Optimization of a Standalone Energy Community with Vehicle-to-Comunnity and Load Shifting under Extreme Events

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***Abstract*—The frequency of extreme weather events on a global scale has increased significantly in recent years, presenting a risk to the electrical infrastructure, especially in communities isolated from large urban centers. Energy communities (ECs) play a key role in ensuring the reliable supply of electricity, integrating economic, environmental and social benefits, in addition to increasing autonomy and efficiency. Characterized by decentralized generation and storage systems, ECs allow energy production closer to the place of consumption, which facilitates controllability of consumption. However, for these systems to function properly, it is crucial to develop efficient approaches for resource planning and operation that cope with uncertainties associated with extreme events. This work proposes a stochastic model for the planning of PV generation and battery energy storage systems, which takes advantage of load shifting and vehicle-to-community (V2C) as a support to supply the demand of a standalone EC under the influence of extreme events. The proposed method was tested in an EC, considering different levels of solar irradiation. Four test cases were carried out to demonstrate the main trade-offs between cost and operation under extreme scenarios, considering load shedding, load shifting, and V2C. The results demonstrate that V2C integration with load shifting offers balance, while fully self-sufficient systems provide no shedding at higher costs, and load management alone cannot meet demand during extreme events.**

Keywords*—*electric vehicles, extreme scenarios, load shifting, standalone energy community, stochastic programming.

I. Introduction

In the transition toward a greener future with reduced pollution sources, renewable energy and storage systems have been increasingly deployed to establish energy communities (ECs). According to the European Commission, ECs are citizen-driven collective initiatives that contribute to the energy transition by promoting efficiency and enhancing citizens well-being [1].

The integration of renewable sources and storage assets, including electric vehicles (EVs) and batteries, can enhance system reliability during high-impact events such as natural disasters [2]. Changes in the nature, intensity, and frequency of extreme events – such as storms, floods, droughts, severe heatwaves, and wildfires – increase the risk of power system failures, especially at the community level [3].

Thus, distributed resource planning in ECs can play a crucial role in protecting the system against extreme events, as the greater decentralization of generation and storage, with resources such as photovoltaic (PV) panels located closer to demand, also enhances demand-side controllability.

II. Literature Survey

Several studies have proposed energy system planning for ECs. For instance, [4] proposed the optimal planning of renewable ECs using a mixed-integer linear programming model. Similarly, [5] presented an optimal sizing approach for battery energy storage and PV systems for renewable EC participants, applying mixed-integer linear programming combined with a two-stage stochastic model. Moreover, [6] studied the planning and management of microgrids for communities; however, uncertainties were not incorporated into their Monte Carlo-based scenario set. In addition, a heuristic method based on a multi-objective genetic algorithm was developed by [7], focusing on the sizing of a hybrid renewable generation and storage system for an EC.

Regarding the integration of resilience aspects, [8] proposed a framework for energy system planning that incorporates operational flexibility and resilience to extreme weather events, using piecewise linear models to quantify the impact of severe heatwaves and droughts. Reference [9] applied multi-objective optimization to distributed generation systems considering extreme wind and lightning events. Finally, [10] proposed an integrated electricity and natural gas planning model accounting for grid resilience against storms, earthquakes, and floods. Despite the extensive literature on grid resilience in the face of extreme events, with a primary focus on enhancing the reliability of electric power services, few studies have specifically examined the role of extreme event uncertainties in the planning of resources within ECs.

As a result, a gap remains in addressing how such uncertainties affect the planning of ECs. Aiming these goals, this work proposes a stochastic programming model for the planning of PV generation and energy storage systems to supply the demand of a standalone EC under the influence of extreme events. To ensure efficient operation of energy resources, load shifting, load shedding and vehicle-to-community (V2C) as a support to supply the demand of a standalone EC during extreme events. The proposed method was tested on an EC considering the supply of a load under scenarios with different solar irradiance levels.

The remainder of this paper is organized as follows: the mathematical formulation of the stochastic model is presented in Section 2; Section 3 shows the study case. Section 4 presents and discusses the results of the test conducted; and finally, Section 5 concludes the discussions of this work.

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III. Mathematical Formulation

The mathematical expressions used in the proposed MILP model are presented and discussed in this section. The operational state of charge of EVs and energy storage batteries are characterized, along with expressions modeling PV generation sizing, load shifting, and power balance.

The set H consists of 24 hours in a day. The uncertainty related to the variability of renewable energy generation is addressed using a scenario-based stochastic programming approach. A set of scenarios S is adopted to model variation in solar irradiation, which directly impact PV generation. Extreme events are represented by the subset $S^E \in S$. Each scenario is associated with a probability π_s.

The EC scheme adopted in this work consists of a community load power to be supplied, a set of batteries B, a set of PV panels P, and a set of EVs K, as illustrated in Fig. 1. The installation decision variable for each battery $b \in B$ is defined as y_b, a binary variable such that if y_b =1, battery b is installed. Similarly, the installation decision variable for each panel is z_p, where $z_p = 1$ indicates that panel p is installed. Thus, the panels can supply a power that feeds the community load at hour h in scenario s, charges the EV battery through the charging power $P_{khs}^{EV,c}$, and charges each storage battery through $P_{bhs}^{BAT,c}$. The EC demand is represented by a nominal power $P_h^{EC,nom}$ that can be optimized through flexible load shifting during extreme events. Thus, the actual demand of the EC corresponds to the variable P_{hs}^{EC}.

During extreme events, EC demand may not be fully met due to low solar incidence during rainy seasons or unavailability of panels. In such cases, this unmet demand is represented by the auxiliary variable P_{hs}^{U}; introduced to represent the portion of unmet power, ensuring the power balance and representing the load shedding in extreme events.

Additionally, a set of K vehicles is assumed to be available from community residents, which can supply energy to the EC through their discharging power $P_{khs}^{EV,d}$, but only during extreme events—for which they are highly compensated. In summary, the energy exchange among community components operates as follows: the EC load only consumes energy, PV panels and batteries provide power, while EVs can charge but serve as a discharge backup exclusively in extreme scenarios.

A. Objective Function

The optimization goal formulation in (1) aims to minimize the total costs, covering both the investment costs associated with PV generation and batteries planning and the operational costs, which include penalty terms. The objective is to optimally size PV generation and battery storage systems for an autonomous EC in extreme scenarios. The solution can use energy from EVs of the EC residents as a backup, available with compensation, along with load shifting strategies. As a last resource, load shedding may be applied, though this could impact user satisfaction. The first two terms in (1) represent the investment costs related to the installation of battery systems and PV panels, respectively. The third term represents the present value of operational costs associated with load shifting, reflecting the penalty for user dissatisfaction due to displaced loads, calculated as the module of the amount displaced throughout the day. The fourth term represents the payment for energy purchased from EV owners residing in the community, i.e., the payment for V2C, and finally, the fifth term represents the penalty associated with the unmet power in cases of extreme events, in other words, load shedding. The third, fourth and fifth terms are costs modeled as a linear function comprising the load shifting, represented by $P_{hs}^{LS+} + P_{hs}^{LS-}$ associated a λ_{1h} hourly penalty; the energy by EVs $P_{khs}^{EV,d}\Delta_t$, subject to a cost λ_2, which represents EV owners compensation; and the unmet energy $P^U\Delta_t$, penalized by λ_3 for load shedding. The present value is given by $\alpha = N^{days}\left[1-(1+\phi)^{-N^{years}}\right]/\phi$, and π_s denotes the probability of occurrence of each scenario s.

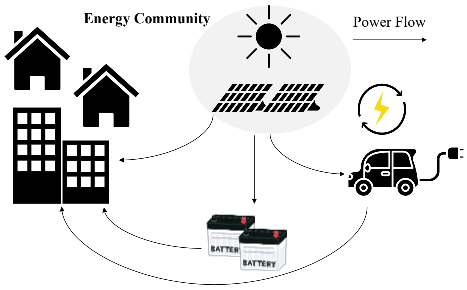

Fig. 1 Energy community scheme.

$$\min \sum_{b\in B} y_b c_b + \sum_{p\in P} z_p c_p + \alpha \sum_{s\in S^E}\sum_{h\in H} \pi_s \lambda_{1_h}\left(P_{hs}^{LS+} + P_{hs}^{LS-}\right) + \alpha\lambda_2 \sum_{k\in K}\sum_{s\in S^E}\sum_{h\in H} \pi_s\, P_{khs}^{EV,d} + \alpha\,\lambda_3 \sum_{s\,\in S^E}\sum_{h\in H} \pi_s\, P_{hs}^{U} \quad (1)$$

B. Battery Energy Storage Constraints

This section presents the modeling of the power variables and the state of charge of each battery b based on the installation variable y_b. Thus, constraints (2) limit the charging and discharging power of each battery to the battery installation decision variable y_b.

$$P_{bhs}^{BAT,c} + P_{bhs}^{BAT,d} \le \overline{P}^{BAT} y_b, \qquad \forall\, b \in B, h \in H, s \in S \quad (2)$$

To ensure that the battery storage does not charge and discharge at the same hour h, (3) and (4) limit the battery discharging and charging power, $P_{bhs}^{BAT,d}$ and $P_{bhs}^{BAT,c}$, respectively, to the nominal value $\overline{P}^{BAT}$ and the auxiliary binary variable w^{BAT}.

$$0 \le P_{bhs}^{BAT,d} \le \overline{P}^{BAT} w_{bhs}^{BAT}, \qquad \forall b \in B, h \in H, s \in S \quad (3)$$

$$0 \le P_{bhs}^{BAT,c} \le \overline{P}^{BAT}\left(1 - w_{bhs}^{BAT}\right), \qquad \forall b \in B, h \in H, s \in S \quad (4)$$

The energy E_{bhs}^{BAT} of each battery b at hour h is limited by the nominal capacity $\overline{E}^{BAT}$, as shown in (5).

$$0 \le E_{bhs}^{BAT} \le \overline{E}^{BAT}, \qquad \forall b \in B, h \in H, s \in S \quad (5)$$

Constraint (6) defines E_{bhs}^{BAT} for the first hour of the day. Then, for the following hours, (7) computes the battery's state of charge, considering the state of charge from the previous hour and charge and discharge efficiencies.

$$E_{bhs}^{BAT} \le \overline{E}^{BAT}, \qquad \forall b \in B, s \in S, h = 1 \quad (6)$$

$$E_{bhs}^{BAT} - E_{b,h-1,s}^{BAT} = \eta^{BAT,c} P_{bhs}^{BAT,c}\Delta_t - \frac{P_{bhs}^{BAT,d}}{\eta^{BAT,d}}\Delta_t, \quad \forall b \in B, s \in S, h \in H, h > 1 \quad (7)$$

Finally, to ensure that E_{bhs}^{BAT} at the end of the day is the same as at the beginning, (8) specifies that, at the last hour, the battery energy must be the same of the battery energy initially considered.

$$E_{bhs}^{BAT} = E_{b,h-23,s}^{BAT}, \quad \forall b \in B, s \in S - S^E, h = 24 \tag{8}$$

C. V2C Constraints

In this work, the EV operates in V2C mode, i.e., it serves to provide charging to the community only in cases of extreme events. In normal scenarios, EVs are allowed to charge through the system. Similarly to (3) and (4), constraints (9) and (10) ensure that each EV k does not charge and discharge simultaneously. This condition is formulated through the EV charging and discharging power variables, $P_{khs}^{EV,c}$ and $P_{khs}^{EV,d}$, respectively, the nominal power that EV can charge or discharge, $\overline{P}^{EV}$, and an auxiliary binary variable w_{khs}^{EV}.

$$0 \leq P_{khs}^{EV,d} \leq \overline{P}^{EV} w_{khs}^{EV}, \quad \forall k \in K, h \in H, s \in S^E \tag{9}$$

$$0 \leq P_{khs}^{EV,c} \leq \overline{P}^{EV} (1 - w_{khs}^{EV}), \quad \forall k \in K, h \in H, s \in S^E \tag{10}$$

Constraint (11) limits the state of charge of the EV, SoC_{khs}^{EV} to a maximum and a minimum value.

$$\underline{SoC} \leq SoC_{khs}^{EV} \leq \overline{SoC}, \quad \forall k \in K, h \in H, s \in S^E \tag{11}$$

Constraint (12) models the initial state of the EV battery, allowing the model to choose one value to the maximum $\overline{SoC}$. (13) computes the SoC_{khs}^{EV} considering the state of charge from the previous hour, $SoC_{k,h-1,s}^{EV}$, $P_{khs}^{EV,c}$ and $P_{khs}^{EV,d}$, along with the charging and discharging efficiencies $\eta^{EV,c}$ and $\eta^{EV,d}$, respectively.

$$SoC_{khs}^{EV} \leq \overline{SoC}, \quad \forall k \in K, s \in S^E \; h \in H, h = 1 \tag{12}$$

$$SoC_{khs}^{EV} - SoC_{k,h-1,s}^{EV} = \eta^{EV,c} P_{khs}^{EV,c} \Delta_t - \frac{P_{khs}^{EV,d}}{\eta^{EV,d}} \Delta_t, \quad \forall k \in K, s \in S^E \; h \in H, h > 1 \tag{13}$$

D. PV Generation Constraint

To obtain PV generation data, the electrical power P_{hs}^{PV} supplied by each PV panel at the hour h and scenario s, the current and the voltage of the cells are calculated from an hourly solar irradiation profile. All parameters and variables obtained through solar irradiation are scenario-dependent, so that the planning model is correctly dimensioned according to solar availability. The mathematical formulation to calculate the photovoltaic power $\overline{P}_{hs}^{PV}$ is the same as that of the work of [11]. According to (14), P_{hs}^{PV} depends on the number of panels installed z_p and the maximum power each panel can produce, $\overline{P}_{hs}^{PV}$.

$$0 \leq P_{hs}^{PV} \leq \sum_{p \in P} z_p \overline{P}_{hs}^{PV}, \quad \forall h \in H, s \in S \tag{14}$$

E. Unmet Power/Load Shedding under Extreme Events Constraint

Under extreme conditions, an auxiliary variable defined as P_{hs}^{U} represents the portion of power that is unmet to the EC. When there is no PV generation and no available power from batteries or EVs, this variable accounts for the unmet power that would have been consumed by the EC, in other words, this portion represents the load shedding in the EC. Accordingly, (21) bounds P_{hs}^{U} within specified maximum and minimum limits, valid only for the scenarios representing the set of the extreme events S^E.

$$0 \leq P_{hs}^{U} \Delta_t \leq \overline{P}^{U} \Delta_t, \quad \forall h \in H, s \in S^E \tag{15}$$

F. Load Shifting Constraints

Load shifting is implemented in the EC demand profile to enhance electricity consumption efficiency by rescheduling non-essential loads to off-peak periods. The primary objective is to shift the EC nominal load to times of higher energy availability. The load shifting is not required during normal operation scenarios, to prioritize user satisfaction throughout the day. Load shifting is applied to the nominal energy demand of the EC, represented by $P_h^{EC,nom} \Delta_t$, according to a flexible load shifting rate Λ^{LS}. In extreme scenarios, the EC energy is optimized to regulate the nominal energy consumption $P_{hs}^{EC} \Delta_t$, aiming to shift loads to periods of higher generation while minimizing consumption during low-production periods. More significant reductions correspond to larger load shifts relative to the specified rate.

In this context, $P_h^{EC,nom} \Delta_t$ represents the nominal load demanded by the EC, while $P_{hs}^{EC} \Delta_t$ corresponds to the actual delivered load, and P_{hs}^{LS} stores the amount of displaced power. This process is governed by constraint (16), with constraint (17) ensuring that the sum of the nominal energy and the shifted load remains constant throughout the day.

Constraint (18) prevents load shifting during normal operating conditions, thereby prioritizing user satisfaction. Finally, constraints (19) and (20) calculate the absolute value of the displaced power: constraint (19) determines the difference between the nominal power and what is actually delivered to the EC, while constraint (20) ensures the calculation of the absolute load shifting value, accounting for both negative deviations (when load is shifted to another time period) and positive deviations (when additional consumption occurs due to previous shifts).

$$P_h^{EC,nom} \Delta_t (1 - \Lambda^{ls}) \leq P_{hs}^{EC} \Delta_t \leq P_h^{EC,nom} \Delta_t (1 + \Lambda^{ls}), \quad \forall h \in H, s \in S^E \tag{16}$$

$$\sum_{h \in H} P_h^{EC,nom} \Delta_t = \sum_{h \in H} P_{hs}^{EC} \Delta_t, \quad \forall s \in S \tag{17}$$

$$P_{hs}^{EC} \Delta_t = P_h^{EC,nom} \Delta_t, \quad \forall h \in H, s \in S - S^E \tag{18}$$

$$P_{hs}^{LS} = P_h^{EC,nom} - P_{hs}^{EC}, \quad \forall h \in H, s \in S^E \tag{19}$$

$$P_{hs}^{LS} = P^{LS+} - P^{LS-}, \quad \forall h \in H, s \in S^E \tag{20}$$

G. Power Balance Constraints

The power balance of the EC in normal scenarios is given by constraint (21). For extreme scenarios, constraint (22) guarantees the power balance. In constraint (21), the generation is given by the available photovoltaic production and the battery discharge power, while the demand is represented by the battery charge power and the EC power demand. In extreme scenarios, formulated by constraint (22), the power balance of the generation is given by the PV power, the battery discharge, the V2C power and the load shedding, given by P_{hs}^{U}, and the demand is represented by the battery charge, the V2C charge, and the EC's own load.

$$P_{hs}^{PV} + \sum_{b \in B} P_{bhs}^{BAT,d} \geq \sum_{b \in B} P_{bhs}^{BAT,c} + P_{hs}^{EC}, \quad \forall h \in H, s \in S - S^E \tag{21}$$

$$P_{hs}^{PV} + \sum_{b \in B} P_{bhs}^{BAT,d} + \sum_{k \in K} P_{khs}^{EV,d} + P_{hs}^{U} \geq \sum_{b \in B} P_{bhs}^{BAT,c} + \sum_{k \in K} P_{khs}^{EV,c} + P_{hs}^{EC}, \quad \forall h \in H, s \in S^E. \tag{22}$$

IV. CASE STUDY

This section presents the parameters of the test conducted considering the EC scheme shown on Fig. 1. The adopted PV profiles are represented in Fig. 2; scenario 1 represents high solar irradiance with a probability π_s of 30%; scenario 2 represents medium solar irradiance with a probability of 40%; scenario 3 represents low solar irradiance with a 15% probability; scenario 4 presents cloudy weather conditions, and a probability of 15%; scenario 5 represents heavy rain, and a probability of 3%, and finally, scenario 6, which indicates unavailability of the PV panels, which a probability of 2%. Thus, the subset $S^E \in S$ is defined as including the scenarios representing extreme events 5 and 6.

The profile of the EC load throughout the day is shown in Fig. 3. Load of the EC.Fig. 3, which corresponds to a daily consumption of 175 kWh. The intervals of h, Δ_t represent one hour from the total 24 hours in a day. Three EVs belonging to citizens available in the EC were considered as a backup system in extreme scenarios, with a reward for kWh sold to the EC. TABLE I. presents the parameters adopted in the MILP model. The load shifting penalty λ_1 corresponds to \$ 0.1/kWh during solar generation, in $h = 8 \dots 18$, while for other periods λ_1 is \$ 0.5/kWh (encouraging shifting energy demand to high solar production periods).

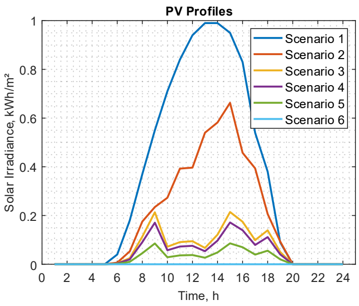

Fig. 2 Scenarios for photovoltaic generation.

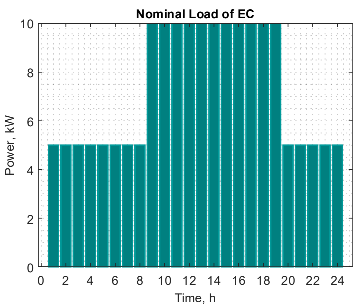

Fig. 3. Load of the EC.

TABLE I. MODEL PARAMETERS FOR THE CASE STUDY

Symbol	Value	Symbol	Value
Δ_t	1 h	c_p	\$ 100
$\eta^{BAT,c}, \eta^{BAT,d}$	95%	$\overline{E}^{BAT}$	15 kWh
$\eta^{EV,c}$	95%	N^{years}	10
$\eta^{EV,d}$	95%	N^{days}	365
Λ^{LS}	30%	$\overline{P}^{BAT}$	15 kW
λ_2	\$ 1/kWh	$\overline{P}^{EV}$	20 kW
λ_3	\$ 5/kWh	$\overline{P}^{PV}_{hs}$	600 Wp
ϕ	10%	$\overline{SoC}$	60 kWh
c_b	\$ 5000	$\underline{SoC}$	6 kWh

The model was implemented in the AMPL programming language and solved using CPLEX on a computer with an AMD Ryzen 7 5700G processor. The solver was executed with its default settings, using its predefined convergence tolerances and no imposed maximum execution time limit.

V. RESULTS AND DISCUSSION

Some tests were conducted to analyze the impact of extreme event scenarios on the sizing and operation of resources in the EC. The first test, in Case A, involved evaluating the sizing of the EC without the V2C and load shedding resources, considering only the normal scenarios. Case B performed the test considering only V2C and without the possibility of load shedding, with the all scenarios. Case C considered only load shedding with penalty and did not consider V2C, with all the scenarios. Finally, Case D allowed the use of all resources considering a penalty for load shedding, with all the scenarios too. The aim was to evaluate how the different resources available in addition to batteries and PV can influence the solution obtained.

A. Case A

For this test case, the system was designed without considering V2C, load shedding and extreme scenarios, i.e., sizing a EC only considering normal irradiation scenarios relying only on PV and batteries, requiring the EC to fully meet demand in all normal scenarios, without purchasing power from EVs or implementing load shedding. The total investment cost was \$ 39,800, considering only the initial capital costs, without any penalties. The sizing resulted in 178.8 kWp of PV capacity (equivalent to 298 panels) and 30 kWh of battery storage (2 units). Fig. 4 displays the battery state of charge throughout the day across different normal scenarios, where negative values indicate discharge to the community and positive values represent charging from the solar panels.

This approach required dimensioning of the EC to ensure continuous demand meeting exclusively through its own generation and storage capacity. However, this configuration can be defined as not very conservative, as it does not consider the occurrence of extreme scenarios in its solution, only normal operation, demonstrating a cheaper dimensioning compared to conservative solutions.

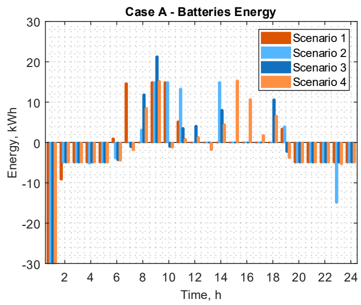

Fig. 4. Energy of the storage batteries in Case A.

B. Case B

This test evaluated a configuration using V2C and load shifting resources, where the EC purchases power or the EVs from residents during extreme scenarios to meet demand, while excluding load shedding options. The results show this solution was computed in 3 seconds, requiring 178.8 kWp of PV generation and 30 kWh of battery storage to fully serve the EC demand. The total system cost reached \$ 49,653, consisting of \$ 39,800 for investment, \$ 100 for load shifting flexibility maintenance, and \$ 9,753 spent on V2C energy purchases from EVs. This combined approach of load shifting and V2C enabled reduced battery sizing compared to previous configurations. Fig. 5 presents the batteries' daily energy profile, showing frequent charging cycles during normal operation scenarios (1-4). EV charging behavior appears in Fig. 6 to Fig. 8, with red line indicating normal charging patterns during standard operation and blue lines showing discharge cycles during extreme scenarios (5 and 6) when EVs supply power to the EC. The load shifting implementation appears in Fig. 9, demonstrating how 1.5 kW of demand was shifted from midnight to noon in scenario 6 and to 6 p.m. in scenario 5, optimizing consumption periods to high generation availability. This configuration demonstrates how strategic use of V2C combined with load shifting can reduce infrastructure requirements while maintaining reliable operation across all scenarios.

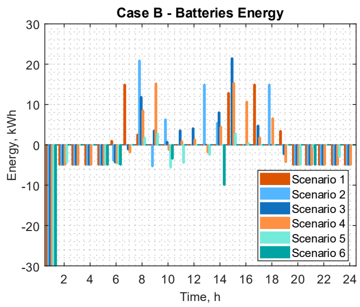

Fig. 5. Energy of the storage batteries in Case B.

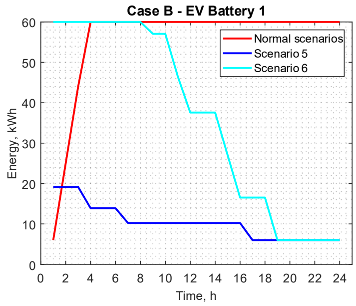

Fig. 6. State of charge of EV1 along the day in Case B.

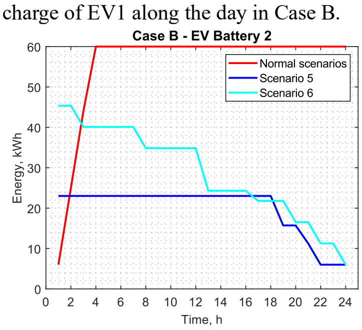

Fig. 7. State of charge of EV2 along the day in Case B.

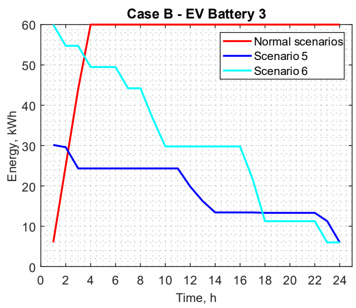

Fig. 8. State of charge of EV3 along the day in Case B.

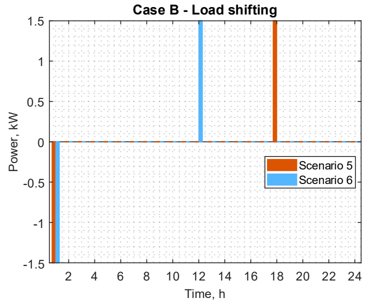

Fig. 9. Load shifting of the EC in Case B.

C. Case C

This test examined operation using only load shifting and shedding, excluding V2C resources. This test case represents critical scenarios where resident EVs are either unavailable or depleted. The result found has a total cost of \$ 78,455 - comprising \$ 59,800 investment, \$ 40 for shift operation, and \$ 18,615 in user dissatisfaction penalties from load shedding. The system requires 178.8 kWp PV capacity and 6 batteries (90 kWh storage). Fig. 10 displays the batteries' daily energy profile. The load shifting implementation was displacement of 1.5 kW of demand from 1am to 3 p.m. Fig. 11 shows load shedding occurring in scenario 6 when PV generation becomes completely unavailable, resulting in approximately 47% of the EC demand going unmet during this extreme scenario. This configuration highlights the operational challenges of relying solely on load management strategies without V2C support during severe generation deficits. The significant penalty costs reflect the substantial impact on the user when forced load shedding becomes necessary in extreme scenarios.

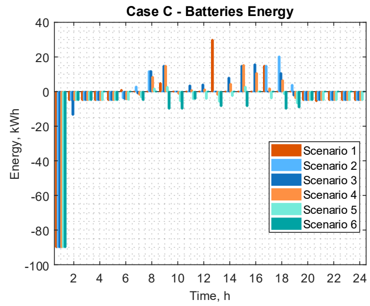

Fig. 10. Energy of the storage batteries in Case C.

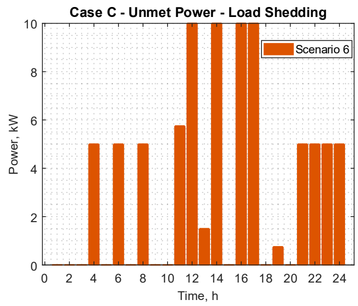

Fig. 11. Unmet Power/load shedding of the EC in Case C.

D. Case D

For this last test, all resources were considered, i.e., load shifting, load shedding and V2C. The optimal solution defines 178.8 kWp of PV generation and 180 kWh of batteries capacity, with an objective function equal to \$ 89,800, composed only of initial investment, without penalty costs. Despite the possibility of V2C, load reduction and shifting, the model opts for the solution that minimizes penalties and operational costs, which involve user dissatisfaction due to load reduction and shifting, prioritizing user well-being.

E. Overall Discussion

TABLE II. presents an overview of the results obtained with the four tests. In general, these cases demonstrate trade-offs between cost and operation under extreme scenarios. Case A was the only study without extreme scenarios, which generated the cheapest solution. Case B (V2C + load shedding) was the most economical with the consideration of extreme scenarios ($ 49,653), balancing the resources. Case C (load shedding only) failed in extreme events (47% of unserved energy), generating high penalties. Case D considered all resources obtaining the most conservative solution, maximizing self-sufficiency, and obviously, it was the most expensive option. The model prioritized user satisfaction, and V2C with load management (Case B) offered the best overall balance.

VI. Conclusions

A stochastic mixed-integer linear programming model for resource sizing in standalone energy community (EC) considering the impact of extreme events has been presented. The standalone EC is based on PV, batteries, and electric vehicles, and used operations such as load shifting, V2C, and load shedding to ensure efficient energy consumption during extreme events.

Four test cases analyzes trade-offs between cost and operation under extreme scenarios. Case A (excluding extreme events) based exclusively on PV generation and storage capacity but demonstrating non-conservative sizing due to extreme-event vulnerability. Cases B-D incorporate extreme scenarios. Case B (V2C + load shifting) proved to be the most economical ($ 49,653). Case C (only load shedding) failed in extreme scenarios (47% of energy not served), incurring high penalties for user dissatisfaction ($ 18,615). Notably, Case D (all resources) was the most conservative and most expensive solution, as optimization prioritized avoiding all penalties, favoring social welfare over flexible resource utilization.

The results demonstrate that V2C integration with load shifting (Case B) offers the optimal balance, while fully self-sufficient systems (Case D) provide reliability at higher costs, and load management alone (Case C) cannot meet demand during extreme events. The model consistently prioritized user satisfaction, even when flexible resources were available.

Future work may include the study of different approaches to characterizing extreme events, such as CVaR, and a greater number of scenarios.

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TABLE II. Results Obtained for Objective Function, Resources and EC Dimensioning in All Cases

Case/Values	**Case A**	**Case B**	**Case C**	**Case D**
Objective function	$ 39,800	$ 49,653	$ 78,455	$ 89,800
Investiment cost	$ 39,800	$ 39,800	$ 59,800	$ 89,800
Operation of load shift	–	$ 100	$ 40	–
Payment for V2C	–	$ 9753	–	–
Penalty for unmet power	–	–	$18,615	–
PV size	178.8 kWp	178.8 kWp	178.8 kWp	178.8 kWp
Battery storage size	30 kWh	30 kWh	90 kWh	180 kWh