizes over individual targets. Uncertainties modelling supposes other important lack in operation of ECs since, as seen in Table 1, most of the related literature assumes deterministic conditions, which may lead to over-optimistic results that do not account for uncertainty in renewable generation or demand. Moreover, existing literature ignores the fact that uncertainties inherent to multiple trading in ECs may have different character and, in consequence, applying the same model may be an unsuitable solution. In this sense, we believe that hybrid solutions that apply different approaches according the features of each uncertain parameters are more adequate but not considered yet in ECs.

This paper aims at filling these gaps. More precisely, the main contributions of this paper are twofold:

- Developing a novel day-ahead scheduling strategy for smart homes integrated in ECs. Unlike other methodologies proposed in the literature, the new proposal considers a variety of energy trading possibilities, as described in Fig. 1. Thereby,

the home under study can exchange energy with a local EC, the utility grid or other peers under different pricing mechanisms. This way, this work supposes, to the best of our knowledge, the first attempt of considering individual interests in EC operation.

- Integrating a stochastic-robust model to account for uncertainties brought by renewable generators and demand in the community and other prosumers as well as dynamic energy prices. These unknowns critically determine the decisions of the concerned prosumer as they may limit the exportable and importable energy through the enabled trading paths. In this sense, the different uncertainty parameters usually present heterogeneous characteristics, for which, a hybrid model is more suitable [27, 28]. In particular, stochastic programming is used for highly volatile uncertainties while robust optimization (RO) [29] is considered for those unknowns that can be predicted with acceptable accurateness.

Thus, the present paper aims at overcoming some of the limitations of existing work. To validate the new proposal, a case study is performed on a benchmark prosumer environment, comparing various cases that allow us to analyse the monetary and energy implications of the different trading mechanisms that are enabled within ECs.

In the rest of this paper, Section 2 provides the necessary background. Section 3 develops the mathematical formulation for integration of HEM within communities. Section 4 presents a case study with results. The paper is concluded with Section 5.

Table 1 - A summary of the related literature

Ref.	Model	Uncertainties	Operator	Remarks
[15]	MINLP	No	EC	Involves various energy carries with storage and conversion devices
[16]	MILP	No	EC	Formulation is based on Alternating Direction Method of multipliers. It focuses on cooperative ECs.
[17]	MILP	Stochastic	EC	A Markovian-stochastic approach is used for uncertainties modelling in renewable generation.
[18, 24]	Metaheuristic	No	EC	A two-phase planning-operation framework is proposed incorporating multi-energy storage devices.
[21]	MILP	No	EC	Incorporates an internal market subroutine to determine the storage capacity in the EC.
[22]	Metaheuristic	No	EC	Determines the optimal capacity sharing among loads to keep the network safe and stable.
[23]	MILP	No	EC	Deals with optimal bidding strategy of ECs involving HEM systems.
[25]	MILP	Stochastic	EC	Coordinates day-ahead scheduling with intra-day decision-making strategies.
[26]	Metaheuristic	No	EC	Compares different building and community configurations under a multi-objective optimization process.
This paper	MILP	Stochastic-RO	Home user	Suitable for energy trading with utilities, communities and peers

## 2 - Preliminaries

### 2.1 - Energy trading within communities

This paper contemplates the possibility of different energy paths within an EC, as depicted in Fig. 1. In this way, a particular prosumer can exchange energy with the grid provider, with the local community or with other peers. Usually, each of these energy transactions are subjected to different pricing mechanisms:

- **Trading with the grid.** Energy transaction with the grid is usually performed under RTP, which is determined by market signals that determine local or global market prices, principally [30, 31]. In this regard, it is considered that both the EC and the smart home under study must adopt a price-taker strategy, assuming that local generation is not capable to influence in upscale market behaviour [32]. Thus, the local retailer, who is responsible of energy provision through the grid, sends price signals to the different consumers. However, these market prices are in essence uncertain and may vary throughout the day, in a way that energy transactions with the grid are actually performed under uncertain conditions [33].

- **Trading with the community.** Community operators normally aim to encourage local participants to provide energy to the community from surplus renewable generation or customer-owned storage assets [21, 34]. To this end, ECs frequently launch a series of incentives to make economically attractive the energy transactions within the community rather than with the grid [35]. Pricing schemes within communities is still an open topic [36, 37], however, dynamic tariffs based on RTP are gaining popularity because their capability to be adapted to upscale market behaviour [38].
- **Trading with peers.** Besides the energy trading described above, a particular prosumer can accord individual P2P transactions with other prosumers inside or outside the community [10]. In this case, the pricing mechanism is agreed between peers, respecting the possible regulatory frameworks imposed in each country or area.

## *2.2 - Uncertainties modelling*

Within ECs, there are multiple uncertainties that may be caused by unpredictable generation, uncertain energy pricing and volatile demand. These uncertainties notably impact on the performance of prosumers and how they determine their scheduling strategies in order to achieve their objectives. Thus, the net demand drawn for other peers and the community limits the energy that can be traded, whereas energy prices influence on the economic objectives of the prosumers and can determine the amount of energy that is exchanged through the trading mechanisms described in the previous section. However, these unknown parameters have heterogeneous features. Thus, while the energy prices and community net demand can be predicted with certain accuracy [39], the energy that can be exchanged with a particular peer is very volatile as it depends on individual human decisions [40].

On the basis of the premises above, it results unsuitable to use only one model to cope with all the uncertainties involved. For example, stochastic programming results useful when uncertain parameters are very volatile or can be easily modelled using fitted distribution functions or historical data. However, this approach may be unsuitable when this information is not available, being necessary to consider other approaches. Thus, we have adopted a hybrid uncertain model, by which predictable uncertainties are treated using RO while highly volatile profiles are modelled using scenarios. This way, the novel approach aims to leverage advantages of different uncertainties modelling. In contrast to other approaches that were described in Table 1, the developed model does not rely in just one model, integrating both stochastic approach and RO in a novel way. Fig. 2 gives an overview of these two approaches, where it is assumed that the unknown parameter  $\xi$  is stochastic, whereas  $\omega$  is solved using robust approximations. As seen in Fig. 2, stochastic programming represents well volatility, being suitable for profiles that vary randomly, while RO is mostly based on predicted intervals, being more suitable for uncertain parameters that can be predicted with certain accurateness or vary scarcely around a forecast profile. Subsequent sections are devoted on explaining stochastic programming and RO concisely.

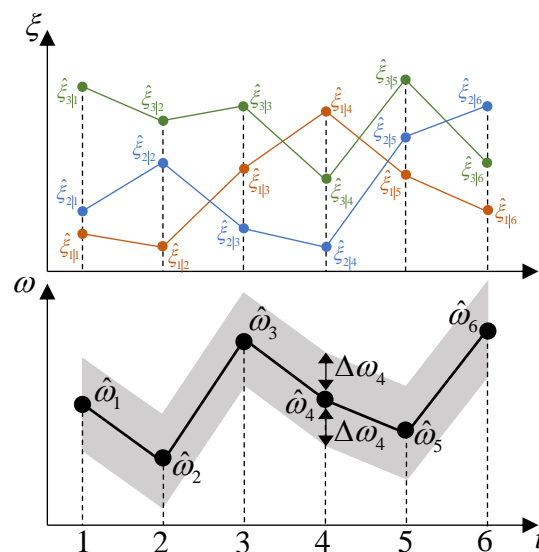


Fig. 2 - Sketches of stochastic programming (top) and RO (bottom)

### Stochastic programming

Stochastic programming is a well-known probability-based uncertain modelling which has been widely used in engineering applications (e.g. see [41-43]). This approach is based on evaluating a large number of scenarios for uncertainties instead of only one, so that the resulting optimization problem is raised, as follows:

$$\min_{\text{variables}} \sum_{s \in S} \frac{\pi_s}{100} \cdot OF_s \quad (1)$$

where  $OF$  is the objective function to be evaluated. The scenario-space can be constructed on the basis of probability distributions, which can be fitted according to well-known models or historical data [44]. Due to there is no need of forecasted profiles, stochastic programming is very suitable for those unknowns that are hardly predictable. One of the main drawbacks of stochastic modelling is the large number of scenarios that must be constructed (~1000-4000 [45]), which may suppose intractability issues. To circumvent this issue, clustering techniques are usually employed, which allow to reduce the original scenario-space to a minimum set of representative profiles. In this paper, we use the k-medoids method due to its good overall features [46].

### Robust optimization

RO is a non-probabilistic uncertain model that aims to overcome the difficulties of stochastic programming [47]. This approach is based on modelling a particular uncertainty by their expected value and corresponding predicted intervals (see Fig. 2), within which the actual value of the parameter will lie with high probability. This way, a particular uncertain parameter  $\omega$  can be modelled as an interval number, as follows [48, 49]:

$$\omega \in [\hat{\omega} - \Delta\omega, \hat{\omega} + \Delta\omega] \quad (2)$$

Thereby, RO is focused on minimizing a particular objective function while maximizing the degree of robustness on a whole. In this case, the robustness is determined

by how far are the uncertainties from their predicted values, which can be expressed as follows:

$$\begin{cases} \min_{variables} OF + \max_{\omega, \alpha_{\omega}} \alpha_{\omega} \\ \text{subject to: } \hat{\omega} - \alpha_{\omega} \cdot \Delta\omega \leq \omega \leq \hat{\omega} + \alpha_{\omega} \cdot \Delta\omega \end{cases} \quad (3)$$

where  $\alpha \in [0,1]$ . To solve the min-max problem above, a variety of methodologies have been proposed based on dual formulations [50] or iterative routines [51]. In this paper, we consider the simplified dual formulation developed in [52].

### 3 - Mathematical models

This section presents the mathematical modelling of the day-ahead scheduling problem for the smart home depicted in Fig. 3, which partakes in various energy paths, as shown in Fig. 1. We firstly elaborate the stochastic-based mathematical notation that models uncertain net demand of peers via scenarios. Secondly, the pertinent modifications required to modelling the other uncertainties (i.e. community's net demand and energy prices) using RO are explained.

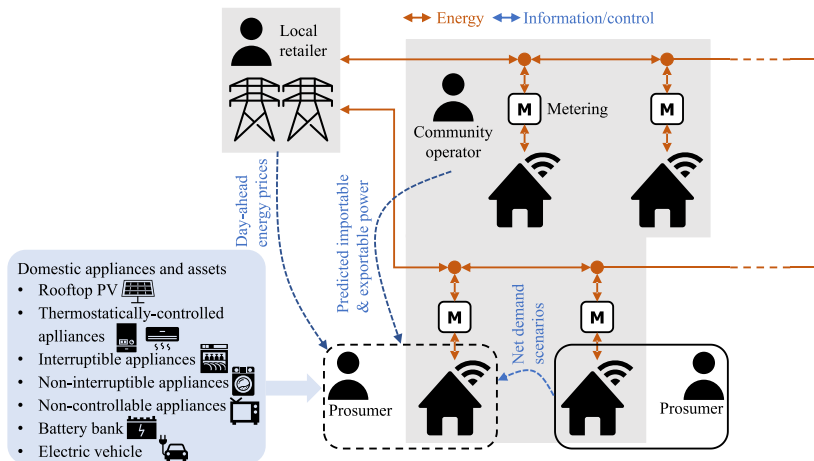


Fig. 3 - Pictorial representation of the studied system

#### 3.1 - Energy trading modelling

It is assumed that physical restrictions limit the amount of energy that can be imported/exported to/from the smart home under study, as said (4), while (5) and (6) limit the energy transactions with the community and peers, respectively.

$$p_{r|t}^{i,j} \leq u_t^j \cdot \bar{p}^{Home}; \forall r \in R \wedge t \in T \wedge i \in \{Grid, Comm, P2P\} \wedge j \in \{Import, Export\} \quad (4)$$

$$p_{r|t}^{Comm,j} \leq u_t^j \cdot \hat{p}_t^{Comm,j}; \forall r \in R \wedge t \in T \wedge j \in \{Import, Export\} \quad (5)$$

$$p_{r|t}^{P2P,j} \leq u_t^j \cdot \hat{p}_{r|t}^{P2P,j}; \forall r \in R \wedge t \in T \wedge j \in \{Import, Export\} \quad (6)$$

The upper bounds in (5) and (6) stand for the actual net demand in the community and other peers, respectively. They model the amount of energy that can be exchanged any time instant with other agents. Since this factor depends on the instantaneous onsite renewable generation and demand, they have been considered uncertain parameters. While the net demand in (6) is fully modelled using scenarios, the importable/exportable from/to the community is treated using RO, as explained later. Finally, the constraint (7) avoids simultaneous purchases and sales [16].

$$u_t^{Import} + u_t^{Export} \leq 1; \forall t \in T \quad (7)$$

### 3.2 - PV modelling

To provide on-site generation, a rooftop PV array is assumed to be installed. The PV potential is a function of weather parameters such as solar irradiance and ambient temperature. In this regard, the PV model developed in [53] has been considered, in order to determine the instantaneous PV potential (in kW), as a function of ambient inputs. As pointed out in other works [12], the considered model may yield unrealistic results, for which additional constraints must be imposed. In particular, the PV outputs are limited to 10% over the nominal capacity of the PV array. Note that these models have not been included here to avoid an abuse of the notation, being referred to the mentioned references for further information.

### 3.3 - Energy storage modelling

Two storage assets are considered, namely BES and EV. In order to fully exploit the capabilities of both devices, vehicle-to-home feature of the EV is enabled [54]. This way,

the instantaneous state-of-charge (SOC) of the storage assets is modelled by (8) and it turns limited by nominal capacities and depth-of-discharge (DOD) settings, as said (9).

$$\varepsilon_{r|t}^i = \varepsilon_{r|t-1}^i + \Delta\tau \cdot \left[ \frac{\eta^i}{100} \cdot p_{r|t}^{i,ch} - \frac{100 \cdot p_{r|t}^{i,dch}}{\eta^i} \right]; \forall r \in R \wedge t \in T \setminus t > 1 \wedge i \in \{BES, EV\} \quad (8)$$

$$\left(1 - \frac{DOD}{100}\right) \cdot \bar{\varepsilon}^i \leq \varepsilon_{r|t}^i \leq \bar{\varepsilon}^i; \forall r \in R \wedge t \in T \wedge i \in \{BES, EV\} \quad (9)$$

In both cases, the amount of power that can be exchanged with the home is limited by (10) [50], while the rated power of chargers restricts the amount of energy that can be extracted/supplied to on-board batteries. In any case, simultaneous charging and discharging is avoided by (11).

$$p_{r|t}^{i,j} \leq u_t^{i,j} \cdot \bar{p}^i; \forall r \in R \wedge t \in T \wedge i \in \{BES, EV\} \wedge j \in \{ch, dch\} \quad (10)$$

$$u_t^{i,ch} + u_t^{i,dch} \leq 1; \forall r \in R \wedge t \in T \wedge i \in \{BES, EV\} \quad (11)$$

Since the model (8) is not defined for  $t = 1$ , it is necessary to establish the initial SOC of the batteries by (12) [12, 50]. To keep the model coherent, the constraint (12) forces the final SOC to be equal to the initial stored energy.

$$\varepsilon_{r|T(1)}^{BES} = \varepsilon_{r|T(\text{end})}^{BES} = \bar{\varepsilon}^{BES}; \forall r \in R \quad (12)$$

While stationary storage banks can be dispatched any time instant, the on-board batteries are only available when the EV is plugged, as modelled (13). In this case, the initial SOC depends on the daily mileage [55, 56], as said (14). Lastly, it is assumed that home inhabitants are keen to get the vehicle fully charged when it leaves the home, which is ensured by imposing the constraint (15).

$$u_t^{EV,j} = 0; \forall t \notin \Theta^{EV} \wedge j \in \{ch, dch\} \quad (13)$$

$$\varepsilon_{r|\Theta^{EV}(1)}^{EV} = \frac{\omega_0^{EV}}{100} \cdot \bar{\varepsilon}^{EV}; \forall r \in R \quad (14)$$

$$\varepsilon_{r|\Theta^{EV}(\text{end})}^{EV} = \bar{\varepsilon}^{EV}; \forall r \in R \quad (15)$$

### 3.4 - Heating-ventilation-air conditioner (HVAC) modelling

The HVAC modelling used in this paper is based on linearized differential equations [57, 58], which calculate the indoor temperature as a function of the ambient temperature and the action of the HVAC devices, as said (16).

$$\theta_{r|t}^{Air,in} = \left(1 - \frac{\Delta\tau}{10^3 \cdot m^{Air,in} \cdot Q^{Air,in} \cdot \mathcal{R}}\right) \cdot \theta_{r|t-1}^{Air,in} + \frac{\Delta\tau \cdot \theta_{r|t-1}^{Air,out}}{10^3 \cdot m^{Air,in} \cdot Q^{Air,in} \cdot \mathcal{R}} + \frac{\Delta\tau \cdot (p_{r|t-1}^{HVAC,h} + p_{r|t-1}^{HVAC,c})}{0.000277 \cdot m^{Air,in} \cdot Q^{Air,in}} \cdot COP^{HVAC}; \forall r \in R \wedge t \in T \setminus t > 1 \quad (16)$$

The initial and final values of the indoor temperature are fixed by (17); whereas (18) ensures the thermal comfort of home users by keeping the indoor temperature within acceptable bounds. The HVAC model is completed by (19) and (20), which limit the power consumption of the HVAC system and avoid to activate its heating and cooling modes simultaneously, respectively.

$$\theta_{r|T(1)}^{Air,in} = \theta_{r|T(end)}^{Air,in} = \theta^{HVAC,sp} \quad (17)$$

$$\theta^{HVAC,sp} - \theta^{HVAC,db} \leq \theta_{r|t}^{Air,in} \leq \theta^{HVAC,sp} + \theta^{HVAC,db}; \forall r \in R \wedge t \in T \quad (18)$$

$$p_{r|t}^{HVAC,j} \leq u_t^{HVAC,j} \cdot \bar{p}^{HVAC}; \forall r \in R \wedge t \in T \wedge j \in \{heat, cool\} \quad (19)$$

$$u_t^{HVAC,heat} + u_t^{HVAC,cool} \leq 1; \forall t \in T \quad (20)$$

### 3.5 - Electric water heater (EWH) modelling

Similar to the HVAC system, the EWH modelling is based on linearizing the hot water dynamics by (21) and (22), depending on the instantaneous water consumption [56, 59]. Finally, (23)-(25) are analogue to (17)-(19) but particularized to the water heater model.

$$\theta_{r|t+1}^{W,hot} = \theta_{r|t}^{W,hot} + (\Delta\tau \cdot p_{r|t}^{EWH} \cdot \eta^{EWH} \cdot Q^W) - (\theta_{r|t}^{Air,in} - \theta_{r|t}^{W,hot}) \cdot e^{\left(\frac{-\Delta\tau}{Q^W \cdot \mathcal{R}^{EWH}}\right)}; \forall r \in R \wedge t \in T \setminus t < \text{size}(T) \wedge v_{r|t}^{W,hot} = 0 \quad (21)$$

$$\theta_{r|t+1}^{W,hot} = \frac{\theta_{r|t}^{W,hot} \cdot (\bar{v}^{EWH} - v_{r|t}^{W,hot}) + \theta^{W,cold} \cdot v_{r|t}^{W,hot}}{\bar{v}^{EWH}}; \forall r \in R \wedge t \in T \setminus t < \text{size}(T) \wedge v_{r|t}^{W,hot} \neq 0 \quad (22)$$

$$\theta_{r|T(1)}^{W,hot} = \theta_{r|T(end)}^{W,hot} = \theta^{EWH,sp}; \forall r \in R \quad (23)$$

$$\theta^{EWH,sp} \leq \theta_{r|t}^{W,hot} \leq \bar{\theta}^{W,hot}; \forall r \in R \wedge t \in T \quad (24)$$

$$p_{r|t}^{EWH} \leq \bar{p}^{EWH}; \forall r \in R \wedge t \in T \quad (25)$$

### 3.6 - CAs modelling

CAs are usually classified as interruptible and non-interruptible [60]. In both cases, the CAs must complete their duty cycles within predefined time windows, as ensured by (26). On the other hand, the constraints (27) and (28) impose continuous operation in the non-interruptible appliances.

$$\sum_{t \in \Theta^c} u_t^c = \frac{\delta^c}{\Delta\tau}; \forall c \in \{C^I \cup C^{NI}\} \quad (26)$$

$$u_t^c - u_{t-1}^c = on_t^c - off_t^c; \forall t \in T \setminus t < 1 \wedge c \in C^{NI} \quad (27)$$

$$\sum_{t \in T} on_t^c = 1; \forall c \in C^{NI} \quad (28)$$

### 3.7 - Power balance

The equation (29) establishes the instantaneous power balance in the dwelling taking into account diverse energy trading, onsite renewable generation and storage assets.

$$\sum_{i \in \left\{ \begin{array}{l} Grid, \\ Comm, \\ P2P \end{array} \right\}} p_{r|t}^{i,Import} + p_{r|t}^{PV} + \sum_{i \in \left\{ \begin{array}{l} BES, \\ EV \end{array} \right\}} p_{r|t}^{i,dch} = \sum_{i \in \left\{ \begin{array}{l} Grid, \\ Comm, \\ P2P \end{array} \right\}} p_{r|t}^{i,Export} + p_t^{NC} + \sum_{i \in \left\{ \begin{array}{l} BES, \\ EV \end{array} \right\}} p_{r|t}^{i,ch} + \sum_{i \in \left\{ \begin{array}{l} heat, \\ cool \end{array} \right\}} p_{r|t}^{HVAC,i} + p_{r|t}^{EWH} + \sum_{c \in \{C^I \cup C^{NI}\}} \{u_t^c \cdot p^c\}; \forall r \in R \wedge t \in T \quad (29)$$

### 3.8 - Objective function

The objective function (30) represents the electricity bill which encompasses monetary expenditures and revenues for energy trading with the utility grid, the community and other peers. In this case, we consider that both energy transactions with the grid and the community are performed under dynamic tariffs (e.g. RTP), while energy exchanges through P2P mechanisms are subjected to fixed prices established by bilateral agreements [36].

$$\begin{aligned}
Bill = & \sum_{r \in R} \left\{ \frac{\pi_r}{100} \cdot \sum_{r \in R} \left\{ \Delta\tau \cdot \left( \hat{\lambda}_t^{Grid,Import} \cdot p_{r|t}^{Grid,Import} - \hat{\lambda}_t^{Grid,Export} \cdot p_{r|t}^{Grid,Export} \right) + \right. \\
& \Delta\tau \cdot \left( \hat{\lambda}_t^{Comm,Import} \cdot p_{r|t}^{Comm,Import} - \hat{\lambda}_t^{Comm,Export} \cdot p_{r|t}^{Comm,Export} \right) + \Delta\tau \cdot \left( \lambda^{P2P} \cdot \right. \\
& \left. \left. \left[ p_{r|t}^{P2P,Import} - p_{r|t}^{P2P,Export} \right] \right) \right\} \quad (30)
\end{aligned}$$

Note that mathematical formulation above corresponds with HEM problem rather than energy management in communities (e.g. [61]). In fact, the problem concerned in this paper is assumed to be performed by home users rather than EC operators.

### 3.9 - Robust reformulation

While uncertainty drawn by connected peers due to their volatile net demand has been already modelled using scenarios, it remains to be discussed how to model the uncertainties from energy prices and importable/exportable demand in the community. In these cases, both parameters can be predicted with acceptable accurateness, since aggregated loads are more susceptible to draw repetitive and predictive profiles than individual consumers. In this sense, we use RO to account for these two uncertain parameters.

Firstly, energy prices are modelled, for which the objective function must be replaced by its robust counterpart (31), while (32)-(35) have to be declared to complete the robust model (see [47, 52] for further details).

$$\begin{aligned}
\widetilde{Bill} = & \sum_{r \in R} \left\{ \frac{\pi_r}{100} \cdot \sum_{r \in R} \left\{ \Delta\tau \cdot \left( \hat{\lambda}_t^{Grid,Import} \cdot p_{r|t}^{Grid,Import} - \hat{\lambda}_t^{Grid,Export} \cdot p_{r|t}^{Grid,Export} \right) + \right. \\
& \Delta\tau \cdot \left( \hat{\lambda}_t^{Comm,Import} \cdot p_{r|t}^{Comm,Import} - \hat{\lambda}_t^{Comm,Export} \cdot p_{r|t}^{Comm,Export} \right) + \Delta\tau \cdot \left( \lambda^{P2P} \cdot \right. \\
& \left. \left. \left[ p_{r|t}^{P2P,Import} - p_{r|t}^{P2P,Export} \right] \right) \right\} + z^{Bill} \cdot \Gamma^{Bill} + \sum_{r \in R} \sum_{t \in T} \sum_{i \in \{Grid, Comm\}, j \in \{Import, Export\}} \left\{ q_{r|t}^{Bill,i,j} \right\} \quad (31)
\end{aligned}$$

$$z_{r|t}^{Bill} + q_{r|t}^{Bill,i,j} \geq y_{r|t}^{Price,i,j} \cdot \Delta\lambda_t^{i,j}; \forall r \in R \wedge t \in T \wedge i \in \{Grid, Comm\} \wedge j \in \{Import, Export\} \quad (32)$$

$$\frac{\pi_r}{100} \cdot \Delta\tau \cdot p_{r|t}^{i,Import} \leq y_{r|t}^{Price,i,Import}; \forall r \in R \wedge t \in T \wedge i \in \{Grid, Comm\} \quad (33)$$

$$\frac{-\pi_r}{100} \cdot \Delta\tau \cdot p_{r|t}^{i,Export} \leq y_{r|t}^{Price,i,Export}; \forall r \in R \wedge t \in T \wedge i \in \{Grid, Comm\} \quad (34)$$

$$z^{Bill}, q_{r|t}^{Bill,i,j}, y_{r|t}^{Price,i,j} \geq 0; \forall r \in R \wedge t \in T \wedge i \in \{Grid, Comm\} \wedge j \in \{Import, Export\} \quad (35)$$

The robust parameter  $\Gamma^{Bill} \in \mathbb{N}$  models the degree of robustness in energy pricing, in a way that the higher  $\Gamma^{Bill}$ , the more robust the scheduling result is against price volatility. On the other hand,  $\Delta\lambda$  stands for the predicted interval as depicted in Fig. 2. In principle, the robust model presented above only admits symmetrical uncertain intervals [52].

The uncertain community net demand (importable and exportable energies) can be modelled similarly, for which the constraint (5) is replaced by (36) and the additional constraints (37)-(39) have to be imposed.

$$p_{r|t}^{Comm,j} - u_t^j \cdot \hat{p}_t^{Comm,j} + z_{r|t}^{Comm,j} \cdot \Gamma^{Comm} + q_{r|t}^{Comm,j} \leq 0; \forall r \in R \wedge t \in T \wedge j \in \{Import, Export\} \quad (36)$$

$$z_{r|t}^{Comm,j} + q_{r|t}^{Comm,j} \geq y_t^{Comm,j} \cdot \Delta p_t^{Comm,j}; \forall r \in R \wedge t \in T \wedge j \in \{Import, Export\} \quad (37)$$

$$u_t^j \leq y_t^{Comm,j}; \forall t \in T \wedge j \in \{Import, Export\} \quad (38)$$

$$z_{r|t}^{Comm,j}, q_{r|t}^{Comm,j}, y_t^{Comm,j} \geq 0; \forall r \in R \wedge t \in T \wedge j \in \{Import, Export\} \quad (39)$$

where  $\Gamma^{Comm} \in \mathbb{N}$  plays the same role that  $\Gamma^{Bill}$ . Note that the robust formulation (31)-(39) extends through the representative-scenario space  $R$ . This is due to representative scenarios for prosumers' net demand are also incorporated together with the other inherent uncertainties modelled using RO. This way, both uncertainty models are hybridized and all the uncertainties are considered on a whole, as explained in Section 2. Once the robust models have been established, the proposed uncertainty-aware HEM problem can be fully described by the following optimization framework.

$$\min_{\Phi, \mathbf{z}, \mathbf{y}, \mathbf{q}} \widetilde{Bill}(\Gamma^{Bill}, \Gamma^{Comm}) \quad (40)$$

Subject to: (4), (6)-(29), (32)-(39)

where the vector  $\Phi$  encompasses the conventional HEM variables (powers, stored energy, and commitment and on/off statuses) and the vectors  $\mathbf{z}$ ,  $\mathbf{y}$  and  $\mathbf{q}$  encompass the additional variables  $z$ 's,  $y$ 's and  $q$ 's, respectively.

It is worth noting that when the representative scenario space is incorporated into the robust formulation (31)-(39) (which is derived from its original form in refs. [47, 52]) the robust properties of this formulation are not lost. Note that the robust formulation in [47, 52] is defined for a single-scenario space and their properties were well-proven in those references. In this sense, when the variable space is extended to  $r$  representative scenarios, the original formulation is just solved  $|R|$  times. Therefore, since the unique variation with respect the original robust formulation is the number of times that the problem is solved, the properties and proofs provided in [47] keep in the formulation introduced above.

One of the main drawbacks of robust optimization is that it optimizes over the worst scenario, which normally leads to conservative solutions. In this regard, distributionally robust optimization has been used as a counterpart to traditional robust problems [62, 63]. However, the proposed formulation does not consider the worst-case scenario necessarily, since the level of robustness is fixed by the robust parameters ( $\Gamma$ ). Instead, uncertainties are modelled as interval numbers and the value of the robust parameters determine if the interval is considered totally or partially. On the other hand, stochastic programming is used because its suitability to model highly volatile parameters, which cannot be easily interpreted as interval numbers. Thus, the proposed hybrid model does not present any critical disadvantage compared to distributionally robust optimization. However, it is still computationally efficient, while DRO needs to typically reformulate the original min-

max-min problem to be tractable [63]. This simplification normally leads to complex formulations that may entail high computational burdens.

#### 4 - Case study

This section presents a case study on a benchmark prosumer installation. All the simulations were run on an Intel Core i7-10700K CPU 3.80 GHz (32.00 GB RAM), taking 30-min time resolution on a 24-h time horizon. The MILP optimization model was solved using Gurobi [64] under Matlab environment, which allows a simple, efficient and amicable codification.

##### 4.1 - Data

Fig. 4 shows the expected solar irradiance and outdoor temperature affecting to the home system under study. Those profiles correspond with real data observing at Madrid (Spain) in the year 2016, and are publicly available in [65]. Fig. 4 also shows the expected non-controllable and hot water demand, whose profiles were derived from [60]. On the other hand, RTP imposed by the grid is extracted from [66], which corresponds with real-time market signals observed in PJM-FE Ohio in the year 2016. To incentive the transactions within the grid, both purchasing and selling prices are bonified by 5 %. It means that purchases from the grid are 5 % more expensive than trading within the community. The concerned home is connected to another peer who which can exchange energy under a fixed tariff of 0.025 \$/kWh [67].

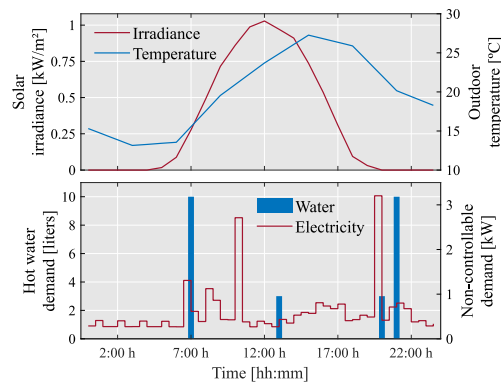


Fig. 4 - Expected weather parameters (top) and demand (bottom)

Fig. 5 shows the expected net demand drawn by the community together the scenarios derived for the connected peer. In the first case, the exportable and importable energies were constructed by progressively running different HEM problems with different non-controllable demand, whose profiles were extracted from [68]. Thus, a six-prosumer community was considered with individual rooftop PV panels ranging from 0.5 to 1.5-kWp for each dwelling. 40 % confidence intervals were imposed on these profiles to account for uncertainties. Regarding the individual peer, the scenarios were constructed similarly, taking the yearly home demand reported in [68] and considering a rooftop PV array of 0.75-kWp. Taking these data, 15 representative scenarios were extracted using the k-medoids method, as described in Section 2.2.

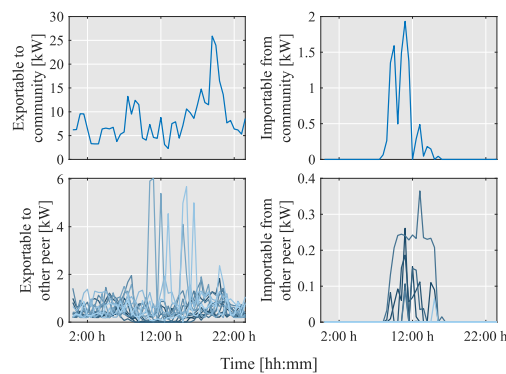


Fig. 5 - Expected exportable and importable power from the community (top) and other peer (bottom)

Thermal data of the building was taken from [19] whereas data regarding HVAC and EWH was derived from [60]. Table 2 reports the data referred to CAs, which is based on [40, 60]. A 22-kWh Renault Zoe was considered, which can be plugged to a 3.7-kW bidirectional charger [69]. The vehicle is expected to leave the home at 9:00-h considering the battery system at 60 % of its full capacity when the charging process is enabled. A Li-ion stationary battery pack is installed with 5-kWh total capacity and 2.5-kW maximum importable and exportable power. Both on-board and stationary BESs have an efficiency of 95 % in charging and discharging modes [50] and a DOD of 80 %. Lastly, the dwelling is equipped with a 1.5-kWp PV system with a panel efficiency of 16.7 % [60].

Table 2 - CAs data

<b>Appliance</b>	<b>Power</b>	<b>Duty cycle</b>	<b>Time window</b>	<b>Type</b>
Washing machine	3-kW	3-h	7:30-11:00 h	Non-interruptible
Dishwasher	2.5-kW	4-h	7:00-16:00 h	Interruptible
Dryer	2.5-kW	2-h	12:00-17:00 h	Interruptible

In order to analyse the role of storage capacity in home operation, two cases are presented and studied:

- Case 1: in which V2H capability is not enabled and stationary battery pack is not installed. This way, this scenario corresponds with a no-storage case in which the home cannot store energy to delay its usage to other more suitable time intervals.
- Case 2: in which fully storage capability with stationary BES and V2H is considered.

#### 4.2 - No robust case

Firstly, we focus on the case without involving robust approximations, in a way that formulation developed in Section 3.9 is not included in the problem. Thereby, only the connected peer's net demand is the unique considered uncertainty, which is fully described by scenarios and stochastic programming. Fig. 6 gives a summary of the different monetary balances in this case. In case of no considering storage capacity (case 1), the expected monetary expenditures reached 0.88-\$, being incremented by 86 % compared to the case 2. Hence, storage components allow to save up to 0.76-\$. Storage capacity enables a more active energy transaction with other agents. As observed, most of the energy was imported from the grid, this is due to limited importable energy from the community and other peers. In contrast, most of the energy sold was exported to the community and the other peer, due to the incentives launched by these agents. However, exportable capacity is notably limited in case of no deploying storage assets, being reduced by 84 % in case of energy exchanging with the community. This way, storage assets permit to increment the benefits obtained by the home installation, thus allowing

to compensate the higher monetary expenditures for energy exchanging with the utility grid. It is worth noting that most of the incomes come from exporting energy to the community rather than other peers, due to the limited energy that can be sent to P2P transactions.

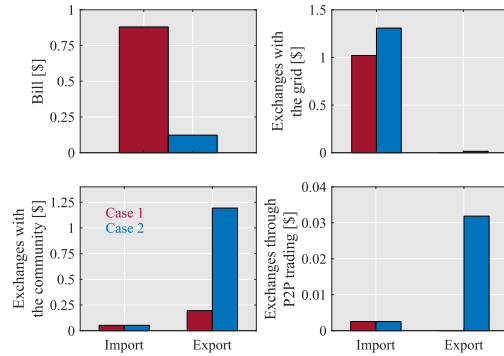


Fig. 6 - Monetary summary in case of no considering robust optimization

Fig. 7 plots the scheduling result for the domestic assets, comparing the two cases studied. As seen, in both cases, CAs are mainly scheduled during morning and midday, when PV generation is high and purchasing prices are still low. During noon, most of the domestic consumption is attributable to EV, which demands much energy to be charged before leaving the home. HVAC systems are continuously operated throughout the day whereas EWH is only occasionally scheduled when users demand hot water and the heater needs energy to keep the water tank temperature. A further view on Fig. 7 allows to compare the two cases studied and analyses the role of storage systems. As seen, V2H capability of EV is exploited during noon while stationary batteries are mainly discharged during noon and evening. Batteries are frequently charged during night in order to recover their SOC at the end of the day.

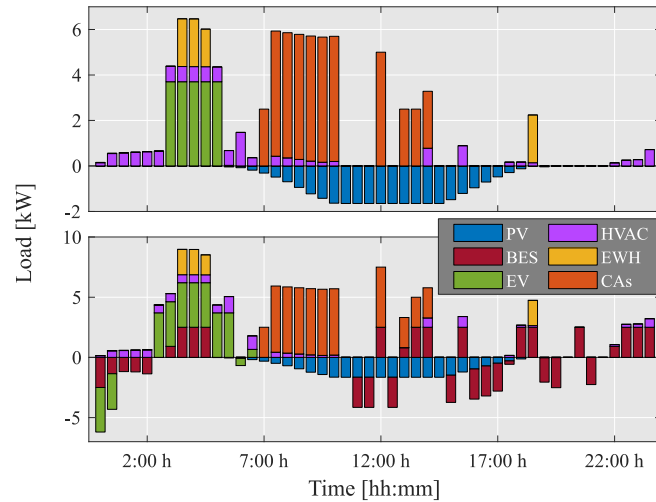


Fig. 7 - Scheduling result for domestic assets in the case 1 (top) and case 2 (bottom). In this figure, negative values indicate to-home flow direction

Similar to Fig. 7, Fig. 8 shows energy trading with the grid, the community and P2P. As observed, most of the energy is imported from the utility grid, which is due to the energy that the home can acquire from the community or other peers is limited to the predicted importable energy. In such case, the home is forced to purchase energy from the grid despite its higher cost. When BES and V2H are not enabled, the home installation is able to export energy during midday, when PV potential reaches its maximum and eventual surplus generation makes possible to export energy, mainly to the community, due to during these hours, the community selling price is higher than the energy cost agreed with other prosumers, which explains why, in contrast, the home prioritizes purchasing energy from other prosumers during afternoon. In case 2, exportable capacity is increased during noon because on-board and stationary batteries are both discharged. This way, the home exploits energy demand from the community and other peer to export energy from their storage devices and thus obtaining a monetary income. Actually, the home is largely exporting energy through the P2P mechanism during noon, due to the attractive price fixed by this trading scheme. BESs are also discharged during midday, as observed in Fig. 7. This process allows to increment the exportable capacity of the home, which leverages high energy prices to export energy community.

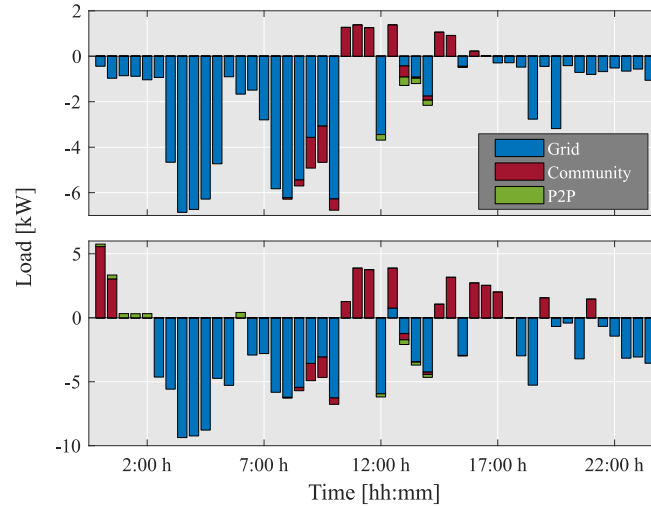


Fig. 8 - Scheduling result for energy trading with other agents in the case 1 (top) and case 2 (bottom). In this figure, negative values indicate to-home flow direction

#### 4.3 - Results with robust formulation

Now, robust formulation described in Section 3.9 is incorporated to account for uncertainties in Community's net demand and prices. This way, results are reported for various values of the robust parameters in order to examine the effect of robustness in final results. Fig. 9 shows the value of the objective function (electricity bill) for different levels of robustness. As expected, the cost is notably higher in the case 1, as explained later, being incremented in the both studied cases as  $\Gamma^{Bill}$  grows. In particular, the objective function was incremented by 25 % when  $\Gamma^{Bill}$  increases from 0 to 50. In contrast,  $\Gamma^{Comm}$  had very few impact on the energy cost (+ 0.11 %). This is due to  $\Gamma^{Bill}$  directly affects to the energy price, which has a direct effect on the monetary profile. Thus, it can be concluded that the cost of robustness for the studied cases is approximately equal to 0.29-\$ and 0.37-\$ in cases 1 and 2, respectively.

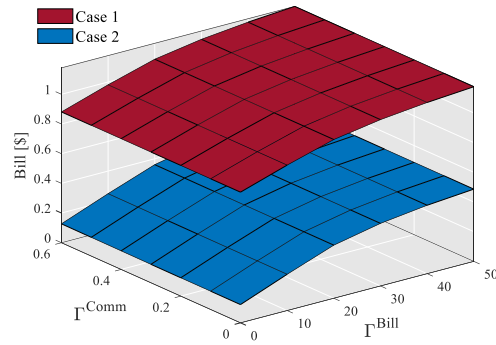


Fig. 9 - Value of the objective function for various values of the robust parameters

Intuitively, the results reported in Fig. 9 are due to the variations assumed in expected profiles of uncertainties, which are measured by the robust parameters. This is better appreciable in Fig. 10. As observed in this figure, the average purchasing price grows with  $\Gamma^{Bill}$  (from 0.044-\$/kWh to 0.059-\$/kWh), observing the opposite trend for the selling price (from 0.039-\$/kWh to 0.0243-\$/kWh). This consideration evidently increments the monetary expenditures of the home installation since the purchasing process is more expensive while reduced benefits can be obtained from exporting energy. Similarly, the energy that can be imported from the community is also reduced with  $\Gamma^{Comm}$  (from 4.88-kWh to 4.06-kWh). Thereby, the dwelling can acquire less cheap energy from the community. These results presented few variations between the cases 1 and 2. However, notable variations can be appreciated when analysing the energy that can be exported to the community. In this case, the energy that can be exported to the community at competitive prices increases with  $\Gamma^{Comm}$ . However, this index is always lower in the case 1 (~8 % with  $\Gamma^{Comm} = 0.5$ ).

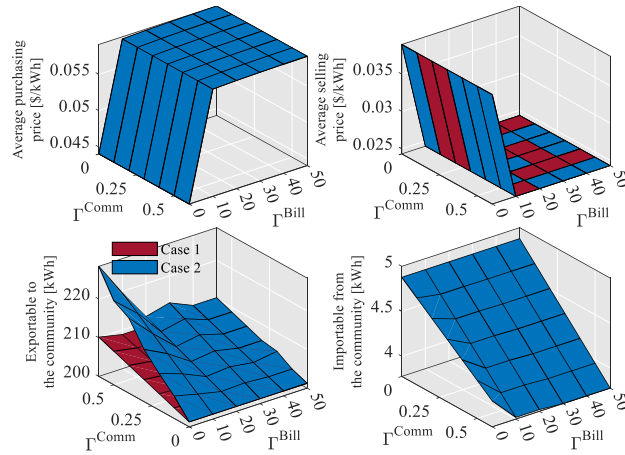


Fig. 10 - Indicative value of the uncertainties for various values of the robust parameters

The results in Fig. 10 are intimately linked with the energetic balance of the home installation, as shown in Fig. 11. As seen, the energy purchased from the grid decreases with  $\Gamma^{Bill}$  because a higher level of robustness implies higher purchasing prices. By the same reason, the total energy that is exported to the grid decreases with  $\Gamma^{Bill}$ . Instead, the scheduling mechanism import more energy from the community and the P2P mechanism, from which energy can be acquired with more competitive prices. It is worth observing the notable increment in the energy acquired from the other peer (+49 %). This is due to energy transactions through P2P trading are not subjected to uncertainty. In this sense, when the level of robustness grows, the scheduling tool prioritizes the P2P energy trading against other exchanging mechanism that are subjected to volatile prices. It is also worth noting that the energy imported from the community varies with both  $\Gamma^{Bill}$  and  $\Gamma^{Comm}$ . This is due to this index is affected by two uncertainties, i.e. energy prices and community's net demand. In general, the energy export to other agents followed the opposite trend, being generally reduced with  $\Gamma^{Bill}$ , as expected. In this regard, the scheduling mechanism always prioritized the energy transactions with the community, that are subjected to more attractive prices. It is worth noting two important results. On the one hand, the energy exported to the P2P mechanism is reduced to zero as  $\Gamma^{Bill}$  increments. This is due to, despite this transaction is not subjected to volatile prices, the

energy exchanges with the grid and the community normally compromise the exportable capacity of the dwelling, thus hindering the capacity of exporting power to other peers. On the other hand, the energy exported falls almost zero in the case 1, thus evidencing that the exportable capability of the home is intimately linked to the installed storage capacity.

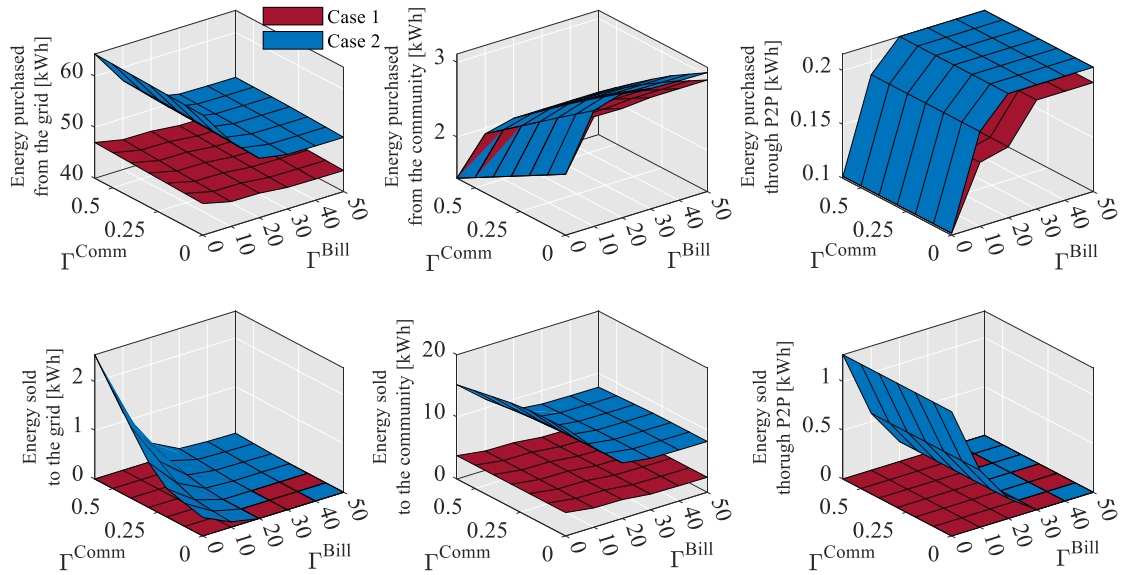


Fig. 11 - Energy transactions for various values of the robust parameters

Uncertainties and RO have a direct impact on energy transactions with the community, since these aspects determine the importable and exportable energy and therefore the amount of energy that the home can exchange with the EC. This aspect is shown in Fig. 12, where instantaneous power transactions with the community are plotted under deterministic and robust ( $\Gamma^{Bill} = 50$ ,  $\Gamma^{Comm} = 0.6$ ) conditions. As seen, most of energy transactions occur during afternoon and evening, when exportable capacity of both the home and community are high due to high PV production. It is notable how imported and exported powers are normally high under deterministic assumptions. In this case, both the home and community expect higher exportable and importable power, propitiating more frequent and profuse energy transactions. It is also worth noting how much energy is exported to the community during night from leveraging V2H capability

of EV, as explained before. However, this advantage cannot be exploited when importable power in the community is scarce, as assumed in the robust case.

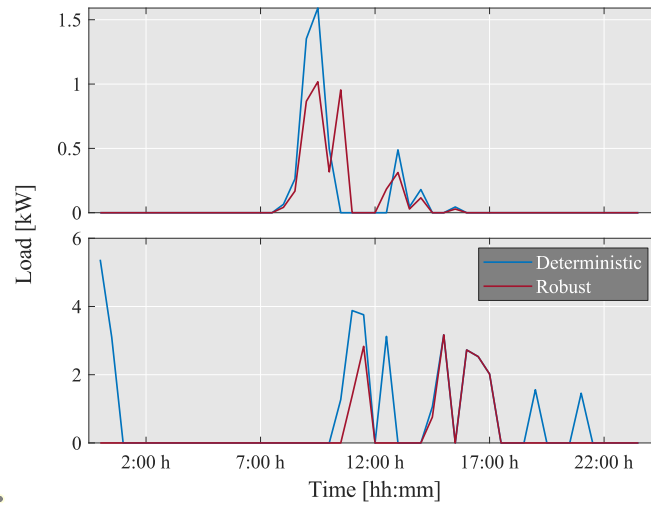


Fig. 12 - Power imported (top) and exported (bottom) from/to the community in case 2 under deterministic and robust ( $\Gamma^{Bill} = 50$ ,  $\Gamma^{Comm} = 0.6$ ) conditions

The results above outline the importance of V2H capability from on-board battery packs. This is an important indicator to decide if investments in bidirectional chargers and infrastructures are profitable or not. As seen in Fig. 13, the V2H use decreases with  $\Gamma^{Bill}$  and is very few affected by  $\Gamma^{Comm}$ . This is due to the energy exported from the EV is mostly exported to either the community or the P2P trading mechanism, as explained in Figs. 8 and 12. Thus, as the energy prices become less competitive, the V2H feature is less profitable, thus converting the vehicle in a pure load rather than a storage asset. In this situation, the marginal energy that is exported from the vehicle is mostly exported to other peers, whose energy transactions are not subjected to uncertainty, or stored in stationary BESs to be later exploited in a more optimal way.

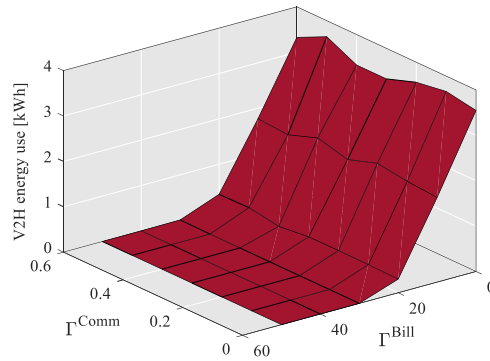


Fig. 13 - Energy exported from the EV through V2H

## 5 - Conclusions and future works

A novel stochastic-robust formulation for optimal participation of prosumers in ECs has been developed. The novel proposal allows to account for uncertainties derived in various energy transactions. Thus, trades with the utility grid, the community and other peers have been considered. The developed hybrid formulation allows to use different uncertainties modelling depending on the characteristics of each unknown parameter. This way, while predictable parameters are modelled using RO, the highly volatile uncertainties are treated using stochastic approach and scenarios. The resulting MILP formulation can be efficiently managed by average solvers.

A case study on a benchmark prosumer has been performed and various results presented, allowing us to conclude that:

- Storage assets allow a more efficient use of energy, incrementing the exportable capacity of the home installation that eventually allows to increment the monetary revenues obtained by selling energy to other agents by 84 %, which allows to reduce the electricity bill by 86 %.
- Incentives launched are of vital importance to encourage prosumers to exchange energy with communities and other peers. Otherwise, the scheduling mechanism may prioritize energy transactions with the utility grid, compromising the objectives of ECs.

- Exportable and importable energy to/from other agents directly impact on the monetary profile of the installation. Assuming more competitive prices in energy transactions with EC and other peers, the amount of energy that can be acquired/sold from/to other agents may alter the monetary balance totally. This aspect may compromise or hinder the integration or participation of other prosumers in ECs or P2P trading.

The formulation developed in this paper is versatile enough to be adapted to other layouts and casuistry. In this regard, future works should be focused on studying the optimal integration of prosumers in upscale structures like microgrids or distribution networks, thus analysing the interactions with other agents like generation companies or distribution operators.

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