

A Robust Strategy for Energy Management in Local Energy Communities

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ABSTRACT

Local energy communities enhance energy self-sufficiency and sustainability by promoting local renewable generation and consumption. However, variations in renewable power generation and consumption are inevitable. Using flexible resources is crucial for ensuring uninterrupted energy supply during interruptions, enhancing local sustainability, and improving emergency response. This paper presents a linear model for scheduling the resources of local energy communities in the presence of energy storage and hydrogen systems. To evaluate the impacts of uncertain demand and renewable power generation, robust optimization is used. The model is formulated as a max-min problem, where the inner sub-problems represent the optimal community operations. Furthermore, the worst-case scenarios of uncertain demand and renewable generation are addressed through outer maximization. The strong duality theorem is employed to solve the max-min problem. Moreover, the big-M method is used to develop a mixed integer linear-based model. Finally, the performance of the proposed model is evaluated by a case study and two scenarios. Simulation results demonstrate that the integration of the hydrogen system improves the flexibility of the community and the total energy supply cost. For example, the cost reduction when the uncertainty budget equals zero is 37.99%.

Keywords: Energy storage, hydrogen system, local energy community, robust optimization, uncertainty.

NONMENCLATURE

Index and set	
t, Φ_T	Index and set of time.
k, Φ_{CN}	Index and set of consumers.
i, Φ_{EL}	Index and set of electrolyzers.
j, Φ_{FC}	Index and set of fuel cells.
Parameters	
π^G	Grid energy price (€/kWh).
π^{ES}	Marginal cost of energy storage (€/kWh).
π^{EL}	Marginal cost of electrolyzer (€/kWh).

π^{FC}	Marginal cost of fuel cell (€/kWh).
E_{ini}	Initial energy level (kWh).
LHV_{H_2}	Lower heating value of H_2 (kJ/mol).
$\eta^{EL/FC}$	Efficiency of electrolyzer/fuel cell
\mathfrak{R}	Gas constant (8.314 J/mol.K).
K^{TA}	Hydrogen tank mean temperature (K).
V^{TA}	Hydrogen tank volume (m ³).
$\eta^{CH/DCH}$	Efficiency in charging/discharging mode (%).
Γ	Budget of uncertainty.
M	Big constant.
Variables	
E	Energy level of storage (kWh).
$p^{CH/DCH}$	Charging and discharging power of storage (kW).
$N^{H_2,EL/TA/FC}$	Hydrogen level in electrolyzer/tank/fuel cell (mol).
p^{TA}	Pressure of hydrogen (bar).
p^{EL}	Power of electrolyzer (kW).
p^{FC}	Power of fuel cell (kW).
p^G	Purchased power from the grid by consumers (kW).
$p^{CB/CS}$	Purchased/sold power from/to energy community by consumers (kW).
p^D	Uncertain consumption (kW).
p^{PV}	Uncertain PV generation (kW).
$x^{+/-}$	Auxiliary variable to model maximum/minimum value of uncertain demand.
$y^{+/-}$	Auxiliary variable to model maximum/minimum value of uncertain PV generation.
Ψ_{DV}	Set of decision variables.
Ψ_{UV}	Set of uncertain variables.
T1, T2, T3, T4	Auxiliary variables to linearize the bilinear term.
λ, μ, e, h	Dual variables.
\bar{X}	Maximum value of variable X .
\hat{X}	Expected value of uncertain parameter X .
\tilde{X}	Maximum variation interval uncertain parameter X .

1. INTRODUCTION

The local energy community refers to a group of consumers, producers, and prosumers in a specific geographic area that collaboratively generates, consumes, and manages electricity resources. These communities often focus on using renewable energy sources to generate electricity for local consumption [1]. The concept emphasizes decentralized energy generation and consumption, allowing community members to share surplus energy, optimize consumption patterns, and contribute to the overall sustainability and resiliency of the local energy system [2-3]. The flexibility of a local energy community represents its ability to respond to variations of uncertain parameters. Fluctuations of uncertain parameters such as renewable generating power and consumption could endanger the reliability of the energy community and lead to interruptions [4]. Therefore, the optimal strategy of the energy community shall be designed in a way that ensures the continuous power supply in real time. Utilizing flexible resources is an effective solution for mitigating interruptions in energy communities. Local energy communities can significantly enhance their flexibility by strategically utilizing flexible resources. Energy storage systems could store excess energy during periods of high generation. This stored energy can be injected into the community during times of low generation or high demand. Moreover, integrating the hydrogen system comprising an electrolyzer, hydrogen storage tank, and fuel cell holds the potential to significantly enhance the flexibility of an energy community [5]. According to Fig. 1, during periods of excess renewable energy production, the electrolyzer efficiently converts surplus electricity into hydrogen, which is stored in the tank for later use. This stored hydrogen can serve as a versatile energy reservoir, readily accessible for powering a fuel cell during high energy demand or grid outages. The fuel cell then converts the stored hydrogen back into electricity. By enabling the storage and on-demand conversion of renewable energy, this integrated system improves the community's ability to withstand disruptions and maintain an uninterrupted power supply.

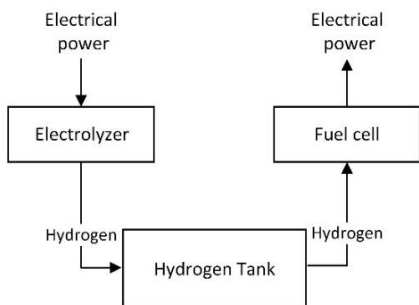


Fig. 1 Generating power by hydrogen systems.

The optimal strategies of local energy communities have been studied in various references. In [6], a hierarchical energy management framework is introduced for local communities. This framework comprises two phases: initially, end-users make optimal choices, followed by coordinated actions driven by community energy storage solutions. In [7], bi-level programming and reinforcement learning are employed to establish and solve internal markets within microgrid communities, fostering interactions between local control systems and microgrid operators. The proposed model [8] integrates demand response plans into the game model to address uncertain power outputs from renewable energy sources. [9] investigates the impact of uncertain demand response on energy systems that interconnect different community segments and incorporate demand response. The model presented in [10] adopts a decentralized approach for local markets, using a sequential decision-making method to plan for the next day while accounting for uncertain parameters. Additionally, a community energy-sharing model is proposed in [11], emphasizing fairness, cost-effectiveness, and sustainability. In risk-based models, robust optimization emerges as a more reliable and risk-averse solution by accounting for a wider range of potential realizations of uncertain parameters. This ensures performance guarantees amid uncertainty, making it suitable for scenarios where precise probabilistic information might be challenging to acquire. In [12, 13], a dynamic model is proposed to address the energy management challenges of communities. This approach involves adjusting day-ahead schedules in real-time to account for worst-case conditions, enhancing the community's adaptability to unforeseen interruptions, and optimizing energy management strategies. By incorporating real-time uncertainty, the power system can maintain reliability and effectively manage fluctuations in supply and demand [14-15]. This methodology aligns with the concept of a max-min optimization problem, where inner minimization represents the scheduling of community resources to minimize operational costs, while outer maximization accounts for worst-case uncertain parameters. This ensures reliable energy community operation in the face of potential disruptions [16-17].

The literature review demonstrates that less attention has been paid to the robust operation of local energy communities. This paper introduces a robust scheduling model designed to optimize the allocation of resources within a local energy community while considering the integration of shared hydrogen systems and energy storage solutions. By embracing the intricacies of these components, the model aims to

enhance the overall efficiency and adaptability of the energy community. Notably, the incorporation of hydrogen systems introduces a dimension of flexibility and sustainability, empowering the community to effectively harmonize energy supply and demand. The focus of the model is on crafting schedules that ensure the optimal utilization of available resources while effectively mitigating potential uncertainties.

In the proposed model, robust optimization is addressed to model uncertainty in renewable energy generation and consumption within local energy communities. The inner sub-problem minimizes system operational costs, while the outer sub-problem identifies the worst-case realizations of uncertain parameters that can still be accommodated. This approach ensures the formulation of energy management strategies that sustain effectiveness and reliability across a diverse spectrum of potential uncertainties. Moreover, the optimal resource scheduling is determined based on the defined budget of uncertainties. This index enables decision-makers to assess the performance of the proposed model in different conditions and unforeseen events. The main contributions of this work are as follows:

- 1- A linear robust model is proposed for scheduling resources in the energy communities. Based on the defined budget of uncertainty, the optimal operation of the energy community is determined.
- 2- The model effectively coordinates hydrogen and energy storage systems, addressing the challenge of variable renewable power generation and consumption. This integration enhances the flexibility of the energy community, balances supply and demand, and supports sustainable energy utilization.

The rest of the paper is organized as follows: section 2 introduces the deterministic model. In section 3, we outline the procedure for modeling uncertain parameters. Section 4 presents the solution approach employed in this study. In section 5, simulation results and discussion are presented. Lastly, section 6 offers our conclusions and includes some additional remarks.

2. DETERMINISTIC MODEL

The scheme of the proposed community market is represented in Fig. 2. Cost minimization is the main objective of local energy communities, as depicted by (1). The first term of (1) reflects consumers' operational costs to purchase energy from the grid. In the proposed model, the shared energy storage and hydrogen systems are proposed to improve the flexibility of the energy community. The hydrogen systems' operational cost

comprises electrolyzer and fuel cell expenses. The second, third, and fourth terms of (1) illustrate energy storage, electrolyzer, and fuel cell costs, respectively. It shall be noted that in the proposed model, it is supposed that shared energy storage and hydrogen systems provide service for the community and do not trade energy with the main grid.

$$\min \sum_{t \in \Phi_T} \sum_{k \in \Phi_{CN}} \pi_t^G \cdot P_{k,t}^G + \pi_t^{ES} \cdot (P_t^{CH} + P_t^{DCH}) + \sum_{i \in \Phi_{EL}} \pi_{i,t}^{EL} \cdot P_{i,t}^{EL} + \sum_{j \in \Phi_{FC}} \pi_{j,t}^{FC} \cdot P_{j,t}^{FC} \quad (1)$$

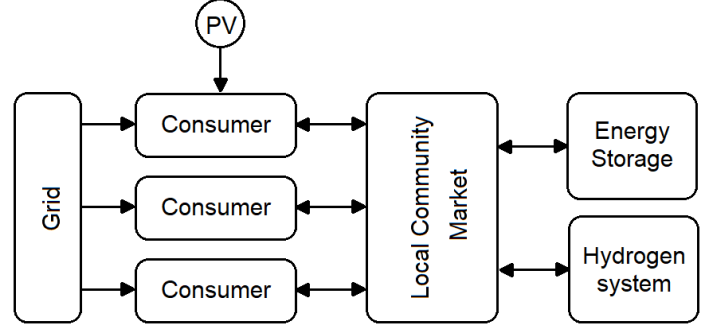


Fig. 2 Structure of the proposed energy community.

The energy level, charging and discharging power capacity, energy capacity, and energy balance at the start and end of the planning period are represented by (2), (3)-(4), (5), and (6), respectively [18].

$$E_t = E_{t-1} + P_t^{CH} \cdot \eta^{CH} - P_t^{DCH} / \eta^{DCH} \quad \forall t, \lambda_t^E \quad (2)$$

$$\bar{P} - P_t^{CH} \geq 0 \quad \forall t, \mu_t^{CH} \quad (3)$$

$$\bar{P} - P_t^{DCH} \geq 0 \quad \forall t, \mu_t^{DCH} \quad (4)$$

$$\bar{E} - E_t \geq 0 \quad \forall t, \mu_t^E \quad (5)$$

$$E_{t=0} = E_{t=T} = E_{ini}, e \quad (6)$$

The relationship between the production of hydrogen and the consumed electric power in an electrolyzer as well as the fuel cell is described by Faraday's law [3]. The produced hydrogen of electrolyzer and the generation of fuel cell are represented by (7) and (8), respectively.

$$N_{i,t}^{H_2,EL} = \eta_i^{EL} \cdot P_{i,t}^{EL} / LHV_{H_2} \quad \forall i, t, \lambda_{i,t}^{H_2,EL} \quad (7)$$

$$P_{j,t}^{FC} = N_{j,t}^{H_2,FC} \cdot LHV_{H_2} / \eta_j^{FC} \quad \forall j, t, \lambda_{j,t}^{H_2,FC} \quad (8)$$

The hydrogen level and the pressure of the hydrogen in the tank are calculated by (9) and (10), respectively [3].

$$N_t^{H_2,TA} = N_{t-1}^{H_2,TA} + \sum_{i \in \Phi_{EL}} N_{i,t}^{H_2,EL} - \sum_{j \in \Phi_{FC}} N_{j,t}^{H_2,FC}, \quad \forall t, \lambda_t^{H_2,TA} \quad (9)$$

$$p_t^{TA} = p_{t-1}^{TA} + \frac{\mathfrak{R} \cdot K^{TA}}{V^{TA}} \cdot \left(\sum_{i \in \Phi_{EL}} N_{i,t}^{H_2,EL} - \sum_{j \in \Phi_{FC}} N_{j,t}^{H_2,FC} \right), \quad \forall t, \lambda_t^{p,TA} \quad (10)$$

The main constraints of the hydrogen system are the pressure of the tank, hydrogen capacity, power capacity, and the hydrogen balance of the tank at the start and end of the planning period, which are represented by (11), (12)-(14), (15)-(16), and (17), respectively [3].

$$\bar{p}^{TA} - p_t^{TA} \geq 0 \quad \forall t, \mu_t^{p,TA} \quad (11)$$

$$\bar{N}^{H_2,TA} - N_t^{H_2,TA} \geq 0 \quad \forall t, \mu_t^{N^{H_2,TA}} \quad (12)$$

$$\bar{N}_i^{H_2,EL} - N_{i,t}^{H_2,EL} \geq 0 \quad \forall i, t, \mu_{i,t}^{H_2,EL} \quad (13)$$

$$\bar{N}_j^{H_2,FC} - N_{j,t}^{H_2,FC} \geq 0 \quad \forall j, t, \mu_{j,t}^{H_2,FC} \quad (14)$$

$$\bar{P}_i^{EL} - P_{i,t}^{EL} \geq 0 \quad \forall i, t, \mu_{i,t}^{P,EL} \quad (15)$$

$$\bar{P}_j^{FC} - P_{j,t}^{FC} \geq 0, \quad \forall j, t, \mu_{j,t}^{P,FC} \quad (16)$$

$$N_{t=0}^{H_2,TA} = N_{t=T}^{H_2,TA} = N_{ini}^{H_2,TA}, \quad h_{H_2,TA} \quad (17)$$

As mentioned before, consumers could supply their required energy from the community market. The energy balance in the community market is represented by (18).

$$\sum_{k \in \Phi_{CN}} (P_{k,t}^{CB} - P_{k,t}^{CS}) + (P_t^{CH} - P_t^{DCH}) + \sum_{i \in \Phi_{EL}} P_{i,t}^{H_2,EL} - \sum_{j \in \Phi_{FC}} P_{j,t}^{H_2,FC} = 0 \quad \forall t, \lambda_t^C \quad (18)$$

Moreover, the energy balance of each consumer is shown in (19).

$$P_{k,t}^G + P_{k,t}^{PV} + P_{k,t}^{CB} - P_{k,t}^{CS} = P_{k,t}^D \quad \forall k, t, \lambda_{k,t}^D \quad (19)$$

The decision variables or Ψ_{DV} include $E, P^{CH}, P^{DCH}, N^{H_2,EL}, N^{H_2,TA}, N^{H_2,FC}, p^{TA}, p^{EL}, p^{FC}, p^G, p^{CB}$, and $P^{CS} (\Psi_{DV} \geq 0)$. As seen in (19), the optimal strategy of the community is affected by uncertain consumption (P^D) and PV generation (P^{PV}). The procedure of modeling the uncertain parameters is represented in the next subsection.

3. MODEL OF UNCERTAIN PARAMETERS

In this section, the uncertain consumption and generating power of PV units are modeled by robust optimization. This method characterizes the potential fluctuations by defining maximum and minimum values rather than expected values, as follows:

$$P_{k,t}^D = \hat{P}_{k,t}^D + (x_{k,t}^+ - x_{k,t}^-) \cdot \tilde{P}_{k,t}^D, \quad \forall k, t \quad (20)$$

$$P_{k,t}^{PV} = \hat{P}_{k,t}^{PV} + (y_{k,t}^+ - y_{k,t}^-) \cdot \tilde{P}_{k,t}^{PV}, \quad \forall k, t \quad (21)$$

$$\sum_{t \in \Phi_T} \sum_{k \in \Phi_{CN}} (x_{k,t}^+ + x_{k,t}^- + y_{k,t}^+ + y_{k,t}^-) \leq \Gamma \quad (22)$$

According to (20)-(21), the distance between realization and expected value for each uncertain parameter is controlled by the set of auxiliary binary decision variables Ψ_{UV} (x and y). As shown in (22), the budget of uncertainty controls the total acceptable deviation level of uncertain parameters from nominal values. By increasing the budget of uncertainty, more realizations could be covered. As mentioned before, in robust optimization, the operation of the energy community is studied in the worst-case realizations of uncertain parameters. Accordingly, the robust objective function is represented by a max-min optimization problem, as follows:

$$\begin{aligned} & \max_{\Psi_{UV}} \min_{\Psi_{DV}} \sum_{t \in \Phi_T} \sum_{k \in \Phi_{CN}} \pi_t^G \cdot P_{k,t}^G + \pi_t^{ES} \cdot (P_t^{CH} + P_t^{DCH}) + \\ & \sum_{i \in \Phi_{EL}} \pi_{i,t}^{EL} \cdot P_{i,t}^{EL} + \sum_{j \in \Phi_{FC}} \pi_{j,t}^{FC} \cdot P_{j,t}^{FC} \\ & \text{s.t.: (2)-(22)} \end{aligned} \quad (23)$$

4. SOLVING PROCEDURE

The strong duality theorem in linear programming allows a max-min problem, where the goal is to maximize the

worst-case scenario among multiple objective functions, to be recast as a max-max problem. This simplification involves formulating the Lagrangian function with Lagrange multipliers for the constraints and creating a dual function. The key insight is that maximizing this dual function, subject to appropriate constraints on the Lagrange multipliers, provides the same optimal worst-case scenario value as the original max-min problem. The dual problem of (23) is recast as follows:

$$\begin{aligned} & \max_{\Psi_{UV}} \max_{\lambda, \mu, e, h} E_{ini} \cdot (\lambda_{t=1}^E + e) + N_{ini}^{H_2,TA} \cdot (\lambda_{t=1}^{H_2,TA} + h) - \\ & (\sum_{t \in \Phi_T} \bar{P} \cdot (\mu_t^{CH} + \mu_t^{DCH}) + \bar{E} \cdot \mu_t^E + \bar{p}^{TA} \cdot \mu_t^{p,TA} + \\ & \bar{N}^{H_2,TA} \cdot \mu_t^{H_2,TA} + \sum_{i \in \Phi_{EL}} (\bar{N}_i^{H_2,EL} \cdot \mu_{i,t}^{H_2,EL} + \bar{P}_i^{EL} \cdot \mu_{i,t}^{P,EL}) + \\ & \sum_{j \in \Phi_{FC}} (\bar{N}_j^{H_2,FC} \cdot \mu_{j,t}^{H_2,FC} + \bar{P}_j^{FC} \cdot \mu_{j,t}^{P,FC}) - \\ & \sum_{k \in \Phi_{CN}} (P_{k,t}^D - P_{k,t}^{PV}) \cdot \lambda_{k,t}^D) \end{aligned} \quad (24)$$

Nonlinear Term

such that:

$$\lambda_t^E - \lambda_{t+1}^E - \mu_t^E \leq 0 \quad \forall t \quad (25)$$

$$\lambda_{t=T}^E + e - \mu_{t=T}^E \leq 0 \quad (26)$$

$$-\lambda_t^E \cdot \eta^{CH} - \mu_t^{CH} + \lambda_t^C \leq \pi_t^{ES} \quad \forall t \quad (27)$$

$$\frac{\lambda_t^E}{\eta^{DCH}} - \mu_t^{DCH} - \lambda_t^C \leq \pi_t^{ES} \quad \forall t \quad (28)$$

$$\lambda_{i,t}^{H_2,EL} - \lambda_t^{H_2,TA} - \frac{\mathfrak{R} \cdot K^{TA}}{V^{TA}} \cdot \lambda_t^{p,TA} - \mu_{i,t}^{H_2,EL} + \lambda_t^C \leq 0 \quad \forall i, t \quad (29)$$

$$\lambda_t^{H_2,TA} - \lambda_{t+1}^{H_2,TA} - \mu_t^{H_2,TA} \leq 0 \quad \forall t \quad (30)$$

$$\lambda_{t=T}^{H_2,TA} + h_{H_2,TA} - \mu_{t=T}^{H_2,TA} \leq 0 \quad (31)$$

$$\lambda_{j,t}^{H_2,FC} + \lambda_t^{H_2,TA} + \frac{\mathfrak{R} \cdot K^{TA}}{V^{TA}} \cdot \lambda_t^{p,TA} - \mu_{j,t}^{H_2,FC} - \lambda_t^C \leq 0 \quad \forall j, t \quad (32)$$

$$\lambda_t^{p,TA} - \lambda_{t+1}^{p,TA} - \mu_t^{p,TA} \leq 0 \quad \forall t \quad (33)$$

$$-\frac{\eta_i^{EL}}{LHV_{H_2}} \cdot \lambda_{i,t}^{H_2,EL} - \mu_{i,t}^{P,EL} \leq \pi_{i,t}^{EL} \quad \forall i, t \quad (34)$$

$$-\frac{\eta_j^{FC}}{LHV_{H_2}} \cdot \lambda_{j,t}^{H_2,FC} - \mu_{j,t}^{P,FC} \leq \pi_{j,t}^{FC} \quad \forall j, t \quad (35)$$

$$\lambda_{k,t}^D \leq \pi_t^G \quad \forall k, t \quad (36)$$

$$\lambda_t^C + \lambda_{k,t}^D = 0 \quad \forall k, t \quad (37)$$

$$\mu_t^{CH}, \mu_t^{DCH}, \mu_t^E, \mu_t^{p,TA}, \mu_t^{H_2,TA}, \mu_{i,t}^{H_2,EL}, \mu_{j,t}^{H_2,FC}, \mu_{i,t}^{P,EL}, \mu_{j,t}^{P,FC} \geq 0 \quad (38)$$

$$\lambda_t^E, e, \lambda_{i,t}^{H_2,EL}, \lambda_{j,t}^{H_2,FC}, \lambda_t^{H_2,TA}, \lambda_t^{p,TA}, h_{H_2,TA}, \lambda_t^C, \lambda_{k,t}^D: \quad (39)$$

$$\text{unrestricted variables} \quad (40)$$

As seen in (24), the dual function includes a nonlinear term. To linearize this term, the big M method is used. The big M method is a linear programming technique used to linearize bilinear terms, particularly when they represent the product of a binary and a continuous variable. It does so by introducing a big constant M to create linear constraints that approximate the bilinear relationship. The resulting model can be solved by standard linear programming methods while ensuring feasibility. By replacing (20)-(21) in (24), the nonlinear term is expanded as follows:

$$\text{Nonlinear term} = (P_{k,t}^D - P_{k,t}^{PV}) \cdot \lambda_{k,t}^D$$

$$= (\hat{P}_{k,t}^D - \hat{P}_{k,t}^{PV}) \cdot \lambda_{k,t}^D + \bar{P}_{k,t}^D \cdot \left(\overbrace{x_{k,t}^+ \cdot \lambda_{k,t}^D}^{T1_{k,t}} - \overbrace{x_{k,t}^- \cdot \lambda_{k,t}^D}^{T2_{k,t}} \right) - \bar{P}_{k,t}^{PV} \cdot \left(\overbrace{y_{k,t}^+ \cdot \lambda_{k,t}^D}^{T3_{k,t}} - \overbrace{y_{k,t}^- \cdot \lambda_{k,t}^D}^{T4_{k,t}} \right) \quad (41)$$

The bilinear term T1, T2, T3, and T4 are linearized by constraints (42)-(54) [18].

$$T1_{k,t}, T2_{k,t}, T3_{k,t}, T4_{k,t} \geq 0 \quad \forall k, t \quad (42)$$

$$T1_{k,t} \leq M \cdot x_{k,t}^+ \quad \forall k, t \quad (43)$$

$$T1_{k,t} \leq \lambda_{k,t}^D \quad \forall k, t \quad (44)$$

$$T1_{k,t} \geq \lambda_{k,t}^D - M \cdot (1 - x_{k,t}^+) \quad \forall k, t \quad (45)$$

$$T2_{k,t} \leq M \cdot x_{k,t}^- \quad \forall k, t \quad (46)$$

$$T2_{k,t} \leq \lambda_{k,t}^D \quad \forall k, t \quad (47)$$

$$T2_{k,t} \geq \lambda_{k,t}^D - M \cdot (1 - x_{k,t}^-) \quad \forall k, t \quad (48)$$

$$T3_{k,t} \leq M \cdot y_{k,t}^+ \quad \forall k, t \quad (49)$$

$$T3_{k,t} \leq \lambda_{k,t}^D \quad \forall k, t \quad (50)$$

$$T3_{k,t} \geq \lambda_{k,t}^D - M \cdot (1 - y_{k,t}^+) \quad \forall k, t \quad (51)$$

$$T4_{k,t} \leq M \cdot y_{k,t}^- \quad \forall k, t \quad (52)$$

$$T4_{k,t} \leq \lambda_{k,t}^D \quad \forall k, t \quad (53)$$

$$T4_{k,t} \geq \lambda_{k,t}^D - M \cdot (1 - y_{k,t}^-) \quad \forall k, t \quad (54)$$

Accordingly, the final mixed integer linear objective function is represented, as follows:

$$\begin{aligned} \max_{\Psi_{UV} \lambda, \mu, e, h} & E_{ini} \cdot (\lambda_{t=1}^E + e) + N_{ini}^{H_2, TA} \cdot (\lambda_{t=1}^{H_2, TA} + h) - \\ & \left(\sum_{t \in \Phi_T} \bar{P} \cdot (\mu_t^{CH} + \mu_t^{DCH}) + \bar{E} \cdot \mu_t^E + \bar{p}^{TA} \cdot \mu_t^{p, TA} + \right. \\ & \left. \bar{N}^{H_2, TA} \cdot \mu_t^{H_2, TA} + \sum_{i \in \Phi_{EL}} (\bar{N}_i^{H_2, EL} \cdot \mu_{i,t}^{H_2, EL} + \bar{P}_i^{EL} \cdot \mu_{i,t}^{P, EL}) + \right. \\ & \left. \sum_{j \in \Phi_{FC}} (\bar{N}_j^{H_2, FC} \cdot \mu_{j,t}^{H_2, FC} + \bar{P}_j^{FC} \cdot \mu_{j,t}^{P, FC}) - \sum_{k \in \Phi_{CN}} (\hat{P}_{k,t}^D - \right. \\ & \left. \hat{P}_{k,t}^{PV}) \cdot \lambda_{k,t}^D + \bar{P}_{k,t}^D \cdot (T1_{k,t} - T2_{k,t}) - \bar{P}_{k,t}^{PV} \cdot (T3_{k,t} - T4_{k,t}) \right) \quad (55) \\ \text{s.t.:} & (22), (25)-(39), (42)-(54) \quad (56) \end{aligned}$$

5. SIMULATION RESULTS

The performance of the proposed model is simulated on a modified community that consists of 16 agents [19]. Characteristics of prosumers and consumers are as follows:

- n1~n8: own a PV generating unit,
- n9~n16: pure demand.

The energy, charging, and discharging power capacity, and marginal cost of energy storage are 60-kWh, 30-kW, and 0.03 €/kWh, respectively. Moreover, the initial energy and efficiency of storage are 30 kWh and 0.9, respectively. Fig. 3 shows the expected values of PV generation, consumption, and grid price. The grid price is equivalent to the mean of import and export prices [20]. The performance of the proposed model is studied in 2 scenarios:

- Scenario I: the community shared units are neglected. In this scenario, the impacts of uncertain consumption and PV generation are studied.
- Scenario II: The impact of shared units is evaluated.

Table 1 Data of hydrogen system.

Hydrogen Tank	Electrolyser	Fuel cell	
\bar{p}^{TA}	10	\bar{p}^{EL} 3000	\bar{p}^{FC} 2400
$\bar{p}_{t=0}^{TA}$	8	$\bar{N}^{H_2, EL}$ 0.011777	$\bar{N}^{H_2, FC}$ 0.010331
K^{TA}	300	π^{EL} 0.035	π^{FC} 0.025
V^{TA}	5	η^{EL} 0.95	η^{FC} 0.95
LHV_{H_2}	242	number 10	number 10

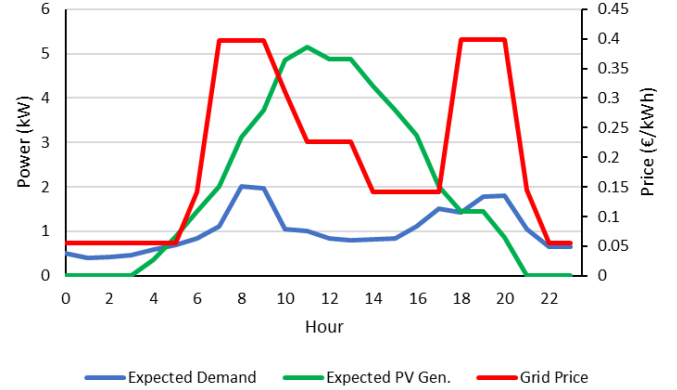


Fig. 3 Initial data of demand, PV generation, Grid price.

- Scenario I

The purchased power from the grid, PV generation, charging and discharging power of shared energy storage in the scenario I are represented in Fig. 4.

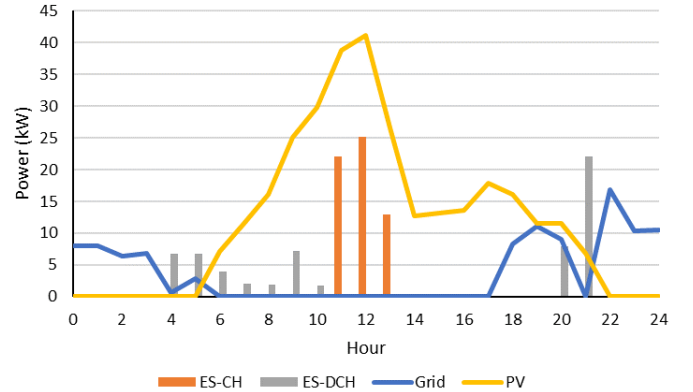


Fig. 4 Community strategy in scenario I.

As seen in this figure, battery energy storage systems play a crucial role in communities by absorbing surplus power during low load periods (11,12,13), and injecting it back into the community during peak demand times (20,21). This dynamic energy management strategy helps balance the supply and demand within the community, ensuring a more reliable and stable power grid. However, it's important to note that isolating shared energy storage systems from the main grid can have some drawbacks. One of the key advantages of remaining connected to the grid is the ability to purchase cheaper energy during low-load periods, which can be stored for later use or distributed within the energy community. By

isolating from the main grid, energy communities may miss out on these cost-saving opportunities, potentially impacting the overall efficiency of their shared energy storage systems.

The total energy supply cost of the community is shown in Fig. 5. In the proposed model, the worst-case scenario for uncertain parameters occurs during the maximum energy demand and minimum photovoltaic (PV) generation. This scenario presents a significant challenge for energy communities, as they must ensure a stable power supply precisely when resources are most constrained. An interesting observation is that as the budget for uncertainty increases, the total cost of managing these uncertainties also tends to rise. This increase in cost can be attributed to the need to increase the purchased power from the grid to mitigate the risks associated with uncertain parameter variations. However, shared energy storage allows the community to alleviate the negative impacts of uncertain parameters, especially in situations with a higher budget for uncertainties. The shared energy storage essentially acts as a buffer, ensuring that even during worst-case scenarios, the community has a reliable source of power.

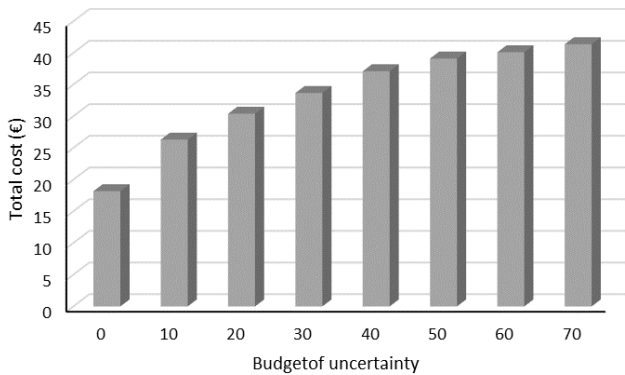


Fig. 5 Energy supply cost for different budgets of uncertainty in scenario I.

- Scenario II

The purchased power from the grid, PV generation, charging and discharging power of shared energy storage, the consumed power of electrolyzer, and generated power of fuel cell in scenario II are represented in Fig. 6. Introducing a hydrogen system improves the flexibility and self-sufficiency of the community. By incorporating an electrolyzer, surplus PV generation during periods like 14-15 can be efficiently converted into hydrogen, effectively storing excess energy for later use. The deployment of a fuel cell for energy supply during peak demand periods, such as 19, 20, and 22, further demonstrates the community's ability to tap into its stored hydrogen reserves, reducing the reliance on external energy sources. This integrated hydrogen system not only enhances the community's

energy flexibility but also significantly decreases its dependency on the main grid. Overall, the incorporation of hydrogen technology enables the energy community to manage its energy resources more effectively, paving the way for greater energy independence and sustainability.

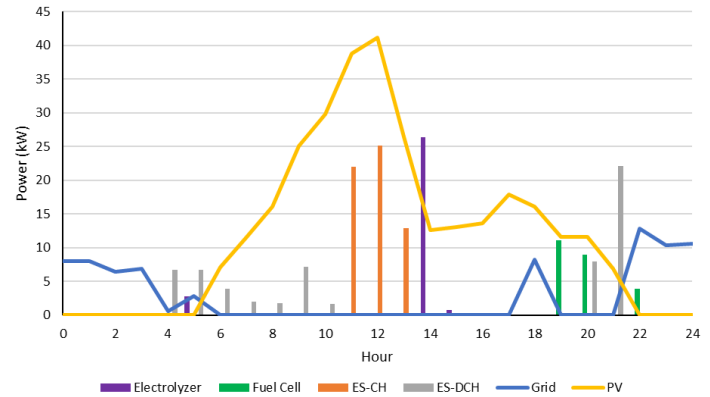


Fig. 6 Community strategy in scenario II.

Fig. 7 shows the total energy supply cost of the community in different budgets of uncertainty. Comparing Figs. 5 and 7 demonstrates that the integration of a hydrogen system within the energy community decreases the total energy supply cost significantly. The cost reduction when the uncertainty budget equals zero is 37.99%. Additionally, the flexibility provided by hydrogen-based units, such as electrolyzers and fuel cells, empowers the community to respond swiftly to fluctuations in PV generation and demand. This adaptability plays a crucial role in mitigating the negative impacts of uncertain parameters, as the community can readily adjust its energy resources to match real-time requirements.

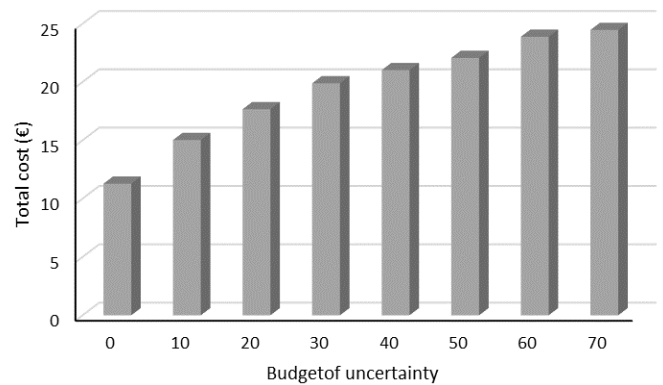


Fig. 7 Energy supply cost for different budgets of uncertainty in scenario II.

6. CONCLUSIONS

The paper addresses the challenges of ensuring uninterrupted energy supply in local energy communities, emphasizing the importance of flexible resources in the face of renewable power generation and

consumption variations. It introduces a linear model for resource scheduling within these communities, incorporating energy storage and hydrogen systems to enhance resilience. The robust optimization approach is employed to tackle uncertain parameters related to demand and renewable generation, resulting in a max-min problem formulation. The study demonstrates that integrating a hydrogen system substantially improves community flexibility and reduces the total energy supply cost, with a remarkable 37.99% cost reduction when uncertainty is eliminated. Simulation results show the role of battery energy storage in stabilizing the grid by absorbing surplus power during low-load periods and releasing it during peak demand. However, it underscores the importance of staying connected to the main grid for cost-saving opportunities during off-peak hours. Moreover, the presented results emphasize the benefits of introducing a hydrogen system, converting surplus PV generation into hydrogen for later use and employing a fuel cell for peak energy demand. This integration not only enhances energy flexibility but also reduces dependency on the main grid, contributing to greater energy independence and sustainability.

As part of future work, the authors plan to implement a distributed optimization approach to enhance the model's scalability, enabling more efficient management of larger-scale local energy communities.

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