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Load Shifting and Demand-Side Management in Renewable Energy Communities: Simulations of Different Technological Configurations

Antonino Rollo , Paolo Serafini, Federico Aleotti , Debora Cilio, Enrico Morandini, Diana Moneta , Marco Rossi *, Matteo Zulianello and Valerio Angelucci

Ricerca sul Sistema Energetico (RSE s.p.a.), Via Rubattino 54, 20134 Milano, Italy; antonino.rollo@rse-web.it (A.R.); paolo.serafini@rse-web.it (P.S.); federico.aleotti@rse-web.it (F.A.); debora.cilio@rse-web.it (D.C.); enrico.morandini@rse-web.it (E.M.); diana.moneta@rse-web.it (D.M.); matteo.zulianello@rse-web.it (M.Z.); valerio.angelucci@rse-web.it (V.A.)

* Correspondence: marco.rossi@rse-web.it

Abstract: This research investigates the optimization potential of Renewable Energy Communities (RECs) through advanced demand-side management strategies. The study simulates a real distribution network and analyzes load profile optimization in a residential REC configuration, comparing two distinct approaches: Demand-Side Engagement (DSE) and Optimized Demand-Side Management (Opt-DSM). The methodology encompasses load-shifting strategies at the appliance level, progressing from spontaneous behavior patterns to algorithmic optimization. Starting from a baseline scenario of conventional consumption patterns, the research evaluates the effectiveness of both user-driven load shifting (DSE) and automated redistribution through genetic algorithms (Opt-DSM). The analysis framework addresses three key dimensions: economic efficiency through incentive optimization, social cohesion via collaborative engagement, and environmental sustainability through the optimal utilization of locally generated energy. Results demonstrate that enhanced generation-consumption synchronization through Opt-DSM yields superior outcomes for both distribution network performance and participant economics compared to DSE. However, successful implementation requires substantial technological infrastructure investment at individual and community levels, alongside significant modifications to established consumption patterns. This research contributes to the understanding of RECs as innovative socio-technical systems and provides figures to support the analysis related to the balance between technological optimization and user engagement in maximizing shared energy potential.

Keywords: energy community; demand-side management; user engagement; grid simulation

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1. Introduction

The imperative to promote the adoption of renewable energy sources, while simultaneously ensuring the stability and resilience of electrical grids, is linked to the objectives of reducing greenhouse gas emissions as stipulated by European regulations and the Italian Integrated National Energy and Climate Plan [1]. The European Community aspires to decarbonize the energy system in the short-to-medium term. For this purpose, it defines a process in which energy flexibility and proactive engagement of end users are increasingly critical to maintaining the stability and balance of the grid amid a growing contribution of energy generated from non-dispatchable sources. This perspective is particularly salient in the context of implementing innovative energy models, such as renewable energy communities and new frameworks to optimize consumption based on locally available generation.

The distinctive characteristics of Renewable Energy Communities (RECs), which can be aptly characterized as archetypes of social and technical innovation, underline the centrality of end-user engagement within the transition process. This engagement is vital not only in terms of responsibility but also in reshaping consumption habits based on community needs. Such a perspective effectively redirects the focus of individual actions towards the optimization of collective benefits. Individual behaviors manifest as a transformation in daily electricity consumption patterns, aimed at maximizing the sharing and collective consumption of energy produced by renewable generation facilities accessible to the REC.

Despite the scientific debate surrounding community energy models having persisted for over two decades, it is only with the EU Directive 2001/2018 [2] (commonly referred to as RED II) that a structured definition of energy communities was finally established. This Directive emphasizes the pivotal role of the end consumer in the ecological and energy transition process, with the explicit aim of increasing the proportion of renewable energy within the European energy mix, promoting self-consumption and the proliferation of energy "prosumerism", fostering social acceptance of new renewable energy installations through localized initiatives, and mitigating dependence on fossil fuel sources.

Even though numerous definitions of "energy community" can be found in the relevant literature [3–8], the REDII (art.2 c.16 p.a,b,c) [2] defines Renewable Energy Communities as a legal entity:

(a) which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity.
(b) the shareholders or members of which are natural persons, [Small Medium Enterprises] SMEs or local authorities, including municipalities.
(c) the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits.

This lays the groundwork for a transformation driven by specific keywords and goals that extend beyond the mere economic dimension [9].

This transformative path, through collective action, not only seeks to ensure access to sustainable energy forms but also to guide towards a more rational use of energy, a more citizen-inclusive electricity market, and marked forms of social inclusion that ensure access to renewable energy for the most vulnerable segments of the population—thus steering towards an energy transition that is not only ecological but also socially fair.

Collective actions can only be realized through the ability, for those materially participating in the process, to consume the energy produced by renewable energy sources available to the energy community at the time it is produced, both individually, through physical self-consumption, and collectively, through what in Italian regulation is called "virtual self-consumption". This aims to maximize the economic value of production for the community, through incentives recognized for energy sharing as regulated in the Italian decree [10]. By promoting the synchronization of the production and consumption (increasing the local consumption of the distributed energy generation) it mitigates the energy losses in the grid (thus reducing the energy flows exchanged with the upstream network) and other benefits.

Although the REC is a specific legal entity, what makes it unique, from many perspectives, is the coexistence of various stakeholders collaborating to achieve a common purpose—the sharing of energy produced through renewable sources and the benefits derived from this action [11]. Depending on the type of installation, ownership structure, and its location, stakeholders assume different, but complementary, roles within the configuration—Producer, Prosumer, and Consumer [12].

On one hand, energy, its generation method, and the ownership of generation assets are enabling factors at the outset of the process; on the other hand, the consumption of produced energy becomes crucial in maximizing benefits (environmental, economic, and social) within the community, for the hosting territories [13], and for the electricity system (generation and demand simultaneity potentially supports the grid balancing between the local production and consumption).

The analysis conducted in this work emphasizes the specific dimension of energy demand, relating the consumption styles of the participants in the REC to their capability to generate profits through the incentive system, which is closely linked to their ability to share produced energy. To achieve this and to ensure the process's sustainability over time, it becomes crucial to define careful management and control systems aimed at maximizing load flexibility and, consequently, optimizing energy sharing within the community at the time of production.

Several studies have investigated the effects of load flexibility (i.e., Demand Side Management—DSM) on energy communities, with different boundaries, scopes, and methodologies. Within these studies, Ref. [14] focuses on Positive Energy Districts in Germany; however, it is driven by dynamic tariffs and not by the Italian incentive scheme for diffuse self-consumption. Similarly to the present work, Ref. [15] also calculates the difference in energy balance in a rural community in Austria by comparing energy self-consumption in DSM scenarios. However, it does not perform network simulation to calculate the grid impact and losses, which represent crucial performance indicators in Italy. The electricity network dimension is considered by [16], which investigates the effects of REC prosumers' participation in the upward flexibility market via voluntary load reduction, assessing the impact of network violations. Furthermore, Refs. [17,18] investigate the distribution network effects of RECs in rural and urban MV+LV grids located in Valle d'Aosta (Italy) by adopting Monte Carlo simulations and hosting capacity calculation. However, the study does not consider DSM practices and the effect of users' engagement in load shifting. Conclusively, Ref. [19] combines all elements of load shifting in Italian RECs and assesses the LV grid impacts. Although similar to [19], this article proposes a more focused analysis of various measures for the control and management of the load flexibility (also indirect measures, i.e., the sensibilization of consumers) with the aim of maximizing the sharing of electricity generated by renewable energy plants accessible to the community. By employing a simulation environment developed with the Python programming language and leveraging real information from participants in an operational renewable energy community in Northern Italy, the study aims at discerning the impact of incrementally enhancing user awareness regarding variations in their energy consumption habits. In this framework, load shifting practices are simulated to optimize self-consumption within the community, necessitating efforts from both economic and behavioral standpoints.

In this context, we have delineated three potential cases:

- **Spontaneous Users** (also reported as the reference case) who engage with the REC in an uncritical manner, maintaining their original consumption patterns without aligning with the operational characteristics of the generation facilities available to the REC.

- **Engaged Users** (or Demand-Side Engagement case, DSE) who participate in the community with a certain level of awareness about the solar generation and incentive mechanism and who adjust their load profiles as necessary.
- **Optimized Users** (Optimized DSM case) who are equipped with technologies that facilitate automatic load shifting in response to the REC requirements through DSM strategies.

The analysis, conducted via simulations performed on real data, seeks to identify the challenges and opportunities inherent in progressively influencing user behavior within an REC framework. It further examines the potential commitments needed by DSM programs, particularly in mitigating the impact that increased production from non-dispatchable renewable energy sources may exert on the distribution network.

From a social perspective, issues pertaining to the acceptance of innovation and users' readiness to alter their consumption habits and embrace new technologies are highlighted. On a technical level, energy communities necessitate innovative solutions to support efficiency, safety, and resilience of networks without compromising their stability.

The paper is organized into five sections. Section 2 introduces the concepts of energy demand flexibility and DSM, supported by a concise literature review. Section 3 examines the evolution of the concepts of extended self-consumption and renewable energy communities within the framework of Italian legislation. Section 4 presents the analysis and the scope of this study, including the methodological approach and the contextualization of the cases to be investigated (different typologies and levels of involvement of users). Section 5 is devoted to the introduction of the identified REC case, while, lastly, Sections 6 and 7 present a discussion of the results and offer concluding remarks.

2. Energy Demand Flexibility and DSM Between Challenges and Opportunities

The potential articulated by RECs, manifested in the scaled replication of a comprehensive energy system through the coordination of production, consumption, and, in certain respects, the management of the energy produced, becomes particularly compelling, especially considering a prospective opening to local energy [20]. This potential is pivotal for the formulation and promotion of DSM strategies. Numerous studies, such as those reported by [21], underscore the potential and benefits of DSM from various perspectives, including the electricity market, economic advantages, impacts on diverse sectors, grid modernization, and electrical system reliability. These studies conclude that a common denominator is the necessity for all stakeholders involved in the programs to derive tangible benefits from enhanced DSM effectiveness. However, achieving this requires a more granular understanding of actual user consumption patterns. This challenge is partially addressed by the gradual implementation of advanced metering infrastructure, facilitated by the deployment of second-generation smart meters, which enable utilities to gather increasingly detailed consumption data. Nevertheless, this process remains susceptible to a degree of unpredictability stemming from load profile forecasting, which is often dependent on entrenched consumption habits, as well as diverse behavioral models that complicate the establishment of standardized and universally applicable DSM programs, complexities further exacerbated by the extensive diversification of appliances associated with consumption. Therefore, it is evident that at the heart of this process, and the complexity it entails, lie the end-users, necessitating a comprehensive understanding of their actions and a meticulous classification of users.

On one hand, there is a concerted effort to address the issues of randomness and complexity associated with the subjectivity of consumption models through increasingly advanced and sophisticated technological approaches, ranging from the simple use of thermostats to sophisticated domestic smart applications. On the other hand, there remains a critical need for a careful process of building awareness and sensitizing users regarding their consumption behaviors, which are directly linked to the characteristics of renewable generation plants from which the consumed energy originates, as well as to prices in a market increasingly influenced by unstable geopolitical dynamics. It is evident, therefore, that this endeavor requires substantial investments both economically (in technologies that are not universally accessible) and socially (in terms of building social networks and trust bonds), as well as strategic decision-making in implementing clear and coherent informational and communicative programs [22]. All these actions, to be effectively realized, demand time, consistency, coherence, and trust.

In the context of redefining the critical issues and optimizing the potential benefits of prospective programs, renewable energy communities demonstrate considerable promise. This potential is particularly pronounced given that the process unfolds within delineated territorial areas (albeit expanded in the definitive Italian implementation of the RED II directive), involving a limited number of stakeholders. The project development process necessitates, ex ante, not only a comprehensive understanding of the socio-territorial context in which the project is situated but also the creation of a network that actively promotes and facilitates its implementation [23]. Furthermore, a fundamental understanding of participants' consumption patterns is crucial. The relatively limited number of users to engage, combined with direct insights and the availability of data, often managed through digital management platforms, can enhance the promotion of virtuous behaviors and support mechanisms that facilitate the dissemination of demand-side management strategies aimed at optimizing community performance.

3. Renewable Energy Communities and Collective Self-Consumption Schemes in Italy

The public debate concerning RECs and collective self-consumption in Italy was catalyzed by the promulgation of [24], subsequently converted into Law No. 8 on 28 February 2020, which preemptively and provisionally integrates Directive EU 2001/2018 (RED II) by embedding the European definitions of RECs and collective self-consumption into Italian legislation. This legislative action inaugurated the experimental phase of these initiatives, further developed through subsequent regulations, including ARERA Resolution No. 318/2020/R/EEL [25], which delineates the requirements, and the Implementing Decree of the Ministry of Economic Development, dated 16 September 2020, which specifies the mechanisms and incentive tariffs for the configurations prescribed by the regulation.

The definitive transposition of EU Directive 2018/2001 was accomplished in December 2021 with the issuance of [26], which substantially broadens the physical and technological perimeters of RECs. This decree redefines the operational domain of a REC to the electrical boundary demarcated by the primary substation, thereby expanding the potential participant base from a few hundred under a secondary substation (low/medium voltage) to several thousand under a primary substation (high/medium voltage). Furthermore, it expands the potential capacity of installations available to the community, establishing a maximum threshold of 1 MW per installation and permitting energy sharing across the entire market area, while maintaining the calculation of incentives on self-consumed energy within the primary substation boundaries. It also extends participation to previously excluded entities, such as third-sector organizations.

This amendment markedly extends the "participation boundary", both substantively, with broader territorial limits and thus RECs that could potentially engage thousands of users, and formally, by incorporating third-sector entities as eligible participants and allowing the availability of installations owned by a "third party", such as Energy Service

Companies and energy utilities. The expansion in participatory potential is followed by increased complexity in both business models and community governance structures [13].

After the decrees transposing the European directives, the ARERA's Integrated Text on Distributed Self-Consumption, effective from March 2023 [27], which, in executing Legislative Decrees 199/21 and 210/21, sets the rules for calculating distributed self-consumption, thereby introducing additional elements to the framework (e.g., Individual Remote Self-Consumer). The final applicability of the definitive regulations on RECs was realized in January 2024 with the enactment of the so-called "CACER Decree" by the Ministry of Environment and Energy Security and the publication of the Operational Rules by the Manager of Energy Services (GSE in Italian) [10], which definitively establishes the incentive regime for distributed self-consumption initiatives. A comprehensive timeline summarizing the key developments in Italian legislation is outlined in Figure 1, which details the major milestones and regulatory advancements that have shaped the country's legal framework on the concept of virtual "shared energy".

Figure 1. Italian regulation timeline on configurations of Self-Consumption for Renewable Energy Sharing Promotion.

The most active regions are predominantly located in northern Italy, with Veneto and Trentino-Alto Adige at the forefront, followed by Piedmont and Lombardy. In the south, Campania is the region with the highest number of projects that have completed accreditation and secured access to incentives. Although these figures are modest, they are trending upward, particularly for collective self-consumption configurations, contributing over 2 MW of new photovoltaic installations within a framework oriented towards the transition to renewable and sustainable energy sources.

Even if the data indicates a growing interest in distributed self-consumption and the development of RECs, the process is still complex due to social innovation and evolving legislative frameworks.

Currently, 80% of REC configurations operate as non-profit entities, while the remaining 20% mostly consists of cooperatives with mutual benefit structures, influencing their governance and operational strategies.

Despite a delay in the incentive decree from the Ministry of Environment and Energy Security, the momentum for RECs remains strong, especially with EUR 2.2 billion allocated from the National Recovery and Resilience Plan for renewable energy in small municipalities. Unpublished data from the GSE shows that as of September 2024, there are 286 active configurations for self-consumption and renewable energy sharing, with over 11 MW of new capacity and 2416 users involved, 39 of them in REC configurations.

Regions like Piedmont and Lombardy are leading in replicating these processes, though the data is continuously updated. To track national interest in RECs, RSE (the authors) is developing a database from various sources to quantify interest and define objectives for related projects. Since September 2024, over 700 REC projects have been mapped across 10 Italian regions, each at different stages of development. However, it is important to note that this data is continuously being updated [28].

With regard to the explicit incentive scheme, Table 1 provides an outline of the mechanism for extended self-consumption, as introduced by the Minister of Environment and Energy Security and further elaborated through the subsequent Italian regulatory framework.

Table 1. Premium tariff incentive applicable to the shared energy as defined by the Ministry of Environment and Energy Security, decree of 24 January 2024 [10,29].

Fixed Component Depending on the Size of the Power Plant		Variable Component Depending Zonal Energy Hourly Price (Pzo)	CAP
P < 200 kW	80 EUR/MWh	+max (0; 180 − Pzo)	Cannot exceed the value of 120 EUR/MWh
200 kW < P < 600 kW	70 EUR/MWh	+max (0; 180 − Pzo)	Cannot exceed the value of 110 EUR/MWh
P > 600 kW	60 EUR/MWh	+max (0; 180 − Pzo)	Cannot exceed the value of 100 EUR/MWh.

The incentive is granted to the self-consumption configuration for 20 years and is applicable to shared energy, which is calculated for each time step as the minimum value between the aggregated energy demand and the aggregated injected energy by all members of the REC configuration [10]. This framework also includes a geographic adjustment for photovoltaic systems to account for the lower productivity potential of this specific technology in different regions. Specifically, a correction factor of +4 EUR/MWh is applied in the central regions of Italy and +10 EUR/MWh in the northern regions.

4. Simulation Methodology

As anticipated above, the objective of the simulation consists of analyzing how the involvement of REC users influences the power flows on the hosting distribution network and to what extent the associated revenues incentivize users to adopt this behavior. For this reason, both technical and economic indicators need to be extracted. To obtain realistic results, the network model and the related input data are based on a real REC configuration. The case study for the analysis is designed based on the existing “Buona Fonte” REC in Riccomassimo, a small rural community located in Storo (Trentino Alto Adige, North-ern Italy). The community behavior and the impact on the electrical system are simulated on the LV network model, kindly provided to RSE by the local grid operator CEDIS (“Consorzio Elettrico di Storo”), and include details about lines, switches, breakers, transformers, and distributed generation. The missing information about the network is filled using the standard characteristics for an Italian rural network [30]. The load flow simulation is run for an entire year with a 15-min timestep, by relying on the pandapower power flow solver [31]. This Python library uses a balanced load flow formulation which, with some approximations due to the non-symmetrical nature of LV systems, provides the numerical solution of the network electrical behavior. Starting from the simulation results, the exchanged energy was computed as the difference between the total energy withdrawn and the total energy injected by all the users and generators. Without neglecting the potential occurrence of voltage and overloading issues, the main investigated outputs were as follows:

- Distribution network quantities.
    - Energy losses of electric lines and the distribution transformer.
    - Energy exchanged with the upstream network (slack node).

- Energy shared among REC participants.
    - ○ Energy injected by the power plants.
    - ○ Energy withdrawn by all users.
    - ○ User energy injected and the relative aggregated value for the configuration.
    - ○ User energy withdrawn and the relative aggregated value for the configuration.
    - ○ Aggregated energy shared by the configuration.
- Energy expenditure and economic savings.
    - ○ User incentive revenues and the relative aggregated value for the configuration.
    - ○ Aggregated cash flow of the project.
    - ○ Cash flow of each member of the energy community.

By means of the selected simulation environment, a comparative analysis of these outputs is performed with heterogeneous user engagement strategies. For these purpose, three different scenarios are simulated:

- **Reference scenario**: REC configuration with unmanaged energy sharing, lacking both optimization systems and behavioral changes of consumers (Figure 2a—details in Section 4.1).
- **Demand-Side Engagement scenario (DSE)**: REC configuration with unmanaged energy sharing and no optimization systems but supported by external stakeholders promoting behavioral change (Figure 2b—details in Section 4.2). Some of the consumers are assumed to voluntarily activate their dwelling loads during hours of high photovoltaic production.
- **Optimal Demand-Side Management scenario (Opt-DSM)**: REC configuration with both unmanaged and optimized consumer behavior (Figure 2c—details in Section 4.3). A centralized Energy Management System directly controls the dwelling loads of some users, while the remaining portion maintains the baseline behavior.

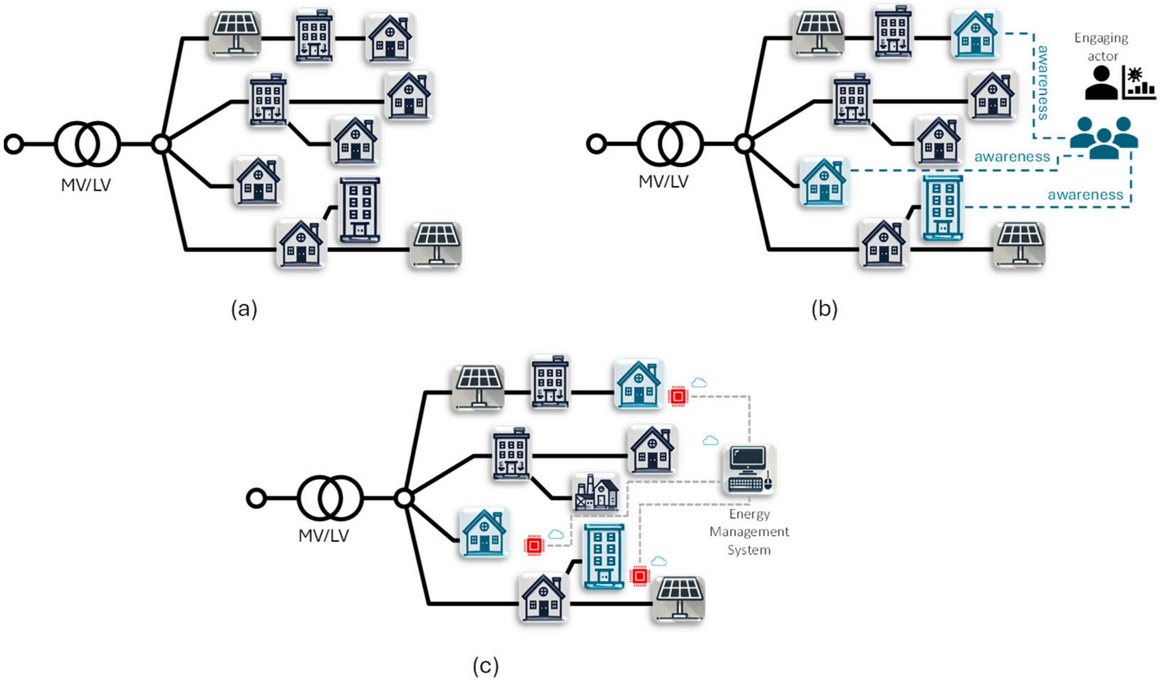

Figure 2. Scheme of the configuration for the Reference case (**a**), for the DSE cases (**b**), and for Opt-DSM cases (**c**).

4.1. Spontaneous Users (Reference Case)

The first simulation aimed to define the baseline for comparing the benefits brought by the user engagement strategy described below. It consisted of simulating the energy behavior of conventional consumers, which was obtained by starting with the consumption patterns of residential appliances (with their power peaks, duration, and fluctuations) and the distribution of activation probability across the average day.

The load simulation strategy consisted of extracting a daily activation time for all appliances using the activation probabilities and then recreating the aggregate load profile of the user by adding all the scheduled appliance load profiles, the fridge base load, and the electricity mains base load. The input for the simulation came from data collected in different households located in Milan and Rome [32]; Figure 3 reports the power profile of some loads, such as the fridge and other aggregated electricity mains, which are characterized by uninterrupted consumption, which is marginally dependent on the interaction with the user; Figure 4 reports the load profiles for other appliances that, in addition to presenting a reduced operating period, have their activation decided by the user.

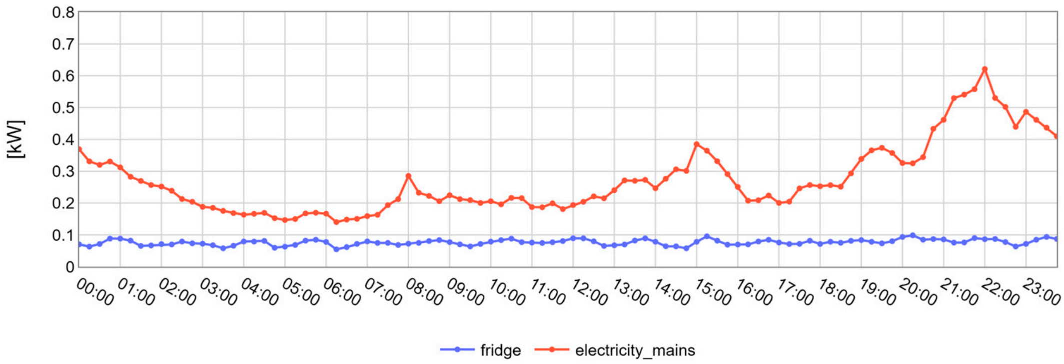

Figure 3. Load profiles of the fridge and electricity mains of a typical domestic user on a daily interval (data extracted and elaborated from [32]).

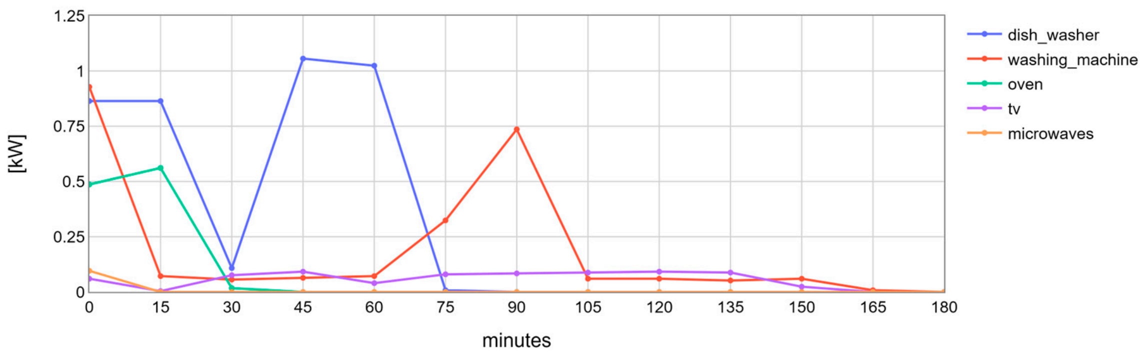

Figure 4. Appliances' load profiles of typical domestic users on a daily interval (data extracted and elaborated from [32]).

As a simulation hypothesis, it was assumed that all the appliances are activated once for each day of the year and that all the users of the configuration have the same appliances' load profile and usage probabilities. This is obviously a simplification of the reality, possibly leading to an overestimation of both revenues and energy bills. However, this assumption also maximizes the benefits brought by user engagement (described in the following subsections), such that the results could be considered the upper limit of the benefits that the considered REC can provide. Finally, the activation probability and the cumulative probability of each appliance are shown in Figure 5 (data are extracted and elaborated from [33]).

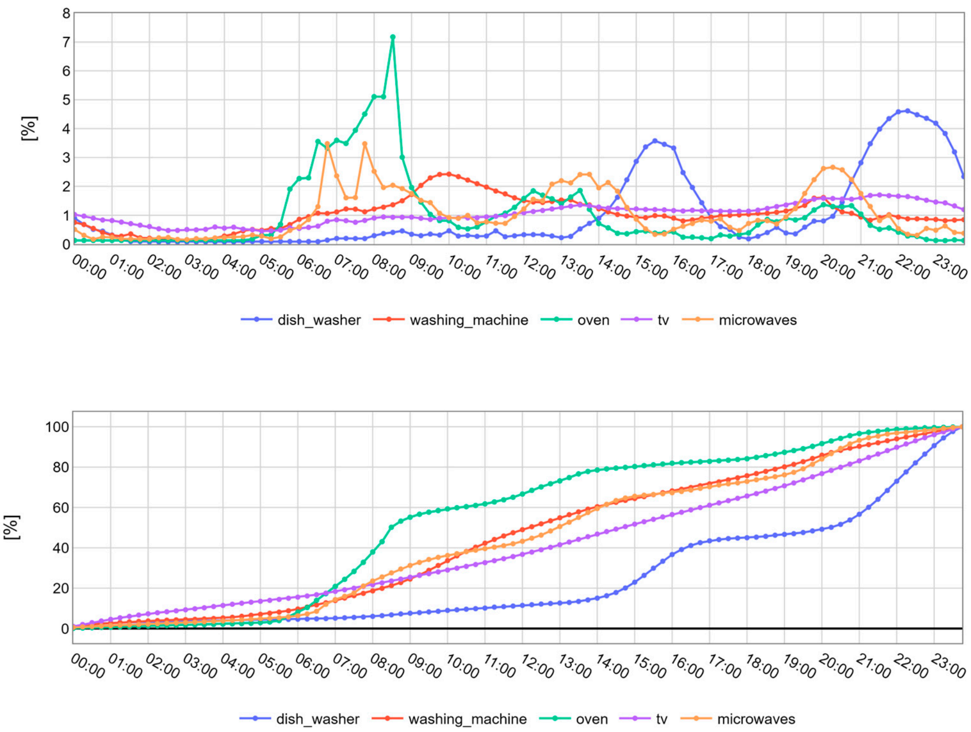

Figure 5. The activation probability (**top**) and the cumulative probability (**bottom**) for all the typical appliances used by a domestic user (data are extracted and elaborated from [33]).

The activation probabilities used in the study are the results of an average of different activation probabilities evaluated during RSE research [32], and they are assumed to be representative of the behavior of a conventional user, who is not subject to any incentive to concentrate energy consumption in specific time windows. However, it must be mentioned that the data collection refers to a small set of households, mainly located in Rome and Milan, and this obviously affects the results. Nevertheless, for the purpose of this paper, this kind of load simulation is very useful, and it allows having total control over the appliances' scheduling. In future research, the results can be improved with a wider dataset.

A summary diagram of the methodology used is shown in Figure 6. In the diagram, a scheduled load for the dishwasher (on the right) is added to the users' base loads (on the left). This strategy is then repeated for all appliances to obtain the total user load profile.

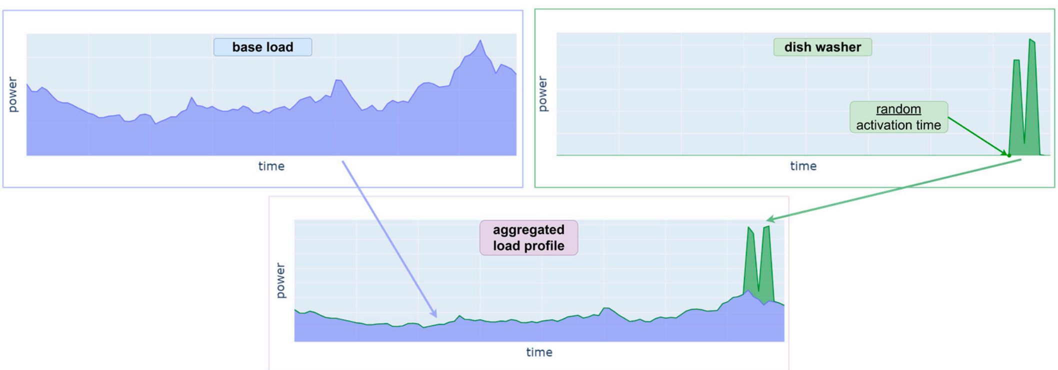

Figure 6. Summary diagram of the methodology used in the load emulator (process repeated for each appliance and each day of the simulated time frame).

4.2. Demand-Side Engagement

DSE Framework represents a behavioral science-driven approach predicated on autonomous modifications in end-user consumption patterns through systematic behavioral interventions. This strategic framework is operationalized through structured community engagement protocols and participatory mechanisms. Upon developing cognizance of the temporal correlation between consumption patterns and photovoltaic generation profiles, participants implement voluntary load modifications. Specifically, consumers are invited to strategically plan the temporal displacement of their programmable loads to synchronize their energy patterns with peak solar irradiance periods. This kind of demand-side management is a variation of the so-called "implicit DSM". Unlike the traditional price-driven approach, in this case, it is motivated by the users' awareness and understanding of the benefits associated with energy consumption during periods of solar production.

For the considered scenario, the most suitable appliances whose activation can be deferred in time with no significant discomfort to the domestic user are represented by the dishwasher and the washing machine. Looking at the data reported in Figure 5, there is a high activation probability for the dishwasher in the early afternoon and late evening, after the main meals. The washing machine, instead, has a peak activation probability in the first part of the morning, when laundry is likely to take place to facilitate the drying process during the warmest hours of the day. To simulate the behavior of a generic aware user, the baseline probability of usage profiles for the flexible loads was edited so that overnight probability goes to zero, by imposing the execution time within the photovoltaic production time window. The activation probability and the cumulative probability used in the DSE cases are plotted in Figure 7.

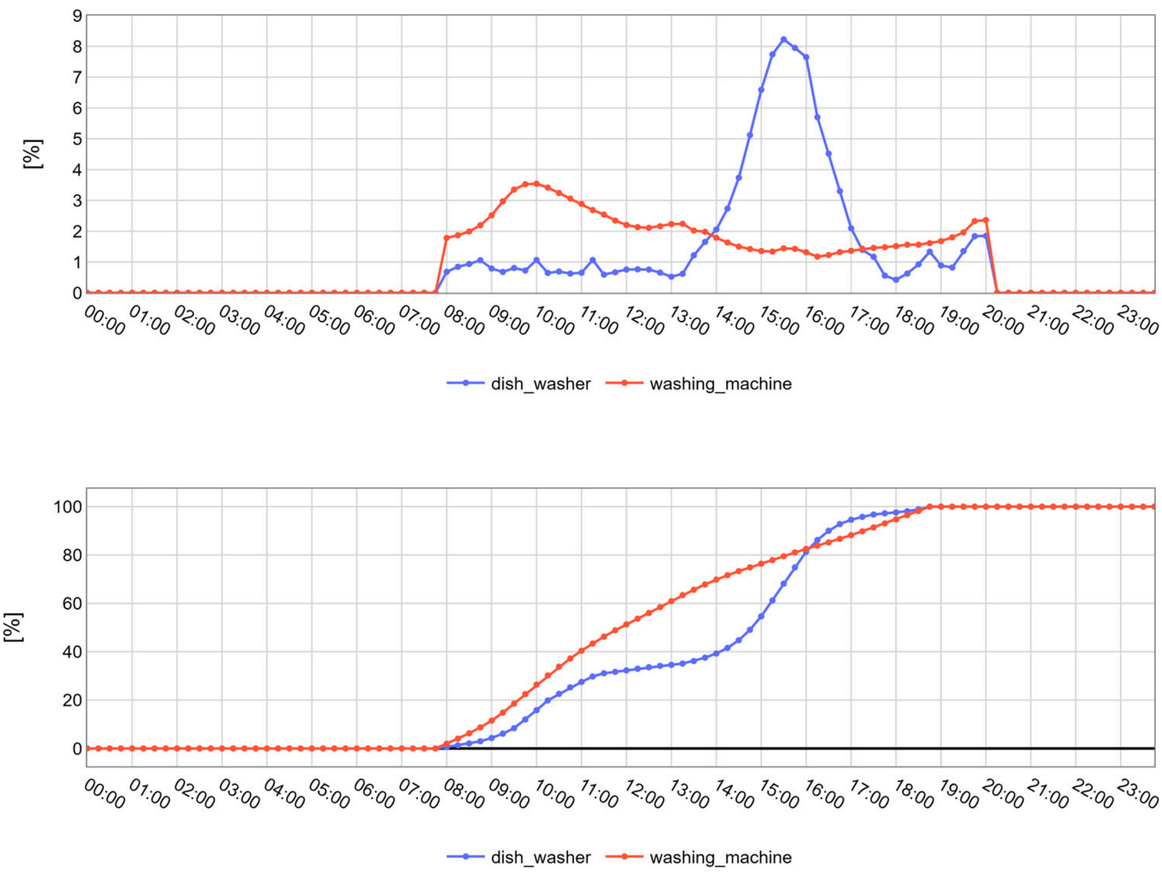

Figure 7. The modified activation probability (**top**) and the cumulative probability (**bottom**) for the flexible loads (washing machine and dishwasher). These probabilities are used only in the DSE cases.

The activation of flexible loads is assumed to be between 7:45 a.m. and 8:15 p.m., and its probability is extracted from the truncation of the ones reported in Figure 5 and opportunely normalized to obtain the activation certainty for the considered days. Once the activation time of the flexible appliance has been identified, the methodology shown in Figure 6 is used to recreate the aggregate load profile of the user.

The efficacy of this methodological framework demonstrates significant dependence on the engagement facilitator's capacity to catalyze and sustain community participation. The empirical investigation implements a tripartite engagement model, analyzing:

- 33% participation rate (minimal engagement scenario).
- 66% participation rate (moderate engagement scenario).
- 100% participation rate (maximum engagement scenario).

4.3. Optimal Demand-Side Management

Opt-DSM constitutes a sophisticated technological paradigm that encompasses an integrated multi-tier architecture incorporating:

- Centralized appliance control architecture.
- Advanced energy management system integration.
- Mathematical optimization algorithms for energy sharing maximization.

Thanks to this approach, the activation of the load is not random, but it relies on the presence of a physical communication channel between a centralized energy system and the controlled appliances of the single users (dishwashers and washing machines). The adopted optimization algorithm is discussed in Section Energy Management System Algorithm for Opt DSM. Once the optimized activation time for the flexible appliance has been identified, the methodology summarized in Figure 8 is applied again in order to recreate the aggregate load profile of the user.

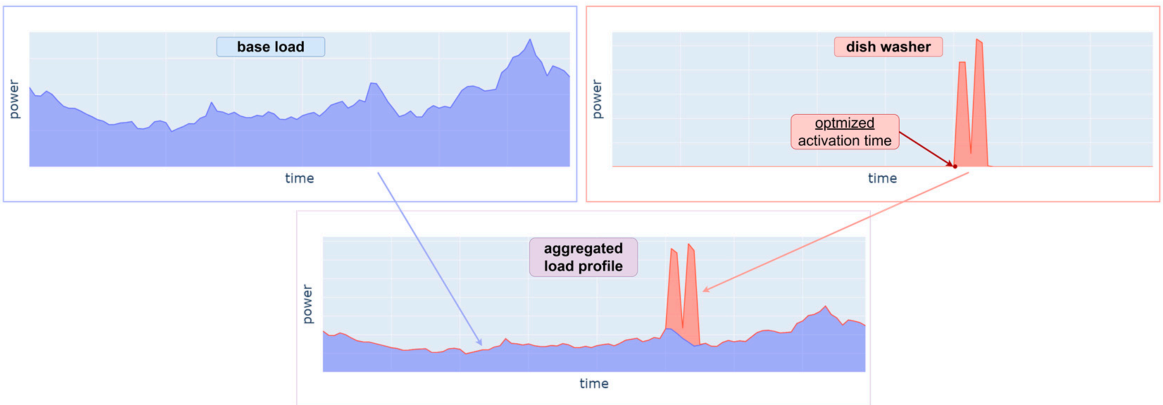

Figure 8. Summary diagram of the methodology used in the Opt-DSM case (process repeated for each appliance and each day of the simulated time frame).

The implementation analysis maintains methodological consistency with the DSE framework through stratified participation tiers (33%, 66%, 100%), facilitating a robust comparative assessment of intervention efficacy. While the scope of this investigation deliberately excludes comprehensive cost-benefit analyses of system implementation parameters, the empirical results provide substantive insights into the potential economic advantages, thereby enabling evidence-based decision-making regarding technological infrastructure investments and resource allocation.

Energy Management System Algorithm for Opt-DSM

The optimal demand-side management methodology used in this paper relies on a genetic algorithm (GA) that is designed to increase incentive revenues by shifting the load to periods with lower energy prices while also maximizing the local use of generated energy, like from photovoltaic sources. The synchronization of energy production and energy consumption generates an increase in the shared energy in the configuration.

The GA operates with an initial population of potential appliance schedules, each representing a different configuration of appliance operation times. Over successive generations, this population is refined by evaluating the fitness of each schedule based on the available feed-in profile and incentives for shared energy. The algorithm proceeds through selection, crossover, and mutation steps to combine and modify schedules, favoring those with major revenues. Key features include the following:

- Fitness Evaluation: The fitness of each solution is determined by calculating the total incentive revenues, considering both energy consumption and incentives for shared energy generation.
- Crossover and Mutation: Solutions undergo crossover and mutation, introducing diversity and allowing the exploration of a wider range of potential schedules.
- Constraints: Appliance operation schedules are constrained by allowed intervals and the maximum power contract, ensuring that solutions remain feasible.

This approach enables the optimal scheduling of energy-intensive devices, increasing overall incentive revenues while maintaining flexibility in appliance operation and responsiveness to variable energy prices and generation. The focus of the DSM strategy is to optimize load shifting of energy consumption for various appliances while increasing incentive revenues. The optimization methodology leverages a genetic algorithm (GA), which is well-suited to handling the complex, multidimensional search space characteristic of DSM problems with multiple appliances and time intervals. The adoption of a genetic algorithm in this study is motivated by its ability to achieve solutions comparable to those obtained through Mixed-Integer Linear Programming (MILP) models while significantly reducing computational costs and execution times. As highlighted in the literature [34], a comparison between an MILP model and a GA demonstrated that while the MILP solver could deliver near-optimal solutions within 15 min, the GA achieved solutions of similar quality in just 1 min. This finding aligns with the results of a broader comparative study [35], which further emphasizes the efficiency and scalability of GA compared to the MILP approach with reduced computational overhead. Considering the computational effort and memory usage required, the GA emerges as a more suitable option for practical implementation, especially in real-world applications where scalability is required to manage a large number of devices.

The adopted approach aims to minimize the energy costs for consumers while maximizing the use of on-site energy generation and taking advantage of time-based incentives from shared energy. Each day is divided into 96 time intervals, t, each representing a 15-min segment (for the maximization of the incentive revenues, defined as in the Italian regulation, it is sufficient to optimize at the hourly level; however, the time interval set in the optimization does not negatively affect the final results). This granularity allows for precise scheduling of appliance operations and a better alignment with dynamic energy pricing and on-site energy availability. The GA operates as follows:

➢ **Initialization of the Population:**

The first step consists of generating a population of potential solutions, each representing a list of load schedules for all appliances. Each solution assigns a time interval for the operation of each appliance while respecting specific consumption profiles and permitted operating intervals. This initialization process promotes diversity across solutions, enhancing the genetic algorithm's ability to explore a broad solution space. For each device i with a consumption profile C_i (a vector representing power consumption in quarter-hour intervals), the GA generates a schedule $A_i(t)$, where t denotes the time interval throughout the day. The schedules are created by inserting the consumption C_i into a zero-filled vector $A_i(t)$ with a randomly selected starting time t_0, where $t_0 \in \{1, \cdots 96\}$, for the consumption profile C_i. For example:

$$A_1 = [\, 0, \cdots, 0, \;\; C_1(0),\, C_1(1),\, \cdots,\, C_1(n),\, 0, \cdots, 0] \tag{1}$$

where A_1 is a vector of length 96 that corresponds to the schedule of the first device, and n is the last index of the profile's consumption vector. It is worth noting that activation constraints (such as arbitrary starting/finishing time intervals) can be easily implemented during the definition of this initial scheduling by acting on the ranges of the randomly selected starting time.

Finally, each solution S is represented as $A_1, \ldots, A_I$, where I is the total number of appliances being scheduled.

➢ **Fitness Function (Cost Calculation):**

The cost function evaluates the total cost of each solution based on energy consumption and incentives for shared energy use. This function accounts for both energy costs and the incentive for using locally generated energy (if available). The energy tariff for the REC's user is flat and does not present an hourly variation during the day. Thus, the energy costs ($E_{total}(t) \cdot cost(t)$) in the cost function do not affect the final result in this case.

The cost calculation for a solution S across T intervals is given by

$$cost(S) = \sum_{t=1}^{T} \Big(E_{total}(t) \cdot cost(t) - \min\Big(E_{total}(t),\, E_{feed}(t)\Big) \cdot inc \Big) \tag{2}$$

where

- $E_{total}(t) = \sum_i A_i(t)$ is the total energy consumption at interval t;
- $cost(t)$ is the energy cost per kWh at interval t;
- $E_{feed}(t)$ is the feed-in energy at interval t (production excess with respect to non-controllable loads. The flexible loads are not considered because these are scheduled only after the optimization);
- inc is the incentive remuneration for the shared energy.

➢ **Selection:**

The top-performing half of the population, based on fitness (cost), is selected for reproduction. This selection process retains the most promising solutions while discarding the least effective ones, ensuring that the algorithm encourages solutions with lower costs (and, thus, higher incentive revenues).

➢ **Crossover and Mutation:**

Crossover combines two parent solutions, $S_{parent1}$ and $S_{parent2}$, selected from the best solutions, to create a new child, S_{child}, solution by swapping segments of each parent. Crossover for solution S can be defined as

$$S_{child} = \begin{cases} A_i \in S_{parent1} & \text{if } i \leq k \\ A_i \in S_{parent2} & \text{if } i > k \end{cases} \tag{3}$$

where i identifies the device, and k is a randomly chosen crossover point within 1 and I (total number of devices). In simple terms, the child solution combines elements by taking k device schedules from the first parent and the remaining $I - k$ device schedules from the second parent. In addition, a mutation process introduces variability by slightly modifying some child device schedules inside the solution, selecting a new start time for certain device operations. Mutation is applied with a certain probability to change the start time of $A_i(t)$ for some appliances, promoting solution diversity, and helping the algorithm avoid local optima.

➢ **Elitism and Diversity Introduction:**

To prevent degradation in solution quality, the best solution from each generation is retained within the population (elitism). Additionally, new random solutions are periodically introduced, encouraging the algorithm to explore new areas of the solution space and to avoid local minima.

➢ **Convergence and Best Solution:**

The algorithm iterates through a specified number of generations (e.g., 100 generations) or until a convergence criterion is met (e.g., minimal improvement over successive generations). The final solution provides an optimal schedule with maximized incentive revenues while satisfying device constraints and maximizing the use of on-site energy.

This methodology ensures that the GA balances cost reduction, incentive revenue increase, local energy utilization, and adherence to device constraints for effective DSM.

Figures 9 and 10 illustrate a demonstration case with 20 appliances (dev_0–19) and a photovoltaic system with an installed capacity of 3 kWp. In particular, Figure 9 shows the injected energy (in green) and all the appliance load profiles before demand-side management. In this situation, the total shared energy is equal to 7.44 kWh. Meanwhile, Figure 10 shows the changes in appliance allocation after demand-side management. In this case, the loads are compressed during the injection period, and the main effect is an increase in total shared energy to 16.04 kWh. In this example, it is possible to observe that the algorithm changes the scheduling of different devices to move the loads inside the productivity interval and maximize the usage of the energy produced by the photovoltaic system.

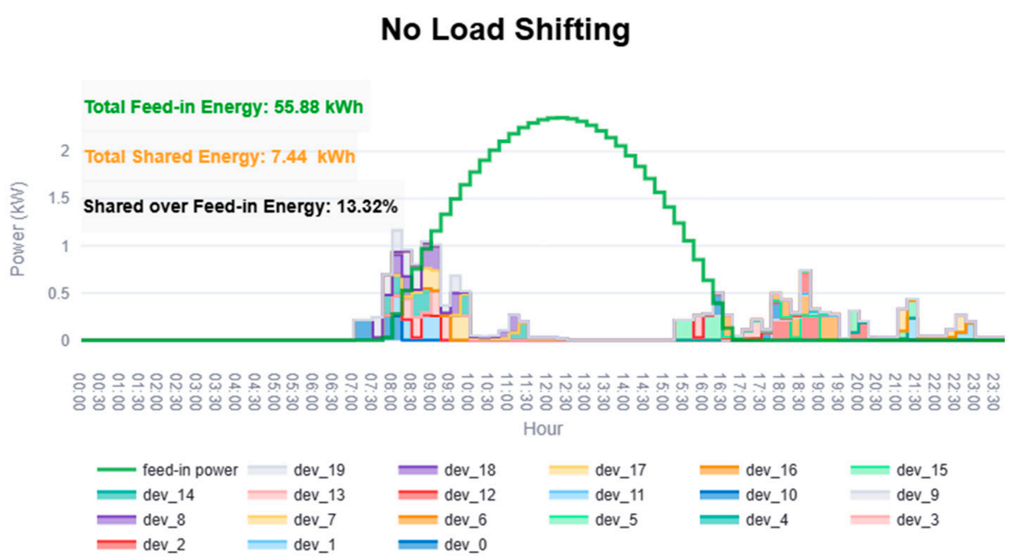

Figure 9. In this figure, the injected energy and the consumption of the household appliances in a typical day before demand-side management of flexible loads are shown.

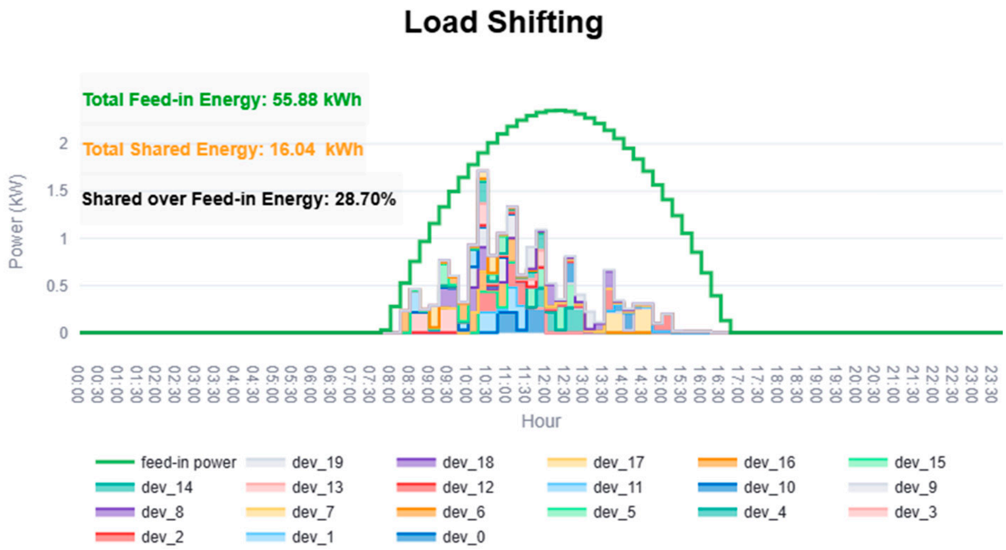

Figure 10. In this figure, the injected energy and the consumption of the household appliances on a typical day after demand-side management of flexible loads are plotted.

As described in Section 5, the case study considers that load shifting is applied to a significant number of appliances (specifically, 92) for each day of the year. The precision of the genetic algorithm, tailored for such a setup, was evaluated across multiple sharing levels. The daily sharing percentage was assessed as the ratio of the energy consumed by all involved appliances over the sum of energy injected into the network.

$$\text{sharing percentage} = \frac{\sum_{t=1}^{T} E_{total}(t)}{\sum_{t=1}^{T} E_{feed}(t)} \times 100\% \tag{4}$$

In order to validate the performance of the adopted algorithm, 100 distinct optimizations were conducted from identical starting conditions for different amounts of injected energy. The performance of the optimization algorithm is calculated by comparing the shared energy with respect to the total energy of controllable loads:

Figure 11 reports, for each sharing level, the achieved optimal percentage of the total consumption (of programmable loads) supplied by the shared energy (photovoltaic production):

$$\text{optimal percentage} = \frac{\sum_{t=1}^{T} \left[\min\left(E_{total}(t), E_{feed}(t)\right)\right]}{\sum_{t=1}^{T} E_{total}(t)} \times 100\% \tag{5}$$

It can be observed that, for sharing percentages less than or equal to 100%, the proposed performance indicator achieves a value of 100% when the controllable loads are fully supplied by REC energy production. Conversely, lower values signify scenarios in which a portion of the REC load is not met by REC production, necessitating energy imports. The results reported in Figure 11 clearly demonstrate that the proposed genetic algorithm maintains near-perfect performance, approximately 100%, for sharing levels below 80%. On the other hand, for levels exceeding 80% (when the energy of loads begins to match the photovoltaic production), a dispersion of optimal outcomes is observed. Different interpretations can be provided for this behaviour:

- The power profile of the simulated controllable appliances is fixed, and even their absolute best scheduling does not perfectly match the curve of the shared energy.
- The considered optimization algorithm does not guarantee the achievement of the absolute optimal scheduling, and it can converge to local stationary points.

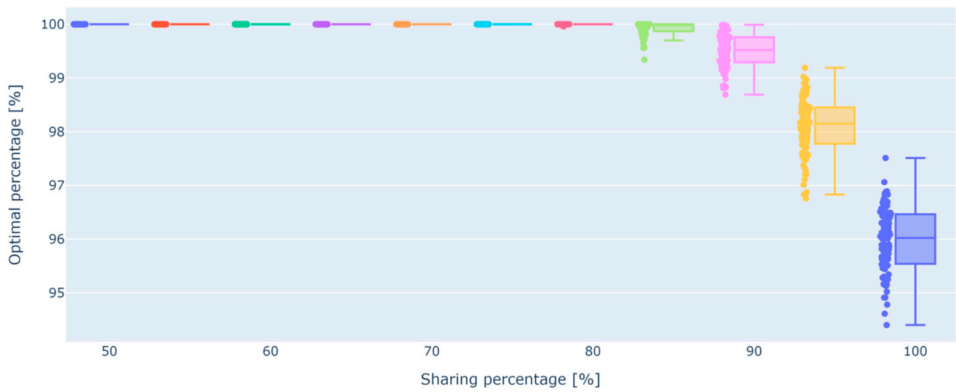

Figure 11. Performance of the proposed optimization algorithm for different values of sharing energy (ratio of REC consumed energy over REC produced energy).

Nevertheless, this test demonstrates that the presumed suboptimality is limited to a few percentage points only when the total energy of controllable appliances matches the shared photovoltaic production. Furthermore, the actual GA performance has been assessed for each day of the simulation time frame (see Section 6) and reported in Figure 12: the optimal percentage is always over 94%, while the ideal optimal solution is achieved with an accuracy of more than 99% for 340 days/year.

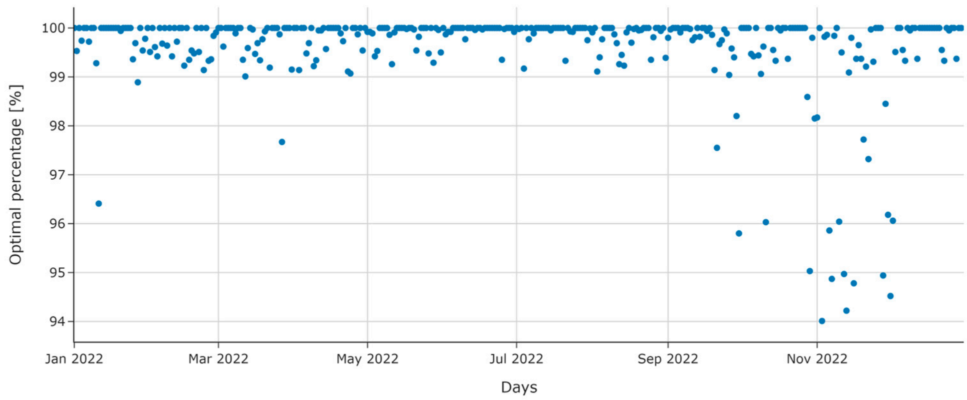

Figure 12. Actual performance of the optimization algorithm featured on the simulated days of the year.

5. The Case Study—"La Buona Fonte" Renewable Energy Community, Riccomassimo-Storo (TN)

5.1. Description of the Existing Energy Community

To carry out the analysis, the real REC "La Buona Fonte", located in Riccomassimo, was chosen as a reference to build the case of study. This selection was motivated not only by the availability of data but also by the distinct nature of this initiative. This community is supplied by a distribution network owned and operated by the historic electric consortium, CEDIS, which has served as the promoter, financier, and manager of the REC.

The project began to take form in 2020 in response to an RSE call for case studies. During a focus group organized by RSE in September 2024, involving community promoters and participants, the proponents described it as a continuation of the consortium's cooperative ethos, established in 1904. In September 2024, the consortium comprises 3321 members across Storo and neighboring municipalities. Recognized as a historic electric consortium, it engages in the production, transportation, and distribution of electricity, primarily generated from hydroelectric plants.

The REC project benefited from intensive promotion and engagement within a small, cohesive community. Riccomassimo, located 755 m above sea level and approximately 8 km from Storo, has a stable population of 44 inhabitants and approximately 50 buildings. Of these, 24 Points of Delivery (PODs) joined the REC configuration. The REC officially received recognition from GSE on 21 June 2022, based on the transitional transposition of RED II implemented through Law 28/02/2020 n.8 [36,37]. This recognition positions it as one of the oldest Italian active configurations and the first one of its regions.

The REC was established as a non-profit association with the scope of directing the incentives generated, after accounting for the dedicated withdrawal of non-self-consumed energy, towards investment recovery for the plant, as well as aesthetic improvement, redevelopment, and potential services for the area (Table 2).

Table 2. Summary Sheet: "La Buona Fonte" Renewable Energy Community.

Region	Trentino Alto-Adige
Province	Autonomous Province of Trento
Municipality	Riccomassimo (Storo)
Promoters	Storo Electric Consortium (CEDIS), RSE, Municipality
Legal form	Social Promotion Association (APS)
Technical partner	Elettro M2 di Ledro, CEDIS
Technology	18 kWp PV systems, Storage/Battery 15 kWh(there are two other plants in the grid that do not participate in the REC)
Objectives	Counteract depopulation of the village; promote social, cultural, environmental, energy, and territorial development
Participants	24 consumer participants
Organizational model	Community Energy Builder (CEB)

This technological and social experiment, conducted over two years, has demonstrated significant potential in terms of the social impact of RECs in micro-communities, despite challenges faced during the formal structuring phase, including notable delays in receiving incentive payments.

Active participation in community life is remarkably high, showing an interesting dimension of enhanced cooperative models in village management, which are the focus of the incentive shares produced by the configuration. Interactions with the REC board and participants have revealed a strong awareness of the challenges encountered, as well as the added value derived from the national visibility of the initiative.

5.2. Description of the Modified Energy Community Used for Simulations

Starting from the real case, a new setup for a REC was assumed to better investigate the impacts on the electricity network of distributed generation combined with DSM practices. The existing REC was therefore used as a reference, and in the simulations, the number of users involved in the configuration was increased, together with a reconfiguration of the generation assets distributed along the network.

The Riccomassimo distribution network is a typical LV rural network characterized by branched topology, 58 Points of Delivery (PODs) consisting of low-consuming households, and three domestic roof-mounted PV power plants. The main characteristics of the network are summarized in Table 3. The interface with the MV grid is represented by a 630 kVA transformer.

Figure 13 shows the network structure. The structure is typical of a rural network with few branch lines.

In the real network, there are only three power plants, respectively with a capacity of 6 kWp, 4.99 kWp, and 18 kWp; while the first two are prosumers, the third is a pure producer. To perform the DSM studies on a larger and more "energy-intensive" REC, 10 random Riccomassimo consumers were assumed to turn into prosumers by installing a new 6 kWp PV system each. So, in the new reference case, the members of the configuration are categorized as shown in Table 4.

Table 3. Total number of the grid components in the modified configuration.

Grid Components	Number
Buses	56
PODs	58
Power plants	13 (with 1 not supplying a behind-the-meter load)
Switches	2
Lines	54
Transformers	1

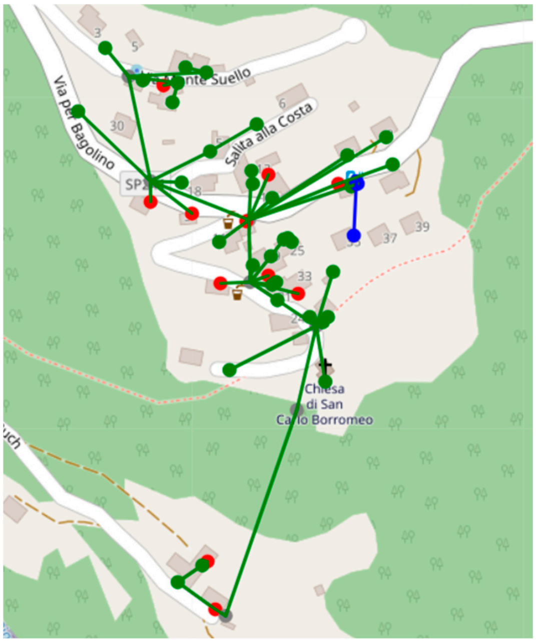

Figure 13. Riccomassimo distribution network on OpenStreetMap. The green circles and lines indicate, respectively, the LV consumers' buses and lines; the red circles are the prosumers' and producers' buses, while the blue circles and lines indicate the transformer.

Table 4. The main characteristics of the members of the REC configuration.

User Type	User Category	Load Profile	Number	PV Capacity [kWp]
Consumer	Households	Emulated	46	-
Prosumer	Households	Emulated	11	6
Prosumer	Households	Emulated	1	4.99
Producer	-	-	1	18

To conclude, the simulations are carried out with 13 power plants for a total REC capacity of 89 kWp. To better generalize the DSM results, no battery systems were considered, and even the 15 kWh existing in the real case were ignored and removed from the model. Another strong assumption is that all the users in the network are members of the energy community, so that the simulations can assess different penetrations of DSM actions.

5.3. Description of the Adopted Economic Scheme and Parameters

To evaluate the economic and energy impacts on the community, a simulation was carried out evaluating the energy flows for each user of the configuration (as the withdrawn, injected, and, if prosumer, the self-consumed energy) and the aggregated REC energy flows.

Then, the economic outcomes were obtained (such as incentives, electricity sales, and bills) for each user, producer, and the entire energy community. The simulation of the financial benefits requires a range of different hypotheses, some of which are summarized in Table 5. As an assumption, the REC is established in the form of a non-profit association, with relatively low starting and operational costs. The REC bears administration costs and generates incentives for the community, and a repartition scheme is needed to redistribute the economic flows and benefits. For this case study, the incentives are set to be equally split between all the members (per capita, regardless of whether they are consumers, prosumers, or producers). The capital and operational costs of the generators are paid by their owners, who then benefit from the entire electricity sales to the grid and their share of incentives (as per the repartition scheme mentioned above). The REC founding costs are paid by all the members, while the administration costs are paid with the incoming incentives, before redistribution.

Table 5. List of the income statement items and summary of the adopted repartition strategy among the REC members.

Income Statement Items	Items Ownership	Repartition Strategy
Incentive revenues from non-flexible loads	All REC members	Equally divided
Incentives revenues from flexible loads (DSE cases)	All REC members	Equally divided among all users
Incentive revenues from optimizable loads (Opt-DSM cases)	Opt-DSM users	Equally divided among Opt-DSM users
Energy sales revenues	PV plants owner (prosumer or producer)	-
Capital costs of the PV plants	PV plants owner (prosumer or producer)	-
Operational costs of the PV plants	PV plants owner (prosumer or producer)	-
Foundation costs of the REC	All REC members	Equally divided
Administration costs of the REC	All REC members	Equally divided

The repartition methodology of the incentives' revenues varies in the optimized cases (Opt-DSM cases). The additional revenues generated through the optimal demand-side management are not divided equally among all the members of the energy community, but they are divided only among the DSM consumers. In this case, this repartition is possible thanks to the energy management system keeping track of the controlled appliances. Therefore, the proposed strategy attributes the additional incentive revenues only to the users that participate in the optimal demand-side management. Obviously, there are other possible repartition methodologies that reward mostly the DSM users, but it is not in the purpose of this study to explore the different benefits obtainable by varying the repartition methodology or to find the optimal repartition methodology. However, the authors believe that it is necessary to change the repartition methodology in the Opt-DSM cases in a way to reward the DSM users and reduce the negative impact of the additional costs due to the DSM systems' software and hardware.

From an energy and financial perspective, the simulation required several inputs, such as the following:

- Number of users and their load profiles.
- Power plants: capacity, number, ownership, capital, and operational costs.
- The capital cost of the energy community (foundation cost of the legal entity, administration costs, IoT device costs, etc.).
- The operational costs per year of the energy community (administration costs, management costs, platform costs, etc.).
- The tax scheme applied in the national regulation for the energy community.

- Energy tariff information (it was supposed to use the typical energy tariff applied by the local supplier [38]).
- Hourly energy price for the market zone.

Not all of these parameters are used in this study (such as the discount rate, the inflation rate, annual energy price variation, etc.). Since some of these input parameters are used in the long-term simulations (with a project lifetime equal to 20–25 years), for the purposes of this study, the financial results analyzed refer to the first year of the simulation.

6. Methodology Applied to the Case Study—Outcomes

As anticipated in Section 4, different quantities are extracted from the simulation results to be analyzed. In particular, the variations in the energy flows in different cases were analyzed to assess the impact of the DSM on the grid, while the financial results determined the economic effects of DSM in different cases to verify the presence of economic drivers for the users. In the context of the simulated scenarios, a time frame of one year, with a temporal resolution of 15 min, is adopted for all the simulated cases. Based on the description of consumer behavior provided in Section 4, the load profiles for the 46 users are generated randomly on a daily basis using the specified probability distributions. Consequently, the simulation window encompasses a wide range of consumption scenarios and a diverse set of environmental conditions, which influence photovoltaic production. This approach ensures a statistically meaningful benchmark for evaluating the proposed simulation cases.

6.1. Energy Flows

As described in the methodology, the Opt-DSM algorithm successfully makes use of the remaining sharing potential to activate the shiftable loads. Figure 14 below reports an example of the activation scheduling for a random day. In the example, the area under the sharing potential is filled by the algorithm, but still leaves room for more shared energy to be allocated (which indicates the potential to enroll further consumers within the community).

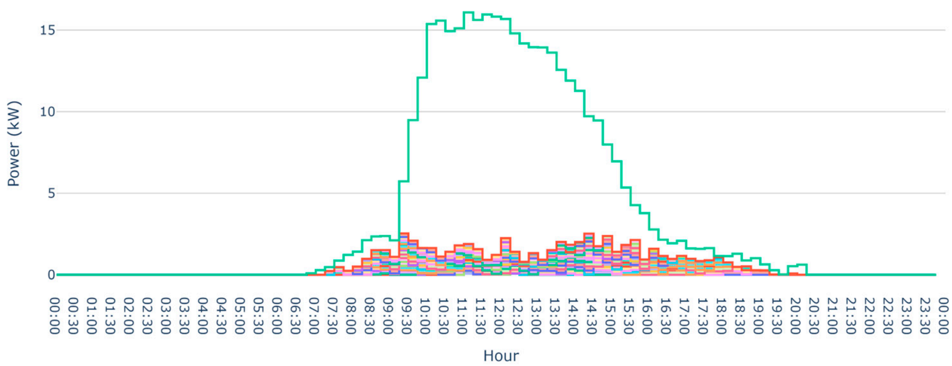

Figure 14. Example of load shifting operated by the DSM optimization algorithm on a simulated day. The upper blue line indicates the total injected energy that is theoretically available for sharing, and the blocks represent the single appliances activated by the algorithm.

As expected, the results show an increase in shared energy in the DSE and Opt-DSM cases, albeit by a small percentage. Specifically, in Figure 15, the breakdown of self-consumed, shared, and non-shared energy is shown over the production. As mentioned in the methodology, each case—DSE and Opt-DSM—is simulated with three different percentages of REC users adopting the DSM practices (33%, 66%, and 100%).

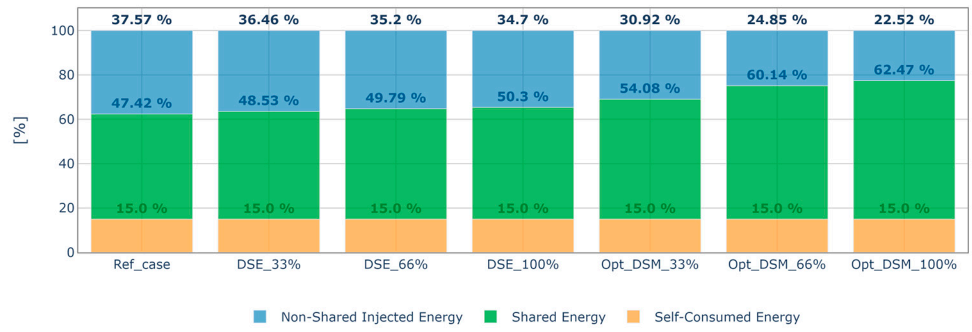

Figure 15. Allocation of the aggregated produced energy for the REC configuration. The percentage of self-consumed energy, the percentage of shared energy, and the percentage of the non-shared injected energy are highlighted with respect to the total produced energy.

Clearly, as the DSM logic is applied only to consumers, the prosumers have the same consumption patterns across all cases; thus, self-consumption remains fixed in absolute and percentage terms, and slightly changes in overall percentage as shared and non-shared energy components vary.

As expected, the DSM generates an increase in shared energy and a consequent decrease in non-shared energy. The greatest increase in shared energy occurs in the case of an optimal DSM with 100% of the consumers carrying out a demand-side management of their loads. The optimal DSM produces a more relevant increase in shared energy consumption compared to the DSE, as the latter operates without a coordinated and optimized strategy and often moves loads when available PV production is already saturated. A non-optimal DSM strategy does not guarantee an increase in shared energy by increasing the number of DSM users. This happens when the load profiles of the users are emulated by using activation probabilities that concentrate flexible loads in central time intervals of the day, regardless of the instantaneous availability of local production. It is worth noting that the DSE strategy leads to a shared energy increase of about 1.1–2.9%, while the adoption of the Opt-DSM strategy resulted in about 6.7–15.0% sharing. This demonstrates that optimizing load scheduling, even for very few units, based on the supervision of the predicted availability of local production, is significantly more beneficial than the highest levels of DSE involvement.

Furthermore, Figure 16 reports self-consumption, shared energy, and non-shared energy over the consumption. In particular, the red area indicates the share of energy withdrawn from the grid without being shared, which remains predominant in all cases, indicating a low independency level from the external grid.

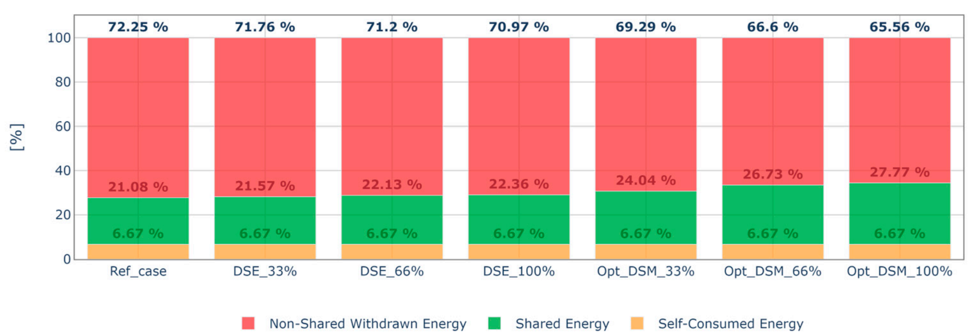

Figure 16. Allocation of the aggregated consumed energy for the REC configuration. The percentage of self-consumed energy, the percentage of the shared energy, and the percentage of the non-shared withdrawn energy are highlighted with respect to the total consumed energy.

6.2. Load Flows Results

6.2.1. Power Exchange with the MV Network

The slack point is a key node that shall be considered when investigating the impacts on the grid, as its daily net exchange profile provides insights into the balance and matching between production and generation in the LV grid (therefore, it represents the power exchange with the upstream MV network). Typically, PV generation creates the so-called "canyon and duck" curves on the MV–LV and M–HV interfaces, as PV systems supply the nearby loads, reducing the net demand during the day, creating the typical deep valley in the daily exchange profile and a steep ramp-up at sunset. In some sections of the grid, PV generation is so predominant that it generates a reverse power flow, which is an injection of power from the lower to the higher voltage level.

Figures 17–19 report the net slack demand for the two solstices (21 June and 21 December) and an equinox (22 September) to explore the phenomenon under different irradiance levels. Compared with the reference case, the canyon depth is reduced around noon time in the Opt-DSM cases and around 4 p.m. in the DSE cases. These different effects are due to the strategy used in the DSE simulations. Specifically, the probability of appliance usage (shown in Figure 7) tends to aggregate the activation of the dishwashers around 4 p.m. and the activation of the washing machine around 9 a.m. or 7 p.m. The nighttime demand, on the contrary, is reduced in all cases, as some reference cases' evening loads are shifted to daytime. In general, in the Opt-DSM cases, load shifting has a "flattening" effect on the daily profile, bringing the net exchange closer to zero. Figures 17–19 show that in the 9 a.m.–1 p.m., 3 p.m.–5 p.m., and 9 p.m.–1 a.m. time intervals, in fact, the red curves are closer to 0 than the reference case in blue. However, this does not happen in the DSE cases, as the simultaneous activation of flexible loads around 4 p.m. generates an increase in demand supplied by the upstream MV network. From the grid's point of view, the load is shifted to a time step in which a reverse flow towards the LV–MV transformer takes place, and the local PV generation is no longer sufficient to cover the grid load, resulting a power demand from the upstream network (slack node). In terms of grid losses on the MV system, we still have a relatively good effect, as load is shifted from on-peak demand to mild demand time steps, thus reducing the circulating current and its quadratically proportional losses.

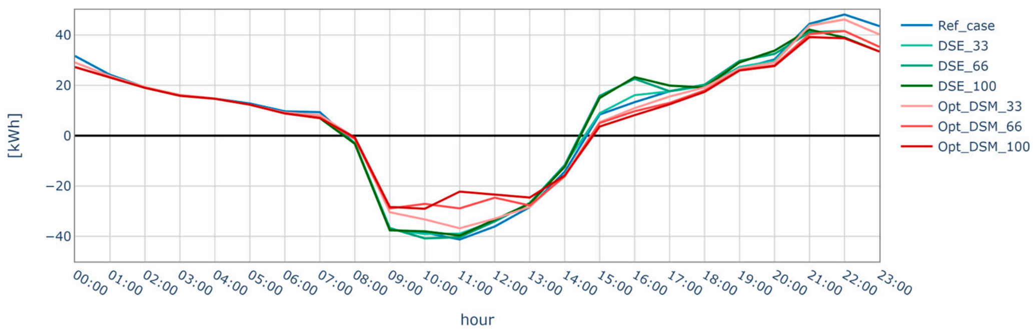

Figure 17. Hourly net energy exchange of the upstream network (slack node) on 21st June for different cases.

Other DSM practices and storage systems would, however, emphasize the good flattening effect.

As for the optimal operation of the distribution network, the ideal case consists of reducing the energy exchange in order to reduce the circulating energy flows (withdrawn of injected) with the upstream network (which passes through the slack node). This "flattening" effect allows for an increase the local consumption of the distributed generation and reduces energy losses in the cables and transformer. This flattening effect is more evident in the Opt-DSM cases, which represent a better solution.

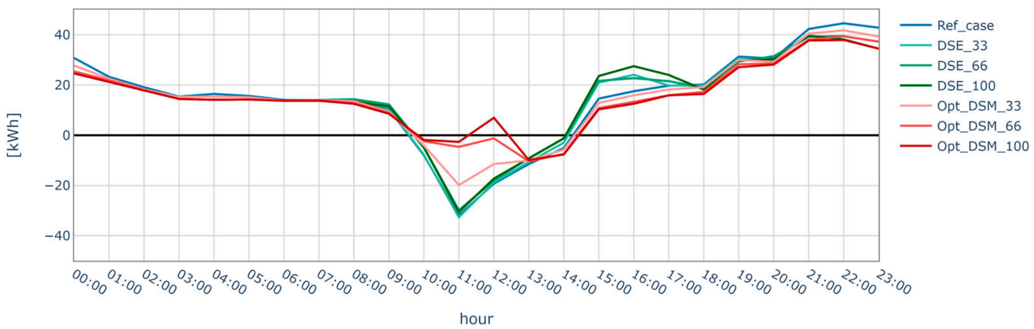

Figure 18. Hourly net energy exchange of the upstream network (slack node) on 22nd September for different cases.

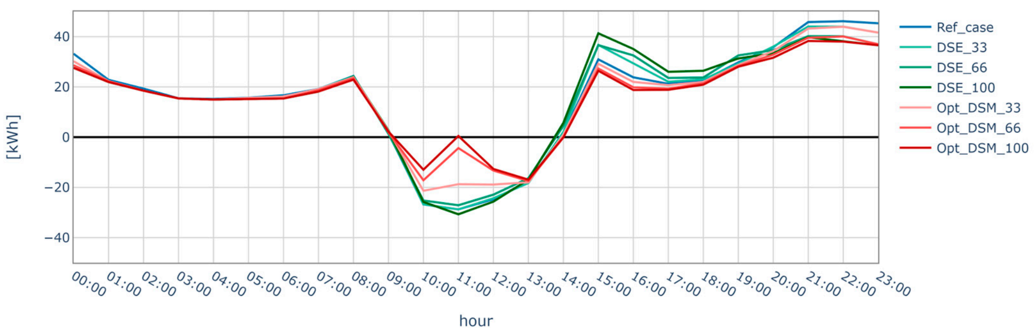

Figure 19. Hourly net energy exchange of the upstream network (slack node) on 21st December for different cases.

Figure 20 shows the difference between the energy withdrawn from the upstream grid for different cases with respect to the reference case. A red zone indicates an increase in the energy withdrawn, and a blue zone indicates a reduction in the energy withdrawn. It is observed that, in all the DSE cases, there is an increase in the imported energy in the afternoon (3 p.m. to 5 p.m.) and a reduction during the night (9 p.m. to 12 a.m.). Furthermore, there is no tangible variation between the DSE cases. Meanwhile, in the Opt-DSM cases, greater changes are observed in the distribution and in the intensity of the variations. In particular, the withdrawn energy increases in the central part of the day (8 a.m. to 2 p.m. in the summer period). Furthermore, variation time-ranges are wider during the summer (thanks to the longer daylight period), and, consequently, the magnitude of the energy variations is more contained. This can be explained by the fact that the load scheduling algorithm naturally tends to distribute the activations uniformly during the PV production availability hours, resulting in lower deviations with respect to the baseline.

The global results for the slack node over the entire year are summarized in Table 6. The table reports the total withdrawn and injected energy for the slack node in different cases and the respective variations with respect to the reference case. It is possible to observe that in all cases there is a decrease in the withdrawn and injected energy for the slack node. The main effect is an increase in the local consumption of the produced energy and a consequent decrease in the losses in the grid. Additionally, from these results it is observed that the major variations in the withdrawn and injected energy happen in the Opt-DSM cases thanks to the optimal shifting of the loads during the production period. Meanwhile, in the DSE cases, the variations are small, and the increase in the number of active DSE users does not necessarily generate a consistent reduction in the withdrawn and injected energy for the slack node.

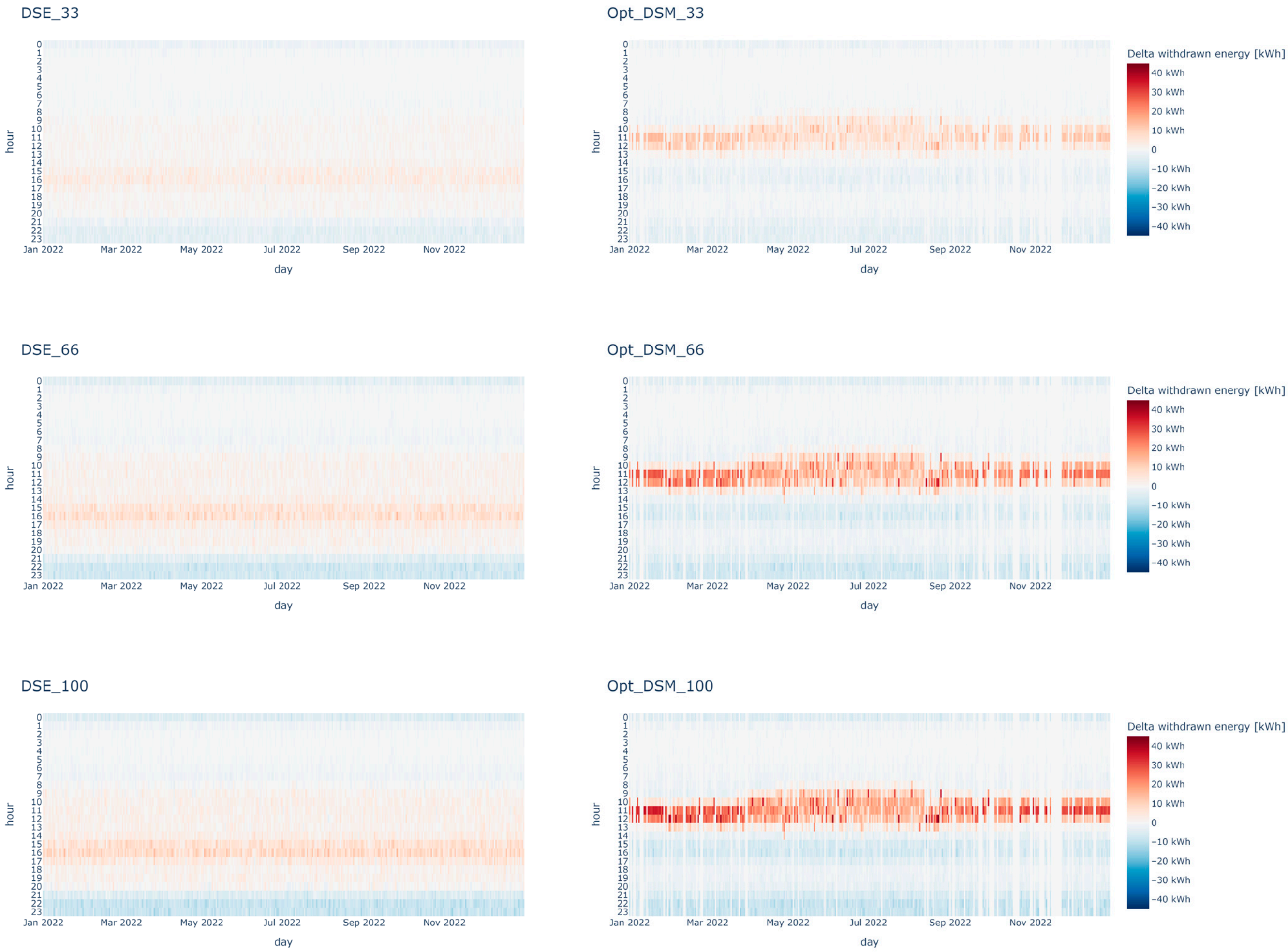

Figure 20. The heatmaps show the hourly difference in the aggregated loads for each case with respect to the reference case in the entire year. In each case, the red zones indicate the hours in which the aggregated load for the entire configuration is higher than the same indicator calculated for the reference case, while the blue zones indicate the hours in which the load is lower.

Table 6. Aggregated withdrawn and injected energy for the entire configuration and their differences with respect to the reference case on a yearly basis.

Case	Withdrawn Energy [MWh]	Delta Withdrawn Energy [MWh]	Injected Energy [MWh]	Delta Injected Energy [MWh]
Ref case	35.24	-	168.91	-
DSE 33%	34.18	−1.06	167.81	−1.10
DSE 66%	32.97	−2.27	166.55	−2.36
DSE 100%	32.48	−2.76	166.05	−2.86
Opt-DSM 33%	28.78	−6.46	162.30	−6.61
Opt-DSM 66%	22.85	−12.39	156.25	−12.66
Opt-DSM 100%	20.57	−14.67	153.94	−14.97

6.2.2. Grid Loss Results

Regarding the energy losses across the LV grid, the DSE results show that the energy losses, which depend on the circulating electrical currents, have a trend similar to that of the variations discussed above. This is shown in Figure 21, in the left column for the DSE cases and in the right column for the Opt-DSM cases. These heatmaps highlight the differences between different cases and the reference cases during the day for the whole year. It is possible to see that some of the aggregated withdrawn energy that was consumed in the late evening (from the charts, generally from 9 p.m. to midnight) gets shifted to daytime.

The DSE methodology tends to spread the energy consumption over the day with small peaks in the afternoon (3 p.m. to 5 p.m.), and this generates an increase in the grid losses. At the same time, it is observed that the DSE methodology tends to reduce consumption at night (9 p.m. to 12 a.m.), with a consequent reduction in the grid losses. The Opt-DSM algorithm concentrates the loads in the morning (10 a.m. to noon), with low redistribution in other hours of the day. It is also interesting to note that in the Opt-DSM cases, the benefits in terms of energy efficiency are constantly positive, with the exception of a few recurring high-loss spikes during the midday hours of the day. The spike phenomenon can be explained by the occurrence of rare situations where activated loads are distant with respect to the available PV sources, determining an increase in energy flows through grid conductors.

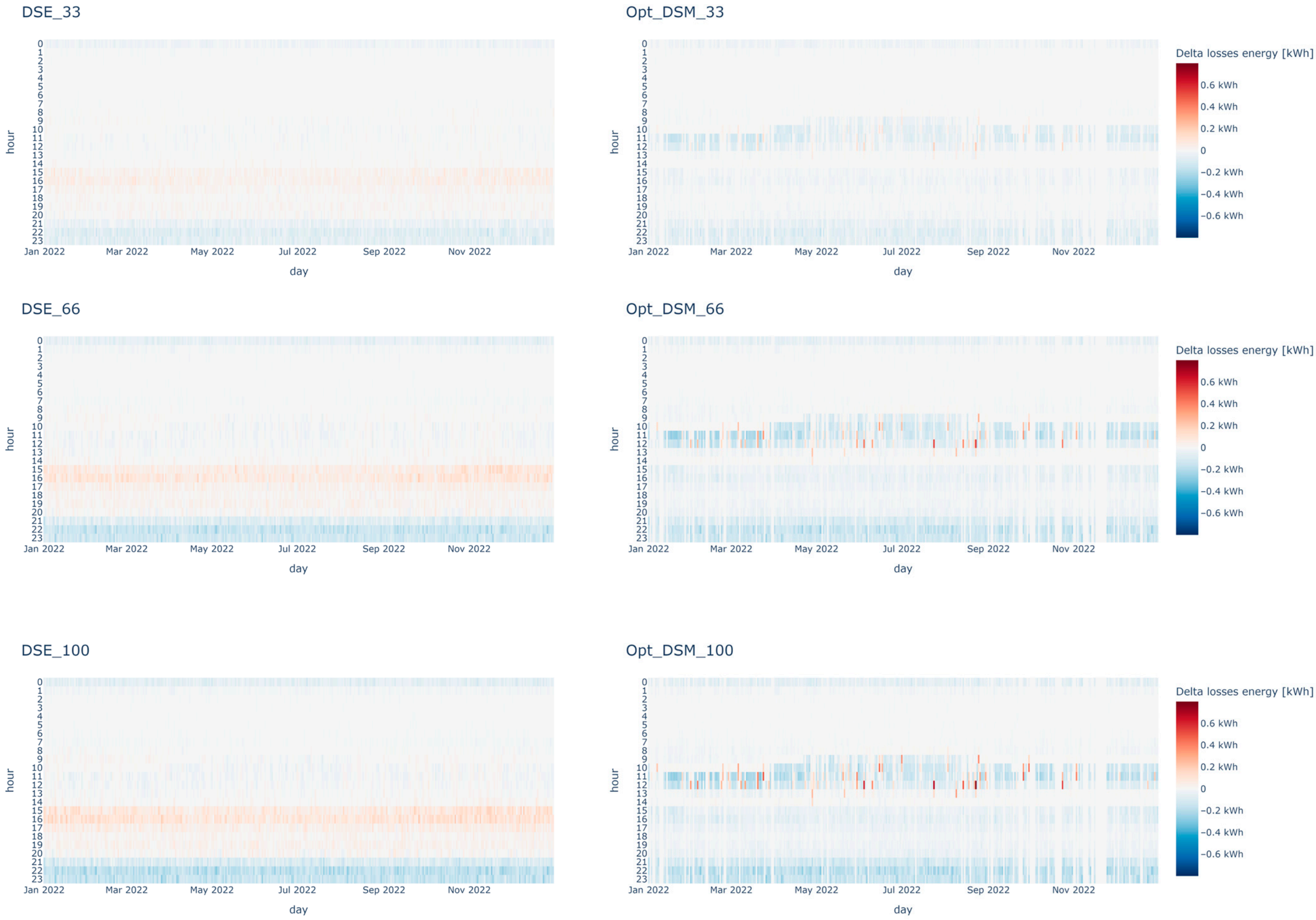

Figure 21. The heatmaps show the hourly difference in the aggregated losses for each case with respect to the reference case over the entire year. In each case, the red zones indicate the hours in which the aggregated losses for the entire grid are higher than the same indicator calculated for the reference case, while the blue zones indicate the hours in which the losses are lower.

Table 7 summarizes the total grid losses for the simulated year in the different cases and their variation concerning the reference case. It can be noted that all the strategies considered generally lead to a global reduction in energy losses, and the greatest contribution is, again, attributable to the Opt-DSM cases.

Table 7. Total losses for the entire grid and their differences with respect to the reference case on a yearly basis.

Case	Total Losses [kWh]	Delta Total Losses [kWh]
Ref case	10,190	-
DSE 33%	10,150	−50
DSE 66%	10,100	−90
DSE 100%	10,090	−100
Opt-DSM 33%	10,050	−140
Opt-DSM 66%	9930	−270
Opt-DSM 100%	9890	−300

6.3. Financial Results

In the following paragraphs, the financial results are summarized at the REC and users' levels.

6.3.1. Configuration Results

Looking at the whole REC configuration, the DSE and Opt-DSM enabled a minimum of 1.10 and a maximum of 14.87 MWh additional shared energy per year, respectively corresponding to a revenue ranging from EUR 154.23 to EUR 2090.49 (Table 8). These amounts, at least for the Opt-DSM, might be perceived as not worth the efforts in setting up the hardware and optimization mechanisms (intentionally not considered in the total costs in order to calculate the total incentive surplus needed to cover these costs). For the DSE case, on the other hand, the change in habits might come in some cases with relatively low efforts, so the economic benefits, even if low, might justify the DSE practice.

Table 8. Aggregated shared energy and total incentive for the entire configuration and their differences with respect to the reference case are summarized on a yearly level.

Case	Shared Energy [MWh]	Delta Shared Energy [MWh]	Total Incentive Revenues [EUR]	Delta Total Incentive Revenues [EUR]
Ref case	46.86	-	6587.35	-
DSE 33%	47.96	1.10	6741.58	154.23
DSE 66%	49.20	2.34	6916.44	329.08
DSE 100%	49.70	2.84	6986.81	399.55
Opt-DSM 33%	53.44	6.58	7511.93	924.57
Opt-DSM 66%	59.43	12.57	8353.86	1766.51
Opt-DSM 100%	61.73	14.87	8677.85	2090.49

6.3.2. REC User Results

Figures 22–24 highlight the revenues, the electricity expenditures, and the electricity savings in different cases for the different typologies of REC users (no-DSM users and DSM users) in the first year.

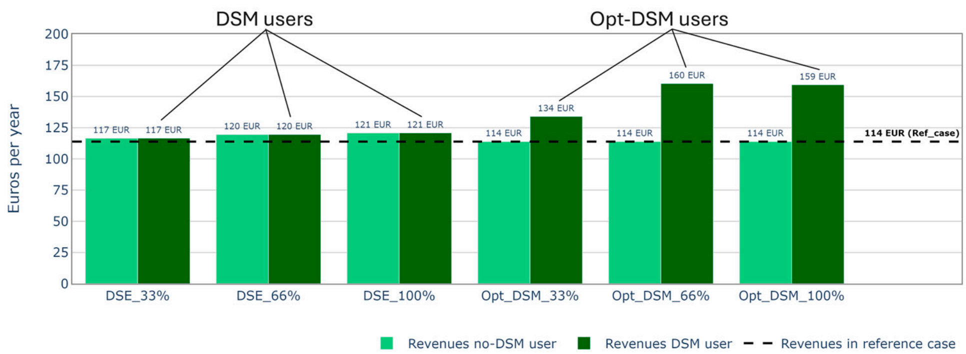

Figure 22. Total yearly revenues for a spontaneous user (light green), a DSE/Opt-DSM user (dark green), and the reference case (black dashed line). All these statement income items are evaluated for the first year of the simulation.

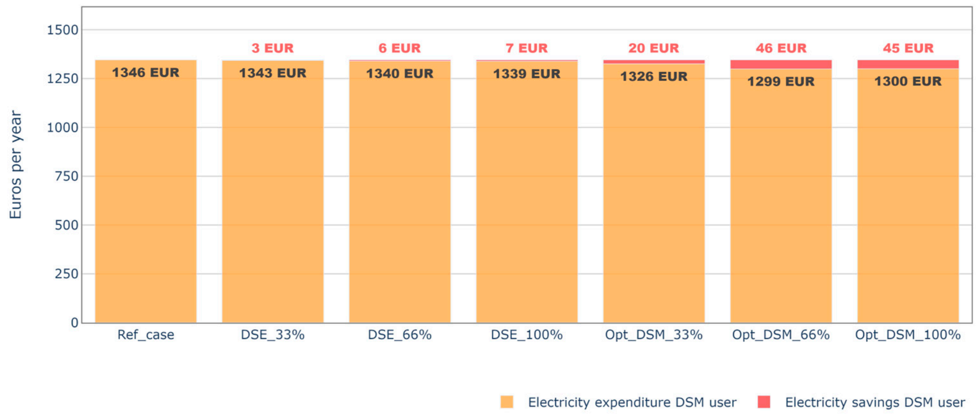

Figure 23. Total electricity expenditure and electricity savings for a user who changes their load profile with a DSE/Opt-DSM strategy in different cases. All these statement income items are evaluated for the first year of the simulation.

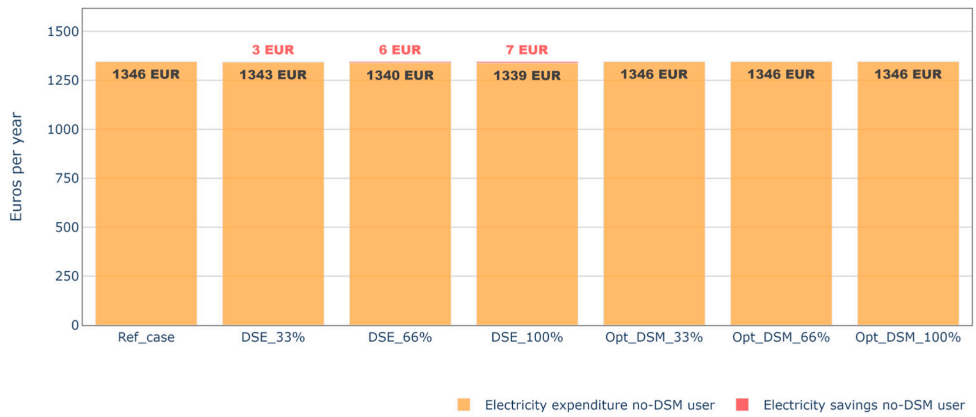

Figure 24. Total electricity expenditure and electricity savings for a "spontaneous user" (no-DSE/Opt-DSM user) in different cases. All these statement income items are evaluated for the first year of the simulation.

The revenues consist of incentives and ARERA valorization (this is a refund of part of the energy tariff [10]). The electricity expenditure is calculated as the difference between the yearly costs (bills, capex, opex, taxes, etc.) and the yearly revenues for the single user. The electricity savings are the difference between the electricity expenditure in the different cases and the electricity expenditure in the reference case.

Figure 22 plots the revenues for the different typologies of consumers, compared to the revenues in the reference case (dashed line). In the DSE cases, all the incentives (including the surplus of incentive led by concentrating flexible loads in daylight time slots) are equally divided among all the REC consumers, and there is no difference between the user typologies. In the Opt-DSM cases, the repartition methodology of the incentives varies, and the DSM users have greater revenues because the surplus of incentives generated through the DSM of the flexible loads is equally divided only among the DSM users. Moreover, increasing the number of Opt-DSM users (e.g., from 66% to 100%) does not necessarily guarantee higher revenues for each individual Opt-DSM user. This is because a larger number of active participants means more consumers sharing access to extra incentives. When the shared energy is insufficient to fully feed the flexible loads, the result is a lower per capita income. This behavior demonstrates the existence of an optimal level of DSM users' involvement, above which the incentives are not proportioned to their load scheduling actions.

The DSE practice generates an additional EUR 3–7 per year for the average user, which increases to EUR 20–46 per year in the case of users participating in the Opt-DSM practice (see Figure 23). In the DSE cases, the results are quite modest since the additional shared energy, as seen, is modest itself; furthermore, the incentive repartition scheme considered is based on fixed per capita shares, without awarding those DSE active users. It is observed that non-optimal load scheduling (as happens in DSE cases) does not guarantee a significant increase in the shared energy and thus in the incentive revenues, even when all users are adapting their behavior to concentrate loads during daylight hours.

Lastly, in Figure 24, the electricity expenditure and the electricity savings in the different cases for a typical no-DSM user are shown. It is observed that the only variations between the reference and the other cases derive from the repartition strategy:

- DSE: Equally split between everyone (also to no-DSM), consisting of EUR 114 existing in the reference case and EUR 3 generated by the DSE.
- Opt-DSM: EUR 114 existing in the reference case going to everyone, with Opt-DSM users only benefiting from an extra EUR 20 to 46 (depending on the case) generated by the Opt-DSM practices.

It is imperative to highlight that the marginal additional economic revenues obtained in the DSE cases are primarily attributable to two factors: the constrained volume of shiftable loads and the distribution methodology's inherent limitations in generating consistent supplementary incentives. Considering that the user base comprises exclusively residential consumers, the flexible loads eligible for temporal displacement are confined to household appliances, specifically washing machines and dishwashers. Consequently, the aggregate flexible load capacity within the REC remains substantially restricted. Moreover, DSE scenarios do not provide assured additional revenue generation through the implemented DSM strategy. In contrast, while Opt-DSM configurations yield enhanced economic benefits for DSM participants, these revenues are exclusively allocated among DSM users.

A modified incentive framework within the Italian regulatory system could potentially enhance the additional revenues generated through DSM strategies. However, the magnitude of such incentives is inherently constrained by international regulatory frameworks designed to prevent the implementation of state aid mechanisms that could introduce market distortions in competitive environments [39].

With respect to the economic feasibility of the configuration, it is fundamental to acknowledge that the generated revenues may prove insufficient to counterbalance the implementation and operational expenditures associated with the centralized optimization algorithm. The latter demonstrates increased potential for economic viability when integrated with solutions that facilitate access to supplementary revenue streams.

Additional opportunities for value creation can be realized through active participation in the distribution flexibility market. In the Italian context, the implementation of load and generator flexibility mechanisms within the distribution network remains in an experimental phase, with a limited number of pilot projects currently operational [40,41]. The potential and economic viability of flexibility mechanisms are among the most active research fields in the electricity distribution sector. Numerous projects, including some in Italy, are currently in progress, demonstrating the profitability of consumers (and RECs too) participating in flexibility markets [42].

Furthermore, enhanced system performance can be achieved through the optimization of energy consumption patterns via micro-grid implementation. Micro-grid systems facilitate increased self-consumption capabilities within the Energy Community, while necessitating sophisticated planning and coordination of diverse generation and storage assets (detailed operational frameworks for micro-grid systems are extensively documented in [43,44]). These technological solutions, combined with active participation in flexibility markets, constitute the primary pathways for ensuring the economic viability of centralized optimization system deployment.

7. Discussion

The main goal of this study is to evaluate the financial impact of user investments and the energetic impact on the grid of different demand-side management strategies. Two different strategies are explored: in the first case (DSE), the load profile of the consumer changes without any scheduling optimization for the flexible appliances (it is supposed to change the activation probability of the shiftable loads to avoid their activation outside the production period); in the second case (Opt-DSM), a scheduling optimization based on a genetic algorithm is adopted to reduce the electricity expenditure and to increase energy sharing.

From the grid's point of view, the losses can be reduced if there are low energy flows in electric lines and in the transformer. Great benefits can be obtained with a great synchronization of consumption with local production. Obviously, the grid losses intensity also depends on the location of the loads and of the power plants in the grid and on the characteristics of the grid (optimized grid configurations and planning allow increasing the efficiency of local energy sharing).

The results show that the DSE strategy does not have a relevant impact in terms of grid losses reduction and the increment of the local consumption of the distributed generation. Furthermore, increasing the number of users shifting their loads does not necessarily bring additional benefits to the grid (and to the involved users). The lack of load scheduling optimization and coordination between the users creates an aggregated load that often exceeds the community's PV generation. Thus, the outcome is that, from the REC's point of view, there is no significant increment in the shared energy. This means that the surplus of energy must be withdrawn from the external grid, without an increase of the local consumption of the distributed generation. The overall impact on the grid is that some losses are moved from nighttime to daytime, without significantly reducing the circulating currents and the reverse flow at transformer level originated by the PV systems. This happens because, without optimization, the flexible load can be shifted to time intervals characterized by low distributed energy generation.

The Opt-DSM, on the other hand, schedules the loads in a coordinated manner, which has the positive effect of flattening the energy exchange profile at the "slack node", making the best use of the local LV generation. The consequence at the grid level is that the overall circulating current and power are reduced, which contributes to reducing the loading of the related MV–LV transformer and of the upstream network at both day- and night-time. These effects lead to the conclusion that the optimized REC reduces the dependency on the upstream grid (only during the daytime in this case, as only PV technologies are considered) and reduces grid losses at the LV network level.

Moving to the economic point of view, the DSE case has negligible effects on additional energy sharing and incentive generation, due to an uncoordinated and uninformed load shifting approach. The Opt-DSM approach, instead, takes advantage of a centralized and data-based approach, leading to an increase in REC revenues. However, the allocation of the new additional incentives shall consider the contributions of the DSM users, who invested in hardware and software and reshaped their consumption habits according to the algorithm instead of their hour-to-hour needs. Although the REC's scopes and social goals shall be the main drivers in the incentive allocation, the DSM efforts may need to be awarded somehow, at least to pay back the expenses and secure the DSM users' commitment and perseverance in the long term. In this regard, this paper considered an equal redistribution of the additional DSM-related incentives between DSM users only, the amount of which is believed to reasonably pay back their efforts.

In conclusion, although many of the considerations discussed are both valid and generalizable, the application of the proposed methodology may lead to significantly different outcomes. Variations in PV penetration levels, user engagement in the REC, and load profiles are expected to return different results. Nonetheless, the patterns identified in this study are expected to remain observable.

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