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A performance-based incentive sharing mechanism for communities of residential end users leveraging an ontology-driven approach [☆]

Rocco Giudice ^{ID}, Marco Savino Piscitelli ^{ID}*, Alfonso Capozzoli ^{ID}

Department of Energy "Galileo Ferraris", TEBE Research Group, BAEDA Lab, Politecnico di Torino, Corso Duca degli Abruzzi 24, Torino, 10129, Italy

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ABSTRACT

Energy sharing, whether physical or virtual, is crucial for optimizing the use of locally generated renewable energy within communities of residential end users, including Renewable Energy Communities (RECs) and Collective Self-Consumption (CSC) groups. By sharing energy, participants can increase self-consumption of renewables while reducing reliance on the grid. To encourage participation, many frameworks provide economic incentives for shared energy, offering financial benefits to those who contribute to community energy goals. However, ensuring a fair allocation of both shared energy and its associated incentives remains a challenge.

This study introduces a novel performance-based incentive-sharing mechanism that dynamically adjusts the allocation of economic benefits based on user ability to shift consumption in response to surplus availability. Different from traditional approaches, the mechanism integrates a dynamic baseline selection process with an ontology-driven metadata model, using SAREF and its domain-specific extensions to ensure interoperability and automation. This semantic framework enables scalable deployment across heterogeneous community configurations while reducing setup complexity.

The process was tested over a seven-month period within a collective self-consumption group of 13 residential users who virtually share energy from a centralized PV system. Results show that users who adjusted their consumption to match surplus availability increased their daily incentives by up to 40% compared to a standard sharing mechanism, while those who performed below expectations experienced a corresponding decrease. These findings highlight the potential of structured data-driven approaches, supported by ontologies, to improve decision-making in community energy management.

1. Introduction

The shift towards decentralized and renewable energy systems in buildings has increased the need for energy-sharing mechanisms among energy customers to minimize mismatches between generation and demand while maximizing local self-sufficiency [1]. Energy sharing can occur mainly in two configurations: Collective Self Consumption (CSC) groups, Renewable Energy Community (REC)s. A CSC group refers to a configuration composed of at least two renewable energy self-consumers who act jointly within the same building or condominium. Differently, a REC spans broader areas but remain limited to members connected by low- or medium-voltage cabins or proximity-based criteria defined by national regulations. The EU promotes these through the Renewable Energy Directive (RED II) – 2018/2001 and the Internal Electricity Market Directive (IEMD) – 2019/944 [2,3].

A REC is a legal entity that allows individuals to collectively produce, consume, and share renewable energy within a defined geographical perimeter [4]. Differently from traditional customer aggregation mechanisms, where energy flows unidirectionally from large-scale producers to consumers, RECs enable a virtual sharing of renewable energy among their members through the national electricity distribution grid [5]. RECs enhance self-consumption of renewable energy, support renewable energy system growth and contribute to grid stability by mitigating the variability associated with distributed generation. By matching local production with consumption, they reduce reliance on centralized imports and lower electricity costs for members [6–8].

RECs consist of three primary categories of participants: consumers, producers, and prosumers. Consumers buy and consume energy but do not own renewable energy assets. Producers own renewable energy systems, injecting locally generated energy into the grid, while prosumers

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* Corresponding author.

E-mail address: marco.piscitelli@polito.it (M.S. Piscitelli).

Nomenclature

EMIS	Energy Management and Information Systems
REC	Renewable Energy Community
CSC	Collective Self Consumption
SS	Self Sufficiency
SS_{add}	Additional Self Sufficiency
SS_{pot}	Potential Self Sufficiency
DR	Demand Response
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
SM	Sharing Mechanism
ML	Machine Learning
PV	Photovoltaic

both produce and consume energy, typically self-consuming part and injecting surplus into the grid [9].

The main objective of members of a REC is to coordinate among themselves to share as much as possible the generated surplus of energy. The concept of shared energy is fundamental for a REC and CSC group, as it is associated to an economic incentive that the involved group of members receive. The shared energy is defined as *the minimum, on hourly basis, between the electricity produced and fed into the grid by renewable production plants and the electricity withdrawn from all associated end customers* [10]. This means that only the energy that is simultaneously produced and consumed within the community, referred to as *virtual self-consumption*, is considered “shared” and taken into account for financial incentives (in Italy is in the range between 80 and 120 €/MWh [11]).

However, a key issue arises when determining how to allocate the economic incentive among community members. Since the energy exchange is virtual, different allocation mechanisms can be defined to fairly distribute the economic benefits of shared energy. Several methods have already been proposed in the literature [12–14], each with its own underlying principles, advantages, and limitations. Some approaches prioritize investment equity, others reward consumption behavior [13], while newer methods attempt to incorporate dynamic and progressive criteria to ensure a fairer and more efficient distribution of incentives [15]. In this context, one of the main challenges is establishing a fair incentive distribution mechanism that balances consumers and prosumers. While prosumers supply surplus renewable energy, they also benefit from multiple revenue streams, including capital subsidies (where applicable), avoided energy costs due to self-consumption, and revenue from feed-in tariffs or market-based energy exports to the grid [16]. However, surplus energy injected into the grid by prosumers can create significant imbalances, increasing the need for ancillary services to stabilize the electricity network [17]. A key solution lies in leveraging the synergy between consumers and prosumers within the community. By adjusting their consumption to align with prosumer surplus generation, consumers help mitigate grid imbalances while enhancing local energy self-sufficiency [18,19]. In this framework, consumers become the primary flexibility drivers within a community. When effectively incentivized, their load-shifting capabilities can improve self-sufficiency across entire neighborhoods when prosumers generate substantial surplus energy that would otherwise be exported to the distribution network with limited local utilization [20–22].

Despite its potential, this aspect has received limited attention, and consumer participation in such legal entities remains insufficiently incentivized, particularly in the residential sector. As a result, consumers often see limited financial returns, making active participation in the

community less attractive. This is partly because aligning electricity consumption with renewable generation typically requires shifting usage to periods when energy prices are higher. In such cases, the resulting increase in energy costs may outweigh the benefits unless offset by targeted incentives that compensate for this effort.

In this context, existing mechanisms still face challenges in fully integrating energy consumption performance and user behavior as a key factor in the allocation process. Current methods often overlook the role of consumers in adjusting their demand to better match renewable generation. Further research is needed to develop allocation mechanisms that explicitly consider virtuous/unvirtuous behavior of individual members towards the achievement of objectives at community level and that could help maintain member engagement to achieve the overall stability and economic viability of the community itself.

To this purpose, adopting performance-based approaches requires characterizing user behavior by defining a reference baseline that estimates the expected energy demand of a community member. This baseline not only estimates consumption but also evaluates whether actual behavior aligns with expectations during key periods of the day (e.g., surplus hours of the community). Building on this, it is crucial to establish incentive-sharing mechanisms that align individual consumption patterns with community-level energy goals.

However, implementing such mechanisms at scale requires managing complex, heterogeneous data from multiple sources, formats, and naming conventions. Additionally, as communities grow and new members join, analytical models and processes must adapt seamlessly without requiring manual recalibration.

Achieving this level of flexibility and automation requires structuring data within a coherent, machine-readable information flow. This necessitates the development of a robust data model that ensures seamless interaction between various services such as load and production forecasting, sharing mechanism algorithms, and baseline development [23].

To address the aforementioned challenges, the paper investigates an experimental CSC configuration involving residential users and proposes an automated, interoperable, and portable framework for allocating incentives based on a novel performance-based mechanism.

In this context the study explores the following research questions:

1. Can individual consumption baselines be effectively used to identify and reward virtuous user behavior within RECs and CSC groups?
2. Does a hybrid redistribution mechanism based on consumption performance improve fairness compared to standard allocation rules?
3. Can an ontology-based data structure support scalable and automated deployment of such mechanisms across heterogeneous community configurations?

The rest of the paper is organized as follow. Section 2 critically reviews the literature about existing incentive sharing mechanisms, baseline development for residential users and semantic model descriptions for interoperable frameworks of analysis. Section 3 summarize then the contributions of the proposed methodology. Section 4 introduces the analyzed case study while Section 5 and Section 6 describe the employed methodological framework and the obtained results. Eventually, Section 7 provides a critical discussion of the results while Section 8 outlines the conclusions and draft the next research steps.

2. Background and related work

This section provides an overview of the state of the art, theoretical foundations, and recent advancements in incentive-sharing mechanisms, the establishment of energy performance baselines, and semantic ontology frameworks, all of which are relevant to the objectives of this study.

2.1. Incentive-sharing mechanisms in RECs and CSC groups

In recent years, various procedures have been proposed to address the allocation of virtually shared energy and the relative economic incentive among members of RECs and CSC groups. These procedures come each with distinct benefits and drawbacks. In general, the shared energy allocation between consumers and prosumers on hourly basis t , can be written as defined in Eq. (1):

$$SE^t = \alpha \cdot SE_p^t + \beta \cdot SE_c^t = \sum_{p=1}^{N_p} SE_p^t + \sum_{c=1}^{N_c} SE_c^t \quad (1)$$

where p represents the p^{th} prosumer, c represents the c^{th} consumer, N_p the total number of prosumers, N_c the total number of consumer, and SE_p^t and SE_c^t , respectively, the amount of shared energy allocated to each prosumer p or consumer c at time t . The coefficients α and β , whose sum must be equal to 1, serve to weigh the portion of total shared energy SE^t that is assigned to each category (i.e. prosumer or consumer).

The final incentive I^t can be obtained multiplying the shared energy for its economic incentive P (in the range between 80 and 120 €/MWh), as reported in Eq. (2).

$$I^t = \sum_{p=1}^{N_p} SE_p^t \cdot P + \sum_{c=1}^{N_c} SE_c^t \cdot P = SE^t \cdot P \quad (2)$$

P is a parameter that depends on the specific legislation of each country, and can be fixed or a variable of other parameters.

The magnitude of the coefficients α and β might depends on different parameters, boundary conditions or might be set a priori.

Among prosumers, one widely recognized approach is the ownership-based sharing mechanism, which allocates incentives based on the ownership share of each member in the renewable energy assets of the community. Under this mechanism, the shared energy allocated to a member is proportional to their share in the power generation plant of the community, without considering their actual contribution [13]. On the other hand, a proportional approach could be used to account for the energy shared by prosumers, incentivizing them based on their contribution to the total energy injected into the grid [12]. However, since the injected energy may not always be fully exploited if there are no available consumers to virtually use it, this approach risks rewarding members who contribute to grid imbalances rather than effective energy sharing.

The fundamental part, which requires more attention, is to assess how to redistribute the shared energy quota intended for consumers, i.e. $SE^t \cdot \beta$.

In the literature can be identified two main Sharing Mechanism (SM) approaches, from which newer and hybrid ones can be derived and defined. These mechanism are widely referred as proportional and progressive sharing.

The *proportional approach* allocates incentives to each member proportionally, based on each member quota of the total energy consumption of the community when shared energy is available. This mechanism rewards members according to their consumption, ensuring that the distributed incentive aligns with their contribution to the overall community self-consumption and self-sufficiency [14]. This approach has the advantage of incentivizing higher participation in energy consumption by directly linking rewards to energy usage. However, a significant limitation arises, since members with higher consumption receive higher incentives. This can discourage energy-saving behaviors and may even incentivize excessive energy use to maximize individual rewards. Thus, while the proportional approach fosters active participation, it risks undermining the sustainability objectives of a REC or CSC group by prioritizing high consumption.

An alternative method is the *progressive approach*, which seeks to allocate incentives equitably among members. This mechanism ensures that all members receive at least the same amount of incentive. Starting

with the member with the lowest consumption, the shared energy is distributed incrementally, matching each user hourly demand until the entire shared energy is allocated. Then the progressive approach emphasizes equal dignity among members and promotes inclusivity within the community [13]. However, this method may not fully reflect individual contributions to the REC, particularly for members with larger energy demands.

Starting from these foundational approaches, new methodologies have been developed. Authors in [12,14] implemented a proportional approach using sharing keys (often referred to as α and β) to allocate benefits equally or proportionally among consumers and prosumers. Benefits are distributed within each category based on exports for prosumers and imports for consumers using dynamic sharing coefficients. In [14] was introduced a variation where a minimum cap ensures that only consumers meeting a threshold receive incentives, with the rest redistributed.

Quiroz et al. [24] assessed the Portuguese REC framework by comparing fixed-equal, fixed-proportional, and variable sharing coefficients in a prosumer-only community. Results showed that variable sharing coefficients, based on a proportional approach, yielded better outcomes for collective PV self-consumption than individual PV usage with surplus sharing.

Eisner et al. [25] evaluated sharing mechanisms in residential-only and mixed-user RECs, analyzing static proportional, dynamic proportional, hybrid proportional, and progressive approaches. They found that small consumers are disincentivized in mixed RECs under purely proportional schemes, whereas hybrid and progressive approaches encourage participation and increase overall benefits. A similar pattern emerged in consumer-only RECs, where hybrid or progressive strategies provided the highest cost savings.

Eventually, in [15] were proposed three dynamic sharing coefficient models: one based on Pearson correlation to assess synchronization between grid imports and surplus exports, a trend-based key evaluating the difference between purchased and injected energy, and a combined method. Their approach prioritizes users who avoid overconsumption during production periods, promoting energy efficiency. Results demonstrated that incorporating production-consumption correlations and trend analysis leads to fairer benefit distribution within RECs, emphasizing efficiency over pure self-sufficiency.

2.2. Development of electric load baselines for residential buildings

Establishing reliable energy performance baselines is essential for assessing individual contributions and enabling fair incentive allocation among REC and CSC group members.

A baseline represents a reference pattern expressed in terms of energy consumption over time, from which deviations are measured to evaluate if or not a user is behaving according to expectations [26].

Despite being extensively studied in energy flexibility [27,28], demand response [29,30], and anomaly detection research [31,32], the baseline estimation problem remains particularly challenging for individual residential users [33]. At higher and aggregated consumption levels, such as for medium and large non-residential buildings, aggregated energy behaviors naturally smooth out individual fluctuations, resulting in more predictable demand patterns [34,35]. However, at the single residential member level, energy consumption is far more variable, driven by individual occupant behaviors, appliance usage, and lifestyle aspects. These factors introduce significant uncertainty, making it difficult to establish accurate and reliable baselines for single residential users. [36].

Various organizations and initiatives worldwide have developed baseline methodologies tailored to regional needs and regulatory frameworks [29], including the ENA Open Networks Project (UK), the North American Energy Standards Board (NAESB), the New York Independent System Operator (NY ISO), the California Independent System Operator (CAISO), and the Australian Energy Market Operator (AEMO). Focusing specifically on methodologies applicable to individual residential users, three primary categories emerge as the most relevant:

- **Historical baselines:** Also known as arithmetic baselines, these rely on past consumption data to establish a reference pattern for a building while excluding non-comparable days such as weekends, holidays, or prior-event days. Typically, they use 5 to 10 days of historical data before the target day for which the baseline is estimated, applying selection and exclusion rules to enhance accuracy. Some variations further remove extreme or low-load days to prevent distortions. The baseline is generally calculated using a simple mean or median across the selected periods. Their simplicity and direct reliance on real consumption data make historical baselines one of the most widely adopted approaches.
- **Regression-based baselines:** These are the most advanced baselines, making use of statistical and data analytics models to predict load based on variables such as schedule, weather conditions, and calendar events. By capturing complex interactions between energy consumption and exogenous variables, regression-based approaches provide a more accurate representation of a customer energy behavior. However, they require a relevant amount of historical data to properly characterize load patterns.
- **Control group baselines:** Primarily used for customers involved in demand response programs, this approach estimates the baseline by averaging the energy consumption of a group of similar users who are not participating to the program. When the control group is carefully selected to match the characteristics of the target users, this method can achieve high accuracy. However, its reliability depends on access to a large dataset with sufficiently diverse yet comparable customer profiles.

Few studies in the literature have focused on comparing individual residential load baseline models in performance-based programs. Jazaeri et al. [37] evaluated five baseline methodologies – namely High X of Y, Last Y Days, Regression, Neural Network, and Polynomial Interpolation – using data from 66 heterogeneous customers participating in a Demand Response (DR) program. Their findings indicated that polynomial extrapolation and neural networks yielded the lowest bias and estimation errors, though the improvement over simpler methods was only marginal. Hatton et al. [38] proposed a novel control group selection approach combined with regression techniques to assess baseline load profiles for 280 customers, using a control group of 433 households in the same geographical area. Their method demonstrated improved accuracy compared to commonly used control group-based approaches. George et al. [39] analyzed over 2000 residential load profiles, testing 21 different baseline models. Their results showed that while weather-matching and regression-based methods offered slightly better accuracy, no single model consistently provided accurate estimates for all customers across all event days. They also found that the widely used 3/5 baseline – a simple historical approach averaging consumption from three of the past five most recent days – performed comparably well against more complex models. For 80% of customers, the 3/5 baseline resulted in errors ranging from –31% to 28%, only slightly higher than the best-performing models, which achieved errors between –24% and 24%. Similarly, Wijaya et al. [40] found that the Low X of Y baseline had the highest accuracy but also the largest negative bias, meaning it underestimated actual consumption, significantly impacting customer revenues.

These findings suggest that historical baselines based on arithmetic averaging techniques often yield the most reliable results, as confirmed by numerous DR program evaluations. However, selecting the most suitable baseline model is not a one-time decision, as its effectiveness can change over time. Factors such as evolving consumption patterns, seasonal variations, technological upgrades (e.g., new appliances or energy storage systems), and shifts in occupant behavior can all impact the accuracy of a previously well-performing baseline. This dynamic nature of residential energy use underscores the need for adaptable methodologies that can reassess and recalibrate baseline models periodically.

Moreover, assessing baseline accuracy for individual residential buildings remains challenging due to the limitations of traditional error metrics, which struggle with the highly volatile and unpredictable nature of household load profiles [41]. Residential consumption patterns frequently include periods of minimal or zero demand, making conventional forecasting metrics such as Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) less effective [42,43]. To overcome these challenges, alternative error metrics have been proposed. One such approach is an adjusted p-norm error metric, which permutes the original forecast to minimize point-wise errors, reducing the double penalty effect caused by slight timing misalignments [44].

2.3. Semantic metadata models and ontology frameworks

To develop a data-driven incentive-sharing mechanism that is both automated and adaptable to diverse and the evolving configurations of REC and CSC groups, a robust and standardized approach to semantic metadata description is essential. Traditional methods for managing energy data often rely on static, manually configured systems that struggle to scale and adapt as new members, energy assets, and operational conditions change. Without a structured representation of energy-related information, integrating new customer, sensors, and control systems into the incentive-sharing process becomes inefficient and prone to errors.

To address these challenges, semantic models provide a machine-readable framework that structures metadata, defining clear relationships between buildings, equipment, sensors, and users through the use of ontologies [45]. In this perspective data-driven incentive-sharing mechanisms can dynamically adapt to changes in the community structure without the need for manual recalibration. This approach improves interoperability, making it easier to integrate heterogeneous data sources, such as energy-related data from different buildings of the same REC or CSC group. At the same time, it automates key processes such as defining and selecting baselines, assessing energy performance, and distributing incentives, reducing the need for manual reconfiguration.

In recent years, the building sector has increasingly adopted semantic models to structure energy-related data using standardized vocabularies and logical relationships, enabling seamless integration across Energy Management and Information Systems (EMIS) platforms [46]. Several frameworks, such as SeeQ [47] and the portable architecture by Chiosa et al. [48], demonstrate the use of semantic models to enhance portability and interoperability. Key applications include building control optimization [49], Fault Detection and Diagnosis [50–52], and smart-home automation [53]. These models are typically implemented as graph-based structures, leveraging RDF [54] and SPARQL [55] for efficient data querying and analysis.

At the core of semantic models are ontologies, which formalize the relationships between entities in buildings and energy systems. Ontologies such as BOT [56], RealEstateCore [57], ifcOWL [58], Brick [59], ASHRAE 223P [60], SAREF [61], and SSN/SOSA [62], provide standardized representations for building topology, device interactions, and energy systems, facilitating interoperability, automated reasoning, and data exchange. While each ontology has a distinct focus, they can often be aligned to ensure integration across different frameworks [49].

Among the available ontologies, SAREF [63] stands out as a particularly suitable choice due to its modular architecture and alignment with ETSI standards, which ensure compatibility across multiple domains within energy communities. Its domain-specific extensions – S4BLDG¹ for building systems, S4ENER² for energy flexibility, S4CITY³ for urban

¹ <https://saref.etsi.org/saref4bldg/v1.1.2/>

² <https://saref.etsi.org/saref4ener/v1.2.1/>

³ <https://saref.etsi.org/saref4city/v1.1.2/>

applications, and S4GRID⁴ for grid-level integration – enable semantic alignment across layers of increasing complexity. This structure is particularly advantageous for REC and CSC configurations, which often span heterogeneous devices, buildings, and actors.

While the application of semantic models in RECs and CSCs remains limited, several notable contributions have emerged. PARMENIDES, proposed by the authors in [64], introduces an interoperable architecture with a custom ontology for modeling energy storage and flexibility profiles. The OpenADR ontology developed by [65] enhances semantic interoperability in demand response systems. Additionally, Chun et al. [66] designed a semantic model to support the integration of diverse energy services, including energy trading within community settings.

3. Contributions of the work

The literature review highlights key challenges in designing fair, robust, and scalable incentive-sharing mechanisms applicable in legal entities such as RECs and CSC groups. Existing methodologies rely on static ex-post incentive distribution approaches that overlook how effectively members contributed to community-level objectives, particularly their ability to adjust consumption in response to renewable energy availability. In contrast, the approach proposed in this study introduces a novel hybrid mechanism that integrates an energy benchmarking framework with a dynamic baseline selection process, enabling context-aware, performance-based incentive allocation. This mechanism not only rewards users based on how closely their behavior aligns with community energy goals, but also promotes fairness, transparency, and active participation, addressing key limitations of traditional methods.

However, the effectiveness of sharing mechanism such as the one introduced in this study, is hindered by the lack of standardized metadata description models, which limits the scalability and adaptability of the underlying analytics pipelines. Without a structured and interoperable data framework, integrating more and diverse users and automating incentive distribution becomes challenging, restricting the practical implementation of these mechanisms in real world scenarios.

In this perspective, this study presents the three following key contributions.

1. A novel incentive-sharing mechanism for RECs and CSC groups, integrating an energy benchmarking approach to reward members who modify their behavior to meet community goals. Differently from traditional methods, it dynamically compares each member energy use against a data-driven baseline retrieved from historical data, enabling a performance-based incentive structure, as reported in [67]. This ensures fair compensation for members who voluntarily adjust their demand to match renewable generation surpluses, promoting a more balanced and equitable benefit distribution.
2. A framework for dynamic baseline selection, ensuring each member performance is evaluated using the most accurate and fair baseline from a pool of model candidates. By implementing a dynamic baseline selection process, the framework tailors reference baseline assessments to individual consumption patterns, reducing biases associated with static or generalized models.
3. A scalable and automated pipeline for shared energy and incentive distribution and baseline computation, leveraging ontology-based metadata modeling. Leveraging SAREF, S4BLDG, and S4ENER ontologies, the approach enables automated updates and dynamic execution of the analytics pipeline, simplifying adaptation to different community configurations and minimizing setup efforts when integrating new members into an existing one.

The proposed methodological framework was tested on a CSC group, configured as described in the following section.

4. Case study

The proposed sharing mechanism and its related semantic pipeline were validated using seven months of real energy consumption data from a CSC group. The case study involves 13 residential consumers located in Italy. While these users do not reside within the same physical building, the experimental setup models them as apartments in a single condominium to realistically represent energy interactions within a CSC group. This configuration aligns with the typical size of a condominium in Italy. Importantly, the size of the CSC does not affect the proposed methodology, as the behavioral assessment is conducted at the individual user level, independently of the total number of members. Similarly, the definition of the shared energy calculation remain consistent regardless of the community's scale.

The CSC group operates with a centralized Photovoltaic (PV) system that supplies electricity to the common areas, a centralized heat pump, and a small battery energy storage system. Any surplus energy is virtually shared among the residential users through a virtual metering scheme. Each apartment, representing a member of the CSC group, is equipped with an individual energy meter that records electricity demand at 15 min intervals.

The shared energy is defined as the minimum between the PV energy injected into the grid and the aggregate electricity demand of all users. In this configuration, the condominium (equipped with the PV system, battery, heat pump, and shared facilities) acts as a prosumer, while the individual members behave as consumers, benefiting from the available surplus.

Fig. 1 provides a visual representation of the CSC configuration considered in this study.

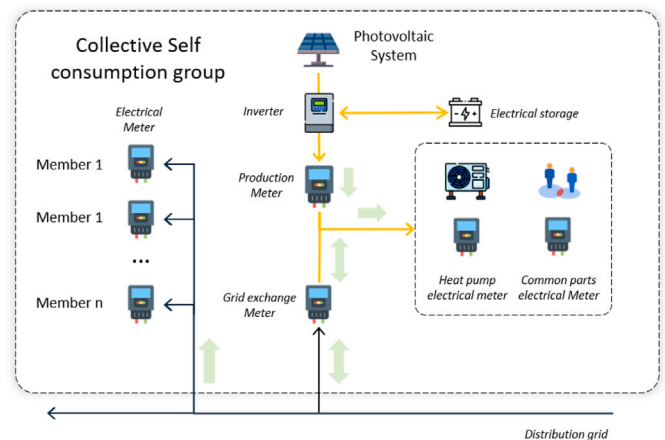


Fig. 1. Schematic representation of the considered collective self consumption group.

Energy production, grid exchange, and individual electricity demand data were collected from January 1st 2023 to July 31st 2023. The available dataset did not include missing or corrupted values, eliminating the need for data imputation or anomaly correction. However, the literature already provides mature and well-documented strategies for handling missing data and outliers which can be integrated as needed in future implementations targeting real-world deployments. Fig. 2 presents the average aggregated daily load profiles for each month, with a breakdown by user. Each shaded area in the figure represents the average hourly power consumption of a member within the CSC group. The data reveal a consistent three-peak pattern in the average monthly load profile, highlighting recurring consumption trends within the community.

⁴ <https://saref.etsi.org/saref4grid/v1.1.1/>

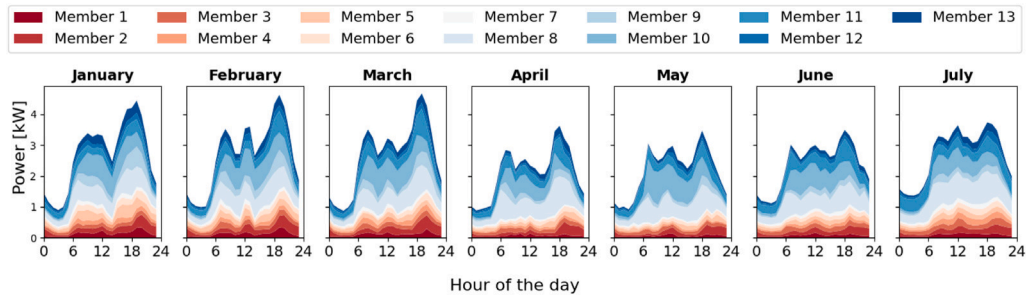


Fig. 2. Average monthly load profile of the CSC group considered.

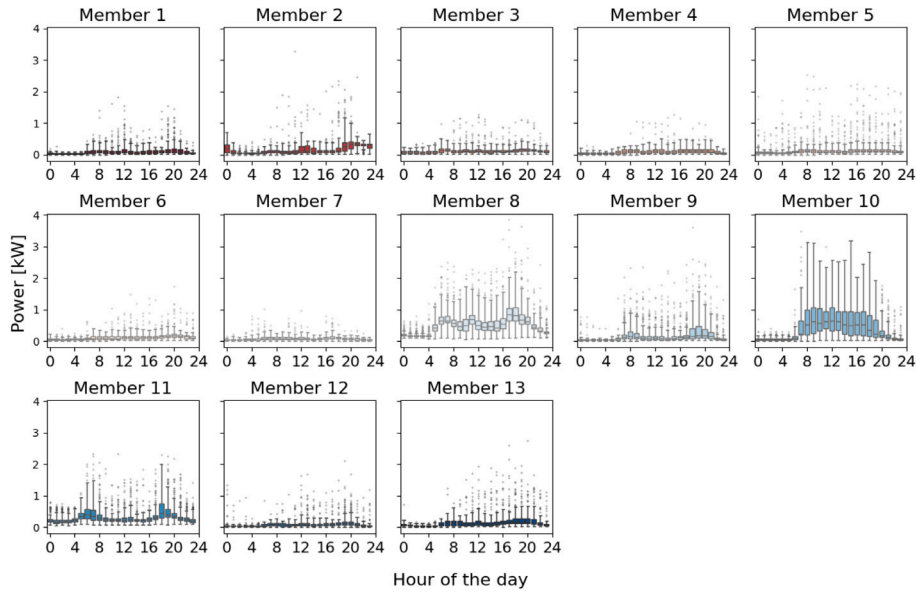


Fig. 3. Hourly electrical load distribution for each member of the CSC group. The electrical load distributions are represented as boxplots.

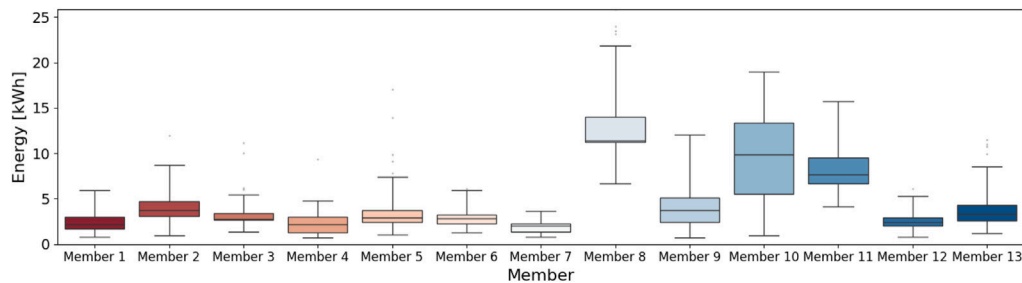


Fig. 4. Distribution of the daily energy demand values of all CSC group members for the entire period of analysis.

More specifically, Fig. 3 illustrates the hourly load profile of each member using boxplots, highlighting the variability in energy consumption over time.

Additionally, Fig. 4 presents the distribution of daily energy demand for each user, providing insights into individual consumption patterns within the CSC group.

The analysis reveals that members exhibit distinct energy consumption behaviors, both in terms of magnitude and pattern shape. Specifically, low-consumption members have relatively stable electrical loads with minimal fluctuations, whereas high-consumption members, such as Member 10, are characterized by significant variability in both hourly and daily energy usage. These high-consumption members play a crucial role in providing flexibility to the CSC group, as they have greater capacity to shift, increase, or decrease their own energy consumption. While limited in scale, the group exhibits sufficient

diversity in consumption patterns to effectively assess the feasibility and adaptability of the proposed mechanism. The observed variability, ranging from low and stable to high and fluctuating loads, makes it well suited for testing both dynamic baseline selection and incentive redistribution logic. Although larger communities may present increased heterogeneity and coordination complexity, the modular design of the proposed ontology-based framework ensures approach scalability and robustness.

5. Methodology

The methodological framework proposed in this study addresses three main tasks:

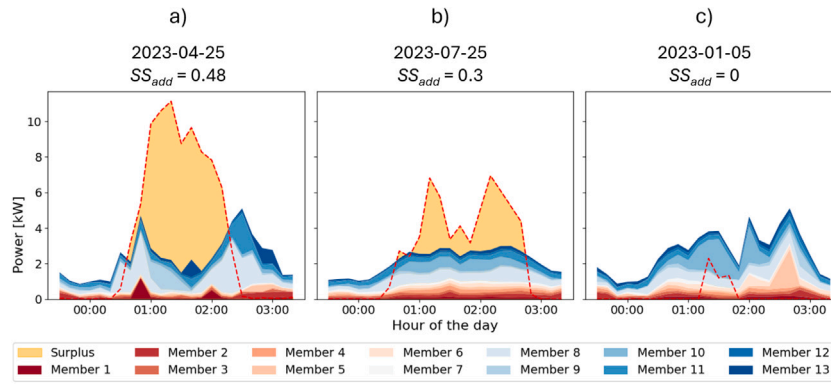


Fig. 5. Daily additional Self Sufficiency SS_{add} of the CSC group the for three different days.

- Definition of a performance-based process to distribute virtual shared energy among community members, ensuring a fair allocation of economic incentives;
- Development of a process to provide each member with dynamic and context-aware baselines that evolve over time, ensuring a robust and fair assessment of their contribution to community objectives;
- Implementation of a scalable and interoperable approach using appropriate ontologies to support the seamless deployment of the analytics pipeline in real-world scenarios.

In the following all the three tasks were described and discussed.

5.1. Definition of a performance-based sharing-mechanism

The sharing mechanism introduced in this study and preliminary explored by authors in [67] is based on the concept that at times when the available surplus of renewable energy is fully virtually shared among community members, the fairest incentive sharing mechanism is the progressive one. In fact, in that case all the members would be associated at least with the same amount of shared energy and the same is for the incentive. Details on the redistribution of shared energy using a progressive approach are provided in Section 2.1 and [13].

However, a different approach is needed when the community surplus, is not fully self-consumed by the consumers, due to a mismatch between consumers' demand and available surplus of energy.

In fact, during these periods a shift of the members' load during surplus period would have increased the daily Self Sufficiency (SS) of the entire community. In this case it is crucial to reward consumers who actively shifted their load in surplus hours with respect to their past energy consumption behavior. For this reason, the sharing mechanism illustrated here introduces, during surplus hours, a hybrid remuneration mechanism.

This mechanism defines the quotas of virtually shared energy, and so the incentive, distributed to each member as a function of two components: the first is the actual energy consumed by a member, while the second takes into account the deviations that exist between the actual consumption and a reference performance baseline defined starting from the characterization of its historical data. The latter is called *performance-based* component, because is obtained through an energy benchmarking process that quantitatively assesses if a member contributed (virtuous behavior) or not (unvirtuous behavior) in increasing the daily SS of the community with respect to its past behavior.

To balance both components, the daily Additional Self Sufficiency (SS_{add}) indicator is used. This metric represents the difference between daily Potential Self Sufficiency (SS_{pot}) i.e., the maximum achievable self-sufficiency if surplus energy were fully virtually shared, and the actual daily self-sufficiency of the community. A higher SS_{add} value

indicates that consumer demand was poorly synchronized with the available surplus, meaning greater potential for sharing energy if load had been shifted from non-surplus to surplus periods.

Eqs. (3)–(5) provide the mathematical formulation of, respectively, SS, SS_{pot} and SS_{add} .

$$SS = \frac{E_{cons} - E_{imp}}{E_{cons}} \quad (3)$$

$$SS_{pot} = \frac{\min(E_{cons}, E_{inj})}{E_{cons}} \quad (4)$$

$$SS_{add} = SS_{pot} - SS \quad (5)$$

where E_{cons} is the daily energy consumption, E_{inj} is the energy exchanged with the grid and E_{imp} is the net import from the grid.

For example, if the community daily SS is 70% and its potential self-sufficiency (SS_{pot}) is 80%, this indicates that the total daily energy demand exceeds available energy production, as SS_{pot} would be 100% if generation potentially fully covered the daily consumption. The remaining 10% (SS_{add}) represents energy consumed outside surplus production periods. If this portion had been shifted to hours of available surplus, the community could have reached its maximum potential self-sufficiency. A high SS_{add} value therefore reflects significant energy consumption occurring outside of surplus periods, emphasizing the potential for improved load shifting to optimize self-sufficiency.

As a result, the proposed mechanism dynamically adjusts the weight of the performance-based component based on the community additional self-sufficiency (SS_{add}), thereby incentivizing consumers who actively align their consumption with surplus availability. Furthermore, the use of SS_{add} can prevent disproportionate rewards for marginal behavior, particularly on days with limited surplus. As SS_{add} is low during such days, the performance-based incentive component is minimized, ensuring that rewards are primarily based on actual consumption, rather than small shifts that might otherwise be over-rewarded.

Fig. 5(a) shows the energy consumption of the community when a substantial surplus was available. In that case, the surplus could have entirely covered the energy consumption of the community, if the load was perfectly matched with the surplus. In this case, since the actual SS of the community was 0.52 and the SS_{add} was 1, the SS_{add} assumes a value of 0.48. On the other hand, Fig. 5(b) shows the energy consumption of the community where the surplus could not have covered entirely the energy consumption. In that case, the SS_{add} was lower than the previous case, so the performance-based component in the proposed sharing-mechanism would weigh less. Eventually, Fig. 5(c) shows the daily energy consumption of the community when the surplus is fully exploited by consumers. In this case, the performance-based approach is not employed, since SS_{add} is 0 and the energy is virtually shared among members by means of a progressive approach.

Eq. (6) provides the general formula for assigning the quota of virtually shared energy to a consumer c during surplus hours.

$$SE_c^t = (1 - SS_{add}) \cdot E_{c,cons}^t + SS_{add} \cdot (E_{c,cons}^t + a_c^t - d_c^t) \quad (6)$$

where $E_{c,cons}^t$ represents the actual energy consumption of consumer c at time t , while a_c^t and d_c^t correspond to adjustments based on the user's behavior. Specifically, a_c^t (additional shared energy assigned) reflects a virtuous behavior, when the consumer exceeds its baseline consumption, contributing to a greater utilization of available surplus energy. Conversely, d_c^t (shared energy deduction) accounts for unvirtuous behavior, when the consumer falls below its baseline consumption during the considered surplus hour. At any given time t , only one of the two values a_c^t and d_c^t can be greater than 0, meaning a user is either rewarded or penalized based on its consumption pattern relative to the baseline — but never both simultaneously.

Eventually, by summing up for each member the amount of shared energy, the total amount is then multiplied for the considered economic incentive (between 80–120 €/MWh according Italian legislation [11]).

The procedure behind the performance-based redistribution ($E_{c,cons}^t + a_c^t - d_c^t$) is reported in the following.

The first step of the procedure is the evaluation of the virtuous or unvirtuous behavior, in terms of energy consumption, for each member. As previously stated, for each hour t the energy consumption of each member is compared against its own baseline $E_{i,baseline}^t$ and the difference is computed, as reported in Eq. (7).

$$\Delta E_i^t = E_{i,cons}^t - E_{i,baseline}^t \quad (7)$$

In particular, a positive difference represents a virtuous behavior while a negative difference means that the community member is acting under expectations. The ΔE_i^t value must be capped to a minimum of $-E_{i,cons}^t$, since the virtual shared energy quota that would be deducted from unvirtuous members, cannot be greater than their actual consumption.

The following step of the procedure is the calculation, at time t of the cumulative energy A^t , which is considered as the virtual amount of shared energy that can be proportionally distributed among virtuous members and proportionally deducted from unvirtuous members, starting from their actual energy consumption $E_{i,cons}^t$. A^t is calculated as the minimum value between the cumulative quota of positive differences ΔE^{t+} and the cumulative quota of negative differences ΔE^{t-} , where the calculation of both ΔE^{t+} and ΔE^{t-} is reported respectively in Eqs. (8) and (9), and the calculation of A_t is reported in Eq. (10).

$$\Delta E^{t+} = \sum_{i=1}^{VM} \Delta E_i^{t+} \quad (8)$$

$$\Delta E^{t-} = \sum_{i=1}^{UM} \Delta E_i^{t-} \quad (9)$$

$$A^t = \min(\Delta E^{t+}, |\Delta E^{t-}|) \quad (10)$$

where the superscript VM indicates the virtuous members in the CSC group, and UM indicates the unvirtuous members group.

The reason for using the minimum value in Eq. (10) is that is not possible to deduct to unvirtuous members more than their cumulative unvirtuous energy (if $|\Delta E^{t-}| < \Delta E^{t+}$) and reward virtuous members more than the cumulative unvirtuous energy (if $|\Delta E^{t-}| > \Delta E^{t+}$).

The final step is the calculation of the quota that is assigned a or deducted d to each member i at time t . This is obtained for each virtuous member in the VM group using Eq. (11) and for each unvirtuous member in the UM group using Eq. (12).

$$a_i^t = \frac{\Delta E_i^{t+}}{\Delta E^{t+}} \cdot A_t \quad (11)$$

$$d_i^t = \frac{\Delta E_i^{t-}}{\Delta E^{t-}} \cdot A_t \quad (12)$$

Eventually, the final amount of shared energy using the hybrid redistribution approach is evaluated through Eq. (6).

It is worth to note that, during a surplus hour, two main conditions might occur:

- All the members are associated at the same time with a virtuous or unvirtuous behavior: In this case no one is further remunerated/penalized respect to the starting amount of shared energy that is already fair respect to the individual contributions. In fact, the amount of energy A^t would be equal to 0 and no addition a neither deduction d is applied.
- Co-presence of virtuous and unvirtuous members: this is the case in which it is possible to further remunerate or penalize members according to their behavior. In this case, the minimum value between cumulated positive and negative differences pertaining virtuous and unvirtuous members is selected as the quota of virtual shared energy that can be proportionally redistributed among virtuous members performing a deduction to unvirtuous ones.

5.2. Definition of reference baselines for community members

As previously discussed, at the core of the proposed sharing mechanism there is a reference baseline definition for each member of the community. To this purpose, in this stage of the methodology a set of possible baseline models categorized into arithmetic and regression-based approaches were considered.

This model pool, combined with a dynamic selection framework, ensures individualized, context-sensitive baselines, which are essential for assessing behavior and supporting a fair incentive allocation.

The considered models, identified through the literature review in Section 2.2, are described in the following.

- Arithmetic models (7 model configurations): These models estimate the baseline load by averaging historical hourly consumption from a set of admissible days (X) within a specified time window (Y) in the past, relative to the target day for which the baseline is being evaluated. The admissible days are those of the same type as the target day (i.e., weekdays, Saturdays, or Sundays).
 - *High X of Y*: The baseline is derived from the Y most recent admissible days ($Y = 5$ or $Y = 8$). For each hour of the day, the X highest power values ($X = 3, 4, 5, 6, \text{ or } 7$) are selected, and their mean is computed to form the baseline profile.
 - *Medium X of Y*: The baseline is calculated using the last Y admissible days ($Y = 8$). For each hour, the maximum and minimum loads are discarded, and the mean of the remaining X values is computed to construct the hourly baseline profile.

According to this nomenclature, the final 7 arithmetic baseline models are namely: High 3 of 5, High 4 of 5, High 5 of 8, High 6 of 8, High 7 of 8, Medium 4 of 8 and Medium 6 of 8.

- Regression model (1 model): a Machine Learning (ML) model i.e., XGboost, was used to develop a reference baseline using features including the previous 24-hour energy consumption data, the type of the target day and the hour of the day. To ensure it adapts to evolving patterns, a weekly retraining strategy was implemented, employing K-fold cross validation to avoid overfitting. This retraining process incorporates all historical data available up to that time, smoothing out possible infrequent and anomalous patterns.

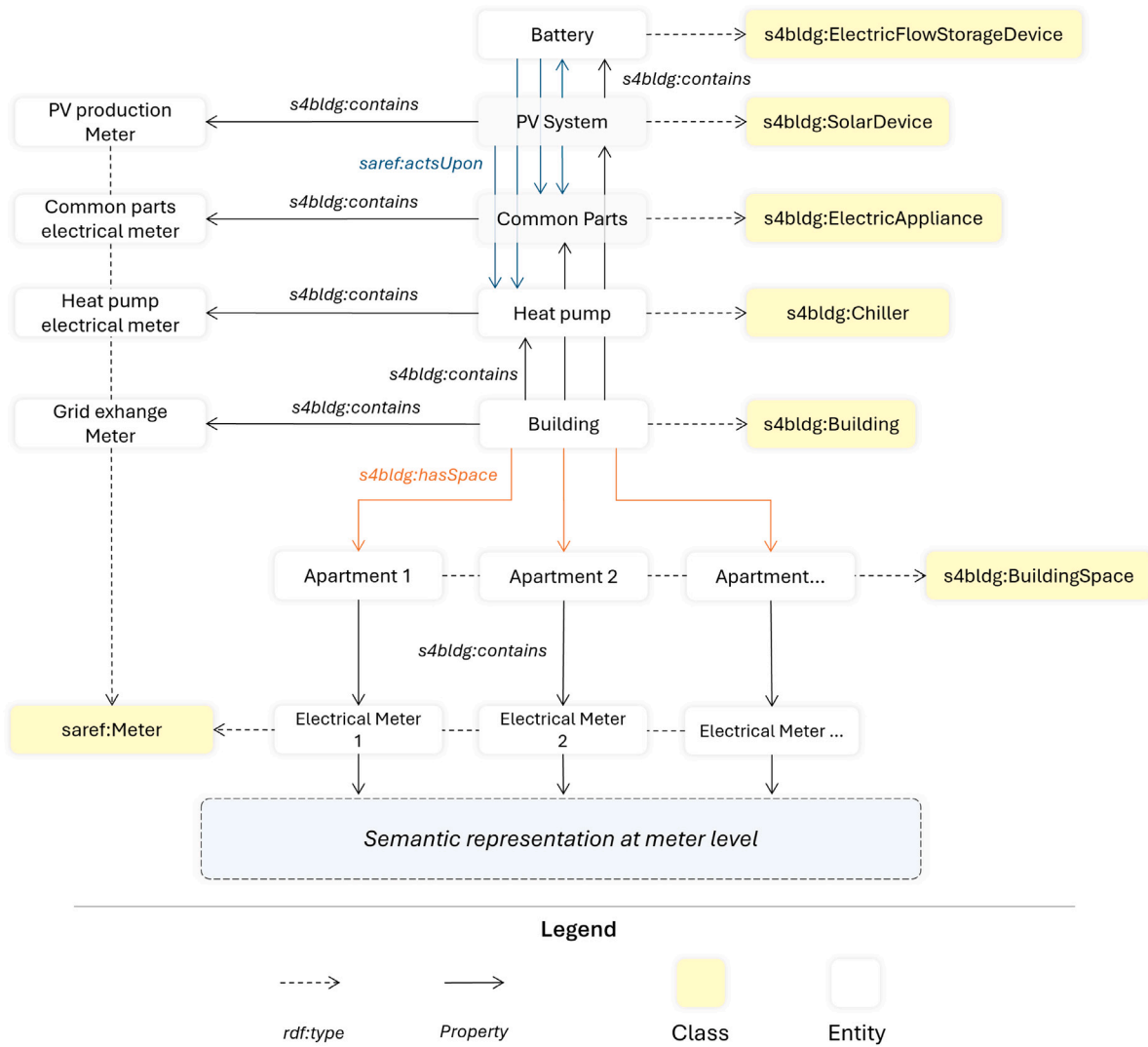


Fig. 6. Semantic representation of the CSC group.

To ensure that the best possible model was always used for each member, a dynamic baseline selection framework was implemented. To this purpose an adjusted version of the root square mean error $RMSE_{adj}$ was used as quality measure of the baseline performance.

In particular when a baseline model provides a reference load profile for the target day a permutation mechanism is applied to the estimated values to reduce inaccuracies caused by timing misalignment. To illustrate the impact of the adjusted RMSE, it is possible to consider a scenario where a baseline model predicts a peak in energy consumption at 11:00 AM, while the actual peak occurs at 12:00 AM. A traditional Root Mean Squared Error (RMSE) metric would penalize this discrepancy twice: first, for underestimating consumption at 11:00 AM, and second, for overestimating it at 12:00 AM. This leads to the well-documented double penalty effect [44], where minor temporal shifts in peak timing significantly inflate the error metric, even if the overall consumption pattern is well captured.

To mitigate this issue, $RMSE_{adj}$ incorporates a permutation mechanism that allows a flexible realignment of the predicted load profile during surplus periods. Instead of strictly comparing predicted and actual values at exact timestamps, the metric allows small time shifts in the predicted load profile, rearranging it to better match actual consumption patterns. In the provided example, the peak predicted at 11:00 AM would be shifted to 12:00 AM, where the real peak occurred, reducing the penalization caused by minor misalignment. To prevent

unrealistic realignments, the permutation is strictly limited to a single value per day, allowing at most a ± 1 h shift from its original position only during energy surplus periods. As a result, for each day, the mean $RMSE_{adj}$ over the past five days is computed considering all baseline models. The model with the lowest rolling mean $RMSE_{adj}$ is then selected to generate the baseline for the following day, ensuring that the most accurate and adaptive approach is used based on recent performance.

5.3. Semantic modeling of the use case and analytics pipeline

The third step of the proposed methodology proposed an approach to semantically model the CSC group analyzed in this work and to structure the pipeline for baseline calculation/selection and shared energy allocation among members.

To this aim SAREF ontology and its extensions were employed to develop the semantic model of the CSC group and its members, using an RDF graph. Specifically, SAREF, S4BLDG, and S4ENER ontologies were integrated to leverage their respective strengths.

6. Results

This section presents an overview of the results obtained for the considered case study. It begins with the semantic models developed to

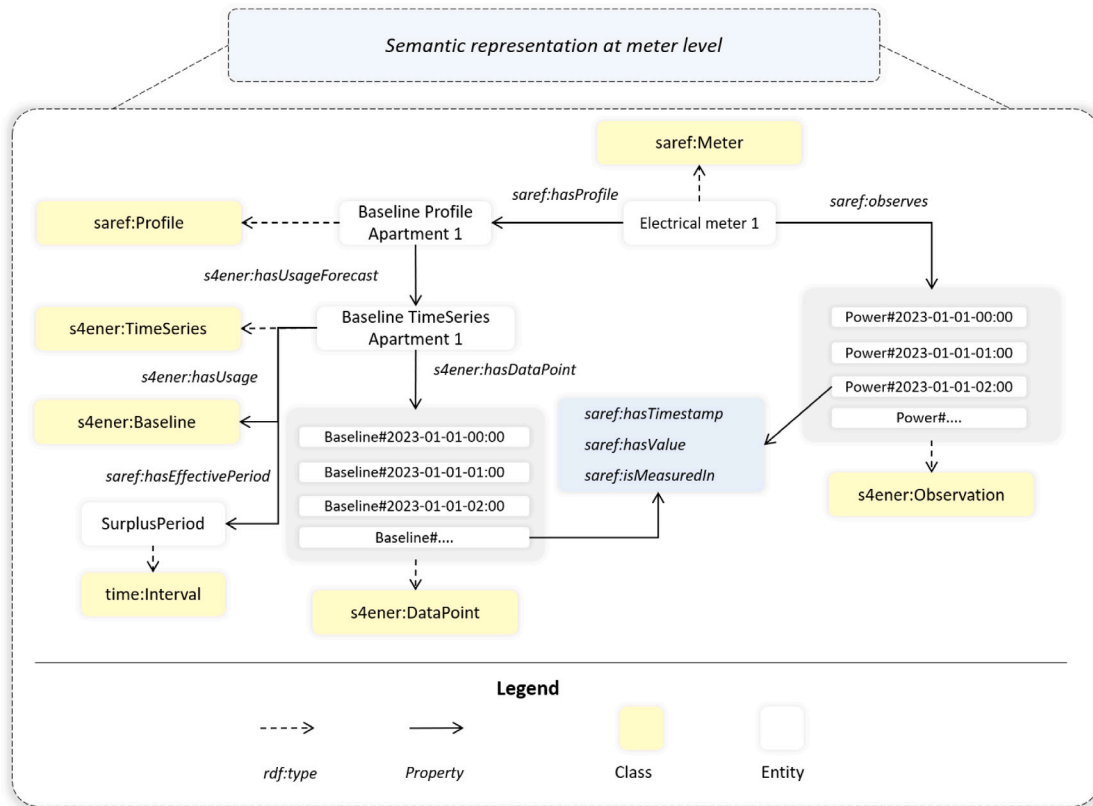


Fig. 7. Semantic representation of meter information for each member in the considered CSC group.

describe the CSC group and support the implementation of the analytics pipeline behind the proposed sharing mechanism. The analysis then focuses on baseline development and selection, followed by an evaluation of the impact of the sharing mechanism on community members over representative periods of time.

6.1. Semantic modeling results

Fig. 6 presents the high-level structure of the semantic model adopted. In the experimental setup, the CSC group corresponds to a multi-family building consisting of 13 apartments, with each building unit serving as a conceptual representation of an individual community member. The *Building* entity is represented as a `s4bldg:Building`, which consists of multiple `s4bldg:BuildingSpace` instances, each one representing an apartment. The building is equipped with various energy systems, including an heat pump (`s4bldg:Chiller`), shared electrical appliances, such as lighting system and the elevator (`s4bldg:ElectricAppliance`) and a PV system with a battery storage system (`s4bldg:SolarDevice` and `s4bldg:ElectricFlowStorageDevice`)

As detailed in Section 4, the PV system exclusively serves shared appliances, including the heat pump, elevator, and the common area lighting system. Any surplus energy not immediately consumed is either stored in a battery or, if the battery is fully charged, exported to the grid. When community members consume energy simultaneously with surplus energy injection, this consumption is treated as virtually shared among the members of the CSC group, enabling an indirect utilization of locally generated renewable energy.

To model this energy flow, the `saref:actsUpon` relationship was used to represent the direct connection between the *PV System* and the *Battery* and the shared appliances/loads. Since the *PV production Meter* records total energy production, it was essential to distinguish between directly self-consumed energy and exported energy to the

grid, which then can contribute to the virtual self-consumption of the CSC. The PV surplus is computed as the positive difference between the energy recorded by the *PV production Meter* and the sum of the *Heat pump electrical meter* and *Common parts electrical meter* energy consumption. The virtually energy shared is then determined as the minimum between this PV surplus and the total energy consumption of the CSC members. This calculation is performed preliminary by the sharing mechanism pipeline as illustrated in Fig. 9.

The semantic model of at the meter level is instead depicted in Fig. 7.

Each electrical meter, conceptually associated to a CSC group member, records consumption data at each timestamp, represented as `saref:Observation`. Each observation is characterized by a timestamp (`saref:hasTimestamp`), a value (`saref:hasValue`), and a unit of measure (`saref:isMeasuredIn`).

Additionally, each meter encodes the baseline daily load profile for the member, represented as `saref:Profile`. This profile contains a `s4ener:TimeSeries`, specifically labeled as a `s4ener:Baseline`, and includes all hourly energy consumption values of the reference baseline, structured as `s4ener:DataPoint`.

Both `saref:Observation` and `s4ener:DataPoint` share a common structure — each containing timestamps, values, and units of measure. However, they represent distinct concepts: `saref:Observation` refers to measured energy consumption data, while `s4ener:DataPoint` is a general entity that can also be calculated, as in the case of energy consumption values retrieved from the baseline. These baseline values are determined using the previously introduced model selection process, ensuring the best characterization as possible of member energy consumption patterns over time.

The dynamic baseline selection procedure operates as follows, with reference to Fig. 8.

For each day the *Baseline calculation* module is executed, where each baseline model is computed for the five previous days using the

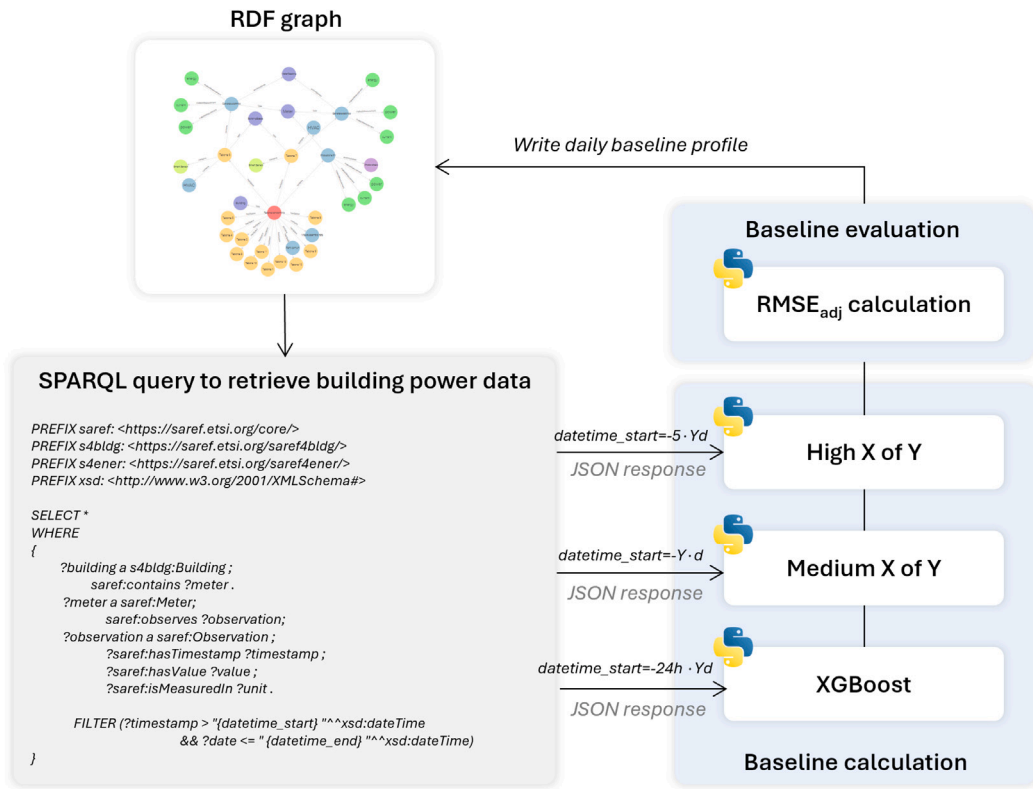


Fig. 8. Representation of the dynamic process for baseline model selection.

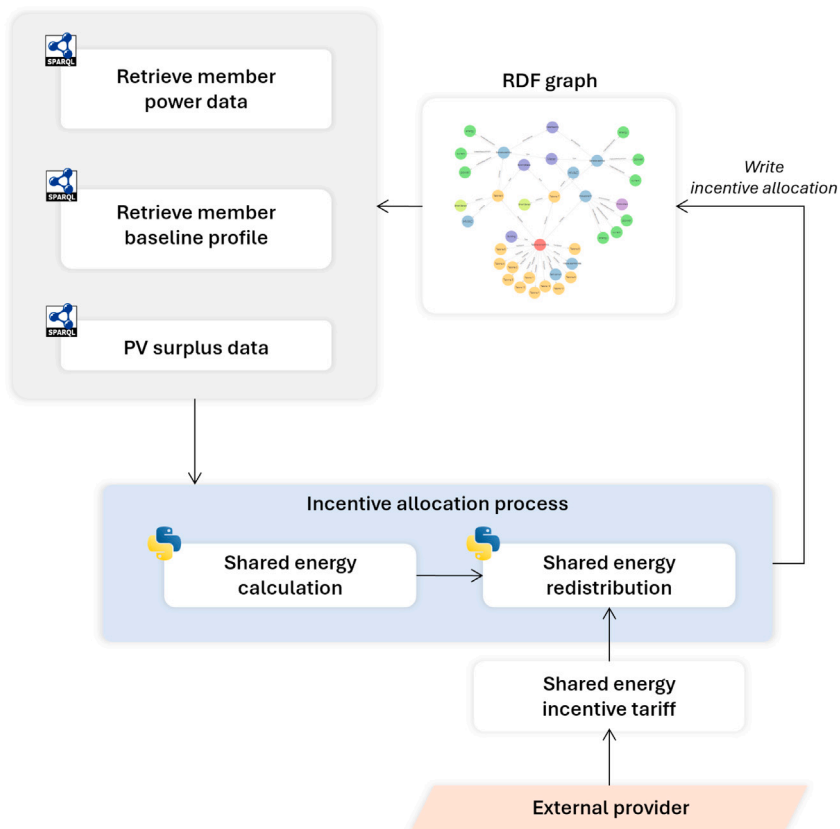


Fig. 9. Information flow behind the sharing mechanism calculation.

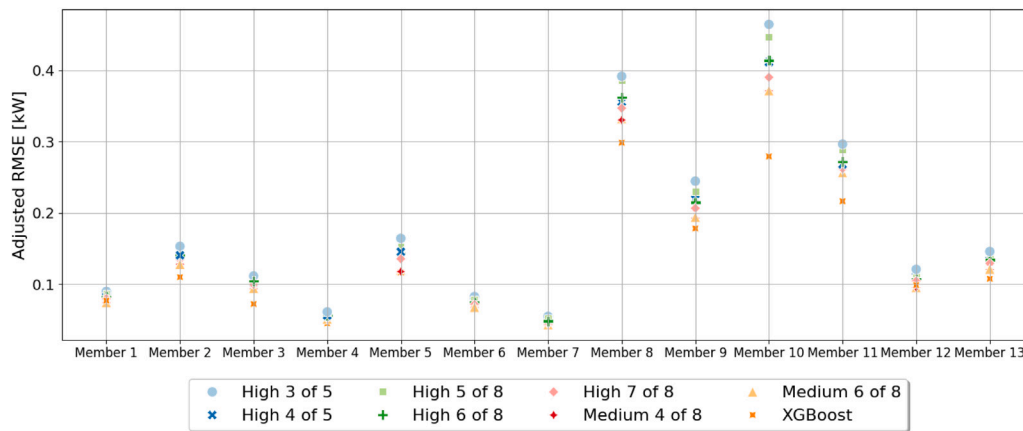


Fig. 10. Mean $RMSE_{adj}$ evaluated on the reference seven-month period for each baseline model and member.

energy consumption data recorded by each meter. The daily baseline performance is then evaluated on the previous five days to the target day by using the $RMSE_{adj}$ to select the model with the lowest error, as for the *Baseline evaluation* module. Then, this model is used to generate the daily baseline that will be used as reference for enabling the sharing-mechanism implementation.

The dynamic baseline selection procedure, illustrated in Fig. 8, follows a structured process to determine the most accurate baseline model for each day.

The process begins with a SPARQL query to the RDF graph of the community, retrieving the last Y days of energy consumption data for a given meter, where Y is defined by the selected baseline model. The retrieved data consists of `saref:Observation` entities recorded under `saref:Meter`, containing timestamps, power values, and units of measurement. The queried data, formatted as a JSON response, is then processed by Python modules responsible for computing the baseline load profile.

The *Baseline Evaluation* module then assesses the performance of each baseline model over the previous five days by computing the adjusted RMSE ($RMSE_{adj}$). The model with the lowest error is selected to generate the final daily baseline load profile, which serves as a reference for the sharing mechanism implementation. Once obtained, the baseline is written back into the RDF graph under the `saref:Profile` of the corresponding meter, with the `s4ener:Baseline` usage type, as illustrated in Fig. 7.

Eventually, Fig. 9 represents the flow behind the sharing mechanism calculation.

As illustrated, the process begins with retrieving the following data: (i) energy consumption profiles for each member, (ii) baseline load profiles, and (iii) previously calculated PV surplus data. Energy consumption and PV surplus are used to compute the shared energy, while the resulting shared energy, along with baseline profiles and consumption data, are used to determine the final shared energy allocation (Shared Energy Redistribution), as described in Section 5.1.

To compute the final incentive allocation, the incentive tariff is also required. This information could be retrieved from an external provider via an API request in case it is dynamic over time. For instance, in Italy, these tariffs are static and can be sourced from the Gestore Mercati Energetici (GME) [68], the operator of the Italian electricity market.

Finally, the incentive allocation results are stored in the RDF graph as an instance of the `s4ener:Incentive` class, ensuring structured and machine-readable integration within the semantic framework.

Furthermore, in the case a new user joins or leaves the community, the semantic model can be updated through automated scripts that populate and link new instances with existing classes and relationships. This allows the analytics pipeline to retrieve relevant metadata and execute baseline estimation, load profile evaluation, and incentive

redistribution seamlessly. Although initial setup may involve manual configuration or supervised validation, the need for recalibration is minimized. The modular nature of the ontology ensures that model selection, performance evaluation, and incentive logic remain scalable and reusable as the community structure evolves over time.

6.2. Development of electric load baselines of the CSC group members

This section presents the results of the evaluation and selection process applied to the eight baseline models over a seven-month period for the 13 members of the considered CSC group.

Fig. 10 presents an overall evaluation of the adjusted root mean square error ($RMSE_{adj}$) for each baseline model across all community members.

In general, the *Medium 4 of 8*, *Medium 6 of 8*, and *XGBoost* models exhibited superior performance. As shown in the figure, for most community members, the choice of baseline model has a minimal impact, as the error metric calculated over the entire period remains similar across all evaluated baselines. However, for some members, such as Member 5, Member 9, and Member 10, the $RMSE_{adj}$ relative difference between the best and worst-performing models is substantial, reaching 40%–50%.

The performance of each baseline model varied among members due to differences in energy consumption patterns. Fig. 11 illustrates this by comparing the baseline load profiles generated by each model for Member 1 and Member 10 over a two-week period. These cases highlighted how consumption variability influenced the effectiveness of different baseline models.

As shown on the right side of Fig. 11, Member 10 exhibited substantial daytime electricity usage. The *XGBoost* model effectively captured both the consumption pattern and short-term behavioral shifts, whereas arithmetic models consistently overestimated electricity usage, even in the absence of significant behavioral changes.

On the left side of Fig. 11, Member 1 exhibited low and stable energy consumption with isolated peaks. In this case, the *XGBoost* model did not provide significant improvements over simpler arithmetic models, such as *Medium X of Y*. Additionally, the *High X of Y* models systematically overestimated energy consumption, as their estimations were based on the highest recorded consumption values from previous days, resulting in an inflated baseline on average.

Eventually, Fig. 12 presents the results of the dynamic model selection process for each member. As explained in Section 5.2, one out the eight available baseline models is selected over time (considering performance in past five days) to characterize the reference behavior of each member in the most robust and fair way as possible.

Fig. 12 illustrates the percentage share of each baseline model selected for each member of the CSC group over the seven-month

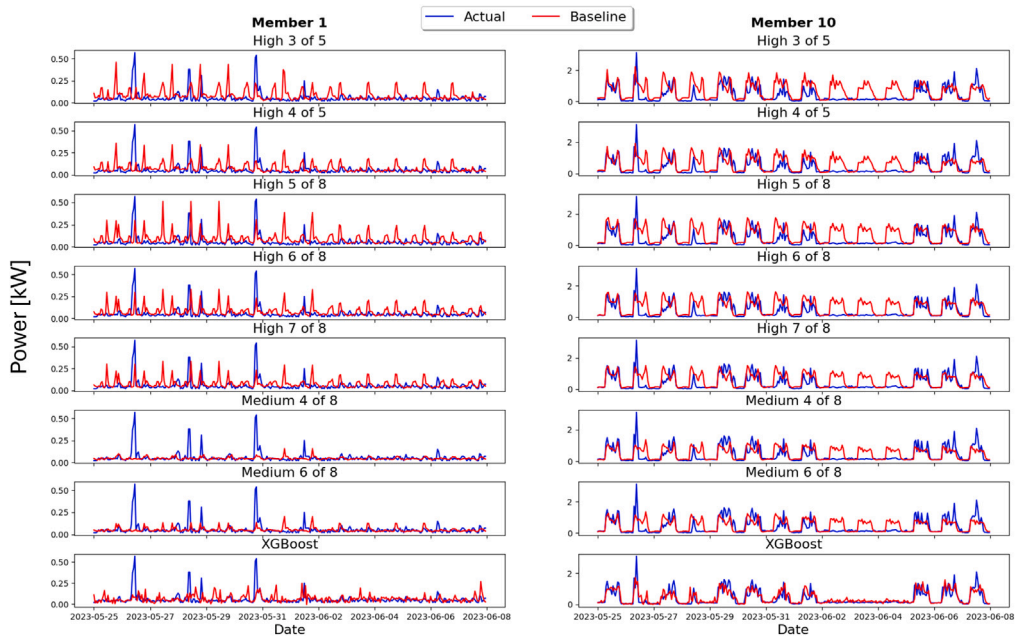


Fig. 11. Performance comparison of different baseline models for Member 1 and Member 10 over a two-week period.

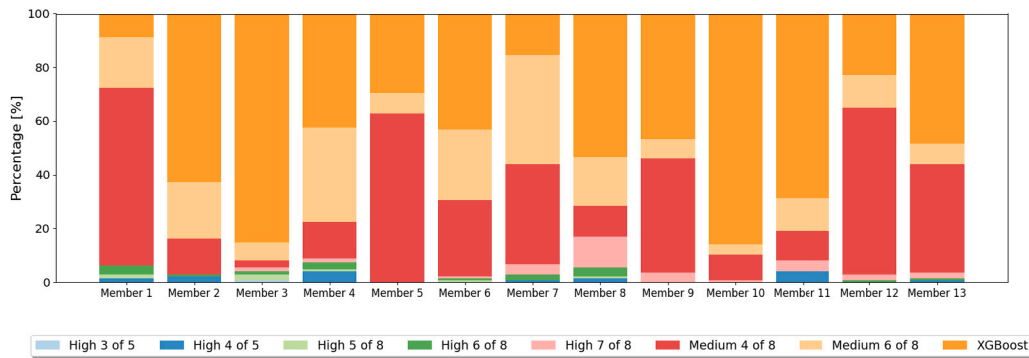


Fig. 12. Percentage share of each baseline model selected for each member of the CSC group over the seven-month reference period.

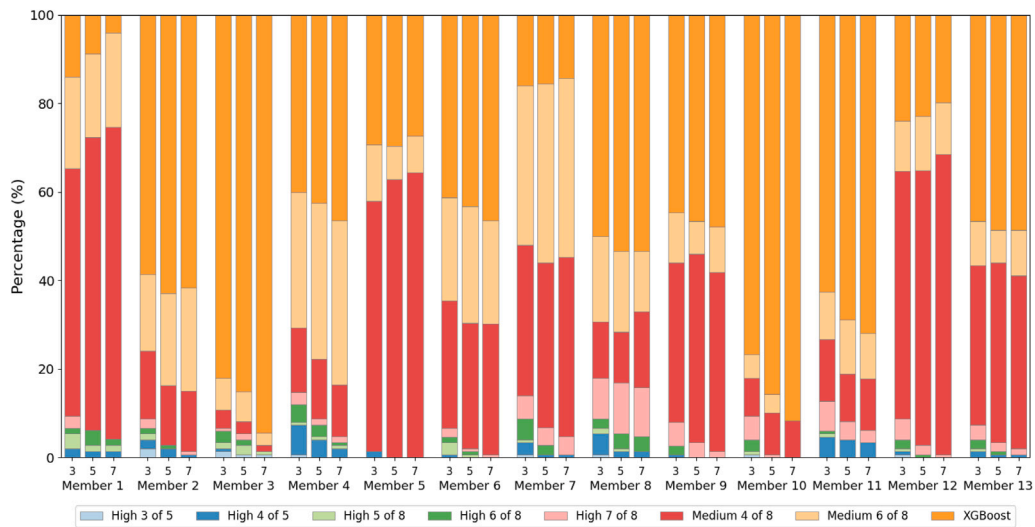


Fig. 13. Sensitivity analysis for the dynamic baseline selection process considering different time windows (3, 5 and 7 days).

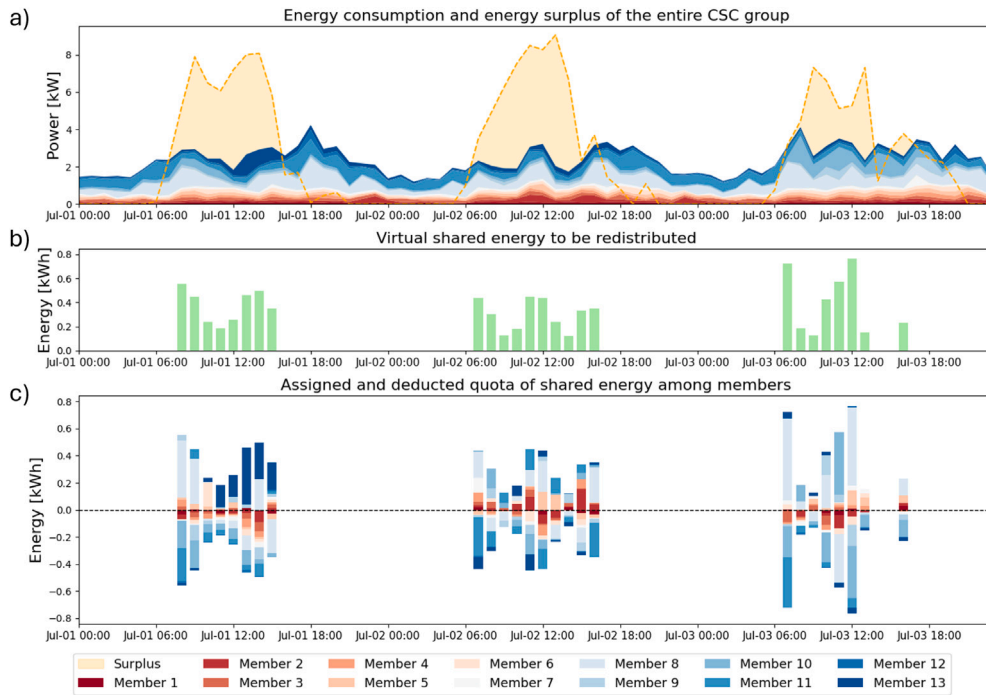


Fig. 14. (a) Stacked area plot of the energy consumption of the CSC members for the analyzed three-day period. (b) Amount of the virtually shared energy that can be redistributed among members (A') with virtuous behavior and deducted from unvirtuous ones. (c) Assigned (positive) and deducted (negative) quotas of virtually shared energy among the members.

reference period. The most frequently chosen models align with the results presented in Fig. 10, namely *Medium 4 of 8*, *Medium 6 of 8*, and *XGBoost*, which on average demonstrated superior performance. The results indicate that for certain members, such as Member 2 and Member 10, the selection of *XGBoost* as the baseline model was particularly significant. In the case of Member 10, *XGBoost* was identified as the best-performing model for more than 80% of the days in the reference period. This finding demonstrates that machine learning-based baseline models can more effectively capture residential energy consumption patterns compared to arithmetic models, particularly for users with higher variability in their energy consumption over time. As a final remark, all members exploited a set of baseline models, with each member being associated with a minimum of three and a maximum of eight different models over the reference period. This outcome highlights the effectiveness of the proposed dynamic approach, which adapts to individual consumption patterns over time.

In addition, the robustness of the model selection process was evaluated by testing the performance of the baseline models also over three and seven days preceding the evaluation period (in addition to the five days period previously considered). The results are showed in Fig. 13. Specifically on the x -axis, each group corresponds to a specific community member, with subgroups indicating the different time window lengths (3, 5 or 7 days) while on the y -axis, it is reported the percentage of days each baseline model was selected over the evaluation period. As shown, the distribution of selected models remains relatively consistent across the three window lengths for most members. The overall difference in model choice is generally below 5%, supporting the choice of a five-day window as a balanced trade-off.

6.3. Sharing mechanism results

This section provides the results obtained by employing the proposed sharing-mechanism as discussed in Section 2.1. To better exemplify how the developed mechanism works, a calculation example for a three-day period was provided below.

The selected period consisted of three consecutive days during which the community's SS_{add} was significant, increasing the influence of the performance-based component as defined in Eq. (2). Fig. 14(a) illustrates the energy consumption and PV surplus of the CSC group over this period. Fig. 14(b) presents the amount of virtually shared energy (A') available for redistribution during surplus hours, where shared energy was reallocated from unvirtuous members to those who demonstrated virtuous behavior. Finally, Fig. 14(c) details the shared energy redistribution among individual members, showing how the incentive mechanism was applied.

To provide a more clear understanding of the shared energy redistribution process, a detailed analysis was in the following reported for a specific time interval, illustrating how energy quotas available for redistribution are evaluated. The selected example focuses on 12:00 AM on the last of the three analyzed days (July 3rd), when $SS_{add} = 0.30$. For this interval, each calculation step is reported in Table 1 where the amount of virtually shared energy A' is proportionally added to virtuous members and in Table 2 where the same amount A' is proportionally deducted from unvirtuous users.

The first step is the calculation of the difference between the actual energy consumption $E_{i,cons}^t$ and the baseline $E_{i,baseline}^t$, obtaining for virtuous members the positive differences reported in the column $\Delta E_{i,+}^t$ in Table 1 and for unvirtuous members the negative differences reported in the column $\Delta E_{i,-}^t$ in Table 2. In particular, the minimum value of the negative difference is capped to the value $-E_{i,cons}^t$, because in the following step, to an unvirtuous member cannot be deducted an amount of virtually shared energy higher than its own consumption. For the case examined, the sum of all positive and negative differences is, respectively, 766 Wh and 904 Wh. The minimum value between the two ($\min(766, 904)$) is used to define the amount of shared energy (i.e. the quota A') to be deducted by unvirtuous users and assigned to virtuous ones, which in this case is equal to 766 Wh. This amount is distributed among virtuous and deducted from unvirtuous members proportionally, based on their own share on the total sum of positive ($\frac{\Delta E_{i,+}^t}{\sum \Delta E_{i,+}^t}$) and negative differences ($\frac{\Delta E_{i,-}^t}{\sum \Delta E_{i,-}^t}$) respectively.

Table 1
Redistribution of shared energy among members with virtuous behavior at 12 AM of July 3rd.

User	$E_i^t, cons$ [Wh]	$E_i^t, baseline$ [Wh]	ΔE_i^{t+} [Wh]	$\frac{\Delta E_i^{t+}}{\Delta E_i^{t-}}$ [%]	a_i^t [Wh]	$E_i^t, cons + a_i^t$ [Wh]	SE_i^t [Wh]
Member 1	120	113	8	1.0	8	128	122
Member 4	120	93	27	3.5	27	147	128
Member 5	230	120	110	14.4	110	340	263
Member 7	160	125	35	4.6	35	195	171
Member 8	1056	482	574	74.9	574	1630	1229
Member 12	120	108	13	1.6	13	133	124
			766		766		

Table 2
Deduction of shared energy among members with unvirtuous behavior at 12 AM of July 3rd.

User	$E_i^t, cons$ [Wh]	$E_i^t, baseline$ [Wh]	ΔE_i^{t-} [Wh]	$\frac{\Delta E_i^{t-}}{\Delta E_i^{t+}}$ [%]	d_i^t [Wh]	$E_i^t, cons - d_i^t$ [Wh]	SE_i^t [Wh]
Member 2	100	157	-57	6.3	48	52	85
Member 3	136	138	-2	0.2	1	135	136
Member 6	120	191	-71	7.8	60	60	102
Member 9	200	385	-185	20.5	157	43	153
Member 10	550	1003	-453	50.1	384	166	434
Member 11	256	343	-87	9.6	73	182	234
Member 13	120	170	-50	5.5	42	78	107
			-904		766		

The shared energy distributed to each virtuous member is reported in column a_i^t in Table 1 while the deducted shared energy to each unvirtuous member is reported in column d_i^t in Table 2. The performance-based quota is reported in the column $E_i^t, cons + a_i^t$ for virtuous members and $E_i^t, cons - d_i^t$ for unvirtuous members. Eventually, for each member, Eq. (6) was applied, obtaining the final amount of shared energy SE_i^t .

Throughout the analysis, three representative members – Member 5, Member 7, and Member 10 – were examined in detail to illustrate distinct behavioral patterns in the context of the proposed shared energy redistribution mechanism: virtuous, balanced, and unvirtuous. Among the three analyzed members, the most virtuous one - Member 5 in Fig. 15 - voluntary adjusted consumption to align with surplus energy availability, maximizing the shared energy and contributing to the self-sufficiency of the CSC group during the three days under consideration. In contrast, the most unvirtuous member during the same period - Member 10 in Fig. 16 - exhibited consumption patterns misaligned with surplus periods failing to consume energy as much as expected. The balanced member - Member 7 in Fig. 17 demonstrated an intermediate profile, with consumption patterns that included both aligned and misaligned behaviors, resulting in a neutral impact in terms of shared energy that is virtually added (a_i^t) and deducted (d_i^t) to the member over the same period. Figs. 15–17 provide an intuitive visual representation of the shared energy redistribution for these members, respectively.

Each figure consists of three key components:

- (a) highlights the identification of positive (ΔE_i^{t+}) (green) and negative (red) differences ΔE_i^{t-} between the baseline and the actual consumption occurring during surplus periods (indicated by the orange background).
- (b) illustrates the shared energy quotas assigned and deducted during surplus hours. The green points represent the allocated shared energy quotas (a_i^t) for each member, while the green bars indicate the ideal maximum amount of energy that could have been reallocated (ΔE_i^{t+}). Similarly, the red points correspond to the deducted shared energy quotas (d_i^t), while the red bars show the ideal maximum amount of energy that could have been deducted (ΔE_i^{t-}). The closer a point is to the top of its corresponding bar, the greater the assigned or deducted shared energy quota is relative to the maximum possible amount.
- (c) illustrates the assigned (a_i^t) and deducted virtual shared energy (d_i^t) cumulated over the entire three-day period.

In the examples provided, Member 7 (Fig. 17) exhibited a balanced behavior, as the assigned (a_i^t) and deducted quotas (d_i^t) of shared energy remain nearly equal at the end of the period (Fig. 17c). This suggests that during surplus periods, its load fluctuated around the identified baseline, leading to a neutral effect on shared energy redistribution.

Conversely, Member 10 (Fig. 16) consistently demonstrated an unvirtuous behavior given that it behaved under expectations, resulting in continuous penalization and a progressive reduction of its assigned (a_i^t) shared energy quota. On the other hand, Member 5 (Fig. 15) displays a consistently virtuous behavior, that led to a steady increase in its cumulative assigned shared energy (a_i^t).

Eventually, to further exemplify the effect of proposed sharing mechanism, Fig. 18 reports for the entire seven-month period and for each member, the amount of virtual energy added (a_i^t) and deducted (d_i^t) following the performance-based redistribution. It is possible to see that all the members were associated with both virtuous and unvirtuous behavior. Some members, such as 1, 5, 6, 9, 12, and 13, exhibit a positive balance between a_i^t and d_i^t , while others, like 10 and 11, show a negative balance. For the remaining members (2, 3, 4, and 7), the added and deducted shared energy quotas are similar, indicating that their performance aligns with expectations, without significant penalties or rewards.

After the virtual redistribution of shared energy among members during surplus hours, the performance-based incentive is calculated. This is not the final considered incentive, given that a weighted average between the progressive and performance-based approach is performed according to the value of SS_{add} (for the considered day SS_{add} is 0.30). Considering the member 8, its actual shared energy at 12:00 AM of July 3rd is $E_{i,cons}^t = 1.06$ kWh, while its benchmark value is $E_{i,baseline}^t = 0.48$ kWh (as reported in Table 1). Considering a hypothetical incentive tariff of 109 €/MWh, following the progressive approach, it should be remunerated with an amount of incentive equal to 1.06 kWh · 0.109 €/kWh = 0.12€, while after the virtual redistribution of shared energy for the performance-based approach, the member 8 is associated with an amount of shared energy equal to 1.63 kWh ($E_{i,cons}^t + a_i^t$) that corresponds to an incentive of 0.18€. Following the (6) the final amount of shared energy is then equal to $SE_i^t = (1 - 0.3) \cdot 1.06$ kWh + 0.3 · 1.63 kWh = 1.23 kWh that corresponds to an incentive equal to 1.23 kWh · 0.109 €/kWh = 0.13€.

Performing the same calculation of the hybrid progressive/performance-based remuneration mechanism for the remaining surplus hours over the 7-month evaluation period, it is observed that a member daily incentive can increase or decrease by up to 40% compared to

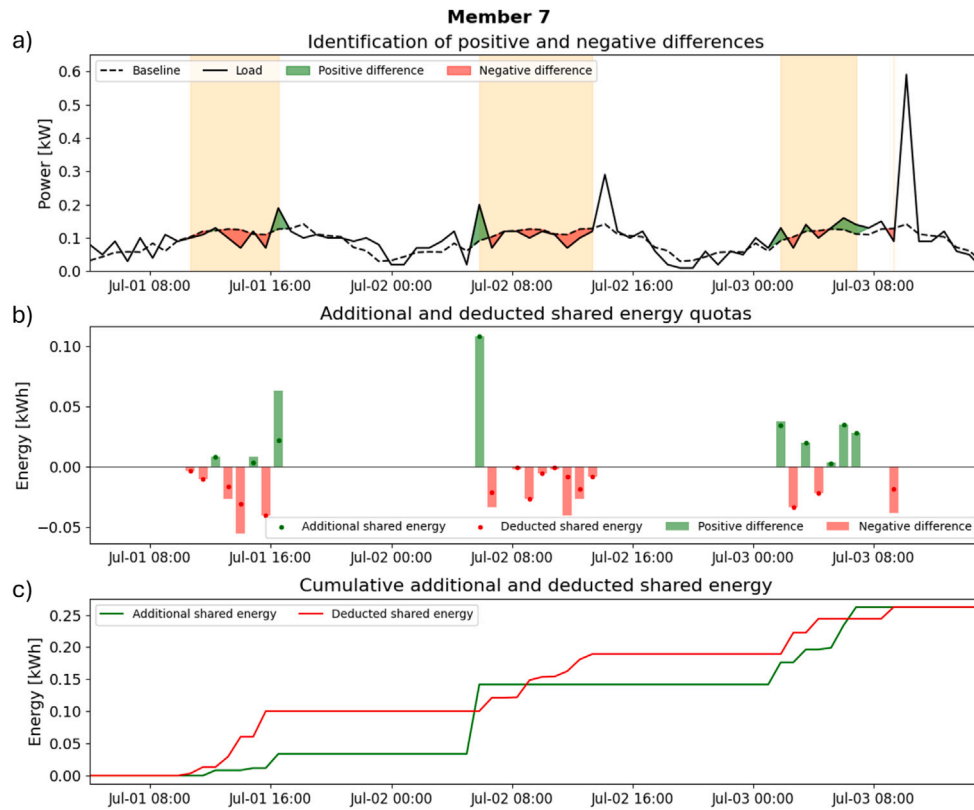


Fig. 15. Application of the performance-based sharing mechanism for Member 5. (a) Identification of the positive ($\Delta E_i^{'+}$) and negative differences (ΔE_i^{-}) between the actual consumption and the baseline. (b) Identification of the additional (a_i') and deducted (d_i') shared energy quotas. (c) Additional and deducted shared energy quotas in absolute value cumulated over the considered period.

the simple progressive approach. This 40% variation should not be interpreted as a generalized outcome, but rather as an observation of possible redistributions of shared energy quotas arising from the interplay between individual and collective behaviors. Moreover, this result does not account for how uncertainties in baseline estimation may propagate through the redistribution logic and affect the final incentive allocations, particularly for users with high load variability.

7. Discussion

This work addresses the key limitations identified in Section 3 by introducing a performance-based mechanism that rewards members for consuming energy during renewable generation surpluses, along with a semantic pipeline that automatically derives baseline load profiles from historical data. Traditional approaches lack such behavioral approach and standardized analytical frameworks, limiting their scalability and practical deployment.

The effectiveness of the proposed mechanism was demonstrated in an experimental CSC group of residential users, showing its ability to ensure a balanced and equitable distribution of economic incentives. While the study focused on a CSC, the mechanism can be extended to the broader context of RECs. In such settings, incentive allocation would also include a dedicated share for prosumers, as outlined in Section 2.1. For instance, 80% of the incentives could be distributed among consumers and 20% among prosumers. This prosumer share could then be subdivided based on criteria such as ownership of renewable assets or the amount of energy exchanged with the grid (or a hybrid of both) to reflect both financial investment and energy contribution fairly.

The results show that all community members had equal opportunities to earn additional financial benefits through virtuous energy

consumption. As illustrated in Fig. 18, the distribution of shared energy was consistent across members, confirming that each could fairly benefit from aligning consumption with community goals.

A key feature of the mechanism was the performance-based component, weighted by the SS_{add} indicator, which incentivized users to consume energy during surplus periods. As members progressively shift their load to align with surplus generation, the reliance on performance-based redistribution decreases (given that SS_{add} declines), allowing the mechanism to revert to the standard progressive allocation (already shown to be a fair approach [13]).

The advantage of this mechanism is even greater when a member has a flat-rate energy contract. In this case, shifting load to surplus hours involves no economic drawback, as the electricity price remains constant throughout the day and making the energy sharing incentive the only driver for behavioral change. However, when users are subject to dynamic or time-of-use (ToU) tariffs, demand shifting becomes significantly more complex and less predictable. In such contexts, electricity prices vary throughout the day, often peaking during periods of high demand. While incentive mechanisms may encourage users to align their consumption with surplus energy availability, these efforts can be undermined if peak pricing overlaps with surplus generation windows. In such cases, the higher cost of electricity may outweigh the benefits of the incentive, thereby discouraging users from shifting their demand even when it would otherwise enhance self-consumption or community-level efficiency.

Compared with incentive-sharing mechanisms proposed in previous studies, the methodology introduced in this work goes beyond simply accounting for the energy consumed by a given user in relation to the available shared energy or solar production at that time [15]. The proposed approach also considers the potential shared energy that could have been realized if users had adapted their consumption

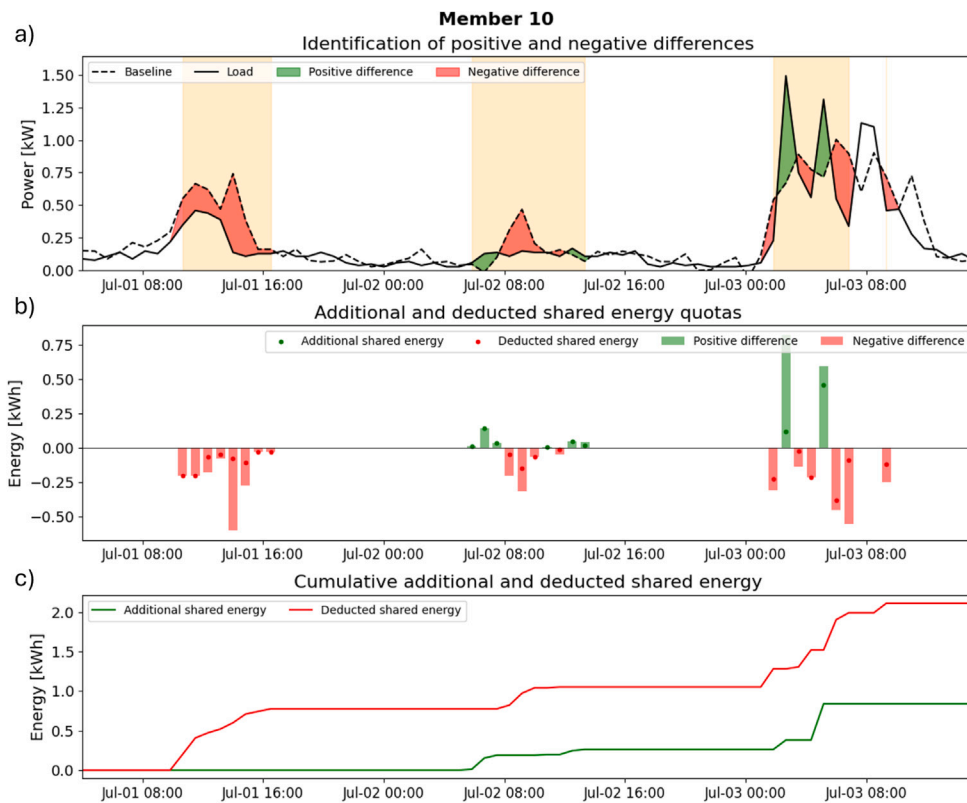


Fig. 16. Application of the performance-based sharing mechanism for Member 10. (a) Identification of the positive (ΔE_i^{++}) and negative differences (ΔE_i^{--}) between the actual consumption and the baseline. (b) Identification of the additional (a_i') and deducted (d_i') shared energy quotas. (c) Additional and deducted shared energy quotas in absolute value cumulated over the considered period.

more closely to the core objectives of energy communities, namely the maximization of self-sufficiency and self-consumption. Moreover, differently from methods that penalize user overconsumption [15] or proportional approaches which conversely tend to reward it [25], the proposed approach applies such penalization only when the community as a whole fails to fully exploit its self-sufficiency potential. In this way, the proposed mechanism balances fairness at the individual level with the collective performance of the community.

Looking ahead, the framework is intended to support the development of a decision support system for energy management in RECs and CSC groups, integrating with other analytics tools to enable near real-time incentive processing. This would overcome delays typical of traditional remuneration schemes (typically up to 12 months), providing timely feedback and dynamically adjusting incentives to strengthen user engagement and promote more sustainable consumption patterns [69]. Policymakers could use this approach to design behavior-aware tariffs that align with renewable energy availability, while energy providers and aggregators may adopt it to deliver responsive, data-driven services. For community managers, the semantic automation and transparent logic offer a scalable solution for member onboarding, and to enhance trust in the management of shared energy resources.

Future work could explore integrating a predictive approach into this envisioned decision support system for community energy management, allowing members to take informed decisions. This requires advanced forecasting capabilities to predict aggregated energy production and consumption within the community, providing real-time insights into available surplus and potential consumption adjustments through baseline estimation.

Aggregators could leverage forecasting and appliance-level data to request load shifting from the most suitable users, enhancing the community's ability to adapt its demand profile. However, such information

is often unstructured, highlighting the need for interoperability as a key requirement for integration into a unified analytical framework. A semantic framework can address this by providing a consistent representation of building flexibility potential [70,71], enabling real-time communication of suggested actions and fostering long-term user engagement [72,73].

While the proposed mechanism demonstrates encouraging results within the studied CSC group, several limitations may affect its generalizability to broader contexts. First, user behavior in residential settings is inherently variable and context-dependent. This variability may compromise the robustness of baseline estimations, particularly in communities with markedly different socio-demographic profiles, occupancy patterns, or access to flexible loads. Second, the framework presupposes a degree of regulatory flexibility in defining and allocating economic incentives among participants. However, in jurisdictions governed by rigid or centrally regulated schemes, such customization may not be feasible, limiting the practical implementation of the approach. Third, the economic viability of the proposed incentive mechanism is highly sensitive to local tariff structures. When electricity prices during peak periods outweigh the perceived benefits of the incentive the financial incentive would be insufficient to justify behavioral changes. To address these challenges and reinforce the robustness and applicability of the framework, future work will pursue several complementary directions. Sensitivity analyses will be conducted on critical design and operational parameters, such as the size and orientation of PV systems, the number and composition of community members, and their level of end-use electrification, in order to assess the framework performance across a variety of technical and organizational configurations. This will help identify the conditions under which the proposed mechanism remains effective and fair. In parallel, particular emphasis will be placed on capturing and modeling user behavioral variability, which

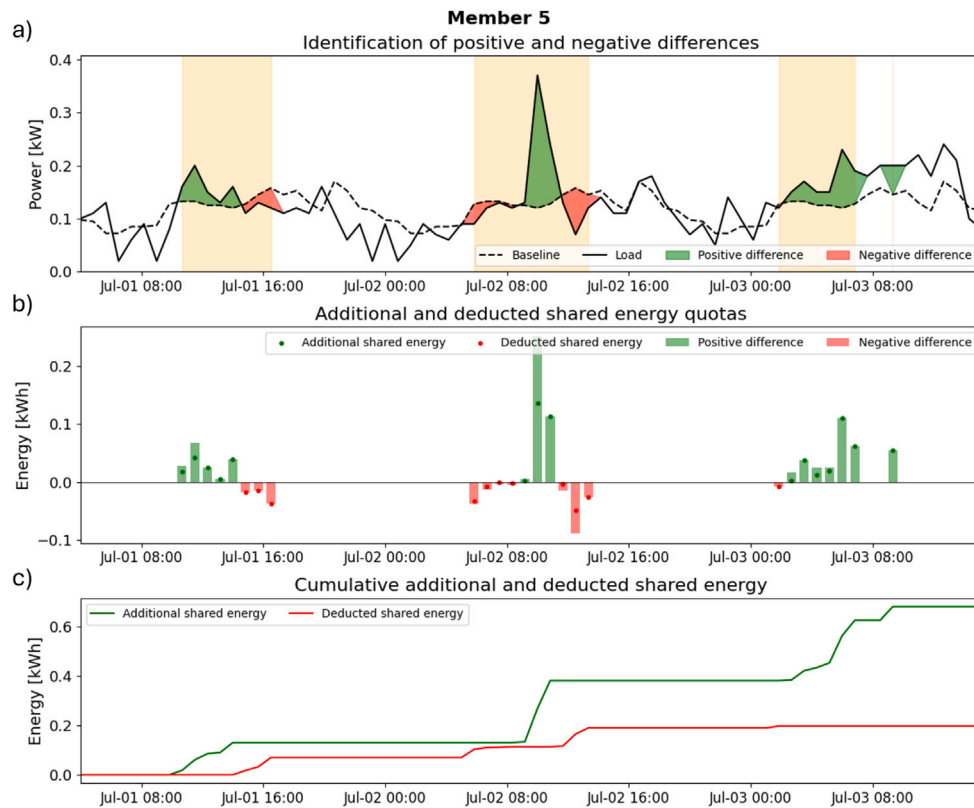


Fig. 17. Application of the performance-based sharing mechanism for Member 7. (a) Identification of the positive (ΔE_i^{+}) and negative differences (ΔE_i^{-}) between the actual consumption and the baseline. (b) Identification of the additional (a_i^+) and deducted (d_i^-) shared energy quotas. (c) Additional and deducted shared energy quotas in absolute value cumulated over the considered period.

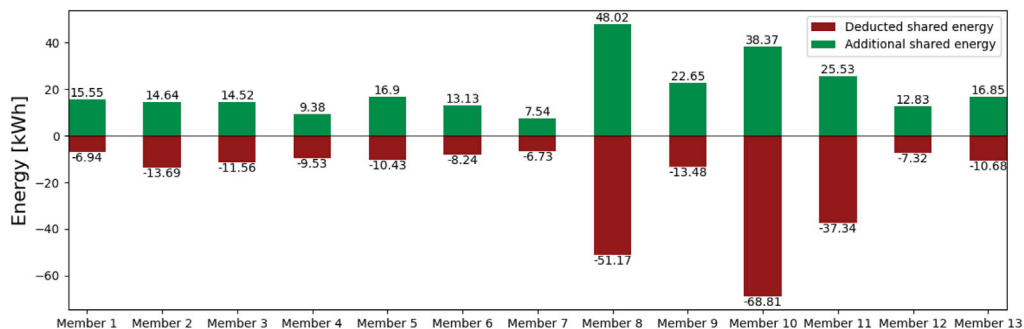


Fig. 18. Redistribution of virtual amount of energy shared among members for the reference seven-month period.

remains the primary driver of energy flexibility at the household level. More refined user models (incorporating factors such as occupancy schedules, appliance usage patterns, and responsiveness to incentives) will support more accurate baseline estimations and more effective tailoring of incentive structures. Finally, the long-term impacts of the incentive mechanism on both individual consumption patterns and collective engagement dynamics will be systematically evaluated. This includes investigating whether the mechanism promotes permanent behavioral change, fosters a stronger sense of participation within the community, and remains effective under evolving market, regulatory, and social conditions.

8. Conclusions

This study introduced a novel framework for a fair and scalable energy sharing mechanism within communities of residential members.

By combining the progressive approach and a novel performance-based sharing mechanism, the proposed hybrid approach encourages

consumers to align their energy demand with community self-sufficiency objectives. Remunerating users also according to their behavior makes the impact of individual actions both visible and financially meaningful, fostering participation, enhancing energy awareness, and reinforcing a sense of responsibility. In addition, the framework leveraged an ontology-based semantic model, incorporating SAREF, S4BLDG, and S4ENER ontologies, to ensure interoperability, automation, and transparency in baseline generation and virtual shared energy allocation. It also reduces the need for manual data mapping and reconfiguration, lowering setup time and operational complexity as RECs and CSC groups evolve. The study also introduced a flexible and adaptive baseline selection process, ensuring that each member performance is always assessed through an individualized and context-sensitive reference model.

While this study focused on a CSC configuration, the proposed incentive mechanism can be easily extended to the wider context of RECs, incorporating incentive-sharing schemes that account for prosumers contributions along with consumers. This adaptability opens

pathways for community-wide optimization strategies that align with evolving regulatory frameworks and energy market structures. Beyond its technical contributions, the framework suggests relevant implications for policy and governance. From a policy perspective, it supports a shift towards dynamic and decentralized incentive models, where the aware user participation in community goals is both recognized and rewarded. Regulators may consider enabling such mechanisms through flexible tariff schemes and supportive guidelines for fair shared energy allocation. In terms of governance, the framework underscores the importance of trusted intermediaries, such as community managers or aggregators, who play a central role in supervising baseline generation, managing incentive distribution, and upholding transparency and fairness within the group.

In addition, real-time capabilities will be integrated into the framework, enabling users to adjust consumption proactively. This will require advanced forecasting models, live data streams, and personalized decision support. In this context, Large Language Models (LLMs) could enhance user engagement by providing intuitive, real-time recommendations in natural language, helping users shift consumption in response to incentives and market signals [74].

CRedit authorship contribution statement

Rocco Giudice: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Savino Piscitelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization. **Alfonso Capozzoli:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used AI-powered tools, such as Grammarly, ChatGPT 4o, Quillbot, in order to improve readability and language in specific portions of the manuscript. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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