

Information Gap Decision Theory-based day-ahead scheduling of energy communities with collective hydrogen chain

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Abstract. This paper focuses on day-ahead scheduling of energy communities with integrated collective hydrogen storage system. To this end, a three-stage methodology is developed in which the first level is focused on individual home energy management, the second level handles with peer-to-peer energy trading among prosumers and the last level determines the energy exchanging profile with the utility grid together with the scheduling of the hydrogen chain. To handle with uncertainties from renewable sources, demand and energy price, the Information Gap Decision Theory (IGDT) is employed, by which an uncertainty-aware scheduling program can be obtained minimizing the negative effects of uncertain parameters. A case study is performed on a six-prosumer energy community with electrolysis, hydrogen vessel and fuel-cell, allowing both purchasing and selling energy with the grid. The results serve to illustrate the operation of the considered system along with validating the novel tool. The impact of uncertainties is also highlighted, showing that pessimistic scenarios can be considered but at expenses of incrementing the operating cost, peak demand and total imported energy by 50 %, 11 % and 25 %, respectively. It is also discussed the practical application of the new proposal, concluding that its computational cost is independent of the community size and privacy of users is preserved, thus supposing a valuable contribution applicable to any other community or microgrid layout.

Keywords: energy community; prosumer; hydrogen storage; fuel cell; information gap decision theory.

Nomenclature

Indexes (Sets)

$i, j(Q)$	Prosumer
$t(T)$	Time
$a(A^i)$	i^{th} customer-owned controllable appliance
Θ	Allowable time window

Superscripts

pur/exp	To-be-purchased/exportable
PV	Photovoltaic
$EV, ch/dch$	Electric vehicle in charging/discharging mode
NC	Non-controllable
$air, in/out$	Indoor/outdoor air
$build$	Building or dwelling
$HVAC, h/c$	Heating-ventilation-air conditioner system in heating/cooling mode
$W, h/c$	Hot/cold water
EWB	Electric water heater
sp/db	Setpoint/deadband
EC	Energy community
$grid, buy/sell$	Bought/sold from/to the utility grid
EZ	Electrolyser
FC	Fuel-cell
HSS	Hydrogen storage system
$\underline{(*)}/\overline{(*)}$	Minimum/maximum value

Functions

$\mathbb{E}(*)$	Expected value
$size(*)$	Number of elements of a set

Parameters & constants

ϑ	Solar irradiance [kW/m ²]
θ	Temperature [°C or K]
η	Efficiency [p.u.]
$\Delta\tau$	Time step [h]
δ	Duty cycle [h]
m	Mass [kg]
C	Heat or thermal capacity [kJ/(kg·°C) or kWh/°C]
R	Equivalent thermal resistance [kW/°C]
COP	Coefficient of performance [p.u.]
v	Volume [gal or m ³]
λ	Energy price [\$/kWh]
κ	Capital cost [\$/kW]
$\mathfrak{T}$	Lifetime [h]

μ	Maintenance cost [\$/kWh]
γ	Start-up/shutdown cost [\$]
LHV	Lower heating value [J/mol]
RD/RU	Ramping down/up rate limit [kW]
$\Re$	Gas constant [(m ³ ·bar)/(K·mol)]

Decision variables

p	Power [kW]
u	Commitment status [binary]
ε	Energy [kWh]
on/off	ON/OFF status [binary]
n	Molar hydrogen [mol]
g	Hydrogen pressure [bar]

1 - Introduction

Decarbonizing the electricity sector is one of the main concerns nowadays [1]. In 2021, global CO_2 emissions rebounded by nearly 5% [2], of which electricity generation contributed with nearly 40% [3]. In this context, governmental entities encourage the use of renewable sources and thus to reduce the dependency of fossil fuels. In this emerging paradigm, energy storage will likely play a vital role to reduce the intermittency of renewable resources [4]. Currently, battery energy storage (BES) is the most viable technology for energy storage, as pumped-hydro plants have a direct environmental impact. However, BES systems have a very limited energy density, which hinders their capability to store large amounts of energy. In this context, hydrogen storage systems (HSSs) present much higher energy densities [5], allowing to store high quantities of energy in much smaller spaces, thus supposing an interesting alternative to BESs.

Hence, hydrogen likely play a vital role in the future decarbonization of the electricity industry [6]. Among its multiple applications, this energy carrier may improve energy storage, replacing or complementing traditional battery banks. However, low efficiency and high cost of hydrogen-based devices, as well as the difficulty for hydrogen delivery, make unfeasible the implantation of HSSs at the residential level [7]. In this regard, onsite generation through electrolysis may suppose a good alternative. However, the efficiency of mature hydrogen-conversion technologies lies around 60-75 % [8, 9], making the hydrogen chain much less efficient when compared with batteries. In this sense, onsite hydrogen generation is only feasible at high powers [10], thus hindering its application at small-scale installations like dwellings.

However, emerging paradigms like energy communities (ECs) may change this concept, making viable the installation of hydrogen chains in the domestic sector. An EC is a relative novel paradigm that consists on clustering a set of prosumers that share

common interests [11]. Thus, they are operated in a centralized way and can share resources on pursuing a more efficient energy usage. Within this structure, HSSs can be viable as they could be exploited collectively, so that all the prosumers within the community can take advantage of this installation. This idea allows to use large-scale devices (dozens of kW) at residential level. However, energy management of ECs is still a challenge. Indeed, as pointed out in multiple references (e.g. see [12]), the efficient scheduling of ECs requires the use of energy management tools, which should be properly adapted to emerging and novel devices and layouts such as collective hydrogen systems while accounting for inherent uncertainties. This paper is focused on this issue.

Despite the apparent advantages commented above, the related literature is still narrow. Jannati and Nazarpour [13] developed an optimal energy management tool for MGs integrated with intelligent parking lots. The Mixed-Integer Linear programming (MILP) model encompasses electrolyzers (EZs) and fuel-cells (FCs) enabling both power-to-hydrogen (P2H) and hydrogen-to-power (H2P) paths. In [14], a stochastic framework is proposed to optimal scheduling of a MG based on combined heat and power cycles. The system encompasses a hydrogen reservoir to complement the proton-exchange-membrane units in the combined heat and power devices. Likewise, the Ref. [15] supposes an improvement of [14] including reliability in the operation of the system.

In [16], a multi-objective optimization framework is developed, which accounts for minimization of energy purchasing and peak load management. The system encompasses a charging station for electric vehicles (EVs) along a hydrogen chain with P2H and H2P paths. Seyyedeh-Barhagh et al [17] developed a MILP bi-objective model for optimal scheduling of MGs integrated with HSS. The scheduling tool accounts for both economic and environmental issues, for which a fuzzy decision-making method is used to determine the most trade-off solutions. In [18], an energy management tool for charging-discharging

electric vehicles and HSS is developed. The uncertainties from energy price are modelled using interval optimization whereas a time-of-use scheme is considered as internal demand response program.

The Ref. [19] proposes a multi-objective optimization model for day-ahead scheduling of MGs under real-time pricing. The formulation encompasses a hydrogen chain formed by EZs and FCs coupled with renewable generators. The multi-objective paradigm resulted in a nonlinear model that is solved using metaheuristic techniques. Yu et al [20] proposed an optimal scheduling mechanism for MGs integrated with demand response and HSS. Uncertainties from renewable generation and demand are captured using stochastic programming. In [21], a coalitional game-based transactive mechanism for peer-to-peer (P2P) energy trading in competitive ECs is developed. The developed model considers utility functions in order to account for the impact of applying demand response programs on home inhabitants. Mehrjerdi [22] studied a P2P strategy in the presence of photovoltaic (PV) units and HSS. To this end, an energy management tool was developed and a case study encompassing three buildings was performed.

In [23], the integration of a wind farm in electricity markets is studied. To manage the non-curtailed wind generation, the use of HSSs is proposed, by which surplus renewable energy can be converted into electricity and posteriorly traded in hydrogen markets. Lilla et al [24] developed a day-ahead scheduling strategy for cooperative ECs. The model is based on the alternating direction method of multipliers, which allows to preserve the privacy of prosumers within the P2P mechanism. In [25] a comprehensive MILP model for multi-energy MGs encompassing electric, natural gas and hydrogen subsystems. In this model, the presence of different vehicles is considered as well as the role of power-to-gas chain. Gough et al [26] focused on interconnected virtual power plants. To this

end, a blockchain-based transactive energy framework was developed, in which uncertainties are modelled via scenarios.

The Ref. [27] incises in the role of battery energy storage in ECs. In this case, customer-owned batteries are considered. In [28] a hybrid uncertainty modelling approach was developed to manage with the heterogeneous sources of uncertainties in multi-energy MGs. Thus, while point estimate methods are considered for renewable generation, Information gap decision theory (IGDT) and stochastic programming are employed for electric and hydrogen demand from fuel-cell electric vehicles, respectively. In [29] an iterative-interval scheduling approach was developed to cope with uncertainties in isolated MGs. The model considers the presence of HSSs and various types of demand response initiatives. Jordehi et al [30] proposed a bi-level day-ahead scheduling for MGs including wind turbines, dispatchable generators and fast response units. In this model, uncertainties from demand and renewable generation are treated via scenarios.

The presumable advantages of HSS integrated in ECs were identified in [31], however, the operation of hydrogen chains in these systems have not been addressed yet. As deduced from the review above, the literature regarding HSSs is mainly focused on MGs instead of ECs, thus neglecting some important topics such as P2P energy transactions among prosumers. Other detected issue is the lack of comprehensive uncertainties modelling that account for renewables, energy price and demand. This issue has been well-addressed in some papers related to MGs (e.g. see [28]), however, its study in ECs is still scarce. This paper aims at solving these issues. In this regard, this work presents some advantages compared with other references. For example, the formulation is MILP, being so modular and solvable with average solvers efficiently [32]; P2H and H2P processes are both modelled and analysed; and uncertainties from renewables,

energy pricing and demand are considered and, for the first time in ECs, treated using IGDT. For simplicity, the main contributions of this work are listed below.

- Developing a day-ahead scheduling framework for cooperative ECs encompassing collective hydrogen chain.
- Proposing a three-level operating strategy for the community including home energy management (HEM) for prosumers, P2P energy transactions and purchasing/selling processes with the utility grid.
- Incorporating risk considerations within the scheduling framework using IGDT, thus accounting for unfavourable scenarios of demand, renewable generation and energy pricing.

To validate the developed methodology, a case study on a six-prosumer EC is performed. The different stages involved in the developed solution procedure are explained via numerical results, highlighting their operativity and effectivity to deal with energy management in ECs. Finally, the case study also serves to analyse the role of collective hydrogen chain in cooperative ECs.

In the rest of this paper, Section 2 presents the EC under study and the proposed three-level operating strategy. The mathematical modelling of this work is explained in Section 3. Section 4 develops the solution procedure for the considered day-ahead scheduling problem, incorporating IGDT modelling of uncertainties. A case study with results is discussed in Section 5. Finally, the paper is concluded with Section 6.

2 - The EC under study

2.1 - Foundations

It is clear that, nowadays, battery-based systems are the most widely facilities for electricity storage. This fact seems conflictive with the topic of this paper, which relies on the use of hydrogen as auxiliary carrier for energy storage. Currently, hydrogen

generation and transportation are still challenging, due to low efficient and costly processes involved [33, 34]. However, recent progress in energy storage have led to consider this technology as a possible complement or even replacement of conventional battery-based technologies [35].

This paper therefore focuses on this emerging trend, by which hydrogen-based technologies play a crucial role in electricity storage worldwide. In this regard, hydrogen vessels present some advantages compared to batteries, which make them suitable for ECs such as a higher energy density [36]. This feature allows to store a huge amount of energy in limited spaces, thus reducing the requirements of space for storage banks. In this sense, we consider that the EC layout explained below is perfectly feasible nowadays. On the other hand, this paper does not discuss about the possible challenges in hydrogen transportation and generation, since in the considered system these issues are limited due to the scale of the devices deployed.

2.2 - EC structure and agents

The conceptual scheme of the studied EC is shown in Fig. 1. This community is formed by prosumers that are operated in a coordinated way under a supervision of a central operator. This paper focuses on cooperative ECs, which assumes that all the participants share their resources without expecting a monetary counterpart [24]. In other words, all the prosumers pursue the collective welfare. In this regard, prosumers do not receive monetary considerations by P2P energy transactions. Hence, it is assumed that all the participants account with a rooftop PV system and a series of controllable assets such as smart appliances or EV [37]. Thereby, all the prosumers contribute to the social welfare by increasing the flexibility of the system. All the prosumers are assumed to be geographically near each other and connected to the same feeder, which is a feasible assumption in ECs [24]. A hydrogen chain, with enabled P2H and H2P processes, is

installed, from which all the community can take benefit by increasing the storage capacity of the community and the capability to exchange energy with the utility grid. All the transactions with the grid are assumed to be performed under market price signals, which are, a priori, unknown and volatile [38]. As commented, the system is operated in a centralized way, for which is necessary to deploy suitable communication channels among agents [39]. These channels must be bidirectional with the aim of enabling the communication flow in both directions. All the communications flow to the operator, who uses this information to perform the day-ahead scheduling program for the community as explained in the following section.

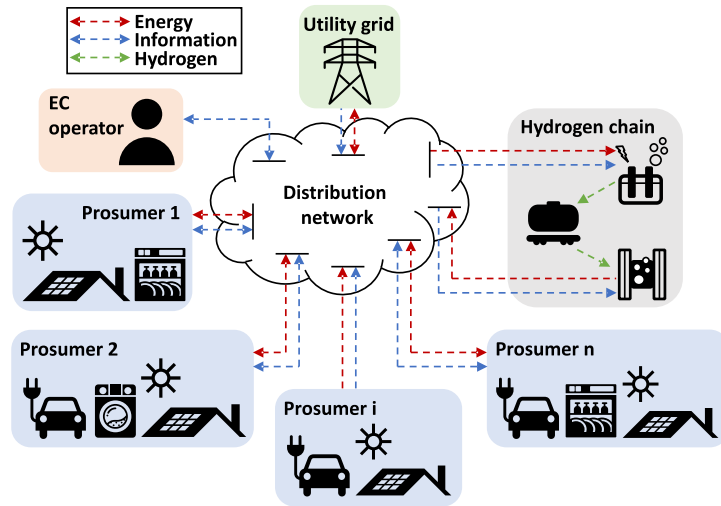


Fig. 1. Conceptual scheme of the EC under study

2.3 - Operating strategy

Optimal scheduling of ECs is a challenge because the variety of agents implied [40]. Moreover, each prosumer account with different assets, for example, a particular prosumer could own an EV while others not. This heterogeneity makes difficult the operation of the system since each agent should be operated under different principles. To solve this issue, a three-level operating strategy is proposed in this paper. The scheme of the conceived operational principle is presented in Fig. 2. In the 1st level, the HEM for each prosumer is individually performed. This problem is executed once by each home

user and aims to schedule the controllable appliances (CAs) and onsite rooftop PV units [41], to reduce the energy that cannot be met by onsite generators and therefore must be satisfied by other means. In the same way, eventual surplus energy is made available to other consumers in the second level, where the P2P energy transactions take place. In this stage, each prosumer can benefit from the excess of renewable generation from other prosumers and thus reducing his own demand. In the third operational level, the operator receives the exportable energy from the P2P mechanism as well as the individual demand that could not be covered through P2P transactions. To cope with this, the operator decides the scheduling strategy for the collective hydrogen chain. This plan results in the scheduling profile with the grid which, in last case, is responsible of satisfying the energy that cannot be supplied through onsite generators or P2P transactions. Moreover, the hydrogen chain along the exportable energy can be managed to be sold to the grid and thus obtain a monetary counterpart.

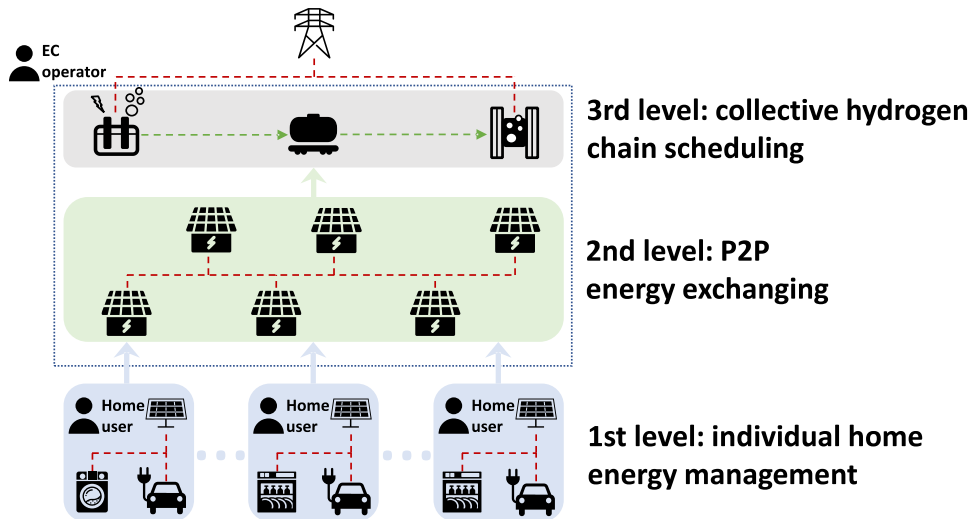


Fig. 2. Scheme of the three-level operating strategy for the EC under study

3 - Mathematical formulation

3.1 - 1st stage: HEM problem

As previously explained, the 1st level of the developed operational procedure is focused on the individual HEM for each prosumer. This problem is performed under a

deterministic point of view, from which each prosumer must predict his own non-controllable demand and PV generation. With this information, the problem aims to schedule a set of CAs and onsite generators with the aim of reducing the energy that must be met by other means (utility grid or P2P transactions). This way, the economy of the system is improved. Therefore, the EC operator does not take part in this problem and he is only informed of the results. The HEM problem has been well-studied in the literature (e.g. see [42, 43]), thus, the formulation presented below is a modified version of other references, whose expressions have been adapted to the problem under study.

$$\mathbb{E}(p_{i|t}^{pur}), \mathbb{E}(p_{i|t}^{exp}) \leftarrow \min_{\Psi^{HEM}} \Delta\tau \cdot \sum_{t \in T} \{p_{i|t}^{pur}\}; \forall i \in Q \quad (1)$$

Subject to:

$$p_{i|t}^{pur} + p_{i|t}^{PV} + p_{i|t}^{EV,dch} = p_{i|t}^{exp} + p_{i|t}^{EV,ch} + p_{i|t}^{NC} + \sum_{a \in Ai} \{u_{i|t}^a \cdot p^a\}; \forall i \in Q \wedge t \in T \quad (2)$$

$$p_{i|t}^k \leq u_{i|t}^k \cdot \bar{p}_i; \forall i \in Q \wedge t \in T \wedge k = pur \vee exp \quad (3)$$

$$u_{i|t}^{pur} + u_{i|t}^{exp} \leq 1; \forall i \in Q \wedge t \in T \quad (4)$$

$$\phi_{i|t}^{PV} = \bar{p}_i^{PV} \cdot [0.25 \cdot \vartheta_t + 0.03 \cdot \vartheta_t \cdot \theta_t^{air,out} + (1.01 - 1.13 \cdot \eta_i^{PV}) \cdot \vartheta_t^2]; \forall i \in Q \wedge t \in T \quad (5)$$

$$p_{i|t}^{PV} \leq \begin{cases} \phi_{i|t}^{PV}, & \text{if } \phi_{i|t}^{PV} \leq \bar{p}_i^{PV} \\ \bar{p}_i^{PV}, & \text{o. w.} \end{cases}; \forall i \in Q \wedge t \in T \quad (6)$$

$$p_{i|t}^{EV,k} \leq u_{i|t}^{EV,k} \cdot \bar{p}_i^{EV}; \forall i \in Q \wedge t \in T \wedge k = ch \vee dch \quad (7)$$

$$u_{i|t}^{EV,ch} + u_{i|t}^{EV,dch} \leq 1; \forall i \in Q \wedge t \in T \quad (8)$$

$$\varepsilon_{i|t}^{EV} = \varepsilon_{i|t-1}^{EV} + \Delta\tau \cdot \left(\eta_i^{EV} \cdot p_{i|t}^{EV,ch} - \frac{p_{i|t}^{EV,dch}}{\eta_i^{EV}} \right); \forall i \in Q \wedge t \in T \setminus t > 1 \quad (9)$$

$$\underline{\varepsilon}_i^{EV} \leq \varepsilon_{i|t}^{EV} \leq \bar{\varepsilon}_i^{EV}; \forall i \in Q \wedge t \in T \quad (10)$$

$$\sum_{t \in \Theta_i^{EV}} \{u_{i|t}^{EV,ch} + u_{i|t}^{EV,dch}\} = 0; \forall i \in Q \quad (11)$$

$$\varepsilon_{i|T(1)}^{EV} = \varepsilon_{i|0}^{EV}; \forall i \in Q \quad (12)$$

$$\varepsilon_{i|\Theta_i^{EV}(\text{end})}^{EV} = \bar{\varepsilon}_i^{EV}; \forall i \in Q \quad (13)$$

$$\sum_{t \in \Theta_i^a} \{u_{i|t}^a\} = \frac{\delta^a}{\Delta\tau}; \forall i \in Q \wedge a \in A^i \quad (14)$$

$$u_{i|t}^a - u_{i|t-1}^a = \text{on}_{i|t}^a - \text{off}_{i|t}^a; \forall i \in Q \wedge t \in T \setminus t > 1 \wedge a \in A^i \quad (15)$$

$$\sum_{t \in T} \{\text{on}_{i|t}^a\} = 1; \forall i \in Q \wedge a \in A^i \quad (16)$$

$$\theta_{i|t}^{air,in} = \left(1 - \frac{\Delta\tau}{10^3 \cdot m_i^{air,in} \cdot C^{air} \cdot R_i^{build}}\right) \cdot \theta_{i|t-1}^{air,in} + \frac{1}{10^3 \cdot m_i^{air,in} \cdot C^{air} \cdot R_i^{build}} \cdot \theta_{i|t-1}^{air,out} + \frac{p_{i|t}^{HVAC,h} - p_{i|t}^{HVAC,c}}{0.000277 \cdot m_i^{air,in} \cdot C^{air}} \cdot \text{COP}_i^{HVAC}; \forall i \in Q \wedge t \in T \quad (17)$$

$$p_{i|t}^{HVAC,k} \leq u_{i|t}^{HVAC,k} \cdot \bar{p}_i^{HVAC}; \forall i \in Q \wedge t \in T \wedge k = h \vee c \quad (18)$$

$$u_{i|t}^{HVAC,h} + u_{i|t}^{HVAC,c} \leq 1; \forall i \in Q \wedge t \in T \quad (19)$$

$$\theta_i^{HVAC,sp} - \theta_i^{HVAC,db} \leq \theta_{i|t}^{air,in} \leq \theta_i^{HVAC,sp} + \theta_i^{HVAC,db}; \forall i \in Q \wedge t \in T \quad (20)$$

$$\theta_{i|T(1)}^{air,in} = \theta_{i|T(\text{end})}^{air,in} = \theta_i^{HVAC,sp}; \forall i \in Q \quad (21)$$

$$\theta_{i|t+1}^{W,h} = \theta_{i|t}^{W,h} + \eta_i^{EWH} \cdot p_{i|t}^{EWH} \cdot C^{W,h} - (\theta_{i|t}^{air,in} - \theta_{i|t}^{W,h}) \cdot e^{\frac{-\Delta\tau}{R^{W,h} \cdot C^{W,h}}}; \forall i \in Q \wedge t \in T \setminus t < \text{size}(T) \wedge v_{i|t}^{W,h} > 0 \quad (22)$$

$$T \setminus t < \text{size}(T) \wedge v_{i|t}^{W,h} = 0 \quad (22)$$

$$\theta_{i|t+1}^{W,h} = \frac{\theta_{i|t}^{W,h} \cdot (\bar{v}_i^{EWH} - v_{i|t}^{W,h}) + \theta_{i|t}^{W,c} \cdot v_{i|t}^{W,h}}{\bar{v}_i^{EWH}}; \forall i \in Q \wedge t \in T \setminus t < \text{size}(T) \wedge v_{i|t}^{W,h} > 0 \quad (23)$$

$$p_{i|t}^{EWH} \leq \bar{p}_i^{EWH}; \forall i \in Q \wedge t \in T \quad (24)$$

$$\theta_i^{EWH,sp} \leq \theta_{i|t}^{W,h} \leq \bar{\theta}_i^{EWH}; \forall i \in Q \wedge t \in T \quad (25)$$

$$\theta_{i|T(1)}^{W,h} = \theta_{i|T(\text{end})}^{W,h} = \theta_i^{EWH,sp}; \forall i \in Q \quad (26)$$

As seen in (1), the objective of this stage is reducing the energy that must be imported from either P2P transactions or the utility grid. For which, the decision variables are grouped into the vector Ψ^{HEM} which is described in Appendix A. The Eq. (2) is the energy balance for each prosumer, which ensures that generation (PV production and energy imported) is equal to local consumption including exportable energy, while the

constraints (3) and (4) avoid that a particular prosumer actuate as a buyer and seller at the same time.

The model (5) yields the instantaneous potential PV production as a function of ambient parameters (i.e. solar irradiance and ambient temperature) [44], whereas (6) is included to limit the instantaneous PV generation to the PV array peak power [45]. It is noteworthy that this model assumes that all the prosumers in the community observe the same irradiance and temperature, which is plausible since all dwellings in a community are normally placed near to each other.

The constraint (7) limits the EV charging/discharging power to nominal values (charger rated power), while (8) avoids the simultaneous charge-discharge of onboard batteries. The dynamics of batteries is modelled by (9) as a function of the exchange energy, whereas (10) bounds the state-of-charge (SOC) of the onboard storage system to its nominal capacity and depth-of-discharge settings (note that batteries are typically not fully discharged to avoid their fast degradation). The constraint (11) avoids to schedule the EV when it is not parked at home. In this sense, it is assumed that each EV is equipped with a control system that avoids its operation before 0:00 h, as customary in domestic installations [46]. This way, the initial SOC of the EV is fixed by (12) while (13) assumes that users desire to get the EV fully charged at the departure time [47]. On the other hand, it is assumed that home users partake in a free-of-charge battery rental program, by which EV batteries are replaced once their degradation surpasses a determined level [48].

CAs are modelled by (14)-(16). In particular, (14) ensures that each CA completes its duty cycle within allowable time windows, whereas (15) and (16) impose continuity in their operation. Instantaneous indoor temperature is calculated by (17), which is a linearization of the original dynamic functions. This model represents the indoor temperature for each prosumer as a function of the outdoor temperature and the action of

the heating, ventilation and air conditioner (HVAC) system, which can work in heating and cooling modes to keep the temperature within comfortable bounds. On the other hand, (18) upper bounds the power consumed by the HVAC system to rate values while (19) makes the heating and cooling processes complementary. The constraint (20) ensures that indoor temperature is kept within comfortable bounds, including dead-bands to avoid a continuous operation of the HVAC system. The model is completed by (21) that establishes coherency fixing initial and final values for the indoor temperature. Finally, (22)-(26) pose the electric water heater (EWH) modelling, which is analogue to the already-explained HVAC model. In the HVAC and EWH modelling above, it is assumed that both devices are installed inside the building.

3.2 - 2nd stage: P2P energy exchanging

The 2nd stage is devoted on scheduling the energy exchanging among prosumers, which is frequently referred as P2P trading. In this case, prosumers do not receive any monetary counterpart by these transactions within the cooperative framework that governates the community. This way, this stage aims at reducing energy imbalances in prosumers, taking benefit of eventual surplus energy from other prosumers, thus, surplus generation can be exported to other prosumers who presents high consumption or eventual low PV generation. As this stage involves to all the prosumers partaking in the EC, it is performed by the operator, that accounts for possible inaccuracies in prosumers' predictions. To this end, the operator adds confidence bands over the results obtained in the first stage, as follows:

$$p_{i|t}^k = \langle \underline{p}_{i|t}^k \leq \mathbb{E}(p_{i|t}^k) \leq \bar{p}_{i|t}^k \rangle; \forall i \in Q \wedge t \in T \wedge k = pur \vee exp \quad (27)$$

Indeed, (27) models possible inaccuracies considering that results from stage 1 can actually deviate from expected values. As commented, the objective of this stage is reducing the energy that should be purchased from the utility grid. In other words, the

operator aims at reducing the energy that must be accommodated at the 3rd level. Hence, the objective function of this stage is formulated as follows:

$$ECB = \Delta\tau \cdot \sum_{t \in T} \{ \sum_{i \in Q} \{ p_{i|t}^{EC, buy} \} \} \quad (28)$$

Actually, the interval-based model (27) poses three concerned profiles (expected, pessimistic and optimistic). Thereby, this stage should be performed three times, taking the different considered profiles each time. In particular, the objective function is adapted to each case, as follows:

$$\begin{cases} \mathbb{E}(p_{i|t}^{EC, pur}), \mathbb{E}(p_{i|t}^{EC, exp}) \leftarrow \min_{\Psi^{P2P}} ECB \left(\mathbb{E}(p_{i|t}^{pur}), \mathbb{E}(p_{i|t}^{exp}) \right) \\ \bar{p}_{i|t}^{EC, pur}, \underline{p}_{i|t}^{EC, exp} \leftarrow \min_{\Psi^{P2P}} ECB \left(\bar{p}_{i|t}^{pur}, \underline{p}_{i|t}^{exp} \right) \\ \underline{p}_{i|t}^{EC, pur}, \bar{p}_{i|t}^{EC, exp} \leftarrow \min_{\Psi^{P2P}} ECB \left(\underline{p}_{i|t}^{pur}, \bar{p}_{i|t}^{exp} \right) \end{cases} ; \forall i \in Q \quad (29)$$

As seen in (29), this problem must be performed three times resulting in three possible profiles that are sent to the third stage. Indeed, depending of the input profiles (which are deduced from (27)), different results can be obtained assuming expected, maximum or minimum importable energy from stage 1. This way, the scheduling result accounts for expected, pessimistic or optimistic scenarios. This stage is completed by the following constraints, which properly model the energy transactions among prosumers.

$$\sum_{\substack{j \in Q \\ j \neq i}} \{ p_{i \rightarrow j|t} \} \leq p_{i|t}^{exp}; \forall i \in Q \wedge t \in T \quad (30)$$

$$p_{i|t}^{EC, pur} + p_{i|t}^{exp} + \sum_{\substack{j \in Q \\ j \neq i}} \{ p_{i \rightarrow j|t} \} = \sum_{\substack{j \in Q \\ j \neq i}} \{ p_{i \leftarrow j|t} \} + p_{i|t}^{EC, pur} + p_{i|t}^{exp}; \forall i \in Q \wedge t \in T \quad (31)$$

$$p_{i \rightarrow j|t} - p_{j \rightarrow i|t} = 0; \forall i, j \in Q \wedge t \in T \quad (32)$$

Eq. (30) avoids that a particular i^{th} prosumer could export more energy than the expected value obtained at stage 1. On the other hand, (31) and (32) draw the power balance for each prosumer. In (29), Ψ^{P2P} stands for the vector of decision variables for the 2nd stage, which is described in Appendix A.

3.3 - 3rd stage: hydrogen chain scheduling

Once the P2P mechanism has accommodated as much energy as possible, the remaining demanded energy is satisfied from the utility grid. Furthermore, the EC can eventually send energy to the grid to obtain a monetary income. The 3rd stage is therefore devoted on scheduling these transactions with the grid, for which the operator can take advantage of the collective hydrogen chain to increase the flexibility of the system. Thus, this stage aims at minimizing the community operating cost, which is established as follows:

$$Cost = \sum_{t \in T} \left\{ \Delta\tau \cdot (\lambda_t^{buy} \cdot p_t^{grid,buy} - \lambda_t^{sell} \cdot p_t^{grid,sell}) + \sum_{k=EZ \wedge FC} \left\{ \Delta\tau \cdot \left(\frac{\kappa^k \cdot \bar{p}^k}{\mathfrak{T}^k} \cdot u_t^k + \mu^k \cdot p_t^k \right) + \gamma^k \cdot (\text{on}_t^k + \text{off}_t^k) \right\} \right\} \quad (33)$$

As seen, the objective (33) accounts for energy transaction with the grid as well as maintenance costs of the hydrogen chain, that encompass capital, maintenance and start-up/shutdown expenditures [49]. This stage is divided into two sub-problems. Firstly, it is necessary to calculate the expected operating cost, which is obtained assuming expected values of prosumers' net demand, as follows:

$$\mathbb{E}(Cost), \mathbb{E}(p_t^{grid,buy}), \mathbb{E}(p_t^{grid,sell}) \leftarrow \min_{\Psi^{EC}} Cost \left(\mathbb{E}(p_{i|t}^{EC,pur}), \mathbb{E}(p_{i|t}^{EC,exp}), \mathbb{E}(\lambda_t^{buy}), \mathbb{E}(\lambda_t^{sell}) \right); \forall i \in Q \wedge t \in T \quad (34)$$

Subject to:

$$n_t^{EZ} = \frac{\eta^{EZ} \cdot p_t^{EZ}}{\text{LHV}}; \forall t \in T \quad (35)$$

$$n_t^{FC} = \frac{p_t^{FC}}{\eta^{FC} \cdot \text{LHV}}; \forall t \in T \quad (36)$$

$$u_t^k \cdot \underline{p}^k \leq p_t^k \leq u_t^k \cdot \bar{p}^k; \forall t \in T \wedge k = EZ \vee FC \quad (37)$$

$$p_{t-1}^k - RD^k \leq p_t^k \leq p_{t-1}^k + RU^k; \forall t \in T \setminus t > 1 \wedge k = EZ \vee FC \quad (38)$$

$$u_t^k - u_{t-1}^k = \text{on}_t^k - \text{off}_t^k; \forall t \in T \setminus t > 1 \wedge k = EZ \vee FC \quad (39)$$

$$g_t^{HSS} = g_{t-1}^{HSS} + \frac{\theta^{HSS, \mathcal{R}}}{\bar{v}^{HSS}} \cdot (n_t^{EZ} - n_t^{FC}); \forall t \in T \setminus t > 1 \quad (40)$$

$$\underline{g}^{HSS} \leq g_t^{HSS} \leq \bar{g}^{HSS}; \forall t \in T \quad (41)$$

$$g_{T(1)}^{HSS} = g_{T(\text{end})}^{HSS} = \bar{g}^{HSS} \quad (42)$$

$$u_t^{EZ} + u_t^{FC} \leq 1; \forall t \in T \quad (43)$$

$$p_t^{grid, buy} + \sum_{i \in Q} \{p_{i|t}^{EC, exp}\} + p_t^{FC} = p_t^{grid, sell} + \sum_{i \in Q} \{p_{i|t}^{EC, pur}\} + p_t^{EZ}; \forall t \in T \quad (44)$$

$$p_t^{grid, k} = u_t^{grid, k} \cdot \bar{p}^{grid}; \forall t \in T \wedge k = buy \vee sell \quad (45)$$

$$u_t^{grid, buy} + u_t^{grid, sell} \leq 1; \forall t \in T \quad (46)$$

From (34), the operator receives the expected operating cost but also the expected power exchanged with the grid. The constraints in this sub-problem are mainly devoted on modelling the collective hydrogen chain. The models (35) and (36) establish the instantaneous hydrogen production of the EZ and FC, respectively [50]. On the other hand, (37) limits the power scheduled by EZ and FC to nominal values, whereas (38) imposes ramp constraints. The constraint (39) is necessary to model the start-up and shutdown processes. The model (40) represents the dynamics of the HSS as a function of the inflow/outflow gaseous hydrogen [51]. Note that hydrogen chain modelling derives from the original model based on differential equations (see [50]), which can be linearized assuming discrete steps and steady-state conditions, as usual in energy management and scheduling tools [29, 49].

In practise, pressure inside hydrogen vessels must be kept within safe limits [50], as said (41). To keep the model coherent, the initial and final pressure of the HSS is fixed equal to its upper bound by (42), whereas (43) avoids the simultaneous operation of the EZ and FC. On the other hand, the balance (44) establishes the equilibrium among purchases and sales between the grid and the community. Finally, (45) and (46) avoid the

simultaneous purchases and sales with the utility grid. The vector of decision variables for this stage, namely Ψ^{EC} , is defined in Appendix A.

The first sub-problem is devoted on calculating the expected cost, which is necessary for the second sub-problem which aims at obtaining the uncertainty-aware scheduling plan that accounts for uncertainties. To this end, the energy price should be considered unknown as its value depends on a variety of unpredictable factors [38]. Nevertheless, it is feasible to assume that the day-ahead energy price can be predicted with certain accurateness [52], being possible to model it by its expected value and confidence intervals, as follows:

$$\lambda_t^k = \langle \underline{\lambda}_t^k \leq \mathbb{E}(\lambda_t^k) \leq \bar{\lambda}_t^k \rangle; \forall i \in Q \wedge t \in T \wedge k = buy \vee sell \quad (47)$$

To properly model the uncertainties involved (i.e. energy price and prosumers' net demand), IGDT is employed in this paper. This approach is a non-probabilistic method that seeks for the most unfavourable profile of uncertainties at expenses of incrementing the objective function, but keeping it below acceptable limits [53]. In this regard, the operator may assume a sub-optimal schedule plan if it is immune against the negative effect of uncertainties. This way, the scheduling result is robust and the cost is still controlled and kept under assumable bounds. This assumable increment of the cost is modelled in this paper by the parameter Δ_{Cost} and the constraint (48).

$$Cost(\Psi^{IGDT}, \alpha_t^b, b) \leq \mathbb{E}(Cost) \cdot (1 + \Delta_{Cost}); b \in [p_{i|t}^{EC,pur}, \lambda_t^{buy}, p_{i|t}^{EC,exp}, \lambda_t^{sell}] \quad (48)$$

IGDT models the deviation from the expected profiles of uncertainties by including the so-called uncertain radiuses [54]. In this regard, the uncertainties are allowed to vary in order to seek the most unfavourable profiles that still respect the constraint (48). To this end, the uncertainties (that have been generically denoted by b) are declared variables together with their corresponding uncertain radiuses. Nevertheless, the constraints (49)

and (50) are imposed to avoid the deviation of the uncertainties beyond their corresponding confidence intervals.

$$b \geq \mathbb{E}(b) + \alpha_t^b \cdot (\bar{b} - \mathbb{E}(b)); \forall t \in T \wedge b = p_{i|t}^{EC,pur} \vee \lambda_t^{buy} \wedge i \in Q \quad (49)$$

$$b \leq \mathbb{E}(b) - \alpha_t^b \cdot (\mathbb{E}(b) - \underline{b}); \forall t \in T \wedge b = p_{i|t}^{EC,exp} \vee \lambda_t^{sell} \wedge i \in Q \quad (50)$$

where α_t^b denotes the uncertain radius associated with the b^{th} uncertainty. Since the operator seeks an uncertain-aware result, the uncertainties are assumed to deviate in a negative sense, as observed in (49) and (50). Thus, IGDT seeks for the most robust solution by maximizing the value of the uncertain radiuses. This way, the second sub-problem can be formulated, as follows:

$$\max_{\Psi^{EC}, \alpha_t^b, b} \frac{1}{\text{size}(T) \cdot \text{size}(b)} \cdot \sum_{t \in T} \{\sum_{b \in B} \{\alpha_t^b\}\}; \forall t \in T \wedge b \in [p_{i|t}^{EC,pur}, \lambda_t^{buy}, p_{i|t}^{EC,exp}, \lambda_t^{sell}] \quad (51)$$

Subject to: (35)-(46), (48)-(50)

It is worth noting that considering the energy price as a variable yields a bi-linear term in (47), which can be linearized using advanced piecewise representations (see Appendix B).

4 - Solution procedure

To perform the different stages explained in the previous section, an adequate solution procedure should be established in order to carry out each stage coherently. Fig. 3 shows a flowchart of the developed solution procedure for day-ahead scheduling of ECs with collective hydrogen chain. In the 1st stage, each prosumer performs the HEM problem for his own dwelling, on the basis of predicted profiles for weather and non-controllable demand. These data could be provided by the operator in case of some user does not have suitable tools to forecast such parameters with accurateness. Nevertheless, this stage is performed by each user individually, thus minimizing privacy concerns [55]. It is worth noting that each prosumer can run this process in parallel with others, saving

computational time, which ensures that the computational burden of the problem does not grow notably with the number of prosumers in the community.

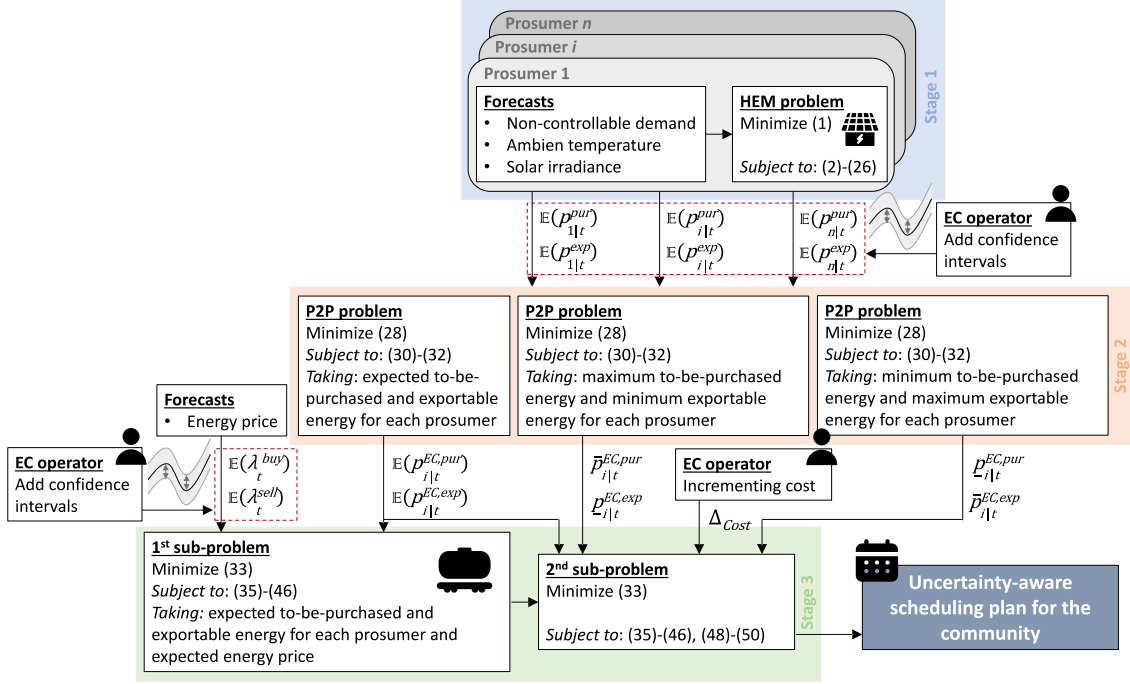


Fig. 3. Flowchart of the developed solution procedure for day-ahead scheduling of ECs

After running the 1st stage, the expected importable and exportable power for each prosumer is obtained. On the basis of this information, the operator adds confidence intervals in order to consider possible deviations in the predicted values. As explained before, this approach results in three possible P2P problems depending on the assumed profiles. Thus, the stage 2 is run three times with the aim of accommodating as much energy as possible through the P2P mechanism, thus minimizing the necessity of purchasing energy from the utility grid. For the 3rd stage, the purchasing and selling energy prices must be predicted and, as previously, the operator adds confidence intervals over expected profiles to prevent possible errors. With this information, the stage 3 is divided into two sub-problems. The first one assumes expected values of all the uncertainties while the second one is based on IGDT in order to calculate uncertainty-aware results. To this end, the value of the incrementing cost Δ_{Cost} must be established, which should be given by the operator on the basis of his own criteria or preferences.

Note that both sub-problems must be performed sequentially since the second one needs the expected operating cost, which is calculated in the first sub-problem.

5 - Case study

This section presents a case study to validate the new methodology. To this end, extensive simulations are performed taking 24-h time horizon with 30-min resolution (i.e. $\Delta\tau = 0.5\ h$). The MILP optimization model was coded under Matlab R2020a using Gurobi as solver [56]. All simulations were run on an Intel® Core™ i7-10700K (32 GB RAM) personal computer. Preliminary experiments carried out by the authors consumed 10-15 minutes by average, which can be considered reasonable for energy management problems that are usually performed with various hours of margin [57]. In addition, the MILP structure of the problem ensures its good scalability to larger problems [58].

5.1 - Input data

A benchmark six-prosumer EC has been considered for simulations. It is assumed that each prosumer can exchange up to 5 kW with others through the P2P mechanism, while the community can exchange up to 50 kW with the utility grid. Each prosumer accounts with a set of CAs as well as thermostatically controlled devices (HVAC and EWH), whose relevant data are collected in Tables 1-3, respectively, and are based on data from [48, 59]. Some prosumers also own EVs, whose features are summarized in Table 4. Fig. 4 plots the expected solar irradiance and temperature, which corresponds to a typical day at Madrid (Spain) in 2016 [60]. As commented, it is assumed that all the prosumers receive the same solar irradiance and ambient temperature as they are placed near to each other. Likewise, the expected non-controllable electrical and hot water demand for each prosumer is plotted in Fig. 5, and has been adapted from [59, 61]. Small-scale rooftop PV panels are installed in each dwelling in order to promote the self-supplying and possible surplus generation, whose data are reported in Table 5 [45]. The data of the hydrogen

chain is collected in Table 6 and have been taken from various references [29, 49, 50]. Finally, the expected energy price is plotted in Fig. 6 and corresponds to real data observed on PJM FE Ohio on July 1, 2019 [62]. For simplicity, the expected selling price has been taken 0.9 times the purchasing pricing [63].

Table 1. CAs data

Prosumer #	Appliance	δ^a	p^a	Time window
1	WM	3 h	3 kW	8:00-12:00 h
2	WM	2.5 h	2.75 kW	7:00-16:00 h
	SD	1 h	2.5 kW	16:30-21:00 h
3	DW	2 h	2.5 kW	18:00-21:00 h
4	DW	2 h	2 kW	11:00-17:00 h
5	WM	3 h	3 kW	10:00-20:00 h
6	DW	1.5 h	2.5 kW	10:00-13:00 h

WM: washing machine
SD: spin dryer
DW: dishwasher

Table 2. HVAC data

Prosumer #	$m_i^{air,in}$	C^{air}	R_i^{build}	COP_i^{HVAC}	$\bar{p}_i^{HVAC}$	$\theta_i^{HVAC,sp}$	$\theta_i^{HVAC,db}$
1	1,778 kg	1.01 kJ/(kg·°C)	$3.2 \cdot 10^{-6}$ kW/°C	1.20	2 kW	23 °C	0.5 °C
2	2,223 kg				2 kW	23 °C	0.5 °C
3	2,667 kg				2.2 kW	25 °C	1 °C
4	1,185 kg				1.8 kW	22 °C	0.3 °C
5	2,371 kg				2.1 kW	23 °C	0.5 °C
6	2,276 kg				2 kW	24 °C	0.5 °C

Table 3. EWH data

Prosumer #	η_i^{EWH}	$C^{W,h}$	$R^{W,h}$	$\theta_{i t}^{W,c}$	$\bar{p}_i^{EWH}$	$\theta_i^{EWH,sp}$	$\bar{\theta}_i^{EWH}$	$\bar{v}_i^{EWH}$
1	0.90	1.52 °C/kW	863.4 °C/kWh	10 °C	2 kW	45 °C	60 °C	50 gal
2					2.1 kW	40 °C		45 gal
3					1.8 kW	40 °C		55 gal
4					2 kW	45 °C		60 gal
5					2.1 kW	40 °C		40 gal
6					1.5 kW	45 °C		50 gal

Table 4. EV data

Prosumer #	$\bar{\epsilon}_i^{EV}$	$\underline{\epsilon}_i^{EV}$	η_i^{EV}	$\bar{p}_i^{EV}$	$\epsilon_{i 0}^{EV}$	Departure time
1	22 kWh	4.4 kWh	0.95	3 kW	10 kWh	9:00 h
4	40 kWh	8 kWh			23 kWh	7:00 h
5	19 kWh	3.8 kWh			11 kWh	8:30 h

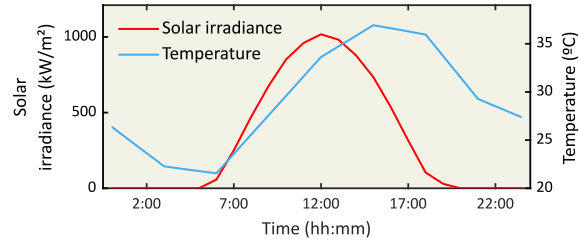


Fig. 4. Expected solar irradiance and temperature in the community

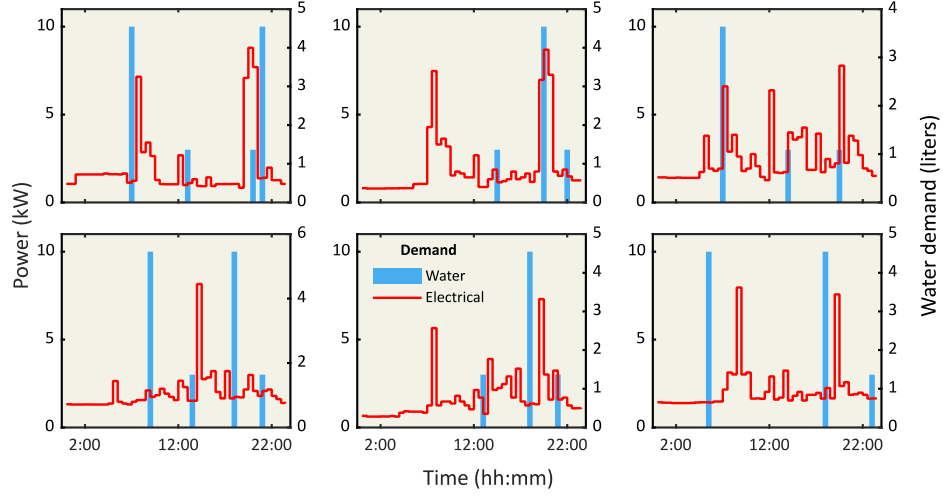


Fig. 5. Expected non-controllable electrical and hot water demand for each prosumer

Table 5. PV data

Prosumer #	$\bar{p}_i^{PV}$	η_i^{PV}
1	1.5 kW	0.167
2	1 kW	
3	1.2 kW	
4	0.75 kW	
5	0.5 kW	
6	0.75 kW	

Table 6. Hydrogen chain data

Parameter	Value	Parameter	Value
$\underline{p}^{EZ}/\bar{p}^{EZ}$	25/2 kW	γ^{EZ}/γ^{FC}	0.15/0.02 \$
$\underline{p}^{FC}/\bar{p}^{FC}$	50/2 kW	μ^{EZ}/μ^{FC}	0.03 \$/kWh
RU^{EZ}/RD^{EZ}	10 kW	v^{HSS}	30 m ³
RU^{FC}/RD^{FC}	10 kW	θ^{HSS}	313 K
η^{EZ}/η^{FC}	0.7/0.7 p.u.	$\Re$	8.314 J/K·mol
κ^{EZ}/κ^{FC}	8.5/32 \$/kW	LHV	39.72 kWh/kg
$\mathfrak{T}^{EZ}/\mathfrak{T}^{FC}$	10,000 hrs	$\underline{g}^{HSS}/\bar{g}^{HSS}$	2/10 bar

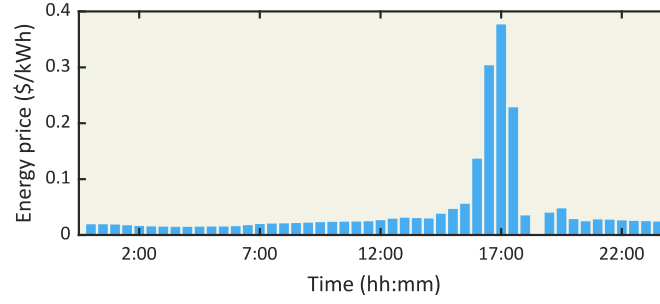


Fig. 6. Expected purchasing energy price

5.2 - HEM and P2P problems

The first two stages of the developed methodology focus on individual HEM and P2P energy exchanging among prosumers, respectively. As commented, the first stage is performed by each prosumer individually while the operator acts as coordinator for the P2P mechanism. The aim of the HEM problem is reducing the energy that should be purchased from other stages (P2P or utility grid). To this end, the different CAs, PV panels and EVs can be scheduled. An example of appliances scheduling after running a HEM optimization is shown in Fig. 7. As seen, the EV is charged during noon to be fully charged at the departure time (7:00 h). The EWH works during night in order to increase the water temperature and kept it within limits during the whole day. CAs were scheduled during evening to take advantage of high PV generation while HVAC was continuously operated from morning to night in order to compensate the high temperatures during those hours and preserve the thermal comfort.

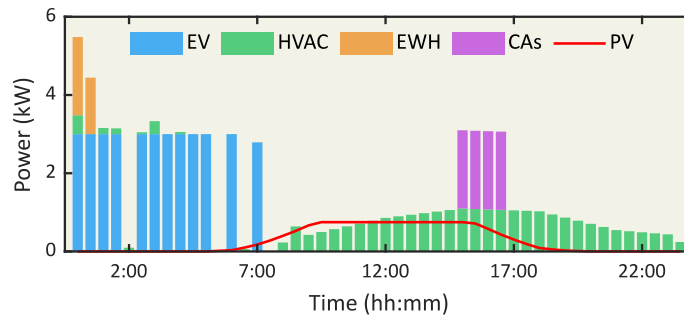


Fig. 7. HEM scheduling (prosumer 4)

In the second stage, the operator performs the P2P mechanism in order to reduce energy imbalances in prosumers and thus reducing the energy imported from the utility grid. In this sense, prosumers can benefit from eventual surplus PV generation observed in others. To perform this plan, the operator adds 20% confidence intervals on the results of the stage 1 to account for possible forecast errors, which result in three possible scheduling plans that are plotted in Fig. 8. As expected, more energy can be exchanged under optimistic conditions, i.e. assuming the maximum exportable energy from prosumers. As observed in Fig. 8, the model performs correctly, determining that exports equal purchases at any time instant. Energy transactions took place during evening mainly, which is logic assuming that only surplus PV generation can be delivered to the community. During these hours, eventual surplus generation from some prosumers is sent to others, thus reducing the overall demand. In total, 5.92 kWh, 4.70 kWh and 2.70 kWh are expected to be transacted through the P2P mechanism if maximum, expected or minimum exportable energy is assumed, respectively. This way, the consideration of different scenarios leads to a reduction of the energy transacted through P2P exchanges in 54 %. Note that P2P mechanism is disabled during noon at late evening, which is coherent since during these hours solar irradiance is null, and therefore PV generation falls to zero, hindering the possibility of exchanging energy among prosumers.

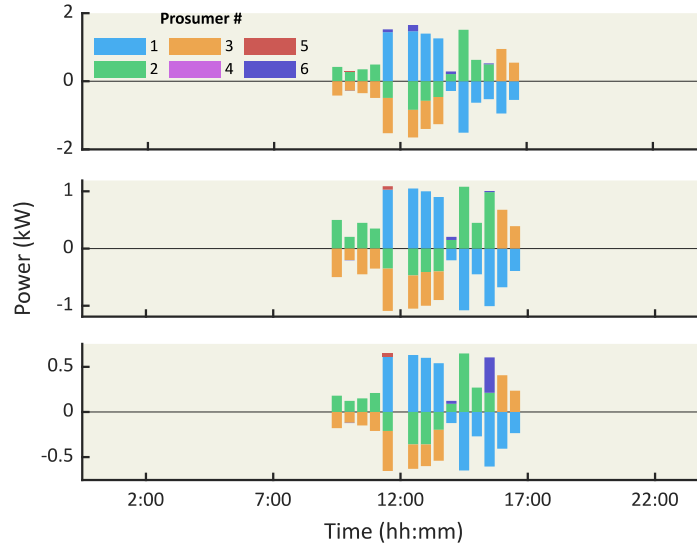


Fig. 8. P2P energy exchanging assuming maximum (upper), expected (middle) and minimum (bottom) exportable energy

5.3 - IGDT results

In the last stage of the developed methodology, the operator performs the robust scheduling of the hydrogen chain using IGDT. In this regard, energy purchasing price is assumed to be variable and modelled using 40% confidence intervals. Then, the operator assumes an incrementing cost, namely Δ_{Cost} , which determines the level in which the expected operating cost may increase on pursuing a more robust result. In literature, this parameter is occasionally called ‘cost of robustness’, since it is the cost that the operator assumes for incrementing the robustness of the system against uncertainties.

It results evident that the higher Δ_{Cost} , the higher deviation of uncertainties from their expected values can be assumed and therefore the scheduling plan turns more uncertainty-aware. This is clearly illustrated in Fig. 9, where the operating cost and average energy price are plotted for different values of the incrementing cost. As seen, the operating cost is increased as more robustness is searched, which allows to consider a more unfavourable scenario for the energy price. In fact, the operating cost grows by 50% while the average energy pricing is incremented by 18%, which allows to assume a very pessimistic scenario for the purchasing energy pricing, yielding a more uncertainty-aware scheduling

plan. Under this situation, the energy is imported from the grid at higher cost, notably increasing the expenditures.

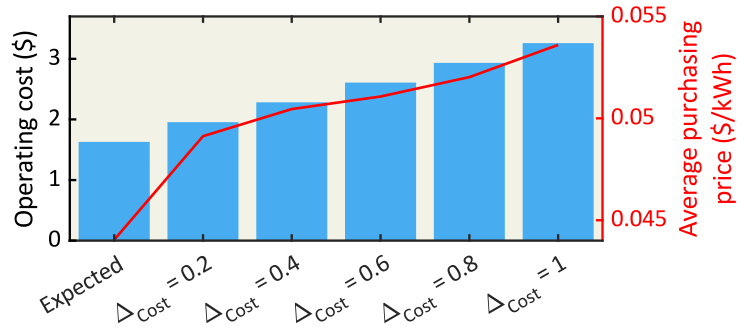


Fig. 9. Operating cost and average purchasing price for various incrementing costs Δ_{Cost}

The level of robustness also impacts on the results obtained from previous stages. It means that the prosumers' net demand drawn at stage 2, may vary between the two bounds marked by the imposed confidence intervals. Thus, for incrementing costs, it is expected to reduce the exportable energy while the importable power increases and approaches its upper bound. In this context, the community is forced to acquire more energy from the grid to cover the incremented demand. This situation is illustrated in Fig. 10, where the power purchased/sold from/to the grid is plotted under expected conditions and taking $\Delta_{Cost} = 1$, which supposes the most pessimistic case. As observed, the total imported energy increases by 25 % when considering $\Delta_{Cost} = 1$ instead of expected profiles.

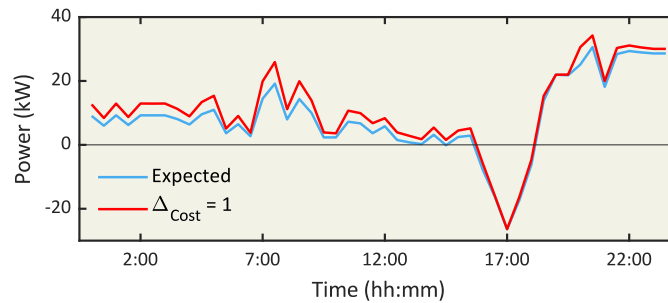


Fig. 10. Power exchanged with the grid. The purchases are positive values while the negative ones denote the sales

It is worth analysing how the grid peak power is incremented by 4 kW (+11 %) in case of $\Delta_{Cost} = 1$. This result is crucial for community operation since maximum importable power is normally limited by contractual or physical limitations. In this sense, the developed scheduling mechanism is able to identify the peak power in different cases, which is very valuable for the EC operator. In Fig. 10 is also appreciated that peak power appears at 22:00 h approximately, when PV generation falls from its maximum to zero in few time and some prosumers observe their peak non-controllable demand (e.g. prosumers 1 and 2). Under these conditions, the community needs to import much energy to cover the local demand. On the other hand, the community is able to export much energy at 17:00 h, when PV generation reaches its maximum. During these hours, each dwelling schedules its own CAs, as seen in Fig. 7, then, exports surplus PV generation to other users through P2P and, finally, continues exporting energy to either the grid or the hydrogen chain, if any. This remaining energy can be stored or directly injected to the grid to obtain a monetary counterpart, depending on the expected selling price.

The operational principle described above affects the operating cost in two ways, incrementing the energy cost and reducing the monetary incomes from selling energy. Table 7 reports these indicators for various values of Δ_{Cost} . As observed, the monetary expenditures in which the community incur for buying energy grow by 12.7% with the incrementing cost, caused by a higher imported energy and purchasing price, while the sales are reduced by 1.8%, in contrast. This evidences that the incrementing cost impacts more directly on the purchases than the sales, which is logic since incrementing the demand and the purchasing prices supposes a more unfavourable operational scenario.

Table 7. Monetary balance from energy purchasing/selling processes (\$)

Process	Δ_{Cost}				
	0.2	0.4	0.6	0.8	1
Purchase	7.66 \$	7.98 \$	8.31 \$	8.55 \$	8.77 \$
Sell	10.51 \$	10.51 \$	10.51 \$	10.43 \$	10.32 \$

As observed in Table 7, the community obtains large revenues from selling energy, which evidences the profitability of this process. To illustrate this, it is suitable to analyse the behaviour of the hydrogen chain and how it helps to improve the economy of the system. Fig. 11 shows the expected scheduling plan for the hydrogen chain. As observed, this installation is mainly dedicated to sell energy through the H2P path, especially above 17:00 h. This is due because at these hours the PV generation (and therefore the exportable energy) is high and also the purchasing energy price, which is traduced in a high selling pricing. The confluence of these two facts make the selling process very attractive. The last hours of the day are exploited to charge the hydrogen tank, taking advantage of falling purchasing prices. This process, although eventually increments the peak power as observed in Fig. 10, results more profitable due to favourable energy prices during night.

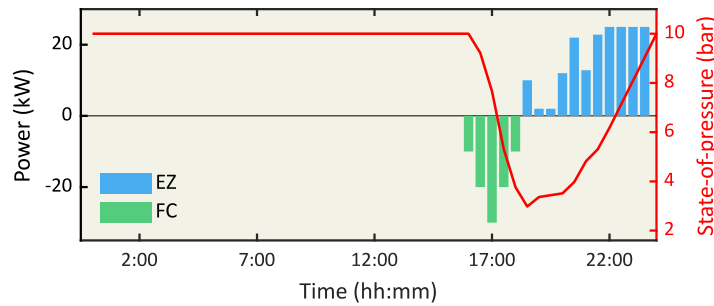


Fig. 11. Expected scheduling plan for the hydrogen chain

5.4 - Practical application and limitations

The new proposal is considered easily applicable in real communities. EC operators face notable problems regarding privacy concerns of users [55]. In this context, prosumers can be reluctant to share their own information with the operator such as CAs features, allowable time windows, expected PV generation, etc. The developed scheduling framework is immune against such concerns since each prosumer is responsible of his own scheduling plan, being no necessary to share private information with the operator.

Thus, each prosumer has to communicate his expected net demand, informing about the importable and exportable power in each case. Intuitively, this information may be quite uncertain, especially if prosumers do not run proper scheduling tools. To overcome this issue, the developed solution methodology considers confidence intervals on the expected prosumers' net demand in order to account for possible deviations of expected values.

Regarding the computational implementation of the developed methodology, it is computationally-friendly due to its low computational burden. Note that stage 1 of the proposed framework is solved individually by each prosumer, so its computational cost does not increment with the number of prosumers partaking in the community. Likewise, stages 2 and 3, which are run by the operator, are not affected by the size of the community since they contemplate overall models. In this sense, the developed solution methodology is considered perfectly applicable to any community layout and size, even when hydrogen storage is not deployed, the developed formulation is easily adaptable, thus supposing a valuable contribution for energy management in EC.

Finally, it is difficult to compare the developed solution framework with other uncertain modelling like stochastic programming, since the proposed community layout is novel and IGDT is firstly applied to this end and in an original way. Nevertheless, computational cost between the two methods can be easily compared and discussed. In this regard, IGDT is expected to be more efficient than stochastic-based approaches, since these methods require to extend the variable space to the number of scenarios considered, which can be eventually large. In addition, stochastic methods require suitable models for scenario generation, which can be derived from either historical data or probability functions [45]. This information, however, is not always available. In this regard, IGDT is considered more suitable as it only requires forecast profiles that can be easily obtained using conventional methods. Finally, stochastic methods obtain average results among

the scenarios considered. This information may be limited and its importance is evidently lower than those results obtained with IGDT. Indeed, IGDT allows to directly obtain expected and pessimistic/optimistic results, which allow to easily establish the limits within which the expected operating cost will lie. This information is undoubtedly more valuable than simply obtaining an average result that hardly allows to draw further conclusions.

6 - Conclusions

This paper has developed a novel day-ahead scheduling tool for cooperative ECs. One of the main novelties of this methodology is the consideration of a collective hydrogen chain with enabled P2H and H2P paths, from which the whole community can take advantage to improve its economy and self-sufficiency. The novel proposal is based on a three-level operating strategy and, therefore, is decomposed in three coherent stages. In the first stage, each HEM problem is individually performed by each prosumer, preserving his privacy, while the P2P exchanging and hydrogen chain scheduling are performed by the operator in the second and third stages, respectively. In the last stages, an original IGDT-based formulation has been developed to account for uncertainties in renewable generation, demand and energy prices.

A case study has been analysed and various results discussed on a benchmark energy community formed by six prosumers and a collective hydrogen chain with EZ and FC. The results show the coherency of the developed methodology, thus validating it. The case study also serves to analyse the impacts of uncertainties in this kind of tools along the possibility of orienting the operation towards a more uncertainty-aware point of view. Thus, the energy price can be assumed to be incremented by 18% with respect its expected value, however, to achieve such robustness in the results, the expected cost should be decremented by 50%. Other results have been also highlighted, thus, the peak power was

observed to increment by 11 % while the total imported energy increases by 25 %. The role of the hydrogen chain to improve the economy of the system has been also analysed, especially incrementing the capability of the community to sell energy to the utility grid. However, it is also worth to analyse how the peak demand could be incremented due to the action of FCs, which may eventually import much energy in order to fill the hydrogen vessels.

The practical application of the developed methodology is proved and therefore it supposes a valuable contribution for any EC layout and size. In this regard, future works should be conducted on considering other possible collective installations like large-scale battery banks or gasifiers. Other possible research line could be the application of other uncertainties modelling.

Appendix A - Decision variables

The vectors of decision variables used in the formulation explained in Section 3 are described below.

$$\Psi^{HEM} = \left\{ \begin{array}{l} p_{i|t}^{pur}, p_{i|t}^{exp}, p_{i|t}^{EV,ch}, p_{i|t}^{EV,dch}, p_{i|t}^{PV}, u_{i|t}^a, \\ u_{i|t}^{pur}, u_{i|t}^{exp}, u_{i|t}^{EV,ch}, u_{i|t}^{EV,dch}, on_{i|t}^a, off_{i|t}^a \\ \varepsilon_{i|t}^{EV}, p_{i|t}^{HVAC,h}, p_{i|t}^{HVAC,c}, p_{i|t}^{EWH}, \theta_{i|t}^{air,in}, \theta_{i|t}^{W,h} \end{array} \right\}; \forall i \in Q \wedge t \in T \wedge a \in A^i \quad (A1)$$

$$\Psi^{P2P} = \{p_{i \rightarrow j|t}, p_{j \rightarrow i|t}, p_{i|t}^{EC,pur}, p_{i|t}^{EC,exp}\}; \forall i, j \in Q \wedge t \in T \quad (A2)$$

$$\Psi^{EC} = \left\{ p_t^{grid,buy}, p_t^{grid,sell}, p_t^{EZ}, \right. \\ \left. p_t^{FC}, u_t^{EZ}, u_t^{FC}, on_t^{EZ}, off_t^{FC} \right\}; \forall t \in T \quad (A3)$$

Appendix B - Linearization of bi-linear terms

When considering the energy purchasing price as a variable, bi-linear terms appear in (33). To linearize them and keep the linearity of the model, advanced piecewise representations have been adopted. More precisely, the approach labeled by ‘nf4l’ in [64] has been used because its good overall features. Assuming x and y both linear variables,

the linearization of their product requires to represent the x -domain as a piecewise curve by (B1) with grid size calculated in (B2).

$$x \approx \langle \hat{x}_k \rangle; \forall k \in \{0, 1, \dots, N\} \quad (\text{B1})$$

$$l_i = \hat{x}_k - \hat{x}_{k-1}; \forall k \in \{1, 2, \dots, N\} \quad (\text{B2})$$

Then, the bi-linear terms resulting from multiplying x by y can be replaced by the linear dummy variable z , for which the following constraints must be imposed.

$$x = \sum_{k=1}^{k=N} \{ \zeta_i \cdot \hat{x}_{k-1} + \xi_{\hat{x}_k} \} \quad (\text{B3})$$

$$0 \leq \xi_{\hat{x}_k} \leq l_k \cdot \zeta_k; \forall k \in \{1, 2, \dots, N\} \quad (\text{B4})$$

$$y = \underline{y} + \sum_{k=1}^{k=N} \{ \delta_{y_k} \} \quad (\text{B5})$$

$$0 \leq \xi_{y_k} \leq (\bar{y} - \underline{y}) \cdot \zeta_k; \forall k \in \{0, 1, \dots, N\} \quad (\text{B6})$$

$$z = \underline{y} \cdot x + \sum_{k=1}^{k=N} \{ \hat{x}_{k-1} \cdot \xi_{y_k} \} + \delta_z \quad (\text{B7})$$

$$\xi_z \geq \sum_{k=1}^{k=N} \{ l_k \cdot \xi_{y_k} \} + (\bar{y} - \underline{y}) \cdot \sum_{k=1}^{k=N} \{ \xi_{\hat{x}_k} - l_k \cdot \zeta_k \} \quad (\text{B8})$$

$$\xi_z \leq (\bar{y} - \underline{y}) \cdot \sum_{k=1}^{k=N} \{ \delta_{\hat{x}_k} \} \quad (\text{B9})$$

$$\xi_z \leq \sum_{k=1}^{k=N} \{ l_k \cdot \zeta_k \} \quad (\text{B10})$$

where ξ 's are additional continuous variables, ζ is a SOS1 variable (see [58]), the subscripts denote the k^{th} grid point and N is the total number of grid points of the piecewise representation.

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