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Development of dynamic sharing keys: algorithms supporting management of Renewable Energy Community and Collective Self Consumption

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Abstract

The potential of sharing energy from production plants is characterized as a new paradigm for the production and consumption of energy from renewable sources. The emergence of Renewable Energy Communities (REC) and Collective Self Consumption (CSC) in the European context has supported the regulation of the concept of shared energy and provided economic saving to its members. Many countries have adopted a virtual scheme for local energy sharing without a physical basis for calculating intra-community energy exchanges and national legislation often provides economic incentives for shared energy within the community. However, many of the management aspects regarding the distribution of shared energy and therefore economic gain are managed internally by members, allowing for various configurations that depending on the type of generation systems, users, and purposes of the community. Since a unique method is not established, it is crucial to define fair criteria for energy allocation among the community members rewarding virtuous behaviour. This work proposes four algorithms for dynamic sharing keys based on participants' contributions to the community: a consumption-proportional key, a Pearson correlation coefficient-based key to evaluate synchronism between electricity drawn from the grid and the surplus fed into the grid, a trend-based key that accounts for the difference between purchased and injected energy, and a combination of the previous two keys. A Renewable Energy Community (REC), under Italian regulation, consisting of eight representative users was simulated using real hourly energy consumption and production profiles. The aim was to perform an annual comparative analysis between the developed methods and identify the different amount of shared energy assigned to each user based on their contribution, highlighting their strengths and limitations. The results show how some of the algorithms assign to users with the highest consumption an amount of shared energy higher than their real sharing potential, while users with greater sharing potential are penalised.

Nomenclature

BESS	Battery energy storage system
C	Energy purchased
CSC	Collective Self Consumption
DSO	Distribution System Operator
E_{inj}	Energy fed into the grid by the production plants
EC	Energy Community
N	Total number of REC members
p	Daily Pearson correlation coefficient remapped from 0 to 1
PV	Photovoltaic
r	Dynamic sharing key
REC	Renewable Energy Community
SH	Shared energy
SH_lim	Shared energy limit
SME	Small and medium-sized enterprise
SR	Sharing rate coefficient
α	Weights for Pearson correlation coefficient
β	Weights for sharing rate coefficient
ξ	Exponential decay constant

Subscript

i	i-th member of the Renewable Energy Community
j	j-th hour

1. Introduction

The evolution of power systems, driven by the widespread adoption of distributed generation through renewable energy sources and the participation of prosumers, has led to substantial challenge [1]. In this scenario, the concept of energy sharing, and energy prosumers has gained prominence within the global energy landscape, specifically involving the distribution of energy among users through electrical networks or decentralized systems. This paradigm shift allows users to trade, sell or acquire energy based on their energy needs and production capabilities, and recently, the concept of "Energy Community" (EC) has been an increasing interest in promoting the aggregation of energy users at the local level [2]. When consumers acquire ownership of renewable systems, they can become prosumers, locally sharing an amount of the energy they consume through local EC [3]. Within an EC, a prosumer can engage in various energy transactions including exchanging energy with the public grid at real-time prices (RTP), trading within their own community, and participating in peer-to-peer (P2P) mechanisms facilitated by bilateral agreements [4,5]. Furthermore, in recent years, an extension of the sharing economy has also occurred in the energy sector [6], in connection with the concept of smart grids [7], aiming to reduce overall costs and the peak-to-average ratio through optimal energy-sharing algorithms [8] and optimization models [9]. This issue is particularly relevant in the European Union, as the establishment of regulatory frameworks for energy sharing is beginning to take place. In 2016, through the "Clean energy package" [10], the European Commission proposed for the first time formal recognition in European legislation for projects aimed at collective self-consumption and energy sharing through the establishment of Energy Communities. The package was finalized over two years later and two directives were defined: the EU Renewable Energy Directive 2018/2001 (RED II) of 11 December 2018 [11] and the EU Internal Electricity Market directive 2019/944 (IEMD) of 5 June 2019 [12]. The RED II allows sharing energy within two different configurations defined in Articles 2: the Collective Self Consumption (CSC) in the paragraph 15 and the Renewable Energy Community (REC) in the paragraph 16. A REC can be defined as a collective initiative involving various stakeholders as citizens, SMEs, local authorities, etc., aiming to generate renewable energy and striving for consumption and sharing within the community, with a focus on self-consumption and self-sustainability. In line with the principles of REC, CSC refers to a specific geographical area, where users are located within the same building or multi-apartment block. Therefore, the two concepts differ from individual self-consumption, which involves a single user producing and consuming energy from renewable sources to fulfil their own energy requirements. By June 2021, EU Member States had to transpose the RED II directive to develop an enabling framework for promoting energy sharing within REC and CSC configurations. However, unlike individual self-consumption, the regulation of collective self-consumption and energy communities in most European countries appears to be incomplete. In relation to the leading European economies, in Spain, France, Italy and Portugal, it is possible to set up a shared self-consumption community in nearby homes using the existing distribution network, while German legislation does not yet provide for this possibility [13]. Italian legislation, on 28 February 2020, promoted the development of energy communities through an experimental framework in anticipation of the definitive transposition of the RED II directive. This framework started through Article 42-bis of Decree-Law 162/19 and was later implemented by Conversion Law No. 8/2020 [14]. Within paragraph 4, letter b) shared energy is defined for the first time as the minimum, in each hourly period, between the electricity produced and fed into the grid by renewable production plants and the electricity withdrawn from all associated end customers. Additionally, the Decree also defines the rights of end customers associated with the configurations of CSC and REC within paragraph 5, letter c). In particular, end customers regulate relations through a private law contract which uniquely identifies a delegated subject responsible for the distribution of shared energy. On 15 September 2020, the Italian Ministry of Economic Development published the implementing decree which defines the incentive tariffs granted for 20 years for the remuneration of the shared energy by renewable plants included in the configurations of CSC and REC [15]. The amount of this incentive corresponds with 100 €/MWh for CSC and 110 €/MWh for REC. Therefore, the shared energy determines the economic savings of an EC and the decreased revenue experienced by the electricity supplier. Policymakers and researchers are particularly interested in two important aspects of energy sharing: internal guidelines for distributing costs and benefits within the community [16], and external regulations that establish the overall regulation framework [17]. In relation to energy distribution, in Spain and Portugal it occurs through distribution coefficients; in

France through a contract between the DSO (distributed system operator) and the legal entity that manages consumers and prosumers; in Germany through an agreement between consumers [18], while under Austrian regulation, DSOs can require a predefined distribution key to allocate electricity among community members, through ex-post algorithm [19]. Under the Italian legislation, end customers regulate relations through a private law contract which uniquely identifies a delegated subject responsible for the distribution of shared energy, therefore, full freedom to manage the benefits deriving from shared energy is granted. The incentivized shared energy is virtually self-consumed and there is no physical basis for calculating the energy exchange between users. At hourly levels two different conditions could lead to a different management of CSC or REC. When the energy fed into the grid by the production plants exceeds the sum of the energy purchased, it could be assumed that the amount of shared energy assigned to each member is equal to its actual hourly consumption. On the other hand, when the energy fed into the grid is less than the sum of the energy purchased, it is not possible to accurately define the amount of shared energy related to each member. Some scholars have defined new cost allocation criteria and quantify the shared energy in the configuration of REC or CSC [2]. Some of the proposed methodologies are based on the definition of sharing coefficients, static or dynamic, which allocate the energy among consumers. For example [20] proposed sharing coefficients that consider different parameters (e.g., energy demand or generation) with ponderation factors, [18] performs a classification of static and dynamic distribution coefficients by observing their results and applicability while [21] proposed four different sharing coefficients that define how the produced electricity is distributed among members. Some studies deal with the management of benefit related to the shared energy according to Italian law, for example [22] proposed an algorithm that distributes equally by assigning each user an amount of shared energy equal to the minimum current consumption, [23] investigated cooperative games in order to fairly distribute the benefits and costs of the community while [24] show that economic savings for REC's participants increase with the amount of energy shared under the adopted virtual scheme. An equitable allocation of shared energy and therefore economic savings represents a crucial challenge for RECs and CSC configurations. To address this challenge several authors have developed innovative approaches to optimize energy distribution, system scheduling, and optimal planning of communities in terms of economic savings. [25] use genetic algorithms (GA) to optimize energy distribution within a REC through multi-objective optimization (MOO) of allocation coefficients, aiming to minimize the discrepancy between individual payback periods and solar energy excess. [26] introduce a new approach to optimize HVAC scheduling aimed at maximizing shared energy and economic efficiency in a REC, while maintaining thermal comfort in the tested buildings. [27] describe a business model for energy community aggregators, integrating a technical optimization problem that addresses crucial aspects such as ensuring equitable reward distribution and estimating the fair payment for the aggregator services. [28] introduce an optimal planning approach for RECs based on mixed-integer linear programming (MILP) for RECs, aiming to size the existing technologies in a way to minimize energy costs and environmental impact. [29] developed a multi-criteria optimization procedure to size the facilities of a REC (PV + BEES) in terms of self-consumption and self-sufficiency, identifying the most competitive community form. [30] analyzed the impact of a bi-objective strategy to optimize the capacity of BESS coupled with PV systems in a REC, maximizing self-sufficiency and minimizing BESS capacity. [31] highlight how incentivizing tariff mechanisms that reward REC members for avoided CO2 emissions can lead to significant environmental benefits. Achieving a fair distribution of benefits not only fosters solidarity and collaboration but also encourages active citizen participation. Through participation, citizens become agents of change, helping to reduce environmental impact, promote the adoption of renewable energy and improve the quality of life in their community. The aim of this work is to support the management of a REC and CSC configuration defining new shared energy allocation criteria. Through the definition of dynamic keys based on different parameters that consider the user's contribution, the developed methods reward the user that consume energy during the hours in which there is an actual availability of renewable energy but at the same time do not increase their consumption after the creation of the energy community. In particular, 4 algorithms for dynamic sharing keys have been developed: a consumption-proportional key, a Pearson correlation coefficient-based key to evaluate synchronism between electricity drawn from the grid and the excess fed back into the grid, a trend-based key that accounts for the difference between purchased and injected energy, and a combination of the previous two keys through two weights to be defined. Each algorithm was implemented on an hourly level using ad-hoc developed Python scripts and were tested on real consumption profiles. In the European context, the study of REC and CSC is becoming increasingly relevant, not only in grey literature but also in scientific literature. Various authors have delved these topics from different perspectives, gaining significant visibility in recent years. Overall, scientific literature often focuses on price optimization or complex optimization schemes in energy sharing or exchange mechanisms, rather than on practical and implementable sharing concepts. This study contributes to a deeper understanding of the new challenges associated with energy sharing, particularly emphasizing the implications of new national regulations adopting a virtual sharing model. The algorithms described herein offer practical solutions that could potentially be implemented in REC and CSC, addressing pertinent issues in this field. Additionally, the accuracy of analysis results is enhanced by the use of data-driven consumption profiles at an hourly granularity. The rest of the paper proceeds as follows: Section 2 describes in detail each method implemented, the logic according to which the algorithm allocates the energy at hourly level and the description of the case study analyzed. Section 3 discusses the results from the annual simulation through a comparative analysis between the used methods while Section 4 shows the final considerations at the conclusion of the present work.

2. Materials and Methods

This paragraph illustrates in detail the methods developed to distribute the shared energy, expressed by the following Equation 1:

$$\sum_i^N SH_{i,j} = min\left(E_{inj,j}, \sum_i^N C_{i,j}\right) \tag{1}$$

These methods are employed only when the energy feed into the grid by the production plants is less than the total energy consumption of the community. Therefore, it can be assumed that the total energy shared by the community ($\sum_i^N SH_{i,j}$) is equal to the energy feed into the grid ($E_{inj,j}$). Specifically, paragraph 2.1 explains the operating principle of each method and provides the definition of the dynamic sharing key. Paragraph 2.2 includes the application of each method to hourly consumption, demonstrating how the shared energy is distributed each hour. Paragraph 2.3 describes the case study on which the sharing methods were tested in order to perform a comparative analysis.

2.1 Sharing Methods

2.1.1 Method M1

This method proposes attributing to each member an amount of SH_i proportional to their consumption. Consequently, it becomes impossible to assign a member a portion of SH_i that exceeds their consumption. Therefore, the shared energy attributable to the i-th member of the REC at any time $SH_{i,j}$ can be expressed by Equation 2:

$$SH_{i,j} = r_{i,j} \, . E_{inj,j} \tag{2}$$

In the case of M1 methodology, $r_{i,j}$ can be expressed by Equation 3:

$$r_{i,j} = \frac{C_{i,j}}{\sum_i C_{i,j}} \tag{3}$$

Obviously, the sum of r_i values assigned to each member is equal to 1, ensuring that the amount of shared energy assigned to each user does not exceed the total shared energy of the community. Therefore, under M1 methodology, a larger portion of shared energy is allocated to members with higher consumption, while those with lower consumption will receive a comparative smaller share. As a result, this approach might not provide incentive for members to reduce their energy consumption; it could unintentionally promote increasing their consumption instead of encouraging energy efficiency and savings. This distribution key is easily calculable and has been proposed and used in other studies on energy communities; [18] uses static and dynamic distribution coefficients including a coefficient proportional to consumption and establishes a hierarchical proposal of distribution criteria based on the savings collected; [21] It proposes new sharing coefficients (hybrid and uniform) comparing them to static and dynamic coefficients proportional to consumption; In the study of [32] each member of the community is assigned a portion of shared energy using a sharing key that changes depending on whether the user net-exports or net-imports energy (proportional to the energy purchased from the grid).

2.1.2 Method M2

The implementation of this method is based on the research outlined in [22]. The decision to adopt this algorithm, already present in the scientific literature, was motivated by the necessity to conduct a comparative analysis among different methods. M2, by design ensures that each user receives at least an amount of shared energy equivalent to the hourly consumption of the user with the lowest energy demand and tends to distribute the shared energy equally among all members. Based on the above, if the members are sorted in descending order according to their energy demands, the shared energy corresponds to the green area shown in ***Figure 1***, while the grey columns represent the portion of energy required that is not covered by renewable sources and is withdrawn from the grid. Further details on the implemented algorithm can be found in Appendix B of the same scientific article [22]. Consequently, the M2 methodology favours members with the lowest hourly electricity consumption, i.e., users who would contribute minimally to the total shared energy. However, M2 could penalize users with high consumption with high sharing potential while users with lower consumption who contribute less to energy sharing would be advantaged.

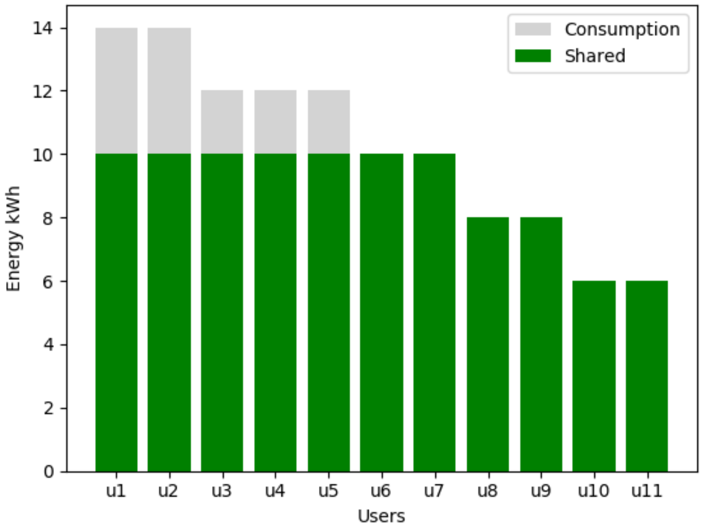

Figure 1. M2 shared energy allocation calculated for hour for all the EC members

2.1.3 Method M3

This method considers the correlation between the energy consumed by the i-th member and the energy injected into the grid by production plants. M3 is based on the use of the Pearson correlation coefficient, with the aim of identifying the daily correlation between the energy consumption of each user and the energy fed into the grid by the production plants. The Pearson correlation coefficient is a statistical measure used to evaluate the strength and direction of the linear relationship between two continuous variables [33]. In order to calculate this coefficient, data related to the daily load curves of energy consumption and production from renewable sources were collected for accounting the energy physically self-consumed by the users connected to the plant. The Pearson correlation coefficient between the two curves was calculated using a Python library dedicated to statistical analysis, specifically *scipy.stats* [34]. When input from renewable plants is high, if the two curves are positively correlated (resulting in a Pearson correlation coefficient close to 1), it suggests that consumption is likely to increase; on the other hand, if the correlation is negative (with the Pearson correlation coefficient approaching -1), it indicates that consumption tends to decrease. A coefficient value close to 0 indicates that the two curves (consumption and injection) are uncorrelated.

This coefficient signifies a virtuous behaviour of the user, as a positive correlation between the injection and withdrawal curves indicates that the user consumes more when renewable energy production is high, effectively increasing the shared energy in the community. Similar to M1, the shared energy attributable to the i-th member of the community at any given time can be expressed through Equation 1. The distinctive feature from the M1 methodology lies in the calculation of the dynamic sharing key $r_{i,j}$, which can be expressed through Equation 4:

$$r_{i,j} = \frac{p_{i,j}}{\sum_i p_{i,j}} \tag{4}$$

As explained earlier, even in this scenario, the sum of the distribution coefficients assigned to the i-th member is equal to 1. In this method a more complex algorithm was defined to ensure that the shared energy assigned to each user does not exceed his consumption.

If this occurs, the Pearson correlation coefficient for that user is set to zero and the amount of shared energy allocated becomes equal to their consumption. For more details on the implemented algorithm, you can refer to the flow diagram shown in ***Figure 2***: after confirming that the energy fed into the grid does not exceed the sum of the consumption of the i-th members, during each j-th iterative cycle the residual energy (RES_j) and the partial (shared) energy (PR_j^i) attributed to each member are calculated to distribute the shared energy $SH_{i,j}$. This iteration continues until the sum of the shared energies attributed to each member is not equal to the energy fed into the network.

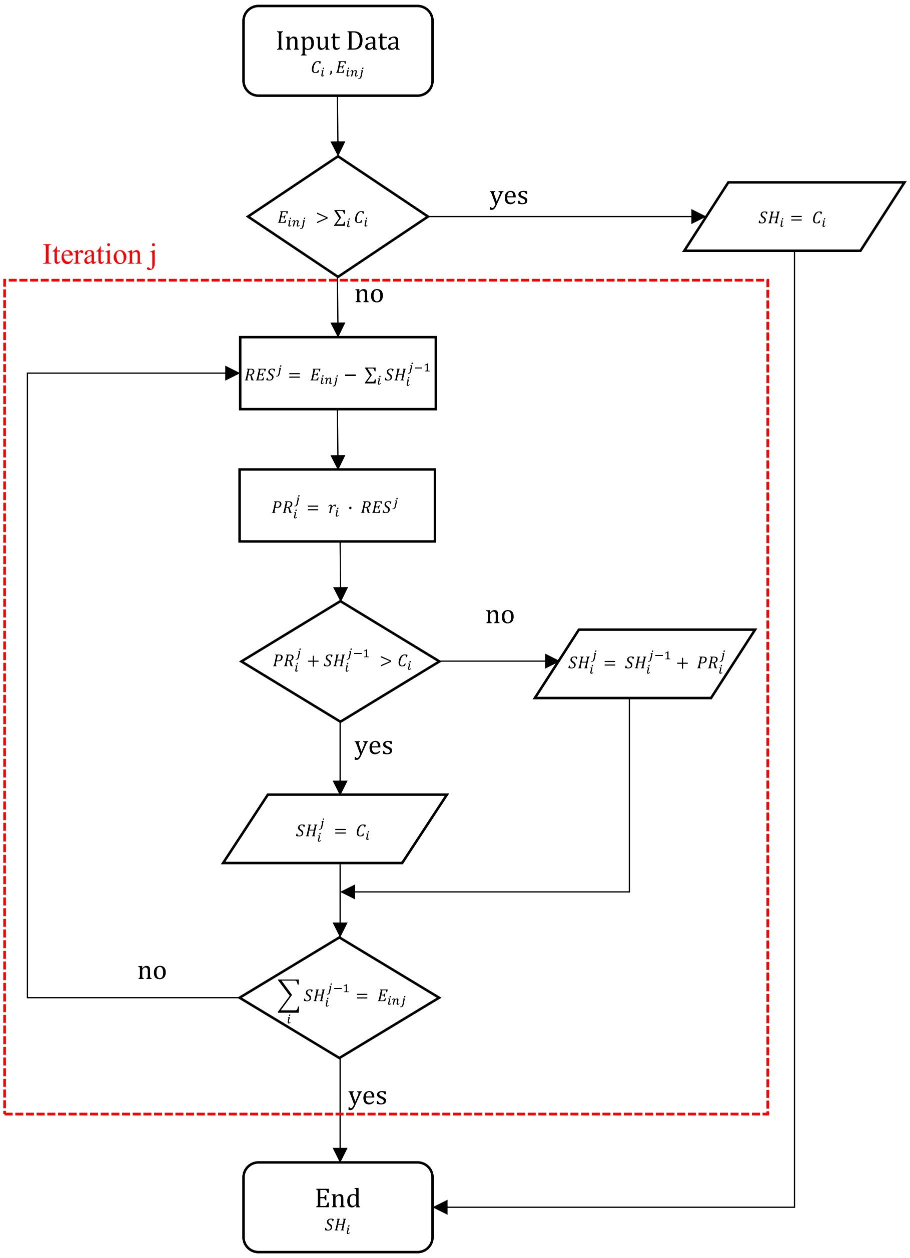

Figure 2. Flowchart of the implementation algorithm based on the dynamic sharing key r_i

2.1.4 Method M4

The operation of M4 follows the principles described in M3, with the distinction that the dynamic sharing key is based on an alternative coefficient known as the “sharing rate” (SR). This coefficient was developed to monitor and potentially penalize users who consume more energy than what is available from the community production plants. Particularly during production hours, energy consumption becomes crucial; however, it is important to discourage overconsumption. A scientifically rigorous approach necessitates maintaining a balance between supply and demand, preventing wastage, and promoting overall energy efficiency.

As shown in ***Figure 3***, the assumed sharing rate SR_i follows an increasing linear trend if the ratio between the user’s consumption and the energy feed into the grid by production plant is less than 1, while it follows an exponentially decreasing trend if the ratio is greater than 1. Consequently, a user who consumes more energy per hour than what is available to the community will be assigned a coefficient that decreases as the disparity between consumption and the energy fed into the grid increases. The decreasing exponential function is shown in ***Figure 3*** , where the y-axis represents the sharing rate, and the x-axis represents the ratio between the consumption of the i-th user and the total energy fed into the grid.

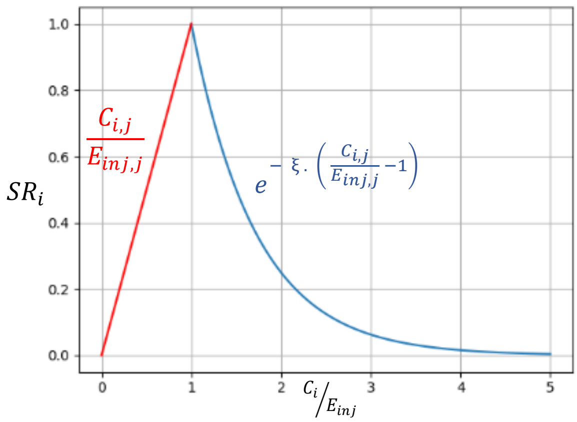

Figure 3. Trend of the defined sharing rate ($SR_{i,j}$) at hourly level

The function is mathematically represented below in Equation 5.

$$SR_{i,j} = \begin{cases} e^{-\xi\cdot\left(\frac{C_{i,j}}{E_{inj,j}}-1\right)}, & \frac{C_{i,j}}{E_{inj,j}} < 1 \\ \frac{C_{i,j}}{E_{inj,j}}, & \frac{C_{i,j}}{E_{inj,j}} \geq 1 \end{cases} \tag{5}$$

To determine the decay constant, in the first analysis it was arbitrarily assumed that the sharing rate is equal to 0.5 when the ratio between the consumption of the i-th member and the energy fed into the network equals 1.5 (i.e., the consumption is 50% more than the input). On the basis of this assumption, the resulting decay coefficient was calculated to be 1.386. The calculation of the dynamic sharing key r_i, in this case is calculated as shown below by Equation 6:

$$r_{i,j} = \frac{SR_{i,j}}{\sum_i SR_{i,j}} \tag{6}$$

As described above, also in this scenario the sum of the distribution coefficients assigned to the i-th member is equal to 1.

2.1.5 Method M5

The operation of M5 follows the principles outlined in M3 and M4, with the distinction that the dynamic sharing key ($r_{i,j}$) is no longer based only on the Pearson correlation coefficient (p_i), or only on the sharing rate (SR_i), but on the combination of both. The methodologies M3 and M4 are then combined by introducing two specific weights, renamed α and β, whose sum is equal to 1. These weights determine the relative importance of each method in relation to the other. For example, if α is given greater than β, more importance is given to the degree of synchronism between consumption and injection; otherwise, more emphasis is placed on the on the amount of energy consumed by the user compared to the energy injected into the grid and potentially shareable. Similar to M1, M3 and M4, the shared energy attributable to the i-th member of the community at any given time can be expressed using Equation 1. In this case, the calculation of the dynamic sharing key r_i was carried out using Equation 7 shown below:

$$r_{i,j} = \frac{\alpha \cdot p_{i,j} + \beta \cdot SR_{i,j}}{\sum_i \alpha \cdot p_{i,j} + \beta \cdot SR_{i,j}} \tag{7}$$

Initially, α and β were assumed arbitrarily equal to 0.5. As described above, also in this scenario the sum of the dynamic sharing key assigned to the i-th member is equal to 1.

2.2 Hourly-tested methods

For a better comprehension of M1, M2, M3, M4, and M5 methodologies, they were applied to the consumption of three typical residential users at hourly level. The hourly consumption and production values were selected in order to highlight and compare the behaviour of the implemented methods. **Figure *4*** shows the users' consumption and the energy fed into the grid in the same time interval (1 hour), which is lower than the sum of the purchased energy of all users. **Figure *5*** displays the amount of shared energy assigned to each user in that hour using M1. As expected, the total shared energy is equal to the energy fed into the grid in this case. Furthermore, it can be observed that the shared energy is distributed proportionally based on the users' consumption, with u3 receiving the largest amount of shared energy while u2 the smallest.

Similarly, M2 was implemented in Python, and applied to the same hourly consumptions of u1, u2, and u3 shown in **Figure *4***. **Figure *6*** demonstrates that this algorithm tends to distribute the shared energy equally among the most consuming members. Once an amount of shared energy equal to the minimum consumption is assigned to u2, the remaining energy is divided equally between u1 and u3, without considering the greater consumption of u3 compared to u1. Consequently, u1 is assigned a larger amount of shared energy than that by M1, increasing from 0.38 to 0.54 kWh of shared energy. So u1 is favoured by M2 as it receives an amount of shared energy equal to its entire actual consumption, almost double compared to that assigned to it by M1.

As for M3, the Pearson coefficients (remapped from 0 to 1) in this case were assumed equal to p1 = 0.64, p2 = 0.23, p3 = 0.51 respectively for u1, u2, u3. As shown in **Figure *7***, u1 has been assigned the largest amount of shared energy, being the user with the consumption most correlated to input, while u2 has received the smallest amount due to its lower correlation. Compared to the previous methodologies, it is important to note that M3 consistently penalizes u3, despite its higher consumption, because u3 has a slightly lower Pearson coefficient than u1, which is the most correlated throughout the day and is consequently rewarded by M3.

As shown in **Figure *8***, u3 is on the decreasing exponential function since its consumption exceeds the amount of energy fed into the grid by the production plants. For this reason, a sharing rate of 78% is attributed to u3. This penalty is due to the fact that the consumption of u3 exceeds the shared energy of the community in that given hour. Instead, users u2 and u1 are assigned an amount of shared energy equal to the ratio between their respective consumption and the overall shared energy. Once the sharing rate and the resulting dynamic sharing key have been calculated, the amount of shared energy attributed to each member of the community is quantified according to the algorithm previously shown in **Figure *2*** for the M3. The results in **Figure *8*** demonstrate that u3 receives the largest amount of shared energy; despite its consumption exceeds the energy actually available, the sharing rate attributed to it is the highest.

M5 was implemented in Python and applied to the same hourly consumption data of u1, u2, and u3. Initially, the Pearson correlation coefficients were assumed to be p1 = 0.64, p2 = 0.23, and p3 = 0.51 respectively, as in M3. Subsequently the sharing rate was calculated similarly to M4. Once these parameters and the resulting dynamic sharing key have been calculated, the amount of shared energy attributed to each community member was computed using the algorithm outlined in **Figure *2***, also used for M3 and M4. As shown in **Figure *9***, u3 continues to receive the largest amount of shared energy.

However, compared to M4, its amount of shared energy is lower because the weight associated with the Pearson correlation coefficient affects the final value by lowering it.

Consumption 🟦 **Injected** 🟨 **Shared** 🟥

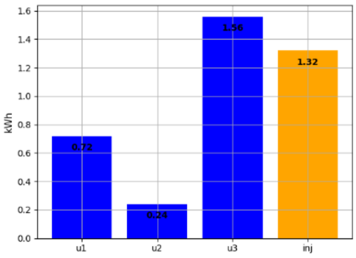

Figure 4. Hourly consumption and Injected energy

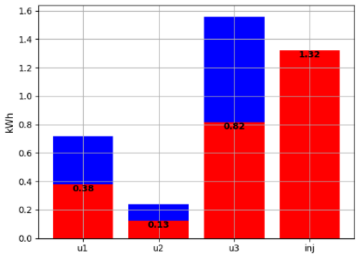

Figure 5. M1 repartition of shared energy

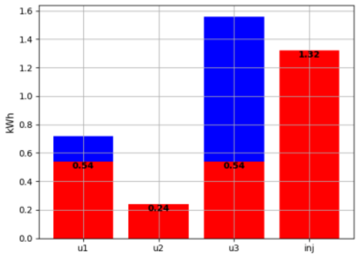

Figure 6. M2 repartition of shared energy

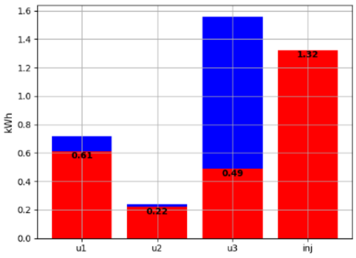

Figure 7. M3 repartition of shared energy

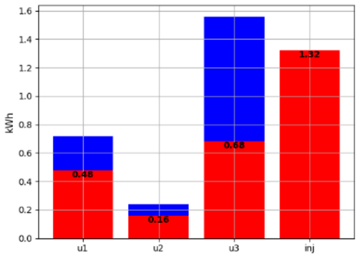

Figure 8. M4 repartition of shared energy

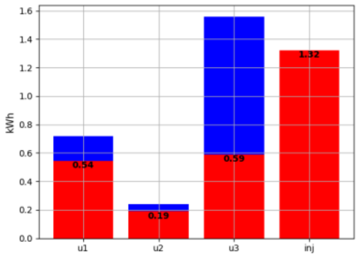

Figure 9. M5 repartition of shared energy

2.3 Case study description

In the previous paragraph, the underlying logic of each method was described, focusing on their hourly operation. The next step in this study is to test the five algorithms using data-driven consumptions at an hourly granularity, and to compare these implemented methods by conducting an annual simulation of a REC. The selected case study concerns the possible implementation of a REC in a city in northern Italy, where consumption and production data (from a photovoltaic system that feeds all generated energy into the grid) refer to users located in this city. In particular, the main characteristics of energy community members are described in ***Table 1***. They include the following real users: a manufacturing company (Small Medium Enterprise, u1) which anonymously provided its consumption data, downloaded from the local distributor's portal; two types of residences (apartments and single-family houses), with consumptions data collected from two family units (u2 and u5; u3 and u4). Additional average consumption profiles for residential customers, different for power classes (u6, u7, and u8), were obtained from ARERA, the Italian Energy Networks and Environment Regulatory Authority. Through the ARERA portal [35], hourly consumption data were retrieved and selected based on their geographic location, in order to integrate them with the other community members. The measurement data processed by ARERA in order to elaborate these average data-driven profiles were made available by the distribution companies through the Integrated Information System [36], an infrastructure managing information flows such as measured energy data. In order to obtain more significant and generalizable results, each hourly residential consumption have been accounted 20 times, thus creating a composite profile representative of 20 identical residential users. This proportion was used to achieve a global energy sharing exceeding 90%, a value technically associated with correct community sizing, which also allows a clear representation of the differences between the methods emerging from the comparative analysis. The simulated period spans one year, as summarized in ***Table 2***. The main objective is to observe the amounts of shared energy assigned to each user by the five methods described in the previous paragraphs.

Table 1. Main features of energy community members

REC members	Users classification	Number of occupancy	Prosumer	Number of users	Power contract [kW]	Area [m^2]	Annual consumption [kWh/y]
u1✦	SME	-	Yes	1	-	-	419,894
u2	residential	3 members	No	20	3	80	31,491
u3	residential	5 members	No	20	3	190	70,950
u4	residential	2 members	No	20	4.5	180	61,743
u5	residential	4 members	No	20	3	145	44,917
u6♦	residential	-	No	20	6	-	190,897
u7♦	residential	-	No	20	4.5-6	-	86,077
u8♦	residential	-	No	20	3-4.5	-	65,760

✦ the SME did not provide any information regarding contract power, number of occupants and available surface area

♦ the data by ARERA are based only on consumption classes and do not provide information on the number of people and occupied area

Table 2. Time period of the simulation

Simulation time	
Start date	01/04/2022 00:00:00
End date	31/03/2023 23:00:00
Timestep	60 minutes

3. Results & Discussion

3.1 Energy analysis

The **Figure *10*** shows the weekly purchased and injection profiles of the SME, along with those of all the residential users within the community. To provide a comprehensive representation of seasonal energy profiles, three weeks were selected within each of the three periods (winter, summer, and mid-season). The selection of representative weeks was specifically aimed at showcasing distinct energy consumption patterns across the different climatic conditions prevalent during these seasons. Although the global amount of shared energy at community level is very high (almost 90% of the energy fed into the grid, equal to 79,855 kWh/year), there is not always synchronism between the withdrawal and the input of energy on the network by the individual user.

In order to implement M3 and M5 methods, the correlation between the consumption curve of each member and the injection curve from the renewable plants was calculated using the daily Pearson correlation. The coefficient was remapped from 0 to 1 and subsequently each user was assigned a normalized coefficient based on the sum of all coefficients for each hour. **Figure *11*** presents a box plot on the distribution of normalized Pearson values for each user. The first quartile for u1 shows significant variations of the correlation coefficient – 50% of its values ranges approximately 0.05 to 0.021 throughout the year – the consumption of which is not always positively correlated with the energy fed injected into the grid; it is still higher if compared to all other members. For member u6, the first and third quartile assume a narrow range of values, ranging between 0.07 and 0.09, and negatively correlated with the energy injected into the grid on many days of the year compared to the other members. However, observing Figure 12 which shows the box plot excluding weekend days, it can be noticed how the variations in the first quartile of u1 are significantly reduced, resulting in the user being the most positively correlated while the other users present a distribution of values similar to the Figure 11. This trend can be attributed to the fact that SME consumption decreases substantially, almost reaching zero, during weekends when it remains closed.

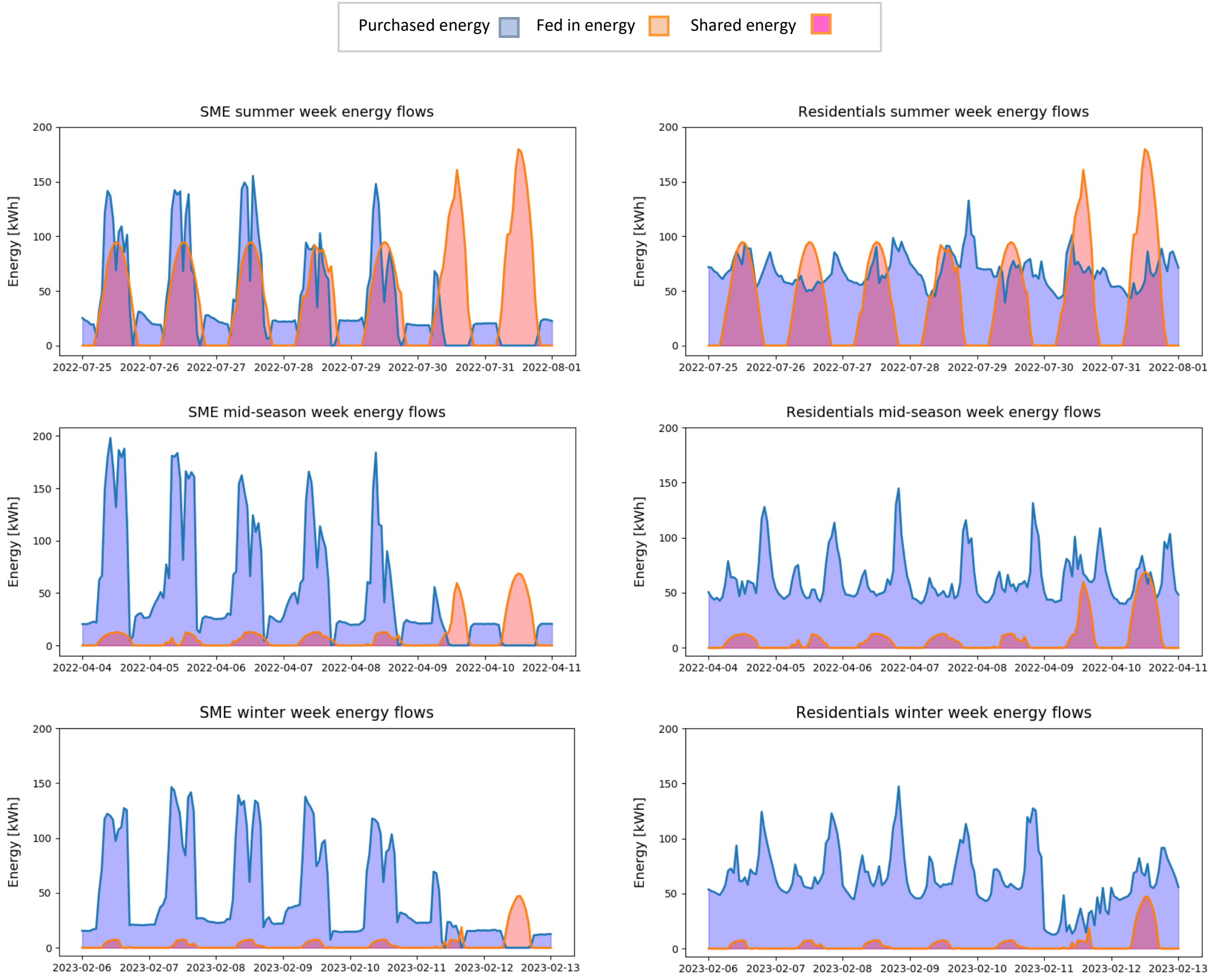

Figure 10. Weekly profiles of energy purchased and fed into the grid for SMEs and residential users

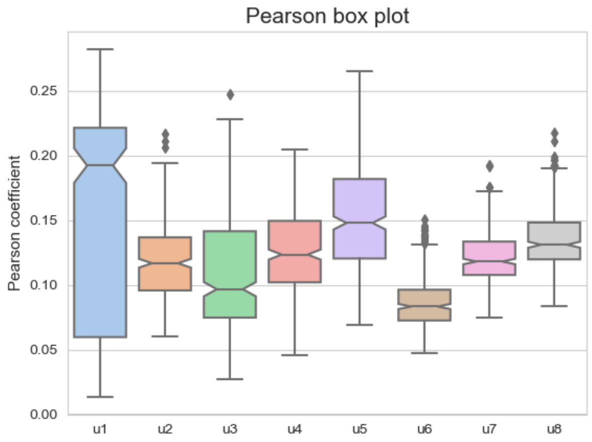

Figure 11. Notched box plot of daily normalized Pearson correlation coefficient

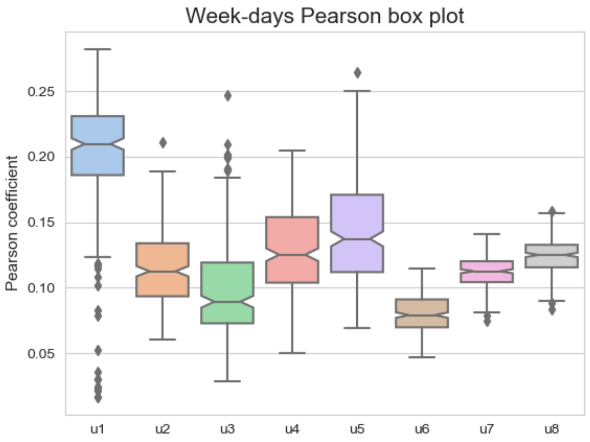

Figure 12. Notched box plot of normalized Pearson correlation coefficient excluding weekends

3.2 Comparative analysis of the methods

Figure *13* shows the amount of shared energy assigned by each method in relation to the user's consumption. This figure illustrates that, regardless of the distribution method adopted, the shared energy assigned to each member is significantly lower than their actual consumption. Moving to **Figure *14***, it presents again the shared energy assigned by each method, but this time the comparison is made not with consumption, but with another parameter named *Shared_limit*, as defined by the following Equation 8.

$$SH\_lim_{i,j} = min(E_{inj,j} , C_{i,j}) \qquad (8)$$

This quantity represents the maximum energy each member could share with the community in the absence of the other members. Specifically, methods M2, M3, M4, and M5 tend to distribute energy almost uniformly among most members, except for u1, u6, and u5, which present a more differentiated distribution among the various methods. Although u6 has the highest annual consumption among residential users, thanks to its contracted power of 6 kW, it is penalized by M3. This could be attributed to the fact that its hourly consumption does not align optimally with the potentially shareable energy profile. Referring to **Figure *11***, 50% of the normalized Pearson values concentrate between 0.07 and 0.09, highlighting a significant decorrelation between consumption and injection into the grid. In the same way, it is interesting to observe how M1 assigns the largest amount of shared energy to u1, the member with the highest consumption, but its actual contribution, i.e., the maximum energy it would share (*the shared limit*), is lower than that of u1 which, however, is attributed a lower energy amount from M1. On the contrary, u2 and u5 appear to be the most penalized members by the M1 method, as they have the lowest consumptions among all the participants and would provide the least effective contribution to the community. In the case of u2, apart from M1, all methods assign similar shared energy values, with M4 showing slight differences probably due to low consumption and often much lower than the energy input at any given time.

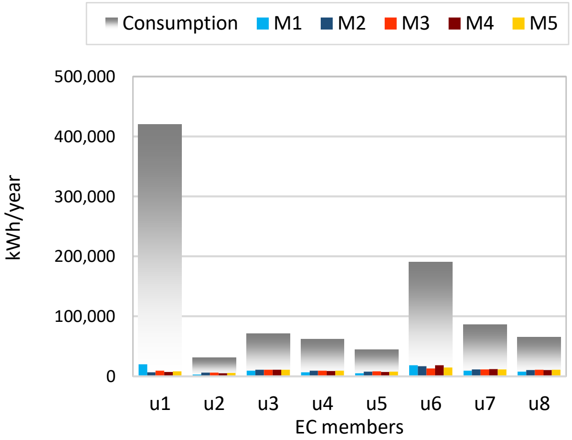

Figure 13. Comparative analysis of the methods used for the allocation of shared energy with respect to total consumption

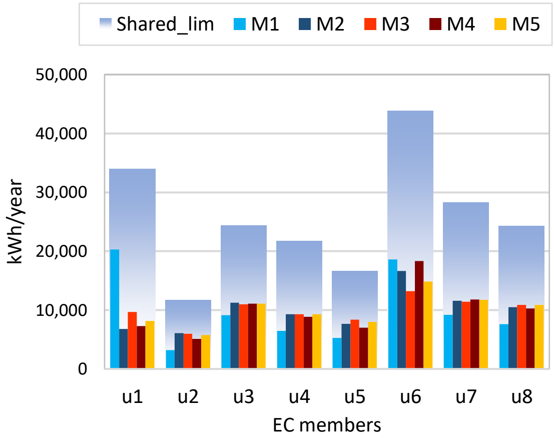

Figure 14. Comparative analysis of the methods used for the allocation of shared energy with respect to the shared energy limit

This trend occurs because M1 only considers energy consumption but doesn't consider its distribution. Since u1 doesn't consume on weekends, it contributes "fewer hours" than u6, which in fact has a higher annual shared_limit, but in the hours in which u1 contributes to the shared energy it consumes a lot. Through **Figure 15** it is possible to explore how the hours of consumption are distributed in relation to the hours of energy feed into the grid during the year for u1 and u6. As regards u1, it can be observed that consumption on weekends is equal to zero, especially in correspondence with high values of feed-in energy (100-175 kWh), while there are high consumption values during the week in correspondence with low values of fed-in energy. As regards u6, it can be observed that during weekends it consumes energy in correspondence with high values of energy input, however, the consumption of u6 also presents high consumption values in correspondence with low energy input.

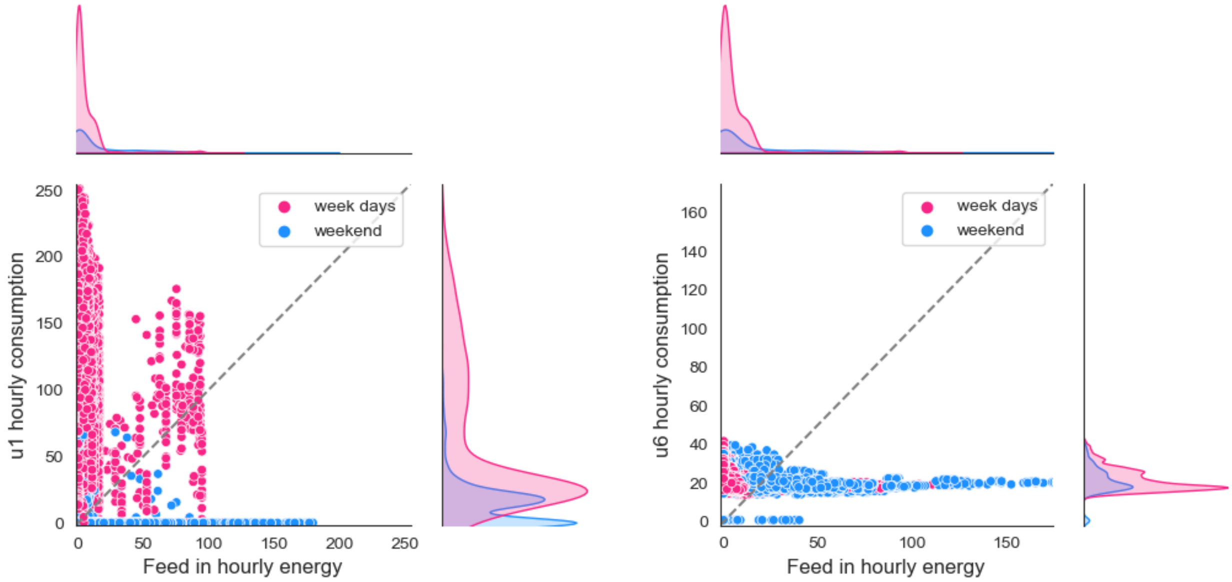

Figure 15. Distribution of consumption hours compared to feed in hours for users u1 and u6

In order to perform a comparative analysis between the methods, they were systematically compared with M1 using scatter graphs shown from **Figure *16*** to **Figure *19***. The shared energy by M1 is represented on the x-axis, while the shared energy by other methods is on y-axis. If the point is above the reference line, it means that the specific methodology assigns a higher shared energy to the i-th member than M1; if the point is below the reference line, it means that M1 assigns a higher share to the i-th member. **Figure *16*** shows the comparison between M1 and M2: most members receive a greater amount of shared energy from the M2 methodology, with the exception of u1 and u6, which are favoured by M1. In particular, u6 is quite close to the reference line, while u1 remains significantly distant, in fact M1 assigns it a much higher energy share than M2. **Figure *17*** shows the comparison between M1 and M3: the results are similar to the previous one, with u1 and u6 favoured by M1; u6 is further from the reference line compared to the previous figure, while u1 approaches while remaining distant from it. **Figure *18*** shows the comparison between M1 and M4: u6 is practically on the reference line, highlighting how M1 and M4 essentially attribute the same amount of shared energy. For the remaining members, the scenario remains similar to what seen previously. Finally, **Figure *19*** shows the comparison between M1 and M5: again, u1 and u6 are favoured by M1 over M5, following a pattern similar to the previous comparisons.

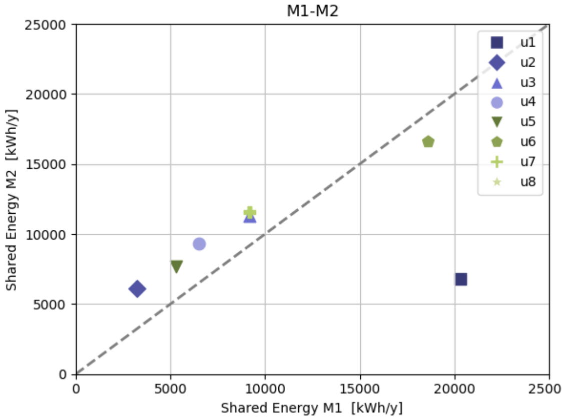

Figure 16. Comparison between the shared energy assigned by M1 and M2

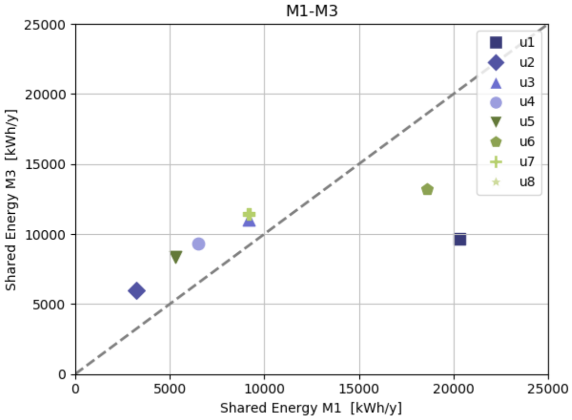

Figure 17. Comparison between the shared energy assigned by M1 and M3

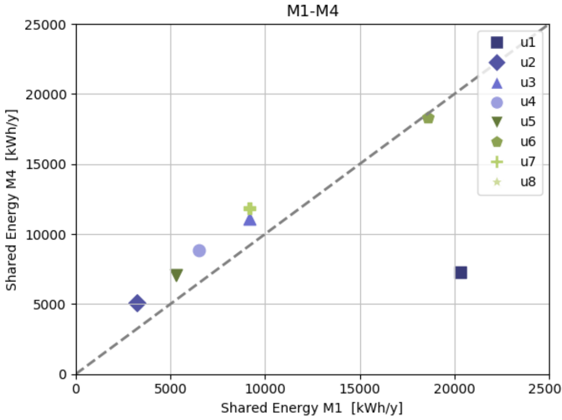

Figure 18. Comparison between the shared energy assigned by M1 and M4

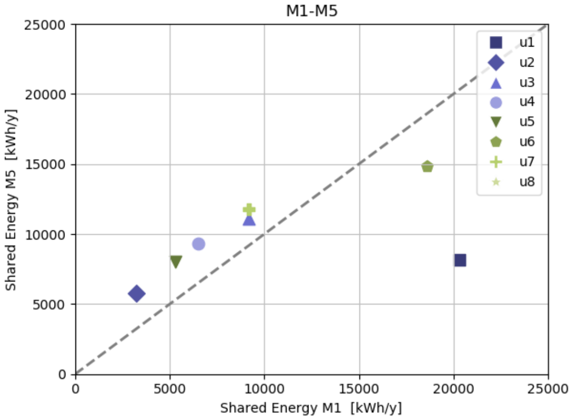

Figure 19. Comparison between the shared energy assigned by M1 and M5

Due to the significant differences observed for users u1 and u6 when compared with M1, a detailed analysis was conducted to examine how the shared energy assigned by M2, M3, M4, and M5 varies for these two users as a percentage relative to that assigned by M1. This comparison for the u1 is presented in **Figure *20***, showing both the trend of the annual shared energy as the distribution method varies, and the percentage variation of this energy with respect to M1. In the case of u1, M2 and M4 penalize the shared energy the most, with a decrease of 66.5% and 64.1% respectively. M2 tends to distribute the shared energy equally among all members penalizing users with high consumption, while M1 method favours users with high consumption and penalizes those with lower one. On the other hand, M4 tends to penalize u1 as it is the major consumer in the community, exceeding the energy fed into the grid in some hours of the day. Consequently, it results in a $SR_{i,j}$ which negatively influences the sharing key determining the amount of energy assigned. The method that penalizes u1 the least is M3: observing **Figure *11***, 52.4% of the normalized Pearson coefficients can take on a wide range of values, correlating positively with the energy fed into the grid on some days of the year.

The same measures are also shown in **Figure *21***, but in relation to u6. The implemented methods do not penalize u6 excessively as they did with u1. However, it is possible to identify in M3 the method that penalizes u6 the most, since $r_{i,j}$ is influenced by $p_{i,j}$: observing again **Figure *11***, 50% of the coefficients fall within a narrow range of values between 0.07 and 0.09, correlating in a negative way with the energy fed into the grid on certain days of the year. As observed previously, M4 assigns an amount of shared energy similar to that of M1; this is because although u6 has the second-highest consumption after u1, it does not exceed the energy fed into the grid by the production plants, thus $SR_{i,j}$ is not excessively penalized.

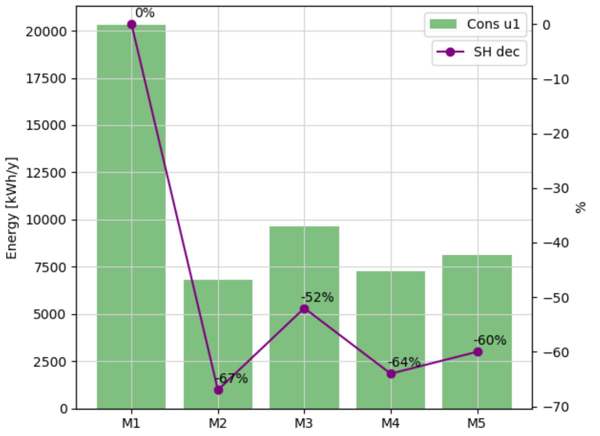

Figure 20. Trend of the shared energy assigned to u1 with respect to M1

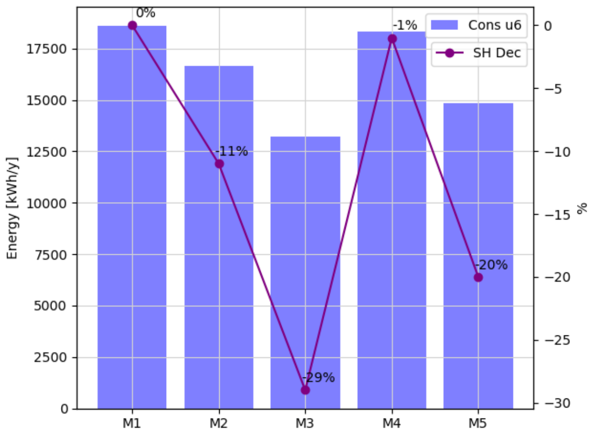

Figure 21. Trend of the shared energy assigned to u6 with respect to M1

Table 3 shows the shared energy contributions by different methods for each member with respect to the energy fed into the grid by the production plants. In summary, it can be observed that:

- Except for u1 and u6, methods M2, M3, M4, and M5 attribute a larger portion of shared energy to the community members.
- Methods M2, M3, M4 and M5 show a tendency to distribute energy quite evenly among most members.
- Users u1 and u6, i.e., the members with the highest consumptions throughout the year, are always favoured by the M1 methodology, which assigns them a greater portion of shared energy than the other methodologies.
- Member u1 is penalized significantly by the other methodologies compared to u6, highlighting how M1 tents to overestimate the shared energy, which is attributed proportionally to its consumption.
- Member u6 is particularly penalized by M3 due to its negative correlation during the year; however, M4 seldom penalizes u6, as it often manages to maximize the share rate compared to other members.

Table 3. Contribution of shared energy of each member compared to the energy shared by the entire energy community

Users	Consumption [kWh/year]	M1	M2	M3	M4	M5
u1	419,894	22.6%	7.6%	10.8%	8.1%	9.1%
u2	31,491	3.6%	6.8%	6.7%	5.7%	6.4%

u3	70,950	10.2%	12.5%	12.2%	12.4%	12.4%
u4	61,743	7.2%	10.3%	10.4%	9.8%	10.4%
u5	44,917	5.9%	8.5%	9.3%	7.8%	8.9%
u6	190,897	20.7%	18.5%	14.7%	20.4%	16.5%
u7	86,077	10.2%	12.9%	12.7%	13.1%	13.1%
u8	65,760	8.5%	11.7%	12.1%	11.4%	12.1%

In order to generalize the obtained results, the five algorithms underwent testing on additional data-driven energy profiles for a second case study i.e., a REC of no. 8 hotel activities in northern Italy (Appendix A). The above-described analyses were replicated to verify the reliability of the main findings outlined in the previous case study. Specifically, **Table A.1** and **Table A.2** illustrate the main characteristics of community members and the period of the simulation, respectively. **Figure A.1** and **Figure A.2** show weekly energy profiles and a representative box plot of the distribution of normalized Pearson coefficients for each user, respectively. Results following algorithm application are shown from **Figure A.3** to **Figure A.9**. In accordance with the first case study, the user with the highest annual consumption (u3) is allocated the largest amount of shared energy by M1. M4 assigns a nearly equal amount of shared energy compared to M1, since for the majority of the year, u3 consumption does not exceed the energy feed into the grid, as illustrated in **Figure A.3**, Conversely, it is notable that the user with the lowest annual consumption (u6) is allocated the smallest amount of shared energy by M1 and M4. Consistently with Figure A.2, users u2 and u7 receive the greatest benefits from M3, as they are more synchronized with the energy feed into the grid. In summary, the algorithms exhibit consistency in their operation when applied to different annual periods and user types, aligning with their operational logic.

4. Conclusions

The aim of this study is to provide support for the internal management of a Renewable Energy Community and Collective Self-Consumption configurations, by developing algorithms to distribute shared energy among its members. This work focuses on modelling and simulating a Renewable Energy Community within a virtual scheme, whose remuneration model is based on energy sharing outlined in the Italian regulation. In particular, four algorithms were developed on the basis of dynamic sharing keys, in order to allocate shared energy on an hourly level addressing the critical condition that arises when the energy feed into the grid is lower than the energy purchased by users. In this scenario, determining the actual contribution of each user without a physical basis to calculate energy exchanges becomes challenging. The algorithms include: M1, based on consumption-proportional key; M2, developed by the University of Turin; M3, based on Pearson correlation key to evaluate synchronism between injected and purchased energy; M4, based on a sharing trend key accounting for the difference between purchased and injected energy; M5, based on a combination of the previous two. The methods were tested through an annual simulation of dynamic energy exchange with hourly resolution in an energy community made up of "typical" users, and a comparative analysis was conducted. In particular, real energy consumption profiles of eight users, including seven residential profiles and one Small to Medium Enterprise (SME) with a PV system available to the community, were used for testing. Some residential consumption data were aggregated at an hourly level and multiplied to create a representative profile of n. 20 residential users. The main objective was to evaluate the allocation of shared energy through the five developed methods. The results show that, apart from users u1 (the SME) and u6, methods M2, M3, M4, and M5 lean to attribute a greater amount of energy uniformly among community members. The two users with the highest annual consumptions (u1 and u6) are those most rewarded by the M1 method, which assigns them a larger amount of shared energy. However, it is worth noting that the use of M1, the most commonly used method, can lead to overestimation of the assigned energy, since it doesn't consider the distribution of consumption's hours compared to hours in which there is a feed into the grid. REC and CSC are European regulated form of energy communities founded on incentivizing shared energy, which is a virtual measure. Since national regulations don't define a univocal method, it is crucial to adopt and define new methods that consider different aspects related to the behaviour of members within the community. It is important rewarding users that consume energy when the community provides surplus energy from renewable sources (M3), this could stimulate users to be more sensitive to theme of energy efficiency and sustainability. At the same time, users should not increase their consumption compared to the pre- and post-community configuration, trying to consume a lower or equal amount of energy compared to that made available by the community (M4). Summarizing, in Europe the study on REC and CSC is gaining importance as several authors delve into these topics in various aspects, gaining considerable attention in recent times. This study addresses emerging challenges in energy sharing, particularly focusing on analyzing new national regulations adopting a virtual sharing model. The implemented algorithms offer a practical solution and represent a conceptual innovation in energy sharing at community level. By utilizing data-driven energy profiles, the accuracy of the results is enhanced, allowing for a more precise evaluation of algorithm simulation. Furthermore, the results obtained can provide tangible support for decision-making and policymaking in the energy sector, contributing both to academic knowledge and to the practical implementation of tools and approaches aimed at improving efficiency and fairness in energy distribution within community members. The crucial point found in this work is that an energy community require the implementation of allocation mechanisms that consider the different types of users who contribute to energy sharing. Other aspects that deserve further studies in the future concern the application of dynamic distribution keys to a larger cluster of users, identifying which algorithms are best suited to the type of user without penalizing them; other studies could consider vulnerable users in energy poverty through the development of social indicators. Furthermore, as members of a REC or CSC can voluntarily enter or exit the established legal entity, future studies will need to evaluate indicators of potential expansion or decline of community members with the same production plants.

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Appendix A. Case study 2

Table A.1 Main features of energy community members

REC members	Users classification	Prosumer	Description	Consumption [kWh/y]
u1	Hotel	Yes	38 room - 1400mq	109,491
u2	Hotel	No	80 seats	123,869
u3	Hotel	No	100 seats	195,349
u4	Hotel	No	-	130,942
u5	Hotel	No	120 seats	117,674
u6	Hotel	No	120 seats	55,360
u7	Hotel	No	-	52,659
u8	Residence	Yes	160 seats -40 rooms	84,127

Table A.2 Time period of the simulation

Simulation time	
Start date	01/01/2022 00:00:00
End date	31/12/2022 23:00:00
Timestep	60 minutes

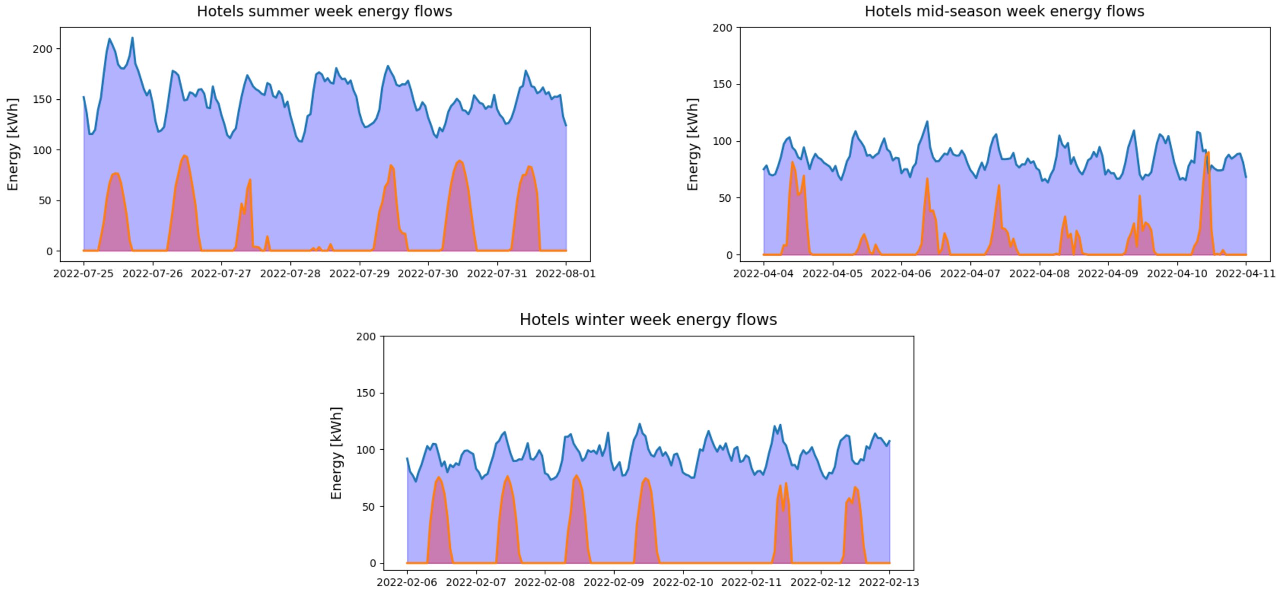
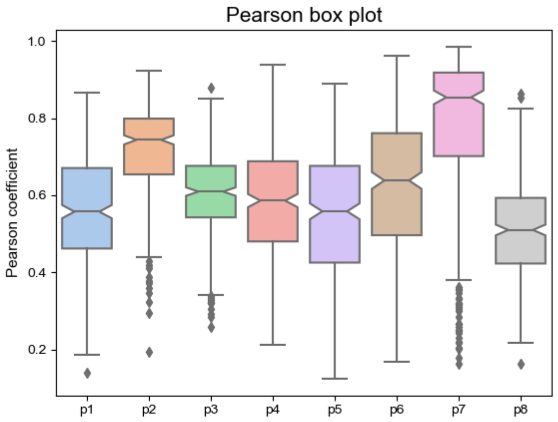


Figure A.1 Weekly profiles of energy purchased and fed into the grid for all users



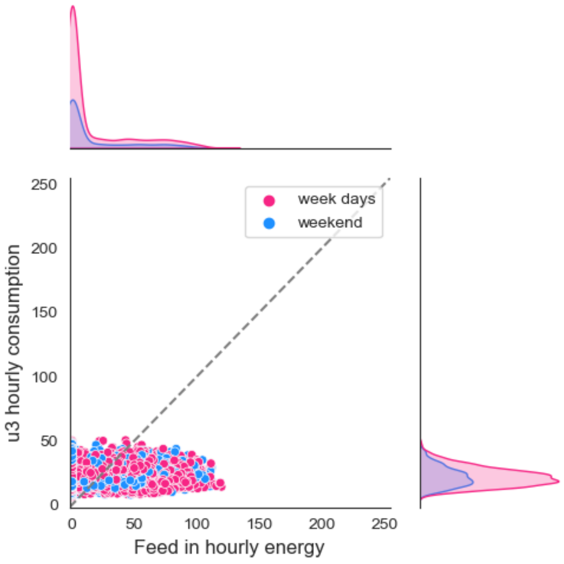


Figure A.2 Notched box plot of daily normalized Pearson correlation coefficient

Figure A.3 Distribution of consumption hours compared to feed in hours for user u3

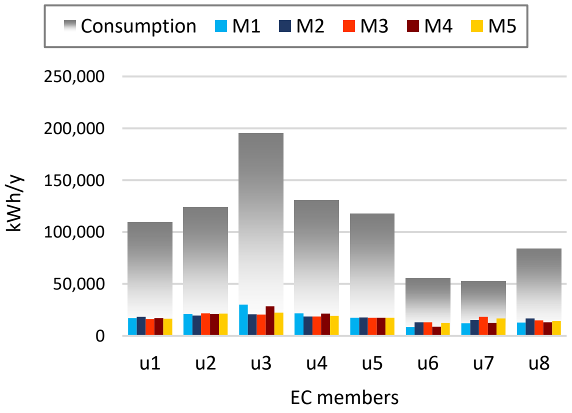


Figure A. 4 Comparative analysis of the methods used for the allocation of shared energy with respect to total consumption

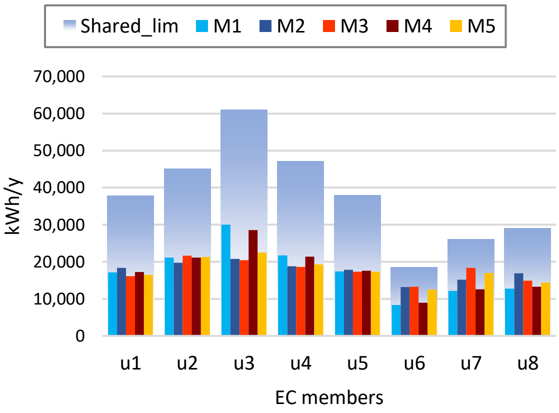


Figure A. 5 Comparative analysis of the methods used for the allocation of shared energy with respect to the shared energy limit

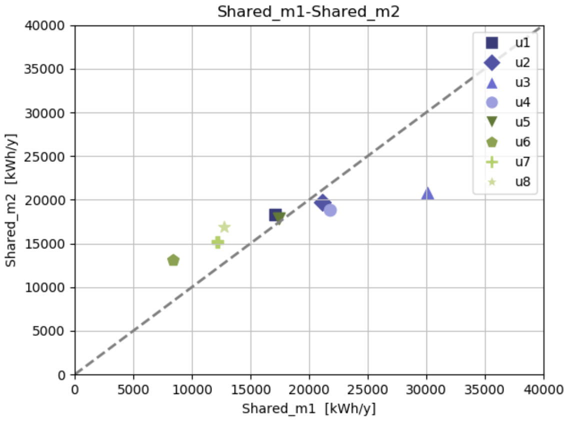


Figure A.6 Comparison between the shared energy assigned by M1 and M2

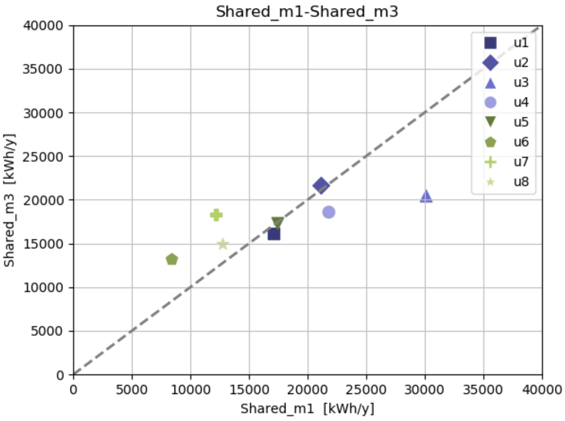


Figure A.7 Comparison between the shared energy assigned by M1 and M3

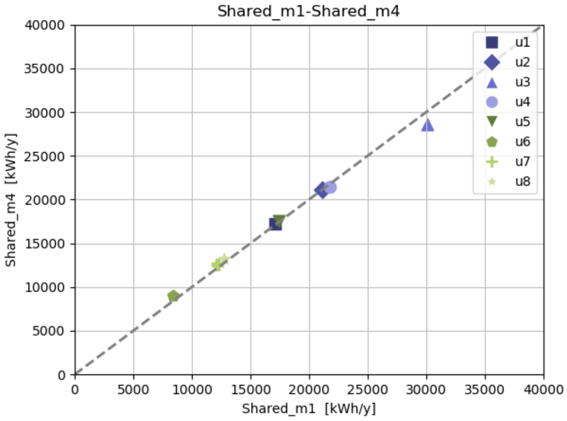


Figure A.8 Comparison between the shared energy assigned by M1 and M4

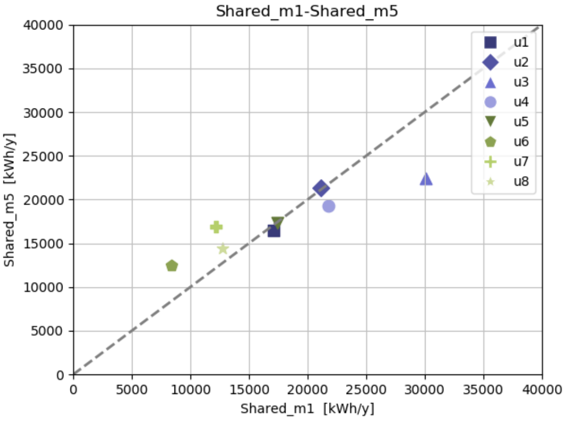


Figure A.9 Comparison between the shared energy assigned by M1 and M5

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