# Optimal Energy Management of Cooperative Energy Communities considering Flexible Demand, Storage and Vehicle-to-Grid under Uncertainties

**Abstract.** With the advent of smart cities, residential consumers have evolved towards the concept of prosumers. This paradigm calls for new businesses like energy communities. Energy management of such frameworks is essential to maximize the collective welfare. This paper addresses this issue by developing an energy management framework that accounts for flexible demand, storage devices and electric vehicles. Its two-level structure allows to address the energy exchanging among prosumers in the 1st stage, while the 2nd stage focuses on optimally schedule the different collective assets. A novel stochastic-interval model is proposed to handle with uncertainties from demand, renewable generation, vehicles' behaviour and energy pricing. A case study is performed on a six-prosumer community. Results serve to validate the new tool and analyse the importance of smart devices. In addition, the new proposal allows to adopt different operating strategies. Actually, the total operating cost may increase by 90% if a pessimistic point of view is adopted while the importance of the vehicle-to-grid capability is marginal otherwise. Furthermore, the energy purchased could be reduced by 7% when adopting a community arrangement, supposing an improvement in the economy and environmental indicators of the network. Other relevant aspects are identified and discussed in depth.

**Keywords:** electric vehicle; energy community; energy storage; renewable energy; smart city.

**Nomenclature**

| | |
|---|---|
| Sets/Indices | |
| $i, j \in \mathbb{P}$ | Prosumer |
| $t \in \mathbb{T}$ | Time |
| $s \in \mathbb{S}$ | Scenario |
| $v \in \mathbb{V}$ | Electric vehicle |
| $b \in \mathbb{B}$ | Battery |
| $a \in \mathbb{A}^{I}/\mathbb{A}^{NI}$ | Interruptible/non-interruptible appliance |
| $\Theta$ | Allowable time window |
| Superscripts | |
| $net$ | Net load |
| $NC$ | Non-controllable load |
| $PV$ | Photovoltaic |
| $buy/sell$ | Buy/sell energy |
| $grid$ | Utility grid |
| $EC$ | Energy community |
| $EV$ | Electric vehicle |
| $BES$ | Battery energy storage |
| $det/pes$ | Deterministic/pessimistic |
| $\overline{(*)}/\underline{(*)}$ | Maximum/minimum value of a variable or parameter |
| $\widehat{(*)}$ | Expected value of an uncertain parameter |
| $\widetilde{(*)}$ | Stochastic parameter |
| $\langle * \rangle$ | Interval number |
| Parameters | |
| $P$ | Rated power of a controllable appliance (kW) |
| e2P | Energy-to-power ratio (h) |
| DOD | Depth of discharge (%) |
| $\Delta\tau$ | Time step (h) |
| $\eta$ | Efficiency (p.u.) |
| $\delta$ | Duty cycle of a controllable appliance (h) |
| $\rho$ | Probability (p.u.) |
| $\lambda$ | Energy price ($/kWh) |
| $\mu$ | Degradation cost ($/kWh) |
| Decision variables | |
| $p$ | Power (kW) |
| $\varepsilon$ | Energy (kWh) |
| $u$ | Commitment status (binary) |
| on/off | On/off status (binary) |
| $\boldsymbol{x}, \boldsymbol{u}$ | Vector of continuous/binary decision variables |

## 1 - Introduction

### *1.1 - Context & motivation*

The adverse effects of climate change are some of the main concerns for governmental agencies at present [1]. During the last decade, the global average surface temperature increased by 0.2 ºC while the sea level rose up to 3.4 mm/year [2]. These worrying signals are leading to adopt less-polluting energy policies in order to reduce greenhouse emissions [3]. Notable examples are the E.U. net zero greenhouse gas emissions target by 2050 [4]. However, electricity demand has steadily grown during the last decade [5], thus supposing a great barrier to achieving the self-imposed goals. In this regard, domestic sector supposes a large portion of the worldwide electricity consumption [6]. This way, residential buildings still present a great opportunity of reducing worldwide energy consumption and greenhouse emissions.

To reduce the amount of emissions up to almost net zeroes levels, it is essential to widely deploy renewable energy sources (RESs) and storage assets [7], in order to reduce the dependency of fossil fuels. This kind of resources can be placed far away from supplying points, in a similar way to conventional generators, or locally sited near to consumers. This emerging paradigm has changed the traditional centralized vision of the electricity sector by a decentralized fashion, in which electricity can be locally generated-stored-consumed [8]. Moreover, the local renewable generators may produce an eventual surplus generation that can benefit to other near consumers. This context calls for new business models that enable the local energy exchanging among consumers on pursuing the collective benefit [9]. When a group of consumers shares similar interests and area, they can be grouped into energy communities (ECs) that can be locally managed [10]. This emerging paradigm has been put in practise in the E.U., U.S., Australia or New Zealand, with promising results [11].

As mentioned, ECs are typically locally operated. Intuitively, optimal operation of such systems requires the use of energy management strategies [12], that are essential to operate the community in an efficient way. The new paradigm requires a further development of conventional management tools to account for local energy exchanging and cross-border energy trading with the utility network. In addition, the wide use of emerging technologies such as battery energy storage (BES) assets, electric vehicles (EVs) and controllable appliances (CAs) complicate the energy allocation and schedule within the community [13], which must be operated under strong uncertain environments caused by intermittent renewable generation, unpredictable household demand and market energy price [14]. To this end, multiple uncertainties modelling and approaches have been developed in the literature for hybrid energy or multi-carrier systems [14, 15]. However, this topic has received little attentions in ECs. In this context, it is necessary to revisit the existing energy management tools in order to tailor them to ECs. This paper tackles this issue.

### *1.2 - Energy management in ECs: literature review*

Long et al [16], developed a peer-to-peer (P2P) strategy based on a bi-level optimization framework, by which the day ahead scheduling plan is performed at the upper level, whereas a rule-based mechanism adjusts the set-points in the lower level by observing real-time measurements. In [17], a mixed-integer nonlinear programming (MINLP) model was developed to jointly design and operate a multi-energy community. The model is based on the decomposition of the system into tractable sub-networks, with the aim of reducing the complexity of calculations. A game-based P2P trading coordination was developed in [18], with the aim of determining the best energy allocation among buyers and sellers in a prosumer community. In this regard, an M-leader and N-follower Stackelberg game approach are used to model interactions between buyers and sellers, using different evolutionary algorithms to solve the optimization framework.

Feng et al, proposed in [19] a coalitional game-based energy management tool for local trading among prosumers within a local EC. The mathematical model accounts for flexible loads that can curtail their consumption according to suited satisfaction functions. However, interruptible and non-interruptible loads were not considered while further possibilities of EVs like vehicle-to-grid (V2G) were not studied. The article [20] develops a day-ahead scheduling for cooperative ECs, based on the alternating direction of multipliers. The model is mixed-integer linear programming (MILP) and encompasses BESs, but flexible loads, EVs and uncertainties were not discussed. Ref. [21] proposes a stochastic-based day-ahead scheduling tool for ECs. The problem is a MILP and a Markovian-based approach is used to model the intermittent behaviour of RESs.

A two-stage scheduling process for local ECs was developed in [22]. This model accounts for BESs and EVs as flexible resources, and it is capable of participating in ancillary services such as frequency reserves. The ref. [23] focuses on the possible intention of prosumers to trade green energy, even when renewable generation entails higher expenditures. Keeping this in mind, a P2P trading strategy is proposed with the aim of maximizing the social welfare while the level of CO2 emissions is reduced. In a similar way, the ref. [24] focuses on the impact of human decisions in P2P energy trading within communities. To this end, prospect models are developed to account for the human thinking and, in this way, including this kind of attitudes within the energy management framework.

Gough et al [25], developed a transactive energy framework for connected virtual power plants that, in essence, can work as an EC. To enable a fair and decentralized energy trading, a blockchain trading mechanism is proposed for the different agents involved in the operation of the system. In [26], an evolutionary-based algorithm was proposed for energy management in a nearly zero-energy community. In this work, the influence of different parameters is discussed and their impact on the self-sufficiency level is highlighted. An internal energy trading for customer-owned BESs is discussed in [27]. In this paper, besides the self-sufficiency of the prosumers within an EC, energy trading among storage assets is carried out through a local transactive market mechanism.

Alternative energy storage assets are analysed in [28], where a P2P trading framework for net-zero energy communities is presented, accounting for hydrogen vehicles. The studied trading scheme exploits the energy stored in vehicles to increase the flexibility and self-sufficiency of the system. Liu et al [29] presented a hybrid evolutionary algorithm for energy management of a multi-energy community, which encompasses three energy carriers: electricity, cold and heat. A two-stage market mechanism for ECs was developed in [30]. The developed model establishes the day ahead market auction at the upper level, while the second layer is devoted to adjusting the scheduling plan of each agent based on one-shot auctions. Javadi et al [31] proposed a pool trading mechanism for communities of smart prosumers. This proposal considers smart energy management in dwelling by performing individual home energy management systems, which account for possible energy trading among prosumers within the community.

### *1.3 - Research gaps & contributions*

Table 1 presents a summary of the main characteristics of the studied literature. As deduced from the above, energy management in ECs is still an open topic which offers multiple research opportunities. For example, the role of EVs and CAs has not been widely studied, only exploring some simple mechanisms to manage these assets in cooperative communities. Moreover, uncertainties modelling in EC operation have received little attentions, only recurring to conventional stochastic models, while other more sophisticated methodologies have not been applied yet. In this regard, this work presents various advantages and improvements with respect to other previously published works:

- The developed formulation is a MILP, which can be efficiently solved using commercial packages. In addition, its structure is versatile enough to be easily adapted to different layouts [32], while its good scalability is ensured, being so valuable for larger communities [33].
- Besides conventional storage systems formed by batteries, opportunities for EVs are fully exploited though V2G capabilities.
- Different types of CAs are considered and modelled, with the aim of reflecting the different behaviours of smart domestic appliances as well as the possible flexibility derived from different operational modes.
- Uncertainties from RESs, domestic loads, EVs and energy pricing are fully considered. For which, a hybrid stochastic-interval methodology is proposed, supposing the first attempt to apply such formulation in ECs.

**Table 1.** Taxonomy of the related literature

| **Ref.** | **Formulation** | **BES** | **V2G** | **CAs** | **Uncertainties** |
|---|---|---|---|---|---|
| [16, 17] | MINLP | Yes | No | No | No |
| [18, 30] | Game-based | Yes | No | No | No |
| [19] | Game-based | Yes | No | Curtailable | Stochastic |
| [20] | MILP | Yes | No | No | No |
| [21] | MILP | Yes | No | No | Stochastic |
| [22-24, 27] | MILP | Yes | No | No | No |
| [25] | MILP | Yes | Yes | Non-interruptible | No |
| [26, 29] | Metaheuristic | Yes | No | No | No |
| [28] | Heuristic | Yes | Yes | No | No |
| [31] | MILP | Yes | No | Non-interruptible | No |
| Present | MILP | Yes | Yes | Interruptible<br>Non-interruptible | Stochastic-Interval |

Therefore, this paper contributes with a novel energy management tool for cooperative ECs, which, in contrast to most of related papers, effectively account with common uncertainties in such structures. For the sake of clarity, the main contributions of this paper are summarized below:

- Developing a novel formulation for energy management in cooperative ECs, which account for uncertainties, different types of CAs and V2G capability from EVs. This proposal is based on an original stochastic-interval formulation, which is founded in the fact that energy profiles of prosumers and EVs can be predicted with acceptable confidence, while the energy price may follow unpredictable patterns.
- Developing an iterative solution procedure, which allows to adopt optimistic or pessimistic perspectives. This way, the effect of uncertainties can be quantified and decisions from operator can be taken in a fairer manner.
- Presenting a case study for a cooperative EC with six prosumers and various results are discussed. This case allows to analyse in depth the role of CAs and EVs in EC operation, as well as to validate the developed methodology.

In the rest of this paper, Section 2 overviews the study EC and its operating procedure. Section 3 presents the mathematical modelling of the optimization problem. Section 4 develops an iterative solution procedure, including stochastic-interval formulation as well as different operating strategies. Section 5 presents a case study with results. Finally, the main conclusions are duly drawn in Section 6.

## 2 - Background

### *2.1 - EC layout*

Fig. 1 shows a pictorial representation of the studied EC. The studied community, formed by prosumers, that actuate in a cooperative way sharing resources. In this regard, it is assumed that each prosumer is equipped with a rooftop photovoltaic (PV) panel, and counts with a storage asset (either BES or EV) and CAs. This way, all the prosumers can be coordinated in a fair way, thus contributing similarly to the collective welfare. For simplicity, it is assumed that all the prosumers are connected to the same distribution line and geographically near to each other, which is a reasonable assumption in ECs [19]. Each prosumer installation is connected to the grid through a proper metering infrastructure, that enable a flexible control from a centralized operator. Thereby, both storage devices and appliances can be controlled by means of demand response programs based on decision variables [34]. Finally, the EC is connected to an upstream grid owned by a local utility, from which can exchange energy with an associated cost.

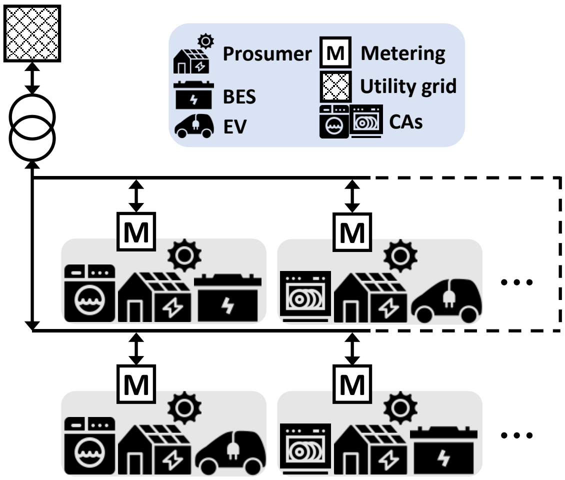

**Fig. 1.** Pictorial representation of the EC under study

*2.2 - EC operational principle*

This paper proposes an operational procedure for the EC under study decomposed into two layers. In the 1st layer, the unique concern is the energy exchanging among prosumers, without accounting for CAs and storage assets. This process is scheduled by the EC operator in a centralized way. This agent forecasts the demand and PV generation of the different prosumers, and adds confidence intervals in order to take into consideration possible deviations. With this information, the prosumers energy allocation plan is obtained. As a by-product of this stage, the exportable/demanded power by the prosumers to/from the community is derived. This result serves as input of the 2nd layer, in which the storage assets, and CAs play the main role. At this stage, the operator schedules the different assets on pursuing the most economic operation of the system, and determines the power that can be exchanged with the grid in order to satisfy the local consumption or obtain an economic profit by selling energy. To this end, uncertainties associated with EVs and energy pricing must be considered [35]. As described later, different uncertainty models are taken for each unknown parameter, resulting in an original hybrid framework. For the sake of simplicity, Fig. 2 schematizes the operational foundations for the studied EC.

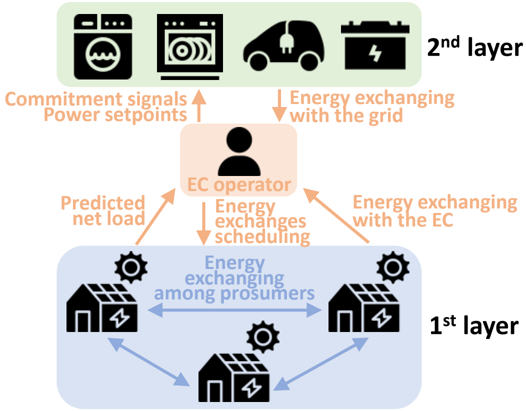

**Fig. 2.** Sketch of the proposed operational principle for the EC under study

A major novelty of the developed framework is the ability to identify the domestic storage assets and CAs as collective units. The individual operation of these devices may hide some opportunities that are only unlocked when they are operated in a collective way, aggregating their characteristics [36]. For example, the storage capacity of grid-connected homes is normally very limited [37], which may bound the benefits that a collective storage asset with higher capacity can offer to the community. In this regard, the aggregation of the storage capacity and flexibility of CAs is more beneficial than operating them individually. The developed scheduling mechanism depicted in Fig. 2 identifies and exploits this advantage in benefit of the collective welfare.

## 3 - Mathematical modelling

The operation of the EC under study is posed as an optimization problem decomposed into two stages. The first one is devoted to the 1st layer described above, while the second stage solves the 2nd layer and therefore defines the energy exchanging with the grid. Each stage is properly formulated and explained in subsequent sections.

*3.1 - 1st layer: energy exchanging among prosumers*

Once the demand and PV generation of each prosumer is predicted (or the information is provided by the users), the operator adds confidence intervals, in order to take into consideration possible forecast errors. On the basis of this information, the expected, maximum and minimum net demand is calculated for each prosumer, as follows:

$$\begin{cases} \overline{p}_{i|t}^{net} = \overline{p}_{i|t}^{NC} - \underline{p}_{i|t}^{PV} \\ \underline{p}_{i|t}^{net} = \underline{p}_{i|t}^{NC} - \overline{p}_{i|t}^{PV}; \ \forall i \in \mathbb{P} \wedge t \in \mathbb{T} \\ \hat{p}_{i|t}^{net} = \hat{p}_{i|t}^{NC} - \hat{p}_{i|t}^{PV} \end{cases} \tag{1}$$

It is assumed that each prosumer is keen to use its own PV generation to satisfy its demand individually, and only eventual surplus energy is available for exchanging. According to the expressions above, if the net power is higher than zero, the prosumer requires energy to meet its own demand, thus having to purchase it from other prosumers, if possible. In contrast, if the net power is negative, it means that surplus energy from PV panels is available, which can be exported in benefit of other prosumers. If the rest of prosumers cannot exploit the energy supplied by others, the remaining energy is passed to the second layer to be further used. Likewise, if the other prosumers cannot cover the instantaneous demand of the other agents, it should be supplied by other means at the 2nd layer. The mathematical modelling of this stage is completed by the constraints (2)-(5).

$$p_{i\to j|t}^{sell} - p_{j\leftarrow i|t}^{buy} = 0; \forall i, j \in \mathbb{P} \wedge t \in \mathbb{T} \tag{2}$$

$$\sum_{\substack{j\in\mathbb{P} \\ j\neq i}} \left\{p_{i\to j|t}^{sell}\right\} + p_{i|t}^{sell\_EC} + p_{i|t}^{net} = \sum_{\substack{j\in\mathbb{P} \\ j\neq i}} \left\{p_{i\leftarrow j|t}^{buy}\right\} + p_{i|t}^{buy\_EC}; \ \forall i \in \mathbb{P} \wedge t \in \mathbb{T} \tag{3}$$

$$u_{i|t}^{buy\_EC} + u_{i|t}^{sell\_EC} \leq 1; \ \forall i \in \mathbb{P} \wedge t \in \mathbb{T} \tag{4}$$

$$p_{i\rightarrow j|t}^{m} + p_{i|t}^{m\_EC} \leq u_{i|t}^{m} \cdot \overline{p}_{i};\ \forall i,j \in \mathbb{P} \wedge t \in \mathbb{T} \wedge m \in \{buy, sell\} \tag{5}$$

Constraint (2) represents the equilibrium in the power exchanged between the $i^{th}$ and $j^{th}$ prosumers at time $t$. Eq. (3) is the individual power balance of each prosumer. Constraint (4) avoids the simultaneous purchases and sales by the same prosumer [20], which is complemented with the Eq. (5), that limits the power that can be exported/purchased to/from by each prosumer.

The operator aims at satisfying as much energy as possible through the mechanisms enabled at the 1st stage since, in this way, the energy that must be purchased from the grid is minimized. The 1st layer should be solved three times, considering the possible scenarios depicted in (1). Thereby, the 1st layer of the developed operational foundation can be mathematically formulated as follows:

$$Energy_{buy} = \Delta\tau \cdot \sum_{t\in\mathbb{T}} \sum_{i\in\mathbb{P}} \left\{ p_{i|t}^{buy\_EC} \right\} \tag{6}$$

$$\begin{cases} \overline{p}_{t}^{buy\_EC}, \underline{p}_{t}^{sell\_EC} \leftarrow \min\limits_{x, u_{i|t}^{buy}, u_{i|t}^{sell}} Energy^{buy}\left(\overline{p}_{i|t}^{net}\right) \\ \underline{p}_{t}^{buy\_EC}, \overline{p}_{t}^{sell\_EC} \leftarrow \min\limits_{x, u_{i|t}^{buy}, u_{i|t}^{sell}} Energy^{buy}\left(\underline{p}_{i|t}^{net}\right) \\ \hat{p}_{t}^{buy\_EC}, \hat{p}_{t}^{sell\_EC} \leftarrow \min\limits_{x, u_{i|t}^{buy}, u_{i|t}^{sell}} Energy^{buy}\left(\hat{p}_{i|t}^{net}\right) \end{cases} ;\forall i \in \mathbb{P} \wedge t \in \mathbb{T} \tag{7}$$

Subject to: (2)-(5)

### *3.2 - 2nd layer: BESs, EVs and CAs scheduling*

At the 1st layer, storage assets, and CAs were not considered. It is assumed that all the prosumers act in a cooperative way, and therefore these devices are considered collective assets that are scheduled in the manner of maximizing the community welfare [20]. The 2nd layer is therefore devoted on scheduling such equipment to improve the economy of the system. Subsequent sections describe the different mathematical models considered at this stage.

#### 3.2.1 - Interval construction

Interval optimization has been widely considered for uncertainties modelling in energy management problems [39, 40]. This approach consists of taking advantage of the confidence intervals that are inherent to possible forecast errors, and thus reproduce uncertainty-aware optimization results. Hence, this formulation is very suitable to model those uncertainties that can be forecasted with acceptable accurateness (e.g. PV generation or non-controllable household demand).

In this paper, interval notation is considered to formulate the uncertainly associated with the net power drawn by the consumers. This information results in the exportable energy from the 1st layer, as well as the energy that cannot be covered through energy exchanges among prosumers. This energy should be provided at the second stage and depending on the net power calculated in (1) will result in expected, minimum and maximum profiles, as expressed in (7). Instead of conventional interval arithmetic that poses large and complex mathematical formulations [38], this paper uses the interval notation proposed in [40], which is notably simpler and more easily tractable. By this approach, the power that must be accommodated in the second stage can be formulated as follows:

$$\langle p_t^{m\_EC} \rangle = \left\{ p_t^{m\_EC} \middle| \underline{p}_t^{m\_EC} \leq \hat{p}_t^{m\_EC} \leq \overline{p}_t^{m\_EC} \right\};\ \forall t \in \mathbb{T} \wedge m \in \{buy, sell\} \tag{8}$$

As seen, the extreme values calculated in (7) are used to model the bounds of the variable. Likewise, the initial energy stored in EVs is considered unknown as this parameter depends on unpredictable driving behaviour of users [41]. In this sense, the following approach is considered for EVs.

$$\langle \varepsilon_{v,0}^{EV} \rangle = \left\{ \varepsilon_{v,0}^{EV} \middle| \underline{\varepsilon}_v^{EV} \leq \hat{\varepsilon}_{v,0}^{EV} \leq \overline{\varepsilon}_v^{EV} \right\}; \forall v \in \mathbb{V} \tag{9}$$

$$\hat{\varepsilon}_{v,0}^{EV} = \frac{\overline{\varepsilon}_v^{EV} - \underline{\varepsilon}_v^{EV}}{2}; \forall v \in \mathbb{V} \tag{10}$$

In this paper, it is assumed that EV owners communicate their departure times to the operator, which is reasonable in order to reduce the uncertainty burden of the problem

[22]. On the other hand, current smart chargers normally exploit off-peak hours to charge the on-board storage system. Keeping this in mind, it is assumed that charging process is only enabled from 0:00 h [42]. In this regard, time windows of EVs have been considered deterministic.

### 3.2.2 - Community balance

Eq. (11) draws the community power balance, which accounts for BESs, CAs, EVs and energy exchanging with the utility grid. It is noteworthy that results from the 1st layer are formulated as interval numbers according to (8).

$$\langle p_t^{sell\_EC} \rangle + p_{s|t}^{buy\_grid} + p_{s|t}^{BES,dch} + \sum_{v \in \mathbb{V}} \left\{ p_{s|t|v}^{EV,dch} \right\} = \langle p_t^{buy\_EC} \rangle + p_{s|t}^{sell\_grid} + p_{s|t}^{BES,ch} + \sum_{v \in \mathbb{V}} \left\{ p_{s|t|v}^{EV,ch} \right\} + \sum_{a \in \{\mathbb{A}^I \cup \mathbb{A}^{NI}\}} \{ u_t^a \cdot P^a \} \, ; \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \tag{11}$$

It is realistic to assume that power exchanged with the grid is upper bounded by physical or contractual limits [37], as expressed (12), whereas the constraint (13) avoids the simultaneous sales and purchases with the upscale network.

$$p_{s|t}^{m\_grid} \leq u_t^{m\_grid} \cdot \overline{p}^{grid} ; \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \wedge \ m \in \{buy, sell\} \tag{12}$$

$$u_t^{buy\_grid} + u_t^{sell\_grid} \leq 1; \ \forall t \in \mathbb{T} \tag{13}$$

We call the reader's attention on the fact that an aggregated model has been considered for BESs, for simplicity [27]; while this approach has not been taken for EVs and CAs as explained later.

### 3.2.3 - BES modelling

It is assumed that individual battery assets are stationary and therefore available during the entire time horizon. By this reason, an aggregated model has been considered, which notably reduces the number of constraints and therefore the size of the problem. According to this, the maximum power that BESs can exchange with the community is fixed by the total capacity and individual energy-to-power ratios [43], as said the constraint (14). On the other hand, Eq. (15) makes the changing and discharging processes complementary.

$$p_{s|t}^{BES,i} \leq u_t^{BES,i} \cdot \sum_{b\in\mathbb{B}}\left\{\frac{\overline{\varepsilon}_b^{BES}}{\mathrm{e2P}_b}\right\};\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \wedge i \in \{ch, dch\} \tag{14}$$

$$u_t^{BES,ch} + u_t^{BES,dch} \leq 1;\ \forall t \in \mathbb{T} \tag{15}$$

Eq. (16) models the dynamics of batteries, yielding the available state-of-charge of storage assets. Constraint (17) limits the energy stored in BESs by the total capacity and individual depth-of-discharge settings. Finally, Eq. (18) sets the initial and final state-of-charge of the BESs.

$$\varepsilon_{s|t}^{BES} = \varepsilon_{s|t-1}^{BES} + \Delta\tau \cdot \left(\eta^{BES,ch} \cdot p_{s|t}^{BES,ch} - \frac{p_{s|t}^{BES,dch}}{\eta^{BES,dch}}\right);\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \backslash t > 1 \tag{16}$$

$$\sum_{b\in\mathbb{B}}\left\{\frac{100-\mathrm{DOD}_b}{100} \cdot \underline{\varepsilon}_b^{BES}\right\} \leq \varepsilon_{s|t}^{BES} \leq \sum_{b\in\mathbb{B}}\left\{\overline{\varepsilon}_b^{BES}\right\};\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \tag{17}$$

$$\varepsilon_{s|1}^{BES} = \varepsilon_{s|\mathrm{end}}^{BES} = \sum_{b\in\mathbb{B}}\left\{\overline{\varepsilon}_b^{BES}\right\};\ \forall s \in \mathbb{S} \tag{18}$$

### 3.2.4 - EVs modelling

In contrast to stationary storage systems, EVs are not plugged at any time instant and therefore cannot be scheduled during the entire time horizon [44]. In this sense, EVs have been modelled individually instead of using an aggregated model, thus allowing to present different time windows according the individual users' preferences. Hence, while the constraints (19)-(21) are analogue to (14)-(16), the expressions (22)-(24) are particular in the case of vehicles.

$$p_{s|t|v}^{EV,m} \leq u_{t|v}^{EV,m} \cdot \overline{p}_v^{EV};\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \wedge v \in \mathbb{V} \wedge m \in \{ch, dch\} \tag{19}$$

$$\varepsilon_{s|t|v}^{EV} = \varepsilon_{s|t-1|v}^{EV} + \Delta\tau \cdot \left(\eta^{EV,ch} \cdot p_{s|t|v}^{EV,ch} - \frac{p_{s|t|v}^{EV,dch}}{\eta^{EV,dch}}\right);\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \backslash t > 1 \wedge v \in \mathbb{V} \tag{20}$$

$$\underline{\varepsilon}_v^{EV} \leq \varepsilon_{s|t|v}^{EV} \leq \overline{\varepsilon}_v^{EV};\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \wedge v \in \mathbb{V} \tag{21}$$

$$\sum_{t\notin\Theta^v}\left\{u_{t|v}^{EV,ch} + u_{t|v}^{EV,dch}\right\} = 0; \forall v \in \mathbb{V} \tag{22}$$

$$\varepsilon^{EV}_{s|\Theta^{v}(\text{end})|v} = \overline{\varepsilon}^{EV}_{v};\ \forall s \in \mathbb{S} \wedge v \in \mathbb{V} \tag{23}$$

$$\varepsilon^{EV}_{s|1|v} = \langle \varepsilon^{EV}_{v,0} \rangle;\ \forall s \in \mathbb{S} \wedge v \in \mathbb{V} \tag{24}$$

Constraint (22) avoids to schedule each EV when it is not parked at home. Eq. (23) assumes that each EV must be fully charged at its departure time while the initial state-of-charge of each vehicle is modelled as an interval number in (24), being so linked with (9) and (10).

### 3.2.5 - CAs modelling

In this paper, interruptible and non-interruptible appliances are considered [44]. The formers can be interrupted while the latter not, therefore, once it has been scheduled, their duty cycle must be completed without interrupting their operation. In both cases, the imposed duty cycles must be fulfilled within predefined time windows, as said (25), while (26) and (27) model the continuous operation principle of non-interruptible appliances.

$$\textstyle\sum_{t \in \Theta^{a}} \{u^{a}_{t}\} = \frac{\delta^{a}}{\Delta\tau};\ \forall a \in \{\mathbb{A}^{I} \cup \mathbb{A}^{NI}\} \tag{25}$$

$$u^{a}_{t} - u^{a}_{t-1} = \text{on}^{a}_{t} - \text{off}^{a}_{t};\ \forall t \in \mathbb{T} \backslash t > 1 \wedge a \in \mathbb{A}^{NI} \tag{26}$$

$$\textstyle\sum_{t \in \mathbb{T}} \{\text{on}^{a}_{t}\} = 1;\ \forall a \in \mathbb{A}^{NI} \tag{27}$$

### 3.2.6 - Interval constraints

As mentioned, the results of the 1st layer together the initial energy stored in EVs are assumed to be unknown and modelled as interval numbers. By this approach, these variables are allowed to vary within their predicted intervals, as said the constraints (28) and (29).

$$\underline{p}^{m\_grid}_{t} \le \langle p^{m\_grid}_{t} \rangle \le \overline{p}^{m\_grid}_{t};\ m \in \{buy, sell\} \tag{28}$$

$$\underline{\varepsilon}^{EV}_{v} \le \langle \varepsilon^{EV}_{v,0} \rangle \le \overline{\varepsilon}^{EV}_{v}; \forall v \in \mathbb{V} \tag{29}$$

### 3.2.7 - Objective function

The EC operator aims at minimizing the operational cost of the community, which is equivalent to maximizing the collective welfare. In the studied case, the operational cost can be expressed as follows:

$$F = \sum_{s\in\mathbb{S}} \left\{ \rho_s \cdot \Delta\tau \cdot \left\{ \sum_{t\in\mathbb{T}} \left\{ \tilde{\lambda}_{s|t}^{buy} \cdot p_{s|t}^{buy\_grid} - \tilde{\lambda}_{s|t}^{sell} \cdot p_{s|t}^{sell\_grid} + \mu^{BES} \cdot \left( p_{s|t}^{BES,ch} + p_{s|t}^{BES,dch} \right) + \mu^{EV} \cdot \sum_{v\in\mathbb{V}} \left\{ p_{s|t}^{EV,ch} + p_{s|t}^{EV,dch} \right\} \right\} \right\} \right\} \quad (30)$$

The expression (30) accounts for the monetary balance of energy exchanging with the utility grid, assuming stochastic modelling of both purchasing and selling prices. Nevertheless, it also includes degradation costs of storage assets. Thereby, it is assumed that prosumers receive a payment to compensate the degradation suffered by storage devices due to their use [45].

## 4 - The developed solution procedure

The proposed mathematical formulation encompasses two uncertainties modelling. On the one hand, the results of the 1st layer together the initial state-of-charge of EVs are both modelled using interval numbers. On the other hand, the energy price is modelled via scenarios. To accommodate both models, a solution procedure has been developed, which carries out various stages. Fig. 3 shows a flowchart of the developed methodology. As observed, the predicted PV generation and non-controllable demand as well as scenarios for energy pricing serve as inputs, along other necessary parameters. Then, the two formulated stages are sequentially solved posing MILP problems that are easily manageable by standard solvers. Also, the 2nd layer is divided into different sub-stages with the aim of accounting for the considered interval notation. Subsequent sections describe in detail the different steps of the developed solution procedure.

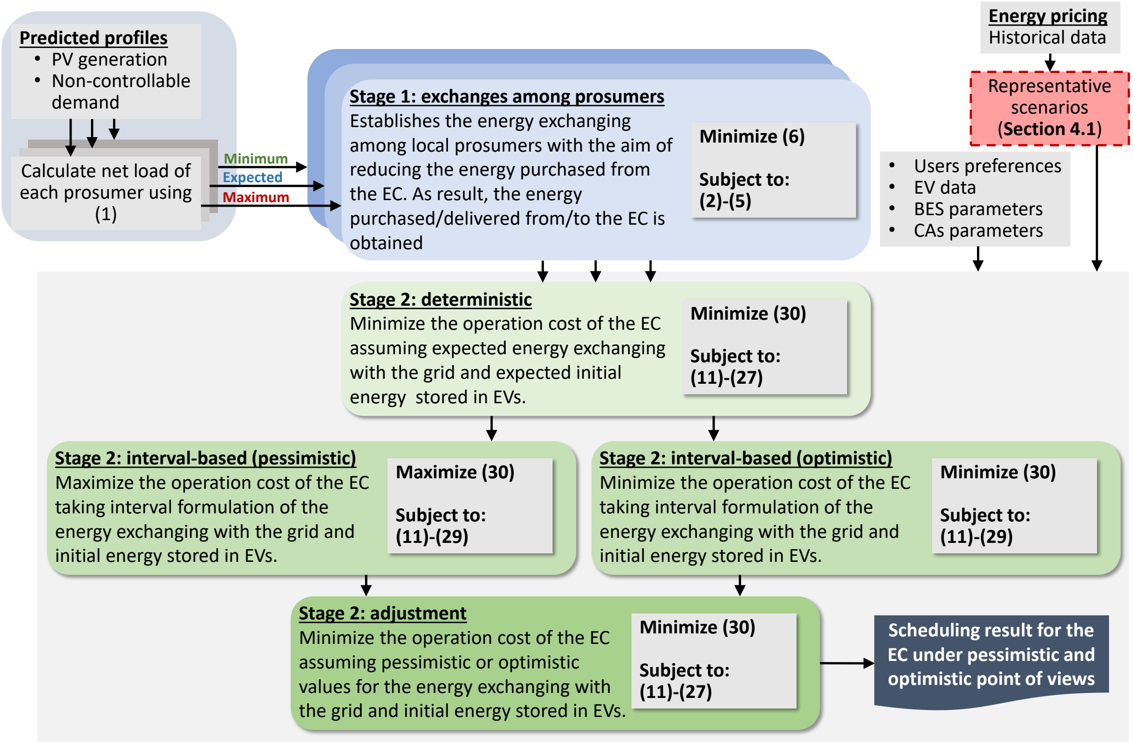

**Fig. 3.** Flowchart of the developed solution procedure

### *4.1 - Representative scenarios*

In contrast to flat tariffs, different dynamic pricing mechanisms have been successfully applied in order to encourage consumers to actively partake in the operation of power systems [46]. Representative examples are time-of-use or real-time-pricing schemes. Whereas time-of-use tariffs are fixed and therefore known, real-time-pricing might be highly unpredictable due to a variety of reasons [47]. However, this pricing mechanism is assumed to be the most suitable for ECs, since it reflects the generation-consumption profile any time instant and taxes the energy purchasing accordingly. For example, the energy pricing is usually low (or even negative) during hours with high renewable penetration, while price will rise during generation deficit in order to reduce the consumption.

By the reasons above, the energy pricing may be hardly predictable and therefore the interval notation is not suitable. In this regard, energy prices have been modelled using scenarios. Stochastic modelling is a probabilistic approach that can use historical information or suited probability functions [48]. In this work, the first approach has been considered assuming that historical profiles can be easily extracted from public databases (e.g. [49]). In any case, a high number of scenarios should be generated in order to faithfully catch the stochastic character of the parameter [50]. However, such amounts of information may entail intractability issues. To circumvent this problem, many papers have used clustering techniques [51]. These techniques reduce a group of data to a minimum set of representative members. This way, only the representative members have to be evaluated instead of all the scenarios. Among the variety of clustering techniques available in the literature, the k-medoids method has been used because its good overall features [52]. To determine the most suitable number of representative profiles to be considered, the methodology described in [53], has been considered in this work, which is based on helpful indicators like the Davies-Bouldin index [54]. Thus, the total number of clusters (i.e. representative scenarios) is progressively increased observing the value of the Davies Bouldin index and the total sum of distances. Once these two indicators are not further enhanced, the number of representative scenarios is determined in order to obtain a trade-off between computational implications and accuracy.

### *4.2 - Interval-based sub-problems*

According to the flowchart plotted in Fig. 3, the Stage 1 of the developed methodology is performed from a deterministic point of view. However, this stage is carried out three times considering the expected, maximum and minimum values of the non-controllable demand and PV generation of each consumer. This procedure allows to determine the energy to deliver/acquire to/from the EC as an interval number, as detailed in Section 3.1. This information is transferred to the Stage 2, which is devoted on yielding the uncertainty-aware scheduling result of the EC. To this end, a multi-step methodology has been designed, inspired by [40, 55], which avoids the implicit use of interval arithmetic, thus reducing the complexity of the problem notably. This procedure allows to contemplate pessimistic or optimistic point of views, depending on the impact of uncertainties [40]. These strategies can be assimilated to the risk-averse and risk-seeker strategies described in [56], respectively.

In the first step, the Stage 2 is solved from a deterministic point of view, assuming expected values of the net loads and initial state-of-charge of EVs, which is expressed in the following optimization problem.

$$\boldsymbol{u}^{det} \rightarrow \underset{\boldsymbol{x},\boldsymbol{u}}{\operatorname{argmin}}\, F\left(\hat{p}_t^{m\_grid}, \hat{\varepsilon}_{v,0}^{EV}\right);\ \forall t \in \mathbb{T} \wedge v \in \mathbb{V} \wedge m \in \{buy, sell\} \tag{31}$$

Subject to (11)-(27)

Assuming the commitment result yielded in (31), the problem seeks for the most unfavourable or favourable values of the interval uncertainties, depending on the operational strategy assumed (pessimistic or optimistic, respectively). This is achieved by solving the following optimization problem.

$$\begin{cases} p_t^{m\_EC\_pes}, \varepsilon_{v,0}^{EV\_pes} \rightarrow \underset{\boldsymbol{x}, p_t^{m\_EC}, \varepsilon_{v,0}^{EV}}{\operatorname{argmax}}\ F(\boldsymbol{u}^{det}) \\ p_t^{m\_EC\_opt}, \varepsilon_{v,0}^{EV\_opt} \rightarrow \underset{\boldsymbol{x}, p_t^{m\_EC}, \varepsilon_{v,0}^{EV}}{\operatorname{argmin}}\ F(\boldsymbol{u}^{det}) \end{cases};\ \forall t \in \mathbb{T} \wedge v \in \mathbb{V} \wedge m \in \{buy, sell\} \tag{32}$$

Subject to (11)-(29)

As seen, the problem (32) seeks the variation of the interval uncertainties by maximizing or minimizing the objective function. Thus, if the objective is to maximize the operational cost, the problem adopts a pessimistic perspective while an optimistic strategy is assumed otherwise. To this end, unlike to the problem (31), the uncertainties are allowed to vary within predefined intervals according to (28) and (29). Finally, assuming the calculated uncertain profiles, the last stage consists of adapting the commitment result to the new interval profiles, as expressed (33).

$$\min_{\boldsymbol{x},\boldsymbol{u}} F\left(p_t^{m\_EC\_p}, \varepsilon_{v,0}^{EV\_p}\right);\ \begin{matrix} \forall t \in \mathbb{T} \wedge v \in \mathbb{V} \wedge m \in \{buy, sell\} \\ p = pes \vee opt \end{matrix} \tag{33}$$

Subject to (11)-(27)

## 5 - Case study

This section presents a case study with the aim of validating the developed solution methodology as well as analysing the role of BESs, EVs and CAs in the operation of ECs. The presented mathematical formulation is a MILP and has been coded under Matlab R2020a, using Gurobi as solver [57]. This tool offers free licenses for academic and research purposes. The different optimization problems were run on an Intel® Core™ i7-10700 K CPU @3.80 GHz (32 GB RAM). All the simulations were performed over a 24-h time horizon with 30-min resolution ($\Delta\tau = 0.5$ hrs), consuming 5-10 minutes by average for a medium-scale EC with six prosumers. This computational burden is perfectly assumable for energy management tools [58]; in addition, its MILP structure ensures its good scalability to larger problems [59].

### *5.1 - Data*

A benchmark EC formed by six residential prosumers is studied. Each prosumer can exchange up to 5 kW with others, while the community can transfer 50 kW to the utility grid. The expected non-controllable demand and PV generation for each prosumer is plotted in Fig. 4, which were extracted from the real datasets in. In particular, the dataset in [60] corresponds with real measurements in a smart home with peak demand 14.7 kW and yearly consumption of 7213 kWh. From these data, average days were used to model the non-controllable demand of each prosumer, omitting some appliances that were modelled as CAs (e.g. dishwasher) in order to reproduce realistic results. On the other hand, the expected PV generation was constructed using winter and summer irradiance scenarios observed at Madrid in 2016 [61] and the peak power of PV panels, which is collected in Table 2 together the panel efficiency [13], corresponding to small and medium-size rooftop domestic installations [62]. In order to account for errors in these forecast data, the operator adds 20% and 10% confidence intervals to the expected non-controllable demand and PV generation, respectively. Since the community is cooperative, it is assumed that each prosumer provides storage capacity and enables active control of its own appliances. Li-ion battery packs or similar are installed in dwellings, as usual [35], whose relevant data is collected in Table 2. It is worth mentioning that the batteries were randomly selected assuming average sizes conventionally used in grid-connected dwellings [37, 53]. Common commercial EVs are considered [63], one of them is hybrid and the other one is pure-electric, with data reported in Table 3. Finally, Table 4 collects the data about CAs, which is based on [53, 64]. For each storage asset, a degradation cost of 2.35 \$/MWh has been taken [65].

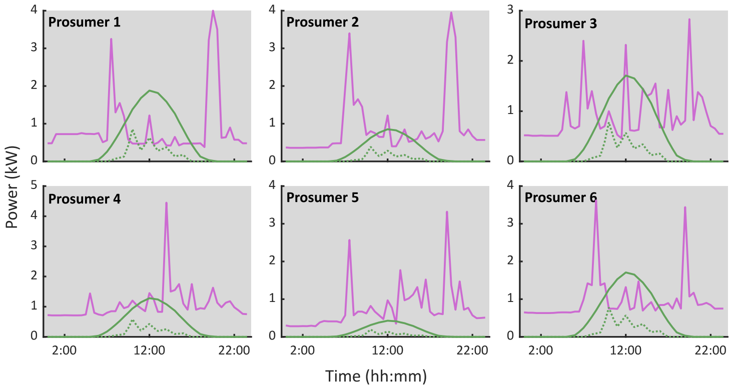

**Fig. 4.** Expected PV generation (green) and non-controllable demand (pink) of each prosumer. Winter scenario for solar irradiance is plotted with dotted lines.

**Table 2.** PV and BES data

| **Prosumer #** | **PV peak power** | **PV panel efficiency** | $\overline{\varepsilon}_b$ | **e2P$_b$** | **DOD$_b$** | $\eta^{BES,ch}$ | $\eta^{BES,dch}$ |
|---|---|---|---|---|---|---|---|
| 1 | 2 kW | 18% | 1 kWh | 1.5 h | 60 % | 0.95 p.u. | 0.95 p.u. |
| 2 | 0.75 kW | | 0.5 kWh | 2 h | 70 % | | |
| 3 | 2 kW | | 0.5 kWh | 2 h | 70 % | | |
| 4 | 1.5 kW | | 1.2 kWh | 2.5 h | 65 % | | |
| 5 | 0.5 kW | | 0.75 kWh | 1.5 h | 80 % | | |
| 6 | 2 kW | | 0.5 kWh | 2 h | 75 % | | |

**Table 3.** EV data

| **Prosumer #** | $\overline{\varepsilon}_v^{EV}$ | $\underline{\varepsilon}_v^{EV}$ | $\overline{p}_v^{EV}$ | $\eta^{EV,ch}$ | $\eta^{EV,dch}$ | **Departure** |
|---|---|---|---|---|---|---|
| 3 | 22 kWh | 4.4 kWh | 3 kW | 0.95 p.u. | 0.95 p.u. | 8:00 h |
| 6 | 40 kWh | 8 kWh | | | | 9:30 h |

**Table 4.** CAs data

| Prosumer # | Appliance | $\delta^a$ | $P^a$ | Time window | Type |
|---|---|---|---|---|---|
| 1 | WM | 3 h | 3 kW | 8:00-12:00 h | Non-interruptible |
| 2 | WM | 2.5 h | 2.75 kW | 7:00-16:00 h | Non-interruptible |
|  | SD | 1 h | 2.5 kW | 16:30-21:00 h | Interruptible |
| 3 | DW | 2 h | 2.5 kW | 18:00-21:00 h | Interruptible |
| 4 | DW | 2 h | 2 kW | 11:00-17:00 h | Non-interruptible |
| 5 | WM | 3 h | 3 kW | 10:00-20:00 h | Interruptible |
| 6 | DW | 1.5 h | 2.5 kW | 10:00-13:00 h | Interruptible |

*WM: washing machine*
*SD: spin dryer*
*DW: dishwasher*

Historical energy pricing at PJM FE Ohio subsystem has been considered to generate the representative pricing scenarios. These data are publicly available in [66], where the day-ahead and real-time energy price is reported for various sub-systems and markets at U.S. For simulations, real-time energy price throughout of 2019 has been considered, from which 15 representative scenarios were generated using the methodology described in [53] (and briefly explained in Section 4.1), which are plotted in Fig. 5. For simplicity, the selling price has been taken 0.9 times the purchase price, which corresponds to the most usual case in which taxes are not excluded of the pricing mechanism [67].

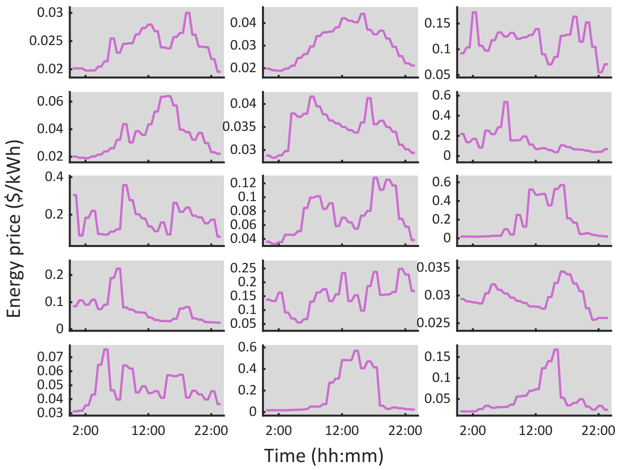

**Fig. 5.** The 15 representative scenarios of purchasing price used in simulations

### *5.2 - 1st stage: results*

As a result of the 1st stage, the operator obtains the amount of energy that must be provided by either the utility grid or collective assets such as BESs. Obviously, the considered net demand drawn by each prosumer affects to this result notably, as observed in Fig. 6. In this figure, it can be appreciated that, when the expected net demand is minimum for each dwelling, the energy that must be accommodated at the 2nd stage is low. In contrast, this profile is maximum when the expected net demand is maximized as well, reaching its peak value (> 20 kW) about 20:00 h, when a low PV generation coincides with typical peak demand, as seen in Fig. 4. In the summer scenario, the energy that must be purchased at the second stage is clearly lower, provoked by a high solar irradiance that eventually boosts up PV generation. More precisely, the prosumers need to purchase up to 30 kWh more in the winter scenario compared with the summer case. It is worth noting that the differences between scenarios are only appreciated during the central hours, since seasonal effects principally impact to PV generation.

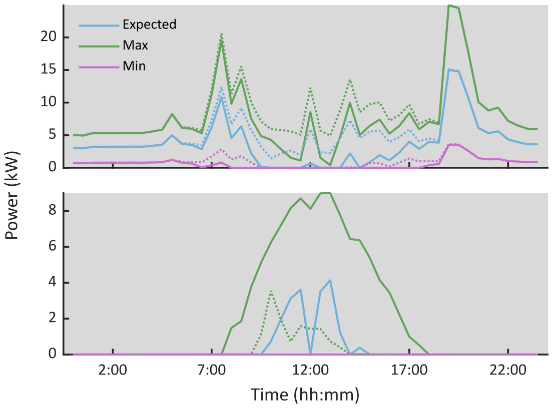

**Fig. 6.** 1st stage results, energy-to-buy (upper) and energy-to-export (bottom). Results for the winter scenario are plotted with dotted lines.

Intuitively, the energy that can be exported from the 1st layer follows the opposite trend. This is due to, when the net demand is minimum, exportable energy from prosumers is maximum since, under this assumption, PV penetration is high and surplus energy can be exchanged among prosumers and eventually sent to the second stage to further reduce the energy acquisition from the upstream grid. It is worth noting that peak exportable energy is observed at midday, coinciding with the highest PV penetration. Differences between summer and winter scenario are observed during midday, when PV penetration is high. In fact, the expected and minimum exportable energies are null under winter conditions, and the maximum does not surpass 4 kW, while the exportable power presents an 8 kW peak for the summer case.

During the first stage, the operator is focused on determining the optimal energy exchanging among prosumers, with the aim at satisfying as much demand as possible through this mechanism. Hence, the energy that must be purchased from the utility grid is also minimized. In order to account possible forecast errors, three scenarios are considered for net demand, according to (1). On the basis of these profiles, the 1st stage is run three times and the results are shown in Fig. 7. As observed, the lack of surplus renewable energy limits the capability of prosumers to self-supply among them. Actually, the total energy exchanged among prosumers was ~2 kWh if considering that each prosumer draws its minimum net demand, while this value is reduced to ~0.6 kWh when each prosumer demands its foreseen maximum net load. This is logic since only eventual surplus PV energy can be delivered on benefit of others prosumers when the net demand is maximum. This is also clearly observed in Fig. 7, since most of energy exchanges happened during midday, when the PV potential is high and eventual surplus renewables are more frequent. It is worth mentioning that the results for winter scenario are not reported in Fig. 7 since the energy exchanging among prosumers was null in this case. This is due to, despite that some energy can be exported under optimistic conditions as shown in Fig. 6, this excess of generation cannot be exploited by other prosumers and, therefore, it is directly sent to the 2nd stage.

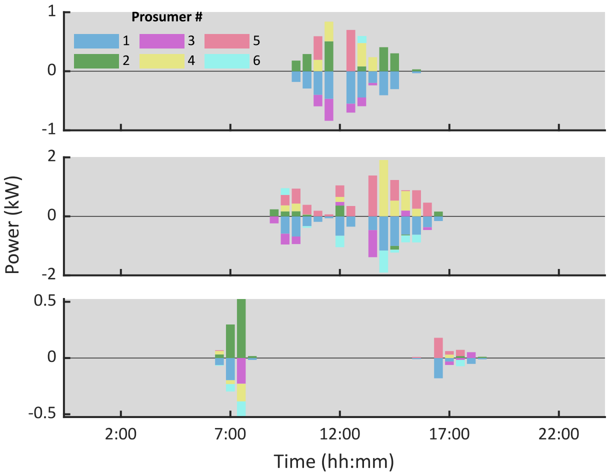

**Fig. 7.** Energy exchanging among prosumers considering minimum (upper), expected (middle) and maximum (bottom) net demands for prosumers

### *5.3 - 2nd stage: results*

Next, the collective assets such as BESs, EVs and CAs are scheduled to enhance the economy of the system. At this stage, uncertainties are handled using scenarios in case of energy pricing or interval modelling. In this case, results from the 1st stage are modelled as interval numbers, taking the bounds showed in Fig. 6, together with the initial state-of-charge of EVs. Two strategy principles can be adopted at this stage: optimistic or pessimistic. This adoption notably impacts on the expected results, as seen in Fig. 8. In this figure, the expected operation cost is analysed assuming deterministic conditions or pessimistic and optimistic point of views. The worst conditions are given in the winter scenario under a pessimistic point of view, as expected. As previously explained, the PV generation is limited under the considered winter scenario, which disables the possibility of exchanging energy among prosumers who must be supplied from either the grid or collective assets. Under such circumstances, the community presumably needs to acquire more energy from the upstream grid at high cost. Intuitively, adopting a pessimistic strategy supposes a step forward unfavourable condition, as mentioned earlier in Fig. 6. Thus, the highest expenditures were observed for the winter scenario under pessimistic conditions, surpassing 10 $, while this cost can be reduced to less than 1 $ under more favourable conditions.

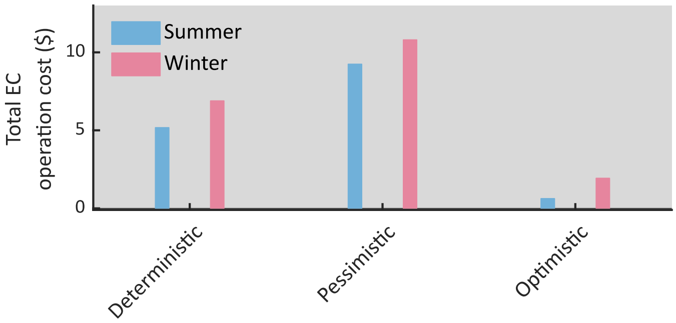

**Fig. 8.** Total operation cost, assuming different strategies

These results above are explained in the fact that the proposed methodology assumes unfavourable patterns for interval numbers in case of adopting a pessimistic perspective. For example, when a pessimistic point of view is assumed, the energy-to-buy probably reaches the maximum profile drawn in Fig. 6, while the exportable power would be minimum. Thereby, the energy that must be accommodated is higher and therefore more energy should be purchased from the grid, increasing the expenditures. Thus, the scheduling mechanism involves the risk associated with uncertainties. This last point is better observable in Fig. 9, where different indicators are shown. As observed in this figure, the purchasing and selling costs followed opposite trends, reaching the maximum expenditures under a pessimistic perspective and the highest incomes when an optimistic point of view is adopted. It is worth commenting the limited capacity of the community to sell energy to the upstream grid in the winter scenario. As observed in Fig. 9, the amount of energy sold and consequently the revenues obtained are very limited for this scenario, only observing marginal profits in the case of adopting an optimistic strategy. This is undoubtedly due to the limited exportable energy from stage 2, which is in turn caused by a limited PV production, as already explained in Fig. 6. This latter result evidences the importance of surplus PV generation in improving the economy of the system, enabling extra benefits from selling energy. This process can be further optimized using BESs, as discussed later.

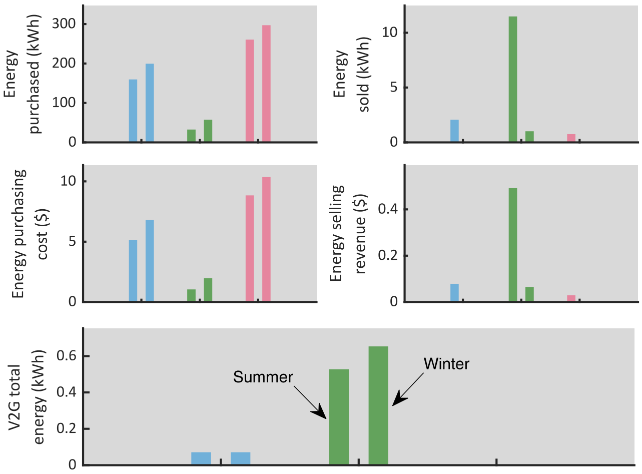

**Fig. 9.** Different indicators obtained following different strategies: assuming expected profiles (blue), taking an optimistic strategy (green) or assuming a pessimistic perspective (pink)

In Fig. 9, it can be also analysed the role of V2G capability from EVs. This feature is further exploited when the favourable values are assumed for uncertainties. This conclusion is logic since in case of assuming an optimistic operational strategy, the initial energy stored in vehicles would be high, making easier the possibility of extracting energy from EVs on pursuing a more economical operation. Actually, the vehicles are assumed to be fully charged at the beginning of the time horizon in case of taking an optimistic point of view. In contrast, the solution procedure assumes that EVs start with 4.4 kWh and 12.9 kWh. The V2G capability is also favoured by a high PV penetration since, in this case, the energy extracted from vehicles can be stored in stationary batteries to be posteriorly exploited to either cover the local demand or be sold to the grid.

The flexibility provided by CAs plays a vital role in reducing the operating cost as well. In this regard, the operator likely schedules the appliances during the most favourable hours within the allowable time windows. This operating principle is evident in Fig. 10, where a scheduling example is plotted (for the sake of simplicity, only the summer scenario is plotted). As seen in this figure, most of the CAs are scheduled about 12:00 h, regardless the operational strategy adopted. In this sense, CAs takes advantage of either low prices or high PV penetration. Some of them were placed at night due to their time windows do not allow to schedule them during noon. Thus, the scheduling tool exploits falling prices during night. Under a pessimistic perspective, a high quantity of energy must be purchased during noon. This is due to the unfavourable behaviour of EVs force to acquire energy to accomplish their requirements before leaving the house. This circumstance disables the possibility of discharging the on-board batteries through the V2G capability, as noted in Fig. 9. Under these assumptions, self-sufficiency of prosumers is also compromised, limiting their capability of partaking as real prosumers. In this context, the entire EC becomes a consumer, having to satisfy the local demand rather than dedicating part of the generation to be sold to the utility grid. Another important point is the peak shaving capacity provided by CAs. As observed in Fig. 10, the peak consumption under a pessimistic point of view reaches near 30 kW, while this value is reduced to ~10 kW when adopting an optimistic strategy. This is an important point since retailers may impose penalizations over peak consumptions [15].

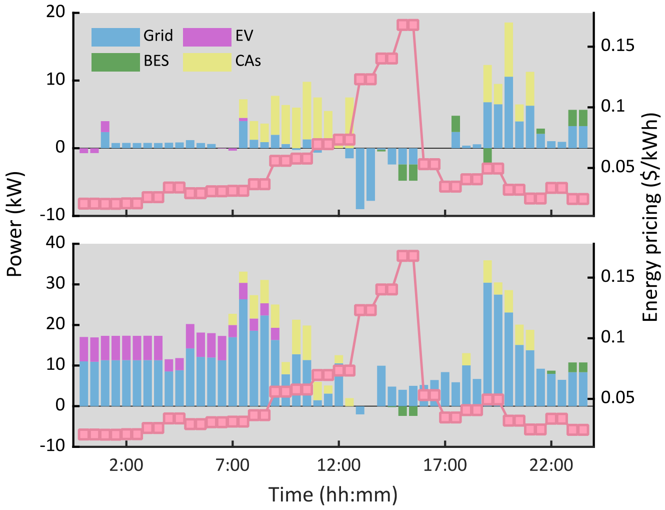

**Fig. 10.** Scheduling result under optimistic (top) and pessimistic (bottom) point of view. In this figure, negative powers mean to-EC flows (generation) and energy purchasing pricing is plotted with pink line

It is also interesting how the central hours of the day are profusely exploited to export energy to the utility grid when an optimistic strategy is adopted. This is due to, at those hours, the purchasing price is high and therefore the selling price is high as well. This circumstance, together a high PV generation, enables high monetary revenues from exporting energy. In this regard, BESs are discharged in order to increase the exportable energy, thus following the logic cycle of discharging during evening and charging during night, when the energy price is falling. This result evidences the importance of storage assets in energy selling processes, allowing to store surplus renewable generation to be exported during high-price periods since, otherwise, PV generation should be sold when it is produced, thus being non-optimally managed. However, this situation is not observed when a pessimistic point of view is assumed. Under these circumstances, only the energy stored in the batteries is exportable, since the low PV generation hinders the possibility of selling more energy to the grid.

### *5.4 - Comparison with no community arrangements*

Finally, it is worth comparing the effect of gathering the prosumers into communities against the case in which each user is operated individually. Thus, we consider that each prosumer operates his own assets, including CAs and storage devices in his own benefit, disabling the possibility of exchanging energy with other participants. For further information, this situation corresponds to the well-known home energy management problem, that has been widely studied in the literature (e.g. see [53]). In this regard, Table 5 compares the results obtained in these two cases in the aforementioned summer and winter scenarios.  As seen, the energy that must be purchased is incremented by 7% when considering individual operation. This is due to collective arrangements allow to exploit collective assets in a more optimal way. Thereby, storage assets from one prosumer can be eventually exploited by others who produce a higher surplus PV generation which must be unused otherwise. In the same way, CAs can be scheduled from a collective point of view, leading to a more optimal collective operation. In the same line, the exportable energy is also increased, thus enhancing the monetary profile. These results evidence the optimality of considering community arrangements against the conventional isolated household operation, as already pointed out in other references (e.g. see [68]). These results are also reflected in a reduction of global CO2 emissions. Indeed, if less energy must be purchased from the grid, the generation from presumably pollutant generators is also reduced. In addition, increasing the exportable energy results very beneficial for grid operation, serving as clean generation that can be exploited by other consumers outside the community (e.g. industries).

**Table 5.** Energy balance considering individual and collective operation

| **Scenario** | | **Energy purchased (kWh)** | **Energy sold (kWh)** |
|---|---|---|---|
| Individual | Summer | 93.2 | 8.7 |
| | Winter | 121.4 | 0 |
| Collective | Summer | 87.2 | 9.3 |
| | Winter | 119.7 | 0 |

### *5.5 - Comparison with fully-stochastic approach*

It is also worth comparing the developed stochastic-interval model with the conventional fully stochastic approach. To this end, instead of considering the prosumers' net demand as interval numbers, they have been modelled as Gaussian numbers in order to account for possible errors [51]. Thus, uncertain net demand can be modelled similar to energy prices. With these premises, Fig. 11 plots the operational cost for various scenarios. As seen, the operational cost considering fully stochastic model was always between those values obtained assuming optimistic and pessimistic strategies and interval notation. This is due to, in contrast to the developed methodology, the stochastic programming only considers a pessimistic perspective, assuming a weighted average of the different scenarios. In this regard, the fully stochastic model is assumed to be less versatile than the new proposal, which allows to adopt different strategies for convenience.

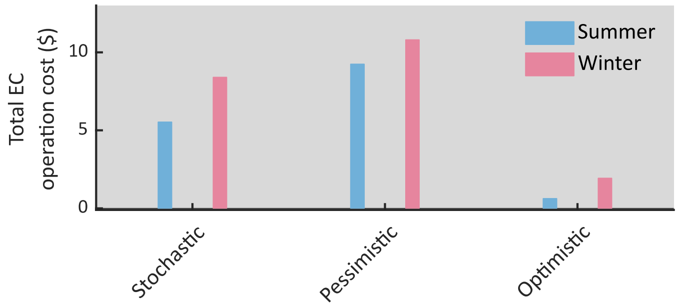

**Fig. 11.** Comparison of the operating cost using stochastic programming and the developed methodology

*5.6 - Limitations*

One of the main advantages of the developed methodology is its MILP structure, which makes the new proposal easily tractable by conventional solvers, modular and ensure the reachability of the global optimum. However, this kind of formulations may suppose a barrier for including nonlinear objective functions or constraints. For example, the well-known power-flow equations, which are strongly nonlinear [69]. Nevertheless, this particular shortcoming is not critical in ECs since, as commented, all the prosumers are connected to the same distribution line and geographically near to each other [19]. In this regard, modelling the distribution network is not a critical issue. Nevertheless, if the power-flow equations are necessary, they could be modelled using some linear tricks as those described in [70, 71] or the well-known linear version of the power-flow problem [72].

## 6 - Conclusions

This paper has addressed the optimal scheduling of cooperative ECs encompassing collective assets such as BESs, CAs and EVs. In order to explore the full possibilities of smart devices, V2G capability is enabled, being so possible to partially discharge the on-board batteries on pursuing a more economic operation of the system. A two-stage optimization framework has been proposed, in which the 1st stage is devoted on energy exchanging among prosumers while the 2nd focuses on scheduling the collective appliances and the energy exchanging with the utility grid. A novel stochastic-interval approach has been developed to accommodate uncertainties from prosumers' demand, renewable generation, EVs behaviour and energy pricing.

A case study on a benchmark EC with six domestic prosumers served to validate the developed approach, demonstrating that the new proposal is able to efficiently handle with the optimal operation of ECs. Moreover, results served to highlight the role of some advances capabilities such as V2G or evaluating the flexibility provided by CAs and storage devices. Results evidenced the importance of such smart devices on improving the economy of the system, however, the impact of uncertainties is high. In fact, the expected operational cost may rise by 90%, depending on the operational strategy adopted while the importance of V2G strongly depends on the expected surplus renewable generation and initial energy stored in vehicles. Several comparisons with individual operation have been also performed, revealing an increment of 7% if households were operated individually instead of considering a community arrangement.

Future works should be focused on exploring and analysing non-cooperative schemes, in which the different prosumers partake in internal P2P markets. Other storage technologies like green hydrogen will be fully analysed as well.

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