



Measuring the Resilience of Renewable Energy Communities: A Scenario Analysis of the Regenerative Capacity

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Abstract

The growing adoption of decentralized renewable energy systems highlights the need to assess their resilience to disruptions. Renewable Energy Communities (RECs), composed of consumers and prosumers, rely on rooftop photovoltaic generation and peer-to-peer (P2P) energy sharing to meet local demand. Although previous studies have evaluated RECs from energy and economic perspectives, the influence of P2P network topology on resilience remains largely unexplored. This study proposes a framework that combines energy performance assessment with graph-based network vulnerability analysis to evaluate REC resilience under targeted disruption scenarios. P2P energy exchanges are simulated to construct directed, weighted energy-sharing networks, and graph-theoretic centrality measures are used to identify critical nodes whose sequential removal mimics targeted attacks. Results show that RECs provide substantial environmental and economic benefits, reducing greenhouse gas emissions to 61% of the baseline and achieving an average energy bill reduction of 22.5%. The self-consumption rate (SCR) indicates that 39.6% of locally generated renewable energy is consumed within the community, while the self-sufficiency rate (SSR) shows that local generation and P2P sharing satisfy 39.2% of total electricity demand. However, removing a small number of highly connected users significantly decreases network efficiency, highlighting the importance of increasing participation and redundancy to enhance REC robustness.

Keywords Renewable energy communities · Resilience · Regenerative capacity

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1 Introduction

Renewable Energy Communities (RECs) are expected to play an important role in the clean energy transition by promoting renewable energy adoption, decentralized generation, energy self-sufficiency, and active participation in the energy system (Blasch et al. 2021; Ahmed et al. 2024). By enabling local energy generation and consumption, RECs can improve the sustainability, reliability, economic efficiency, and resilience of energy infrastructures (Butturi et al. 2018; Panteli and Mancarella 2015). Moreover, local energy generation supported by diversified energy sources, storage systems, and advanced control mechanisms can reduce the susceptibility of energy networks to disruptions and improve recovery capabilities during emergencies (Panteli and Mancarella 2015). In Europe, RECs are supported by the Renewable Energy Directive (RED II), although their implementation varies across Member States due to differences in regulatory, legal, and geographical contexts (Commission 2024; Tatti et al. 2023).

Within REC frameworks, several energy-sharing models can be adopted (Iazzolino et al. 2022; Minuto and Lanzini 2022). Among them, peer-to-peer (P2P) energy sharing allows prosumers to directly exchange energy within the community, increasing self-consumption, self-sufficiency, and economic benefits while reducing dependence on the main grid (Wilkinson et al. 2020; Duvignau et al. 2021; Tanis et al. 2024; Tushar et al. 2021; Barone et al. 2024). P2P energy markets can be implemented through decentralized mechanisms, where peers directly define trading conditions, or through centralized coordination schemes that optimize peer connections (Tushar et al. 2021). Furthermore, clustering consumers and prosumers according to their demand and generation profiles can further improve community self-consumption, self-sufficiency, and economic performance (Barone et al. 2024). The P2P approach has been extensively studied from economic, regulatory, and optimization perspectives (Jogunola et al. 2024; Zhang et al. 2024b). However, comparatively little attention has been devoted to the structural resilience of energy-sharing networks (Akila et al. 2024). Existing studies typically evaluate REC performance through energy and economic indicators, whereas network resilience research rarely examines empirical P2P communities and their response to disruptions.

Beyond energy-related benefits, RECs can support diverse stakeholders across urban and peri-urban areas, contribute to reducing energy poverty, increase resilience to climate impacts, democratize access to clean energy, and strengthen local communities through shared infrastructure and cooperation (Neri et al. 2023; Wuebben et al. 2020; Iazzolino et al. 2022; Petrovics 2024; Vallecha and To 2024). They contribute to the achievement of several Sustainable Development Goals (SDGs), including SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action) (Wuebben et al. 2020; Iazzolino et al. 2022; Petrovics 2024). These characteristics make RECs particularly relevant not only as energy initiatives but also as mechanisms supporting broader community resilience and local development.

Community energy resilience encompasses the ability of local energy systems to maintain energy supply during disruptions while supporting affordability, emissions reduction, and economic development (Boston et al. 2024; Ribeiro et al. 2015).

Charani Shandiz et al. (2020) distinguish three dimensions of community energy resilience: engineering-designed, operational, and community-societal resilience. Distributed energy resources, storage systems, and smart technologies can strengthen resilience by mitigating disruptions and accelerating recovery, whereas socioeconomic and climate-related factors typically influence resilience over longer time horizons (Ribeiro and Bailey 2017). Reviewing resilience assessment approaches for renewable and integrated energy systems, Monie et al. (2025) discuss several resilience metrics, including diversity-based indicators such as the Shannon–Wiener index and composite measures that jointly capture preparedness, mitigation, response, and recovery.

A complementary perspective considers resilience as a property emerging from the structure of energy networks. In multi-energy systems (MES), energy hubs integrate multiple energy sources and contribute jointly to energy supply. Building on this perspective, Zhang et al. (2024a) apply complex network theory to evaluate the resilience of such systems by representing interactions among components as topological relationships between nodes. Network analysis employs techniques and metrics such as centrality and connectivity indices to characterize these structures and identify critical elements. Under a P2P energy-sharing configuration, RECs can be viewed as a simplified form of MES in which prosumers exchange energy directly with one another. As a result, the resilience of the community’s energy-sharing structure can be investigated through network analysis, enabling the identification of key participants and the assessment of the community’s ability to maintain efficient exchanges under disruption scenarios.

This perspective is also consistent with the growing interest in RECs as regenerative business models. The combination of sustainability, resilience, and socio-technological innovation makes RECs regenerative systems capable of generating positive impacts on both natural and human ecosystems (Mangano 2022). According to Caldera et al. (2022), regenerative systems operate through dynamic networks of reciprocal exchanges that generate benefits in multiple directions and support both human communities and ecosystems. In this context, RECs enhance regenerative capacity by improving energy-system resilience, fostering stakeholder value creation, and enabling local reinvestment through prosumer participation and smart energy technologies (Yadav and Yadav 2024; Grijalva and West 2024). Their adoption can be particularly beneficial in inner areas, where local renewable resources can support broader regeneration processes (Mangano 2022).

Understanding how RECs contribute to regenerative capacity while maintaining functionality under disruptions is therefore critical for designing robust and socially equitable energy infrastructures. Using a case-study-based approach, this paper evaluates REC regenerative capacity from two complementary perspectives: the benefits generated under normal operating conditions and the resilience of the system under disruption scenarios. A set of performance indicators is used to quantify the economic and environmental effects of REC adoption. In parallel, we construct directed and weighted energy-sharing networks from empirical hourly production and consumption data and analyze their structural properties through graph-theoretic metrics, identifying highly connected participants that play a key role in local energy balancing.

We then expose these local networks to a disruption scenario simulating targeted attacks, where the most connected prosumers are removed, measuring the variation in the community-network global efficiency as a proxy for the P2P-configured system's regenerative capacity.

By combining energy-performance assessment with network resilience analysis, this study provides a more comprehensive understanding of how local energy communities operate under stress. The results offer practical insights for the design of decentralized energy systems that are not only efficient but also robust, adaptable, and capable of sustaining their regenerative function in the face of disruption. These findings are relevant for energy policymakers, urban planners, and technical designers seeking to develop the next generation of sustainable and resilient energy communities.

2 Methodology

To simulate P2P energy exchanges within REC, we constructed adjacency matrices representing energy transfers between prosumers in each REC. In this study, a prosumer denotes an energy participant represented in the raw data, while the corresponding network node is the graph-theoretic abstraction of that participant in the REC transfer network. This approach enables quantifying how surplus production from one prosumer can compensate for the consumption needs of others in the same geographic area.

The methodology is organized as a sequence of explicit steps, starting from timestamp-aligned hourly data and ending with the recomputation of the resilience indicators after targeted node removal. The preprocessing rules used before any analysis is performed include hourly alignment, deterministic duplicate handling, treatment of missing records, and clipping of non-physical negative production values. We also formalized the main quantities used in the study, such as overproduction, hourly energy transfers between prosumers, and cumulative graph edge weights, so that the implementation can be reproduced without relying on interpretive assumptions.

In addition, the authors are encouraged to clarify more explicitly the extent to which energy storage systems are included in the simulations. A clearer discussion of the role of storage would help the reader better understand the implications of the conclusion that the removal of a few highly connected users significantly reduces network efficiency.

2.1 Dataset

This study utilizes a time-series dataset focused on forecasting hourly electricity consumption and production from Estonian energy customers who have installed photovoltaic (PV) systems. The dataset was released by EESTI Energia as part of a Kaggle forecasting competition and consists of produced and consumed energy data by client, county, customer type, and product type, aligned with hourly time intervals.

Dataset Scale and Composition The Estonian dataset includes over 1,000 prosumer-county combinations and more than 4.3 million hourly observations collected between December 2022 and May 2023. It covers all 15 Estonian counties and includes both residential and commercial PV installations. The geographic aggregation at county level is comparable to the areas served by primary substations in Italy, while the mix of household and business-owned PV systems closely reflects the structure of potential Italian REC. Consequently, the dataset provides a realistic representation of REC configurations in the Italian context.

Data Structure and Variables The dataset reports hourly electricity consumption or production (kWh) for aggregated user groups defined by county, customer type (`is_business`), and electricity contract type (`product_type`). Each record includes a timestamp (`datetime`) and a binary flag (`is_consumption`) identifying consumption or production observations.

Data Quality and Preprocessing The raw data were reshaped into a unified format for each county, business status, and contract type combination. Consumption and production records were merged on the shared keys (`datetime`, `county`, `is_business`, `product_type`), and a new feature, `over_prod`, was computed as

$$\text{over_prod}_{u,t} = \max(\text{production}_{u,t} - \text{consumption}_{u,t}, 0) \quad (1)$$

The preprocessing procedure included hourly timestamp alignment, duplicate removal, clipping of negative production values, and treatment of missing values. The resulting dataset contained complete hourly records for all analyzed user groups.

Given the geographical scope of the data, each county was considered a REC. In the network representation, each prosumer corresponds to a node in the directed weighted graph.

2.2 Reproducibility Protocol

For each county-level REC and each hourly timestamp in the analysis window (24/12/2022–31/05/2023), we applied a standardized processing pipeline including data preprocessing, computation of pre-redistribution energy variables, execution of the redistribution mechanism, graph construction from cumulative energy transfers, computation of baseline network indicators (E , LCC , C , $\mathcal{E}$), and targeted attack simulations for $k = 1, \dots, 7$ with recomputation of all indicators. Intermediate and final outputs, including energy transfers, removed nodes, and network metrics, were stored for each REC and attack scenario. To guarantee full reproducibility, ties between users with identical metric values were resolved by sorting user IDs in alphabetical order.

2.3 Energy Redistribution Algorithm for REC

To optimize the use of locally generated renewable energy, we developed an energy redistribution mechanism that operates within each REC at an hourly resolution. The

objective is to maximize internal energy sharing among members, thereby reducing reliance on external grid energy.

Figure 1 illustrates the overall logic of the redistribution process using a flowchart representation. The procedure begins by computing the net energy balance for each user, defined as the difference between energy consumption and local production for a given time step. This step identifies whether each user has an energy surplus or deficit. Users are then classified into two groups: *producers*, whose production exceeds their consumption, and *consumers*, whose consumption exceeds their production.

The core of the algorithm is an iterative redistribution loop. At each iteration, the system checks whether both producers and consumers are still present. If so, the algorithm matches the producer with the largest available surplus to the consumer with the highest unmet demand. The amount of energy transferred is determined as the minimum between the available surplus and the required demand, ensuring that neither over-allocation nor negative balances occur.

Following each transfer, the remaining energy needs of both users are updated accordingly. In addition, the algorithm records key transaction details, including the amount of energy exchanged and the origin of the transfer. This tracking mechanism ensures full traceability of energy flows within the REC and allows reconstruction of the sharing process at a granular level.

The redistribution cycle continues iteratively until no further transfers can be performed, i.e., when either no producers with surplus energy remain or all consumer demand has been satisfied. At this point, the algorithm proceeds to the final computation phase.

At each hour, producers and consumers are ranked by residual surplus and residual demand, respectively. The matching rule is greedy and deterministic: the producer with the maximum surplus is matched to the consumer with the maximum demand; ties are resolved by ascending user identifier. For a matched pair (i, j) at hour t , the transferred energy is

$$\tau_{i,j,t} = \min(s_{i,t}, d_{j,t}), \quad (2)$$

where $s_{i,t}$ is the available surplus of producer i and $d_{j,t}$ is the unmet demand of consumer j . The loop terminates when either $\sum_i s_{i,t} = 0$ or $\sum_j d_{j,t} = 0$.

In the final step, the energy balance of each user is updated to reflect the effects of redistribution. This includes calculating the adjusted consumption level, the residual

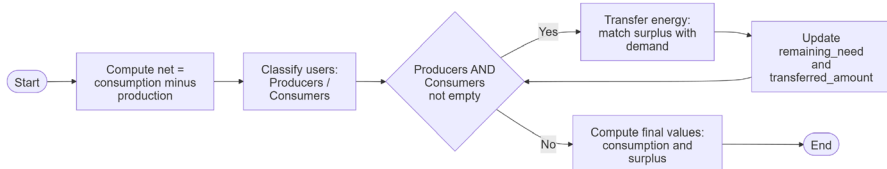


Fig. 1 Flowchart of the iterative energy redistribution algorithm within a REC. At each step, producers with surplus energy are matched to consumers with unmet demand, ensuring balanced transfers while maintaining full traceability. The process repeats until no further exchanges are possible, after which final energy balances and key indicators—such as residual demand, unused surplus, and grid dependency—are computed

surplus (if any), and the remaining dependency on the external grid. In particular, any surplus energy that could not be allocated within the community is explicitly identified, while the final consumption quantifies the portion of demand that must still be met externally.

Beyond enabling efficient energy sharing, the algorithm produces a detailed dataset describing intra-community energy dynamics. For each user and time interval, it captures:

- energy produced and consumed,
- net balance before and after redistribution,
- amount and origin of transferred energy,
- unallocated surplus energy,
- residual dependence on the external grid.

These outputs provide a comprehensive basis for analyzing the effectiveness of local energy sharing mechanisms, assessing the degree of self-sufficiency achieved within the REC, and supporting data-driven policy and planning decisions.

2.4 Energy Performance Indicators

To comprehensively assess the performance of the REC and its positive impact on the local community, we evaluate a set of key performance indicators (KPIs) over the considered period (24/12/2022–31/5/2023). These indicators were retrieved from the reference list drafted by Giannuzzo et al. (2025), quantifying economic, energetic, and environmental outcomes, providing a multidimensional view of the REC's effectiveness and its potential to trigger processes of regeneration.

These KPIs provide the baseline performance against which the effects of the resilience experiments presented in Section 2.5 are evaluated.

2.4.1 Energy Bills Reduction

The Energy Bills Reduction (EBR) quantifies the primary economic incentive for REC participation and represents the direct financial benefit accruing to community members. The EBR quantifies the economic benefit of REC participation by comparing total energy expenditures before and after the REC's establishment:

$$\text{EBR} = \frac{B_{\text{before}}}{B_{\text{after}}} \quad (3)$$

where B_{before} and B_{after} represent the total energy bills before and after REC implementation, respectively. All prices are based on official zonal daily rates published by GME. Values of $\text{EBR} > 1$ indicate cost reduction; a higher EBR reflects greater savings. Economic benefits are essential for community buy-in and the financial sustainability of REC models, and they enable participants to reinvest savings into system improvements or expand local capacity. EBR is therefore a key indicator of the REC's capacity to generate economic regeneration.

2.4.2 Shared Energy

Shared Energy (SE) measures the amount of renewable energy that is successfully exchanged among REC members through the P2P redistribution algorithm, excluding direct physical self-consumption. At each time step t , the redistribution algorithm iteratively matches producers with surplus generation to consumers with unmet demand until either no surplus or no demand remains. Therefore, the total shared energy is

$$SE_t = \min \left(E_t^{\text{grid,withdrawn}}, E_t^{\text{grid,injected}} \right), \quad (4)$$

where $E_t^{\text{grid,withdrawn}}$ and $E_t^{\text{grid,injected}}$ denote the total energy that would be withdrawn from and injected into the external grid, respectively, before applying the P2P redistribution process. Consequently, SE_t represents the maximum amount of energy that can be balanced internally within the REC during time step t . SE quantifies the net balance of energy exchanges with the external grid, with higher values indicating lower net grid dependency. By reducing grid reliance, RECs lower transmission losses, reduce peak demand on centralized systems, and improve overall power system resilience. SE is therefore an intermediate metric bridging local energy independence and system-wide grid stability.

2.4.3 Self-Consumption Rate

The Self-Consumption Rate (SCR) is a key energy performance indicator that measures the fraction of locally generated renewable energy utilized within the REC, either through direct self-consumption or P2P energy sharing, rather than being exported to the external grid. It is defined as:

$$SCR = \frac{\sum_{t \in T} (E_t^{\text{self}} + SE_t)}{\sum_{t \in T} E_t^{\text{prod}}} \quad (5)$$

where E_t^{self} is the renewable energy directly self-consumed by the producing user before P2P redistribution, SE_t is the shared energy, and E_t^{prod} is the total renewable energy produced at time t over the evaluation period T . SCR reflects the effectiveness of P2P coordination in matching local renewable generation with community demand. Higher SCR values (approaching 1, or 100%) indicate that a larger share of locally generated renewable energy is utilized within the community rather than exported to the external grid, demonstrating the added value of REC mechanisms. A high SCR is directly relevant to regenerative capacity because it reduces renewable energy curtailment and grid dependency while maximizing the environmental benefits of installed photovoltaic capacity. A high SCR indicates effective coordination between local renewable generation and community demand, contributing to the efficient utilization of renewable energy within the REC. As such, SCR provides a

useful indicator for assessing the impact of disruptions on the community's energy performance.

2.4.4 Self-Sufficiency Rate

The Self-Sufficiency Rate (SSR) measures the extent to which the REC satisfies its electricity demand through locally generated renewable energy, including both direct self-consumption and P2P energy sharing. It is defined as

$$\text{SSR} = \frac{\sum_{t \in T} (E_t^{\text{self}} + \text{SE}_t)}{\sum_{t \in T} E_t^{\text{demand}}}, \quad (6)$$

where E_t^{self} is the renewable energy directly self-consumed by the producing user before P2P redistribution, SE_t is the shared energy, and E_t^{demand} is the total electricity demand at time t over the evaluation period T . Since the locally utilized renewable energy cannot exceed the total electricity demand, SSR ranges from 0 to 1. Higher SSR values (approaching 1, or 100%) indicate that a larger share of the community's electricity demand is met through local renewable generation and P2P energy sharing, thereby reducing dependence on electricity imported from the external grid. Consequently, SSR provides a direct measure of the REC's energy autonomy and contributes to assessing its regenerative capacity. A high SSR indicates a greater degree of energy autonomy by reducing reliance on electricity imported from the external grid. Consequently, SSR provides a useful indicator for assessing how disruptions affect the community's ability to satisfy its electricity demand through local renewable resources.

2.4.5 Greenhouse Gas Emissions

The Greenhouse Gas (GHG) emissions reduction quantifies the environmental benefit of REC participation, measuring the displacement of grid electricity (typically generated from fossil fuels or a mixed energy mix) with locally produced renewables. Greenhouse gas (GHG) emissions are evaluated as the total carbon footprint (in kg CO₂eq) associated with energy consumption in the REC, accounting for the emissions from the production, operation, and transportation of energy. Only the energy purchased from the grid is considered in the emissions calculation. Emission factors are based on datasets such as the Electricity Map for Northern Italy. The ratio of post-REC to pre-REC emissions quantifies the environmental leverage of the community energy model. Lower ratios indicate greater environmental benefits. GHG reduction is essential for RECs' regenerative capacity because it demonstrates a contribution to climate mitigation goals (SDG 13) and articulates the concrete environmental value delivered to participants. In the resilience analysis, GHG reduction post-attack reveals whether network fragmentation undermines the environmental benefits of the REC model, helping policymakers understand whether resilience interventions (e.g., storage, redundancy, improved topology) are necessary to preserve environmental gains under disruption scenarios.

2.5 Resilience of REC Networks

Theoretical Foundation. Network resilience—the ability of a system to withstand and recover from disruptions—has become a central concern in complex systems science (Newman 2003; Holme et al. 2002). For energy systems in particular, understanding how network structure influences vulnerability to targeted node removal is critical for identifying critical infrastructure and designing robust community energy systems (Chopra and Khanna 2014; Zhang et al. 2024a). We apply graph-theoretic methods to quantify the structural robustness of REC energy-sharing networks under simulated disruptions.

Graph Model and Formal Definition. We model each REC as a directed weighted graph from network science (Newman 2003), denoted $G = (V, E, W)$, where:

- $V = \{u_1, u_2, \dots, u_n\}$ is the set of n users (nodes);
- $E \subseteq V \times V$ is the set of directed edges, where $(i, j) \in E$ if and only if at least one energy transfer from user i to user j occurs during the observation window;
- W is the edge weight function assigning to each edge $(i, j) \in E$ a positive weight $w_{i,j}$ representing the cumulative energy transferred.

In this formulation, network topology refers to the pattern of directed connections in E , while energy exchanges refer to the transfer magnitudes encoded by W and by the hourly quantities $\tau_{i,j,t}$. Thus, topology captures who is connected to whom, whereas the exchange data capture how much energy is actually transferred along those connections.

The edge weight is formally defined as:

$$w_{i,j} = \sum_t \tau_{i,j,t}, \quad (7)$$

where $\tau_{i,j,t}$ denotes the energy transfer from i to j at hour t as computed by the redistribution algorithm. All resilience indicators are computed on the directed graph; weak connectivity (defined as connectivity in the underlying undirected graph) is used for component-based metrics (Newman 2003).

Accordingly, the structural metrics reported below describe topology, while the redistribution algorithm provides the weighted exchange data used to build that topology.

Connectivity Indicators. We compute a suite of graph-theoretic metrics (Newman 2003; Latora and Marchiori 2001) to characterize network structure before and after simulated disruptions:

- **Number of Edges ($|E|$):** Total number of directed energy transfer connections. This metric reflects network density and the breadth of P2P interactions, with higher values indicating more distributed energy sharing pathways.
- **Largest Connected Component Size (LCC):** The fraction of nodes in the largest weakly connected component. As a fundamental metric of network fragmentation (Newman 2003), this indicator measures the proportion of users that remain

integrated within a connected subgraph capable of exchanging energy directly or indirectly. A sharp decrease in LCC after node removal indicates vulnerability to cascading disconnection.

- **Number of Weakly Connected Components (C):** The count of maximal connected subgraphs. This metric quantifies network fragmentation; increases in C following targeted attacks indicate the emergence of isolated communities unable to exchange energy with the broader network.
- **Global Efficiency ($\mathcal{E}$):** The average inverse shortest-path distance between all reachable node pairs in the underlying undirected graph, defined as Latora and Marchiori (2001):

$$\mathcal{E} = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{1}{d_{ij}}, \quad (8)$$

where d_{ij} is the shortest path length between nodes i and j (set to infinity for unreachable pairs). This metric captures the average efficiency of energy propagation through the network topology; it ranges from 0 (completely disconnected) to 1 (fully connected). Global efficiency has been extensively used in network resilience analysis (Latora and Marchiori 2001) to measure both network capacity and vulnerability. *Targeted Attack Procedure.* We precisely specify the attack procedure: copy the baseline graph, compute centrality on the copy, remove the most central nodes one at a time in descending order of total degree (breaking ties by ascending node ID), and recompute indicators using identical functions. This procedure follows established methods in network vulnerability analysis (Holme et al. 2002) and isolates the vulnerability of networks to the preferential disruption of critical nodes. For each $k \in \{1, \dots, 7\}$, we perform the following procedure:

1. Copy the baseline graph $G_0 = (V, E_0, W_0)$;
2. Compute in-degree and out-degree centrality for all nodes;
3. Identify and sequentially remove the top- k nodes in descending order of total degree (in-degree + out-degree), with ties broken by ascending node identifiers to ensure determinism;
4. Recompute all connectivity indicators ($|E|$, LCC , C , $\mathcal{E}$) on the reduced graph $G_k = (V \setminus S_k, E_k, W_k)$, where S_k is the set of removed nodes.

This approach, known as a “remove-highest-degree” attack in network science (Holme et al. 2002), isolates the vulnerability of networks to the preferential disruption of critical nodes—a relevant scenario for energy systems facing cascading failures or strategic infrastructure damage.

The procedure is illustrated in Fig. 2, which summarizes the workflow for computing baseline connectivity metrics, identifying critical nodes by degree centrality, and evaluating the impact of their removal on network fragmentation and efficiency.

Interpretation: This graph-theoretic framework enables the quantification of REC vulnerability through network structural analysis. By comparing pre- and post-attack indicators, we identify critical users whose presence is essential for maintaining energy exchange pathways and network integration. Rapid decreases in LCC and $\mathcal{E}$

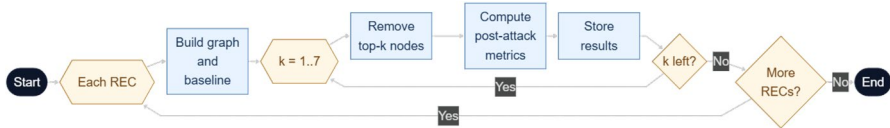


Fig. 2 Workflow for assessing REC resilience via targeted node removal simulation based on degree centrality

, or increases in C , following the removal of low-degree nodes would indicate structural resilience; conversely, sharp degradation with the removal of a few high-degree nodes indicates vulnerability to targeted disruption—a key concern for critical infrastructure resilience (Buldyrev et al. 2010).

3 Experimental Results

In this section, we present the experimental results of our study. We begin by illustrating key figures that characterize the outcomes of the energy sharing procedure, followed by a discussion of various indicators reflecting the performance of the REC. Finally, we simulate network attacks to evaluate their impact, and analyze the resulting changes in overall system efficiency.

Each row in Figs. 3 and 4 represents a producer, while each column corresponds to a consumer. The color intensity reflects the amount of energy transferred (in kWh), with darker shades indicating higher transfer volumes. These visualizations illustrate

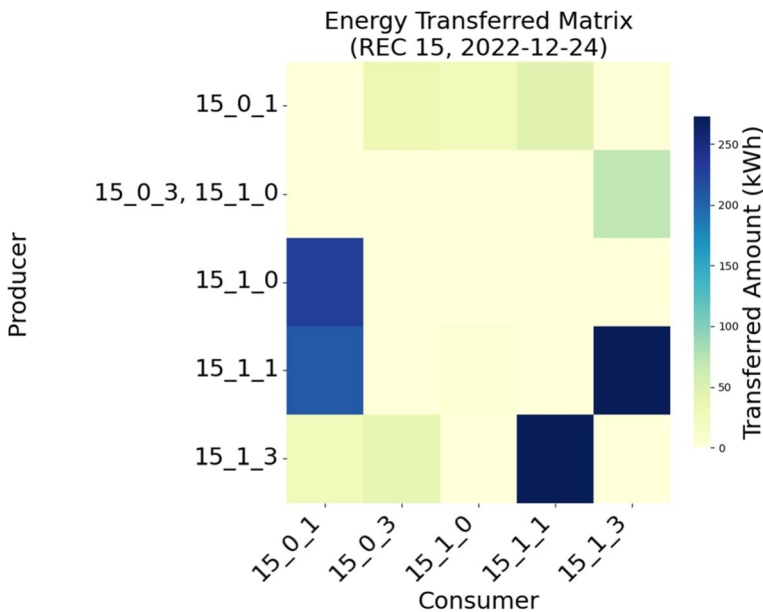


Fig. 3 Heatmap showing the energy transferred between users in REC 15 on 2022-12-24

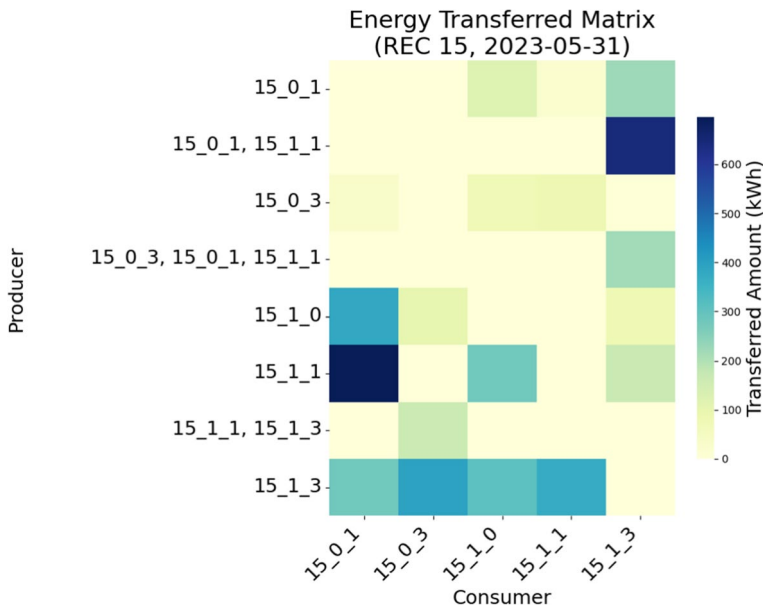


Fig. 4 Heatmap showing the energy transferred between users in REC 15 on 2023-05-31

both the distribution and magnitude of P2P energy exchanges within the community. Notably, the two figures demonstrate that even on December 24th, one of the shortest days of the year, there is still active energy transfer among users.

The Fig. 5 demonstrates that, despite the presence of an active process facilitating energy transfers among users, a substantial quantity of surplus energy remains untransferred and is consequently redirected to the grid. It is important to note that,

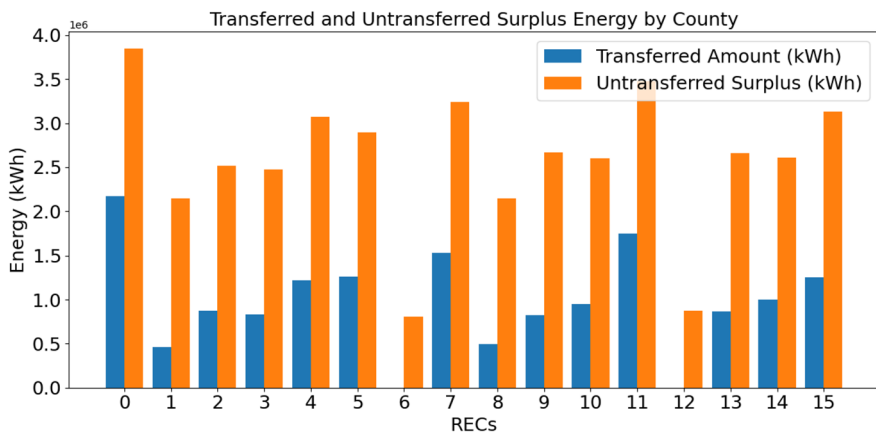


Fig. 5 Grouped bar plot showing, for each county, the total transferred energy (blue) and untransferred surplus (orange) across all time periods. This visualization compares energy sharing efficiency between counties

within our framework, energy exchanges between users are permitted only within the same hourly time interval.

The analysis of the energy community's performance reveals several important insights. Firstly, the implementation of local energy sharing leads to a substantial reduction in GHG emissions, with emissions after sharing amounting to approximately 61% of the baseline scenario, highlighting the environmental benefits of increased self-consumption and P2P energy exchanges. Economically, the community achieves an average EBR of 22.5%, reflecting the replacement of more expensive grid electricity with locally generated renewable energy. The technical indicators further characterize the community's energy performance. Specifically, the self-consumption rate ($SCR = 0.396$) indicates that approximately 39.6% of the locally generated renewable energy is either directly self-consumed or shared within the REC. Similarly, the self-sufficiency rate ($SSR = 0.392$) shows that local renewable generation and P2P energy sharing satisfy approximately 39.2% of the community's total electricity demand. These results demonstrate a meaningful, although partial, contribution of local renewable resources to meeting community demand while indicating that a substantial share of electricity must still be imported from the external grid. The data also show that a significant amount of renewable energy remains untransferred and is consequently exported to the external grid, suggesting opportunities to improve local energy utilization through enhanced coordination among REC members or the integration of energy storage systems, as emphasized by Zidane et al. (2025). Lastly, the economic balance, calculated as the difference between total expenses and income, indicates that although participants benefit from lower electricity bills, the overall framework could be further optimized to improve long-term financial sustainability. Overall, these indicators confirm the environmental and economic benefits of the REC while highlighting opportunities to increase local renewable energy utilization and strengthen community resilience. Overall, these indicators confirm the environmental and economic benefits of the REC while highlighting opportunities to increase local renewable energy utilization and strengthen community resilience.

Figure 6 illustrates the relationship between the number of attacks and global efficiency metrics. It shows the average global efficiency before attacks, the average global efficiency after attacks, and the efficiency drop percentage (red dashed line). The plot highlights how increasing attacks reduce network efficiency.

Taken together, the experimental results show three consistent patterns. First, the REC structure supports active P2P exchange, as reflected in the transfer matrices and the nonzero transfer volumes observed across the analysis period. Second, the system generates measurable environmental and economic benefits, while the corrected self-consumption and self-sufficiency indicators show that approximately 40% of locally generated renewable energy is utilized within the community, and about 39% of the total electricity demand is met through local renewable generation and P2P energy sharing. At the same time, a nontrivial share of surplus renewable energy remains unshared and is exported to the external grid, indicating opportunities for further operational improvement. Third, the resilience simulations show that the network is sensitive to the targeted removal of high-centrality nodes, which confirms that struc-

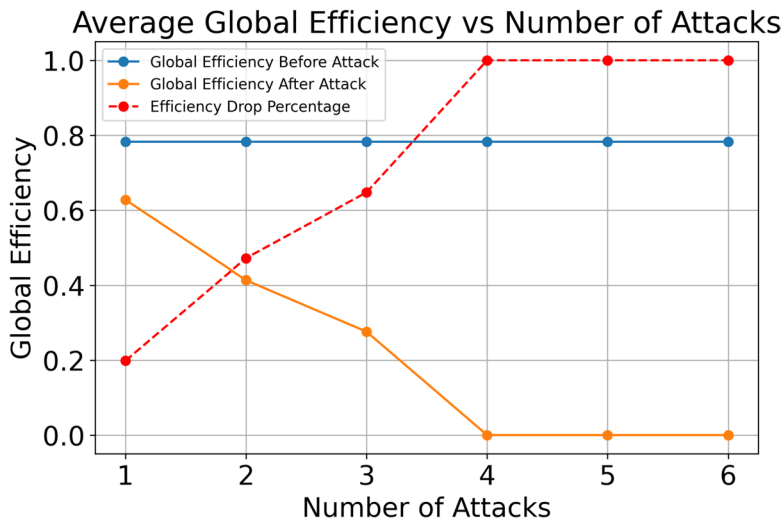


Fig. 6 Average Global Efficiency vs Number of Attacks

tural robustness depends not only on the amount of exchanged energy but also on the topology of the transfer graph. These findings motivate the use of storage, better coordination, and network-aware design to improve both efficiency and robustness.

4 Discussion

As the global energy system transitions away from centralized, fossil-fuel-based infrastructures toward renewable and decentralized alternatives, ensuring the resilience of local energy systems has become increasingly important. Renewable Energy Communities (RECs) are emerging as key actors in this transition, generating environmental, economic, and social benefits while improving local energy resilience. To evaluate these benefits, we adopted energy, economic, and environmental KPIs, which are commonly used to assess community energy projects (Bianco et al. 2021). Consistent with previous studies (Brunoro et al. 2024), our results confirm that RECs can generate multiple positive impacts.

The energy indicators show that the REC is able to utilize a meaningful share of locally generated renewable energy and partially satisfy community demand through local generation and P2P energy sharing, thereby reducing dependence on the external grid. At the same time, the SCR value, together with the observed surplus energy exported to the grid, indicates that a considerable fraction of the available renewable generation is not utilized within the community. This suggests that community performance could be further enhanced through the integration of energy storage systems and advanced digital technologies for balancing local energy flows (Hadjidimitriou et al. 2025). Storage systems can increase local renewable energy utiliza-

tion, reduce exports to the grid, provide flexibility services, and improve resilience during outages (Emma Elgqvist 2021). By acting as temporal buffers between periods of surplus and deficit, batteries can support critical nodes and reduce dependence on a small number of producers.

Economic benefits, quantified through the Energy Bills Reduction indicator, demonstrate that REC participants can achieve tangible savings that may be partially reinvested within the community. According to Grijalva and West (2024), this reinforces the regenerative capacity of RECs by fostering active prosumer participation. At the same time, the modeled P2P exchanges reveal structural dependencies among participants. The network analysis identified highly connected nodes whose removal significantly affects system performance, confirming that protecting critical actors is essential for REC resilience (Chopra and Khanna 2014).

Targeted attack simulations showed that average global efficiency decreases by approximately 50% after the removal of only two highly connected nodes. This finding highlights that resilience depends not only on energy performance but also on the distribution of exchanges among participants. In this context, storage can mitigate vulnerabilities by supporting critical loads and enabling adaptive recovery after disruptions (Mishra et al. 2020). Previous studies further emphasize the importance of properly sizing storage systems to ensure resilience while maintaining economic efficiency (Asfand et al. 2022).

From a policy perspective, REC design should incorporate resilience criteria alongside energy-sharing objectives. Storage deployment, monitoring of critical nodes, and promotion of more balanced exchange structures can improve robustness against disruptions. Graph-based resilience indicators may therefore provide useful decision-support tools for planners and regulators evaluating alternative REC configurations.

5 Conclusion

This study addresses a notable gap in the literature by combining empirical REC performance analysis with graph-based network resilience assessment, applying targeted degree-centrality attack simulations to real P2P energy networks. The results indicate that the REC model delivers measurable environmental and economic benefits while also leaving room for improvement in local energy utilization because a portion of surplus production is still exported to the grid. From a network perspective, the targeted attack experiments show that a small number of highly connected users can disproportionately affect global efficiency and component structure, which confirms that resilience depends on the topology of the sharing network as much as on aggregate energy balances.

These findings support two practical implications. First, increasing the coordination of P2P exchanges and integrating energy storage systems could improve self-consumption, increase self-sufficiency, and reduce the amount of surplus renewable energy exported to the external grid. Second, deploying storage and other flexibility resources around structurally important nodes may strengthen the system against disruptions and improve recovery after failures. Future work should extend the analysis

to additional RECs, compare alternative centrality-based attack strategies, and evaluate how storage and control policies alter resilience outcomes over time.

More broadly, the paper suggests that REC policy should be evaluated based on both efficiency and robustness since a network that performs well energetically may still be fragile if it depends on a small set of structural hubs.

Author Contributions N.S.H., M.A.B., and A.N. conceived the study, wrote the manuscript, developed the simulation framework, and performed the energy-sharing and resilience analyses. R.G. contributed to the methodological design and interpretation of results. M.M. contributed to the algorithmic implementation. R.N. supported the data acquisition and preprocessing. All authors reviewed and approved the final version of the manuscript.

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Data Availability The dataset used in this study is publicly available from the Kaggle competition "Predict Energy Behavior of Prosumers", accessible at: <https://www.kaggle.com/competitions/predict-energy-behavior-of-prosumers>.

Materials Availability Not applicable.

Code Availability 10.6084/m9.figshare.29636318.

Declarations

Competing Interests The authors declare no competing interests.

Ethics Approval and Consent to Participate Not applicable.

Consent for Publication Not applicable.

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