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Optimal PV Sizing and Demand Response in Greek Energy Communities Under the New Virtual Net-Billing Scheme

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Abstract

Energy Communities have emerged as a key mechanism for promoting citizen participation in the energy transition. In Greece, recent legislation replaced the virtual net-metering scheme with a virtual net-billing framework, introducing new economic and regulatory conditions for shared renewable energy investments. This study develops an optimization tool for determining the optimal PV system size and Demand Response actions for individual EC members under this new framework. The model is constructed to align closely with the current regulatory and legal context, incorporating technical, economic, and policy-related constraints. It uses real electricity production and consumption data from existing Greek ECs, as well as 2024 Day Ahead Market prices, grid fees, and surcharges. The results emphasize the importance of customized sizing strategies and suggest that policy refinements may be needed to ensure equitable participation and maximize community-level benefits.

Keywords: optimization; virtual net-billing; Greece; demand response; flexibility; energy communities

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Academic Editor: Peter V. Schaeffer

Received: 6 August 2025
Revised: 10 September 2025
Accepted: 22 September 2025
Published: 24 September 2025

Citation: Chatzigeorgiou, I.-M.; Kitsikopoulos, D.; Papadaskalopoulos, D.A.; Chronis, A.-G.; Xenaki, A.; Andreou, G.T. Optimal PV Sizing and Demand Response in Greek Energy Communities Under the New Virtual Net-Billing Scheme. *Energies* **2025**, *18*, 5082. https://doi.org/10.3390/en18195082

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1. Introduction

Collective citizen-led schemes in localized energy generation, distribution, and governance have been identified, during recent years, as important pillars of a more democratic and ecological sound energy system [1]. They are, also, recognized at the EU level as fundamental enablers of the clean energy transition. The EU law has defined Renewable Energy Communities (RECs) in the Renewable Energy Directive (RED II, Directive (EU) 2018/2001 [2] and Citizen Energy Communities (CECs) in the Internal Electricity Market Directive (IEMD, Directive (EU) 2019/944) [3]. These two definitions establish the legal foundations for community-based energy production, management and consumption across the EU and serving as a foundation for national policies and laws. While RECs focus specifically on Renewable Energy Sources (RESs) and emphasize local benefits, environmental sustainability, and social cohesion, CECs have broader scope and flexibility, encompassing various forms of energy and market-oriented citizen activities without strict geographic constraints.

Greece first enacted a legislation for collective citizen energy initiatives with Law 4513/2018 [4]—adopted before the EU's updated directive. This law created a new form of civil cooperative, the Energy Community (EC), characterized by open and voluntary membership, democratic governance and specific requirements for geographic proximity. In the years between 2018 and 2023, more than 1484 ECs were created [5]. The main activity adopted by citizen-led ECs in Greece is collective self-consumption through a virtual net-metering scheme that allows aggregation of generation and consumption across multiple metering points [6]. Under this arrangement, each member's electricity use is offset against their share of community production, with settlement occurring on a triennial basis.

This virtual net-metering scheme has proven particularly advantageous in the context of Greece's volatile energy market, providing protection against price fluctuations, enhancing energy resilience, and offering stable and fast investment returns. The main RESs used in these schemes are the centralized Photovoltaic (PV) grid-connected systems, shared among members, typically in unequal ownership shares. Centralized PV systems have generally been found more viable for sustainable energy planning than distributed systems, particularly when considering overall system capacity, economies of scale, and cost-effectiveness in both installation and maintenance [7].

However, as highlighted in recent studies [8], several structural barriers continue to limit their scalability and effectiveness of citizen-led energy initiatives in Greece—hereafter referred to as Energy Communities (ECs), including all relevant legal forms. The most prominent among these are the complex bureaucratic procedures, inconsistent or frequently changing legislative frameworks, and limitations in financing mechanisms, particularly for non-commercial or self-consumption-oriented ECs. Many communities still face challenges in securing permissions, accessing land, and maintaining compliance with administrative and metering requirements. Furthermore, Greek ECs have increasingly faced issues of corporate capture, where commercial actors exploit regulatory frameworks by establishing pseudo-community entities, thereby appropriating financial benefits originally intended for genuine citizen-led initiatives [9]. This undermines core principles such as democratic control and local benefit-sharing. Such trends threaten the legitimacy and long-term sustainability of ECs across Europe, including Greece, where regulatory loopholes and insufficient oversight have facilitated this shift.

Subsequent legislative updates brought Greece in closer alignment with EU policy. Law 5037/2023 [10] formally transposed the EU's laws introducing the two distinct categories: RECs and CECs. In September 2024, the virtual net-billing scheme replaced the virtual net-metering scheme. Virtual net-billing, as established by Law 5074/2024 [11], differs from virtual net-metering by accounting separately for energy consumed from the grid and surplus energy exported. Unlike net-metering, where consumption and production are netted over a long settlement period (e.g., annually or triennially), virtual net-billing settlements occur at 15 min intervals.

Across Europe, national regulatory frameworks for energy communities vary considerably. Several countries, including Austria, Germany, and Portugal, have introduced legal frameworks that explicitly enable energy sharing, collective self-consumption, and, in some cases, access to shared storage. Others, such as Croatia, Malta, and Ireland, have transposed the EU directives into their national electricity laws, defining and operationalizing RECs and CECs. Northern European countries, including Denmark and the Netherlands, place particular emphasis on integrating energy communities into broader market participation schemes, often linking them with demand response and flexibility services. This diversity illustrates the wide range of regulatory pathways across the EU and provides a useful backdrop for situating the Greek case, which, while progressive in introducing virtual net-billing, remains more limited in scope compared to many of its European counterparts [12].

In this constantly evolving regulatory landscape, developing tools that can support ECs' creation and growth is increasingly important. Among these, optimizing PV system sizing is essential for maximizing energy production and reducing costs. Optimal PV sizing refers to the process of determining the most economically beneficial PV system capacity for a given application, balancing initial investment, energy generation, self-consumption, and revenue from surplus energy. Various optimization techniques—including traditional methods and modern approaches—have been widely employed to optimize the sizing and placement of PVs, with various objectives such as minimizing costs and emissions and maximizing the utilization of RESs [13].

Demand Response (DR) has also been identified as a promising strategy to increase self-consumption and reduce peaks [14] in collaborative energy schemes. DR "*includes all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption*" [15]. Optimization techniques have also been extensively used in residential DR to achieve bill and discomfort minimization and maximize energy generated by local sources [16]. Finally, research has also been conducted on combined PV and Battery Energy Storage System (BESS) sizing and the potential benefits of communal BESSs [17].

However, optimizing PV system sizing faces several practical challenges, as outlined by Khatib et al. [18]. These include the scarcity of high-resolution weather and load data, the need for highly accurate component models that reflect site-specific conditions and inefficiencies and the difficulty of accounting for the variability in commercial PV component specifications. The authors also mentioned that the optimization of PV system sizing must balance simplicity with accuracy to remain practical.

Various optimization methods have been applied to PV sizing for ECs. These methods can be broadly classified into mathematical methods and nature-inspired meta-heuristic algorithms. The latter include mostly Particle Swarm Optimization (PSO) [19], Genetic Algorithms (GAs) [20], and hybrid metaheuristics [21] approaches. The mathematical methods include Linear Programming (LP) and Mixed Integer Linear Programming (MILP). Iqbal et al. [22] provide a comprehensive review of optimization techniques applied in renewable energy systems, including system sizing, and highlight how different methods—such as linear programming for cost minimization and metaheuristics for complex multi-objective problems—are selected based on the specific characteristics and constraints of the sizing task.

LP and MILP have been used extensively in the literature [18,23,24], due to their ability to deliver globally optimal solutions with guaranteed convergence under linear constraints, as well as the compatibility with grid pricing structures and regulatory requirements. Compared to metaheuristic methods, LP and MILP often require less computational time and avoid issues like premature convergence or the need for extensive parameter tuning.

In the study by Fina et al. [25], a MILP model was developed to maximize the Net Present Value (NPV) of PV investments in energy communities in Austria. The model considered various spatial deployment patterns (urban, traditional, rural, mixed) and enabled sizing both at the level of individual buildings and the entire community, using 15 min resolution data for consumption, and PV systems installed on both rooftops and façades. The results highlighted the strong economic potential of community-based PV investments, particularly through load diversity and the aggregation of available surfaces.

Volpato et al. [26] also developed a MILP model tailored to Italian RECs and CECs, aiming to minimize the total community energy cost under realistic constraints. Their model incorporated DR scenarios, an innovative cost allocation mechanism, and an analysis of complementarity between prosumers in terms of demand and generation profiles. Although the model assumes fixed PV capacity per user, it provides valuable insights

into the regulatory and economic parameters that affect EC performance under the new European framework.

Cosic et al. [27] proposed a MILP optimization model to minimize energy costs and CO_2 emissions in Austrian ECs. The study used real-world data for a nine-user microgrid and incorporated dynamic energy pricing. The model allowed for shared PV generation and battery storage, simulating the provisions of the Austrian Renewable Expansion Act (EAG). Results showed up to 15% cost reduction and 34% emission reduction, confirming the benefits of community participation.

Novoa et al. [28] focused on ECs in the U.S. and developed a MILP model aimed at achieving Zero Net Energy or islanding operation targets, while avoiding transformer overloading. The model used representative day clustering, variable TOU tariffs, and net metering. Results demonstrated that appropriate PV and battery sizing can yield significant technical and economic benefits.

Hascuri et al. [29] examined the sizing of standalone PV systems in Morocco, applying two MILP formulations: one with equalities and a simplified one with only inequalities. The objective was to minimize the initial capital investment. Their 6 h resolution analysis showed that the reduced model achieved comparable results with much lower computational complexity, making it suitable for large-scale planning.

Farrokhifar et al. [30] applied a stochastic MILP approach in U.S.-based EC, combining PV, wind turbines, batteries, and electric vehicles with Vehicle to Grid (V2G) capability. The model aimed to minimize the community's total life-cycle cost while maximizing renewable and storage utilization. It also included flexible and shiftable loads and DR. The results demonstrated the potential of integrated management to enhance system flexibility and sustainability.

Budin and Delimar [31] proposed a two-stage stochastic MILP model for EC design, based on real-world data from Croatia and Germany. A novel feature of their method is the use of unsupervised clustering (k-means, GMM) to represent stochastic load profiles. The model supports shared storage and P2P trading, aligning with RED II and RED III frameworks. Emphasis is placed on fairness and risk management in resource allocation.

Kassab et al. [32] developed a MILP model for the combined sizing and energy management of a DC microgrid, applied to a university facility in France. The system included PV and batteries and examined both islanded and grid-connected scenarios. The objective was to minimize the total life-cycle cost (investment, operation, replacement, management). While theoretical, the model is scalable to EC schemes.

Table 1 provides a comprehensive overview of recent studies employing MILP-based optimization approaches for PV sizing in Energy Communities (ECs), highlighting key modeling choices, assets considered, regulatory contexts, and temporal resolutions.

Table 1. Literature Review of PV sizing optimization studies for ECs using MILP.

Reference	Algorithm	Optimization Goal	Assets	DR	Country	Temporal Resolution	Regulatory Framework
Fina et al. [25]	MILP	Maximize Net Present Value (NPV)	PV, HVAC, Batteries	No	Austria	15 min, for 1 year	Based on Austrian market
Volpato et al. [26]	MILP	Minimize operational cost	PV, Biogas ICE CHP	Yes	Italy	60 min, 3 representative days	Aligned with EU directives (RED II & IEMD)

Table 1. *Cont.*

Reference	Algorithm	Optimization Goal	Assets	DR	Country	Temporal Resolution	Regulatory Framework
Cosic et al. [27]	MILP	Minimize energy cost & CO_2 emissions	PV, Batteries	Indirect via dynamic pricing	Austria	60 min, for 1 year	Compliant with Austrian EAG (Renewable Expansion Act)—shared energy
Novoa et al. [28]	MILP	Minimize investment & operating cost, meet ZNE or islanding goals, avoid transformer overloading	PV, Batteries	Indirect via dynamic pricing	USA	60 min, representative days via k-medoids clustering	Based on SCE utility tariffs (TOU-D-A, TOU-8-B), includes NEM and grid constraints
Hascuri et al. [29]	Two MILP types (i) Original (equalities), (ii) Reduced (inequalities only)	Minimize CAPEX (two MILP variants)	PV, Batteries	No	Morocco	360 min, for 1 year	None indicated
Farrokhifar et al. [30]	Stochastic MILP	Minimize net present cost, maximize RES and storage usage, meet demand via DR and V2G	PV, Wind, Batteries, EVs (V2G)	Yes	USA	60 min, for 1 year	None indicated
Budin & Delimar [31]	Two-stage stochastic MILP with unsupervised clustering (load & uncertainty modeling)	Cost reduction & limiting grid impacts	PV, Shared Battery	Indirect via dynamic pricing	Croatia, Germany	15 min, for 1 year	RED II/RED III—Clean Energy Package, P2P trading
Kassab et al. [32]	MILP	Minimize total system cost (CAPEX, O&M, replacement, energy management)	PV, Batteries	No	France	60 min, for 1 year	None indicated
Our study	MILP	Minimize net investment cost (CAPEX, O&M, operation)	PV	Yes	Greece	15 min, for 1 year	Greek Law 5074/2024 for virtual net-billing in ECs

Furthermore, Fotopoulou et al. [33] developed a day-ahead optimization algorithm for energy communities that integrates PV production, battery storage, and flexible loads under the new virtual net-billing law, enabling peer-to-peer cost-sharing and demonstrating up to 25% cost reduction through cooperative operation compared to individual prosumer setups.

Compared to the existing literature, the present study offers the first systematic application of MILP for the optimal sizing of PV systems in ECs in Greece, under the new regulatory framework of the virtual net-billing Law 5074/2024. It offers a realistic and representative sizing scenario, tailored to Greek RECs and CECs. To our knowledge, no previous study has applied PV sizing methodologies within the scope of this legislation.

The proposed approach integrates real 15 min interval data for consumption, production, and wholesale prices, capturing the dynamics of the Greek electricity market. While recent studies often adopt multi-objective optimization (e.g., minimizing costs, emissions, and discomfort, or maximizing self-consumption [27,34,35]), this study deliberately adopts a single-objective model that minimizes net investment cost. This design choice reflects an emphasis on simplicity, interpretability, and relevance to current financial constraints and planning needs.

The focus is on citizen participation in centralized collective PV projects—the dominant model in Greece—while excluding energy sharing, as it is not yet regulated under Greek

law. Overall, this work contributes a practical decision-support tool tailored to the current legal framework, bridging the gap between technical optimization and legal feasibility. By combining detailed metering data with regulatory and market parameters, the study offers actionable insights for the cost-effective deployment of community energy projects in Greece.

2. Methods

2.1. The Virtual Net-Billing Scheme

Under the Greek virtual net-billing scheme (Law 5074/2024), energy metering and financial settlement are performed in 15 min intervals, in line with EU market standards. In each interval, the injected energy refers to the total electricity generated by the community PV system and fed into the grid. This energy is represented in the DAM market by an aggregator and proportionally allocated to each member based on ownership shares. Simultaneously, the absorbed energy is the electricity drawn from the grid by a member during the same interval. This absorbed quantity is subject to regulated charges (e.g., DSO, TSO, taxes) imposed by the energy supplier.

The netting mechanism identifies the netted energy as the minimum of injected and absorbed energy per interval. This is the energy simultaneously produced and consumed. For this quantity, the aggregator credits the supplier, and the supplier passes on only the balancing cost. The balancing parameter λ_m^N (€/kWh) reflects the cost imposed by the supplier for balancing the netted energy injected into the grid. It is defined as the sum of the Unit Imbalance Price and the three Unit Adjustment Charges ($\Lambda\Pi 1$, $\Lambda\Pi 2$, and $\Lambda\Pi 3$):

$$\lambda_m^N = Imbalance + \Lambda\Pi 1 + \Lambda\Pi 2 + \Lambda\Pi 3 \quad (1)$$

If the injected energy exceeds the consumed energy, the surplus is labeled as surplus energy, which remains on the grid and is compensated at the DAM price. Conversely, if the absorbed energy exceeds the simultaneous production, the difference is owed energy and is charged at the retail tariff of the supplier. In Figure 1, we can see an example of the energy flows during a day of a typical household under the virtual net-billing framework.

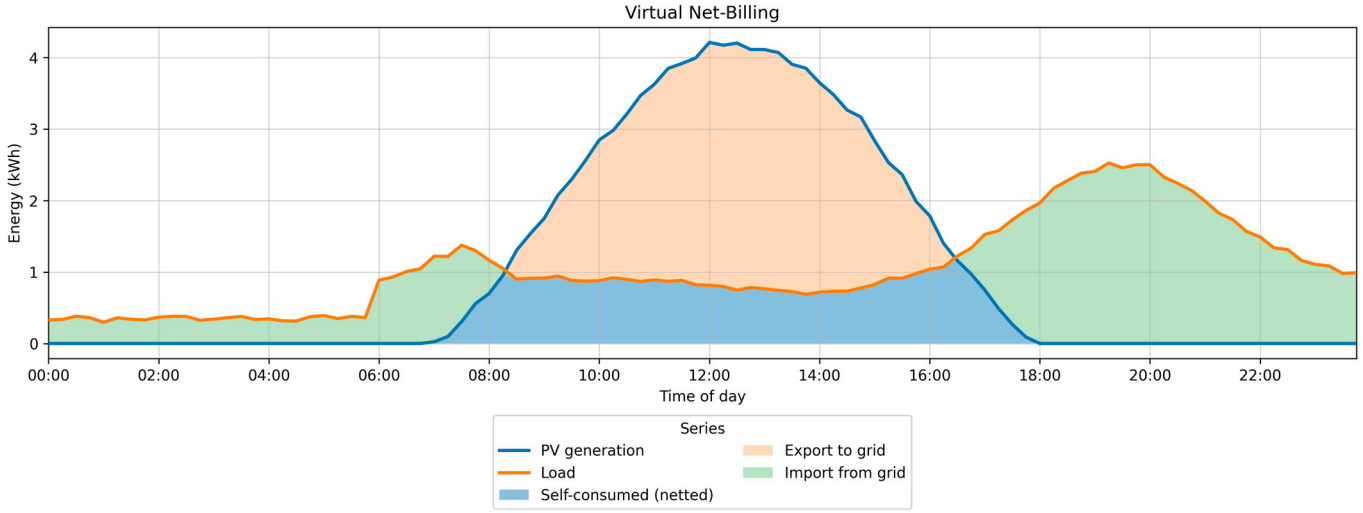


Figure 1. Virtual net-billing energy flows.

2.2. Model

2.2.1. The Objective Function

In this study, a MILP model is developed to assess the optimal sizing of PV systems and the potential contribution of DR for individual members of RECs or CECs under Greece's new virtual net-billing framework. The objective is to minimize the net annualized cost of participation, accounting for the investment, operational expenses, and revenues from surplus energy sold to the grid.

The optimization seeks to minimize the net cost over one representative year, annualized over a 20-year investment horizon. The objective function includes:

- Capital expenditure (CAPEX) for the PV installation including the purchase and installation cost, annualized using a fixed annuity factor based on the assumed discount rate.
- Operational expenditure (OPEX) such as annual maintenance costs per installed kW.
- Electricity purchase cost for grid-imported energy at a fixed retail price.
- Netted cost charge, reflecting regulatory surcharges applied to self-consumed energy.
- Revenue from surplus energy, compensated at the DAM price minus the export charge, which reflects the cost of the aggregator's service for the representation of the PV park to the DAM market.

Mathematically, the objective function is expressed by Equation (2).

$$\begin{aligned} &\min NetCost = \min(\text{Cost} - \text{Revenue}) = \min\left(C^{IMP} + C^{N} + C^{OPEX} + f \cdot C^{CAPEX} - R^{EXP}\right) \\ = \; & min\Big(\sum_{d\in D}\sum_{t\in T}\left(E^{IMP}_{d,t}\cdot\lambda^{R} + \sum_{d\in D}\sum_{t\in T}E^{N}_{d,t}\cdot\Big(\sum_{m\in M}\lambda^{N}_{m} + \lambda^{A}\Big) + c^{op}\cdot P^{sh} + \frac{r\cdot(1+r)^{N}}{(1+r)^{N}-1}\cdot c^{cp}\cdot P^{sh}\right) \\ & - \sum_{d\in D}\sum_{t\in T}E^{EXP}_{d,t}\cdot\left(\lambda^{WM}_{d,t} - \lambda^{A}\right)\Big) \end{aligned} \tag{2}$$

2.2.2. Constraints

The model is defined over 15 min intervals for the full year (35,040 time-steps) of 2024, capturing a detailed variation in consumption, production, and prices. At the same time, it enforces the following constraints:

- Equation (3) The maximum PV share that a household can own.
- Equation (4) Energy balance at each timestep: consumption (including DR-adjusted demand) must be covered by PV generation, grid import, or export (in the case of surplus).
- Equation (8) Daily DR neutrality, ensuring that load shifts are balanced within a 24 h window.
- Equations (6) and (7). Physical limits on DR flexibility, bounded by a percentage of instantaneous demand.

Finally, under the net-billing scheme a prosumer cannot simultaneously import electricity from the grid and export surplus PV production during the same 15 min interval. To reflect this physical and regulatory limitation, the model includes a binary variable (9) that governs the operating mode at each time step. More specifically:

- For $X_{d,t} = 1$ the system is in import mode, allowing energy to be imported from the grid (exported energy is 0);
- For $X_{d,t} = 0$, the system is in export mode, allowing energy to be exported from the grid (imported energy is 0).

This logic is enforced using big-M constraints as defined in Equations (10) and (11). In this context, M is a large constant (e.g., 10^6) that effectively activates or deactivates each energy flow depending on the binary state. This mechanism ensures that only one direction

of energy flow with the grid is active at each timestep, making the model more realistic and compliant with current Greek net-billing implementation rules.

$$P^{sh} \leq P^{max} \tag{3}$$

$$D_{d,t} + E^{DR}_{d,t} = E^{G}_{d,t} + E^{IMP}_{d,t} - E^{EXP}_{d,t} \quad \forall\, t \in T\,,\ \forall\, d \in D \tag{4}$$

$$E^{N}_{d,t} = D_{d,t} + E^{DR}_{d,t} - E^{IMP}_{d,t} \quad \forall\, t \in T\,,\ \forall\, d \in D \tag{5}$$

$$E^{DR}_{d,t} \leq \alpha \cdot D_{d,t} \quad \forall\, t \in T\,,\ \forall\, d \in D \tag{6}$$

$$E^{DR}_{d,t} \geq -\alpha \cdot D_{d,t} \quad \forall\, t \in T\,,\ \forall\, d \in D \tag{7}$$

$$\sum_{t \in T_D} E^{DR}_{d,t} = 0 \quad \forall d \in D \tag{8}$$

$$X_{d,t} \in \{0,1\} \quad \forall\, t \in T\,,\ \forall\, d \in D \tag{9}$$

M a sufficiently large number

$$E^{IMP}_{d,t} \leq M \cdot X_{d,t} \quad \forall\, t \in T\,,\ \forall\, d \in D \tag{10}$$

$$E^{EXP}_{d,t} \leq M \cdot (1 - X_{d,t}) \quad \forall\, t \in T\,,\ \forall\, d \in D \tag{11}$$

BESSs were not included in the present modeling because the Greek virtual net-billing law does not currently allow shared storage within energy communities. While individual household batteries are technically feasible, they remain rare and economically challenging in Greece due to the absence of supporting incentives. Our focus in this study is restricted to scenarios that comply with the existing regulation and market conditions.

2.2.3. Solver and Implementation

The model is implemented in Pyomo and solved using the Gurobi solver. As discussed in the next sub-sections, a sensitivity analysis is performed on key economic and technical parameters, and a scenario analysis contrasts the cost outcomes for a no PV scenario, PV-only and PV/DR scenario.

2.3. Data

Kazmi et al. in [36] highlighted the importance of open-source datasets and tools for ECs and listed 9 widely available datasets with high-resolution data that could support research on optimal design and operation. They also highlighted the fact that despite the availability of datasets, most countries of the world and many climate zones are still not represented. Since their publication, several more datasets have been released, such as two more datasets including Australian ECs [37,38]. At the same time, new datasets filled important geographical gaps, e.g., three datasets with data from Norwegian ECs [39,40], as well as datasets from Ireland, Greece and Portugal [41–43]. Datasets such as NorPEN, iFlex, and Plegma provide high-resolution consumption and generation data, with some including appliance-level monitoring and dynamic pricing experiments. Several also include behavioral or survey data, enabling socio-technical analyses. To summarize the current landscape, Table 2 includes both the earlier datasets and more recent contributions, offering a wider overview of international datasets with household energy community data.

For this study, the focus was placed on collecting data from Greek ECs, following the recommendation of [44], which emphasizes the importance of using data that reflect the local socio-technical context. In particular, the analysis centered on the Commonen EC based in Ioannina [45], which operates two 100 kW PV parks located in Mpafra and Koutselio. In Mpafra, the PV panels are installed on a rooftop, while in Koutselio they are ground mounted. Both systems are currently operating under virtual net-metering

contracts. The houses are not situated in proximity to the PV parks but rather distributed within the same broader geographical region. Representative data were collected and simulated for a single household at each site to assess the benefits and optimal sizing of PV systems under the newly introduced virtual net-billing scheme.

The Mpafra and Koutselio households were chosen because they provided high-resolution, synchronized 15 min data on both consumption and PV generation from households that are active members of Greek Energy Communities, collected specifically for this research. These cases are intended as illustrative validation examples, rather than as a representative sample of Greek households, and allowed us to test the framework under real-world conditions. In parallel, we collected and reviewed a range of international and national open datasets (summarized in Table 2). However, none of these datasets fully matched the requirements of the present validation (synchronized 15 min consumption and PV production data from Greek community members) under the new virtual net-billing framework. These datasets will nonetheless provide a valuable resource for future extensions of this work, where broader validation across a range of socio-technical conditions across urban, rural, and mixed households is planned.

Table 2. List of widely available datasets that can be used to model and optimize energy communities.

Dataset	Country	Year	Number of Households	Duration	Sampling Rate	Data	Ref.
EMBED	USA	2017	3	14–27 days	12 kHz (house), 1 Hz (appliances)	Appliances	[46]
REDD	USA	2011	6	3–19 days	0.5–1 Hz (NILM data)	Household, Appliances	[47]
BLUED	USA	2011	1	8 days	12 kHz	Appliances	[48]
PLAID	USA	2013 & 2014	56	2 weeks	30 kHz	Appliances	[49]
ADRES	Austria	2009 & 2010	30	2 weeks	1 Hz	Household	[50]
REFIT	UK	2015	20	2 years	0.125 Hz	Appliances	[51]
UK-DALE	UK	2015	5	Up to 4 years	16 kHz, 0.17 Hz	Household, Appliances	[52]
DRED	The Netherlands	2015	1	6 months	1 Hz, 1 min	Household, Appliances	[53]
HES	UK	2010–2011	250	1 year	10 s (household), 2 min	Household, Appliances, Interviews	[54]
Dataport	USA	2014	1400 (75 free)	4 years (full), 6 months (free)	1 Hz, 1 min, 15 min	Household, Appliances	[55]
Smart*	USA	2014–2016	3–114–400	4 years	1 Hz	Household, Occupancy Weather, PV	[56]
AMPds	Canada	2012–2014	1	2 years	1 min	Household, Appliances, Weather, water and gas	[57]
ECO	Switzerland	2014	6	8 months	1 Hz	Household, Appliances, Occupancy	[58]
PRECON	Pakistan	2018	42	1 year	1 min	Household, Appliances	[59]

Table 2. *Cont.*

Dataset	Country	Year	Number of Households	Duration	Sampling Rate	Data	Ref.
ENERTALK	South Korea	2016	22	29–122 days	15 Hz	Household, Appliances	[60]
SustDataED2	Portugal	2022	1	1144 days	2–10 Hz	Household, Appliances, Weather, PV, Wind, biomass, hydro	[61]
IHEPCDS	France	2006–2010	1	47 months	1 min	Household, Appliances	[62]
IDEAL	UK	2020	255	23 months	1 Hz	Household	[63]
NorPEN	Norway	2022	6	2 months	10 s	Household, Weather, Irradiance, estimated PV, Interviews	[39]
IEDL	India	2020	1	1 year	1 min	Household, Appliances	[64]
ECD-UY	Uruguay	2022	110,953	21 days	15 min (households), 1 min (appliances)	Household, Appliances	[65]
GREEND	Austria/Italy	2013	8	1 year	1 Hz	Household, Appliances	[66]
Australian Distribution Network PV Dataset	Australia	2010–2013	300	3 years	30 min	Household, PV	[37]
iFlex Dynamic Pricing Dataset	Norway	2019–2021	4483	2 winters	1 h	Household, Weather, PV, Interviews	[67]
SHEERM	Portugal	2021	13	26–450 days	15 min	Household, Weather, PV, Price	[43]
Ireland Energy Community Load Profiles	Ireland	2020	20	1 year	1 min	Household, Appliances, Weather, PV, BESS	[41]
Norwegian Energy Community Dataset	Norway	2015	100	1 year	1 h (households), 1 min (appliances)	Household, Appliances, EV, estimated PV, Weather, Prices	[40]
Plegma Dataset	Greece	2022–2023	13	3–14 months	0.1 Hz	Household, Appliances, Interviews	[42]

The electricity production profiles of the two PV parks and the two households are illustrated in Figure 2. It is noteworthy that the household in Koutselio exhibits significantly higher electricity consumption, and its associated PV park also shows greater electricity production. Both houses have similar basic characteristics and use a heat pump for heating. To reflect actual market conditions, DAM prices were sourced from the Hellenic Energy Exchange (EnExGroup) [68], and their fluctuations are shown in Figure 3.

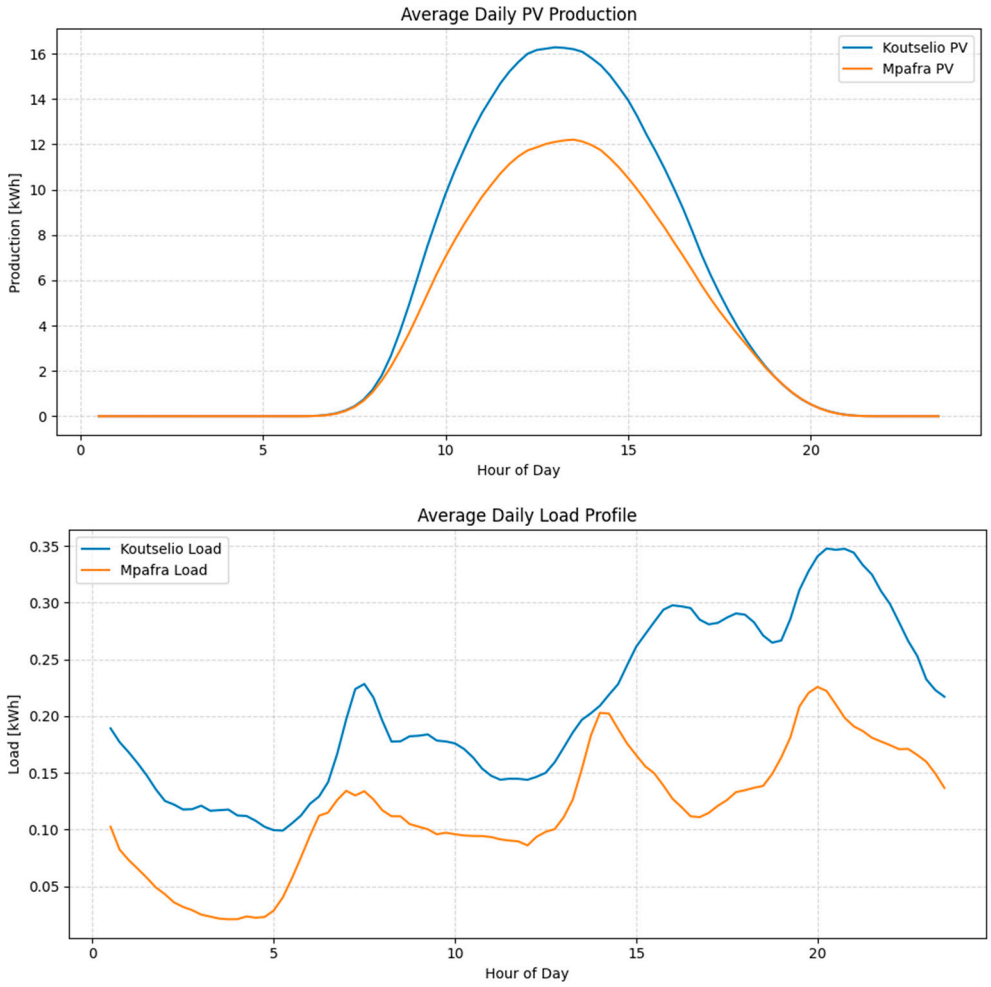


Figure 2. Average Daily Production and Consumption curves for both houses and PV parks.

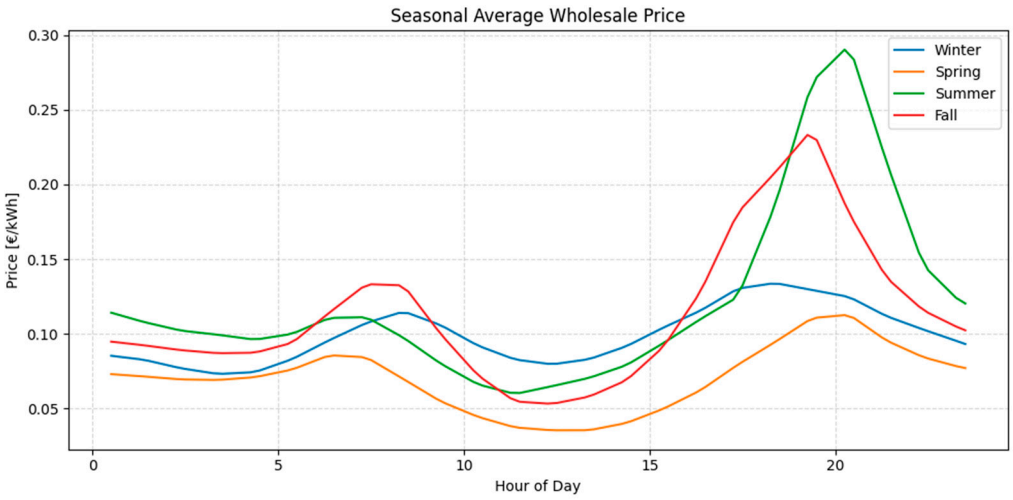


Figure 3. Seasonal average hourly DAM prices in Greece in 2024.

The remaining model parameters were defined in accordance with local market conditions and legal regulations, as summarized in Tables 3 and 4 below.

Table 3. The optimization parameters and their default values.

λ^R	0.15 (€/kWh)
λ^A	0.0025 (€/kWh)
P^{max}	8 (kW)
c^{cp}	850 (€/kW)
c^{op}	20 (€/kW)
r	2 (%)
N	20 (years)
α	0.10
η	0.5%

Table 4. Imbalance and $\Lambda\Pi$ prices.

Month	Imbalance	$\Lambda\Pi$**1**	$\Lambda\Pi$**2**	$\Lambda\Pi$**3**
1	−0.027	2.034	2.142	9.177
2	0.335	1.555	2.002	10.029
3	0.976	1.456	3.019	9.852
4	0.114	1.386	4.365	10.056
5	−0.423	1.844	2.781	7.039
6	−1.080	1.916	3.006	7.398
7	−0.251	2.964	3.461	8.778
8	−2.999	3.162	3.269	9.398
9	−4.932	2.896	4.534	11.691
10	−3.046	2.501	5.927	15.430
11	−2.060	4.091	4.386	17.502
12	0.779	3.384	4.439	15.560

The static parameters used in the model were selected based on current Greek market conditions, regulatory provisions, and typical engineering assumptions for small-scale PV investments. The aggregator fee $\lambda^A = 0.0025\,€/\text{kWh}$ represents the cost charged by the aggregator for managing the PV park's participation in the DAM electricity market. According to the current legal framework, this fee is applied to all exported electricity. The value was sourced from a well-known Greek energy market website that lists aggregator service rates for small producers. The retail electricity price $\lambda^R = 0.15\,€/\text{kWh}$ represents the average residential tariff in Greece and is used to value self-consumed electricity under the virtual net-billing scheme. The balancing charge λ_m^N reflects the cost imposed by the supplier for balancing the netted energy injected into the grid. Regulated charges are not included in the model, since they are charged on the whole imported energy as they would outside the virtual net-billing scheme as well.

The supplier's cost is calculated as the product of the netted energy and the balancing parameter λ_m^N, which is the sum of the Unit Imbalance Price and the three Unit Adjustment Charges ($\Lambda\Pi1$, $\Lambda\Pi2$, and $\Lambda\Pi3$) published for each Balancing Settlement Period by the Greek Transmission System Operator (IPTO). The Imbalance prices and $\Lambda\Pi1$–$\Lambda\Pi3$ charges are published monthly. Their values for 2024 can be found in Table 4. Under the virtual net-billing Law 5074/2024, installed PV capacity is restricted to a maximum of 100% of the contracted capacity of the household. The maximum PV capacity $P^{max} = 8$ kW represents

the standard upper limit for residential installations in Greece (8 kVA). The capital cost $c^{cp} = 850$ (€/kW) and operational cost $c^{op} = 20$ (€/kW) reflect average values derived from local market conditions and installer quotations for residential-scale grid-connected PV systems. The DR activation ratio $\alpha = 10\%$ indicates the portion of total load assumed to be flexible. This value is based on rough assumptions informed by residential DR studies, due to the lack of detailed empirical data in the Greek context.

A discount rate of $r = 2\%$ was adopted to represent a conservative real interest rate, aligning with current European economic conditions and commonly used values in investment analysis. The lifetime of the PV system $N = 20$ years corresponds to the expected operational duration and warranty periods of most PV system components. Finally, the degradation rate $\eta = 0.5\%$ per year reflects standard long-term performance decline for crystalline silicon PV modules, consistent with both manufacturer data and empirical studies.

2.4. Sensitivity Analysis Design

To investigate the influence of key economic and technical parameters on the model's outcomes, a one-way sensitivity analysis was performed. Five parameters were selected based on their practical relevance and policy significance: CAPEX, OPEX, aggregator's fee, the DR capacity limit and the PV panel degradation rate. Each parameter was independently varied within realistic bounds derived from market trends and literature. All details are included in Table 5:

Table 5. Variation in the parameters.

Parameter	Variation for the Sensitivity Analysis
CAPEX	500–1500 €/kW
OPEX	10–80 €/kW
Aggregator's fee	0.001–0.005 €/kWh
DRcap	0–50%
PV panel degradation rate	0–2%

3. Results

3.1. Baseline Cases

Table 6 presents the results for the three baseline scenarios simulated for the two households in the Commonen EC. As expected, the "No PV" scenario leads to the highest annual net cost due to full reliance on grid electricity. When PV is installed, the net cost drops in both locations. Adding DR capability offers a marginal additional improvement in cost—1.5% for the Koutselio case and 1.6% for the Mpafra case.

Table 6. Baseline cases for both houses.

Scenarios	Koutselio		Mpafra	
	Optimal PV Capacity (kW)	Net Cost (€/year)	Optimal PV Capacity (kW)	Net Cost (€/year)
No PV	0	1094.39	0	614.82
PV	8	682.89	8	429.84
PV and DR	8	672.33	8	422.63

3.2. Sensitivity Analysis Results

The results of the sensitivity analysis across both case studies are presented below in Figures 4–8.

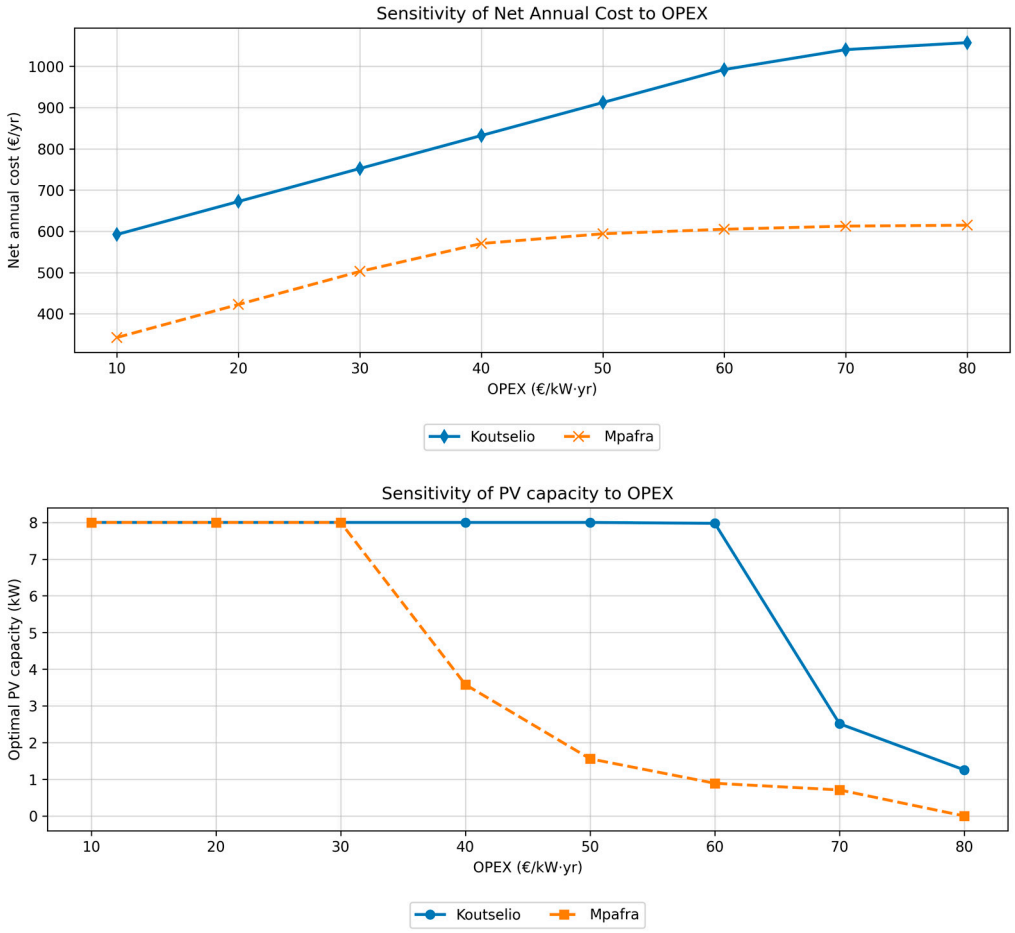


Figure 4. Sensitivity analysis of Net Annual Cost and optimal PV capacity to Operational Expenditure (OPEX) for both houses.

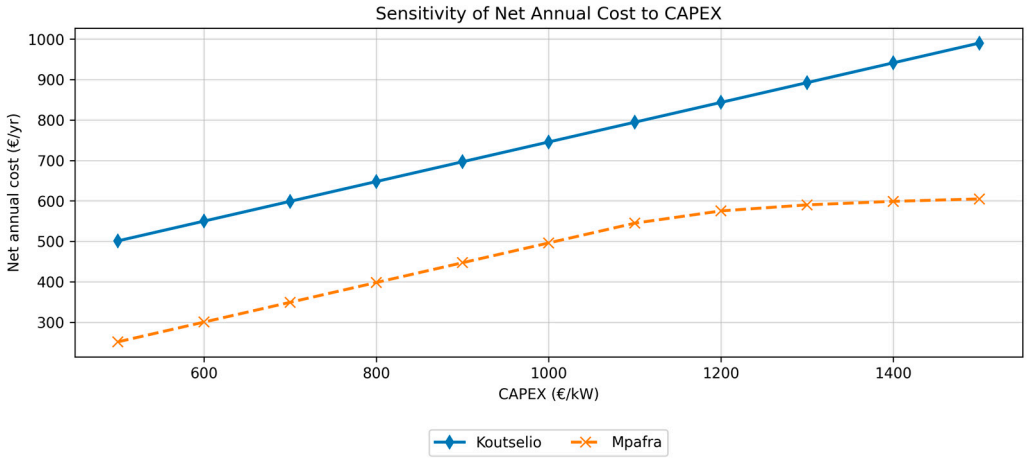


Figure 5. *Cont.*

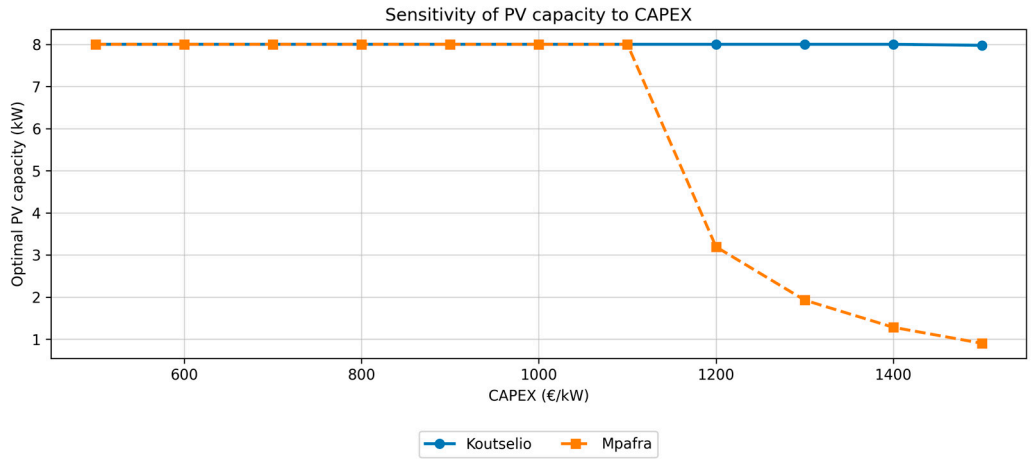


Figure 5. Sensitivity analysis of Net Annual Cost and optimal PV capacity to Capital Expenditure (CAPEX) for both houses.

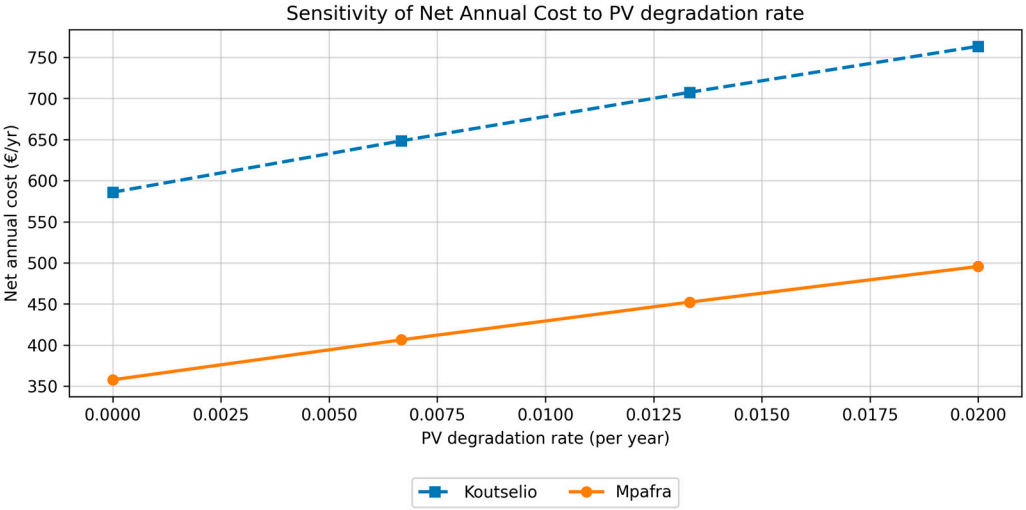


Figure 6. Sensitivity analysis of Net Annual Cost to annual PV degradation rate for both houses.

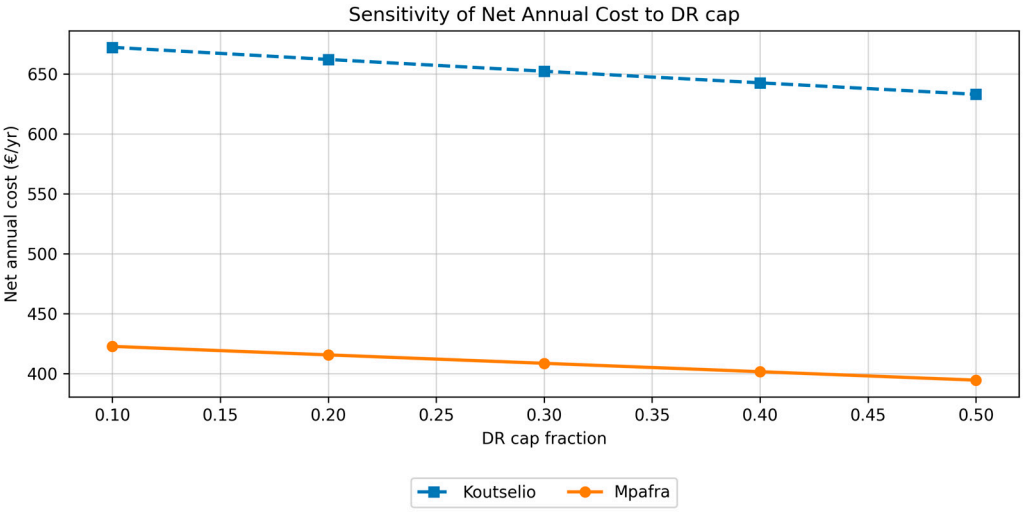


Figure 7. Sensitivity analysis of Net Annual Cost to maximum DR capacity for both houses.

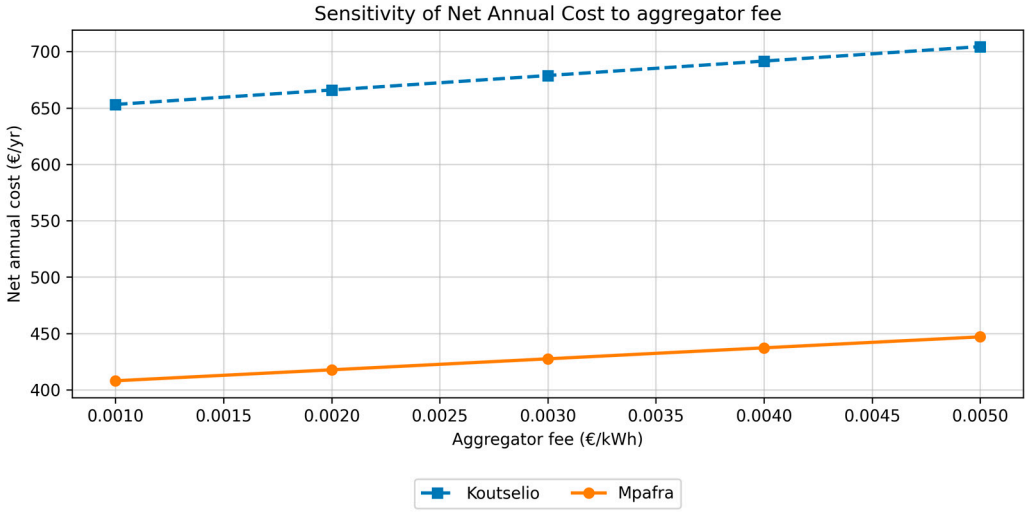


Figure 8. Sensitivity analysis of Net Annual Cost to aggregator's fee for both houses.

The sensitivity analysis of the two representative households—Mpafra and Koutselio—reveals how differences in load and generation profiles shape investment and operational decisions. Mpafra consistently shows lower net annual costs across all tested parameters, largely due to its lower electricity consumption and more favorable alignment of generation with load during critical periods. Mpafra tends to reduce PV capacity earlier than Koutselio when faced with rising CAPEX or OPEX. This behavior is partly explained by its lower PV production potential, which limits the returns from scaling up generation capacity, especially when surplus energy cannot be self-consumed or is under-compensated in the DAM.

Overall, the findings illustrate how site-specific consumption and generation characteristics—particularly load volume—critically influence optimal system design. While Mpafra benefits from lower overall costs, it is less incentivized to maintain large PV capacity when economic conditions become less favorable. Koutselio, with higher demand and better solar potential, justifies larger systems and derives greater benefit from DR. These insights highlight the importance of fine-grained modeling and suggest that future regulatory or financial support schemes should consider both technical resource availability and demand-side potential to promote equitable and efficient EC participation.

3.3. DR Strategy

The DR strategy is modeled as an intra-day, energy-neutral load-shifting mechanism, where per-interval adjustments are capped at a fraction α of the baseline demand. In this study, α is tested at 5%, 10%, 15%, and 30%, capturing a spectrum of flexibility levels. These values approximate the portion of household demand that could realistically be shifted within a single day without compromising essential services. Such percentage-based constraints are a common simplification in DR research, particularly in large-scale models [69,70], and here they provide a first indication of how DR may reduce costs at the household level.

Even under these constraints, DR emerges as a beneficial strategy, lowering net annual costs for both households without affecting PV sizing. As shown in Figure 7, while the DR capacity increases from 0.1 to 0.5, the total annualized net cost gradually decreases, indicating improved economic performance of the energy system. Specifically, the objective drops from €422.63 to €394.42, a 6.67% reduction for the Mpafra case and from €672.33 to €633.09, a 5.84% cost reduction for the Koutselio case.

The results of the implemented DR strategy are presented in Figures 9 and 10 as yearly average for the Mpafra and Koutselio cases, respectively. As we can see, the model shifts consumption from late evening to the morning and noon. The current modeling of DR has its limitations since the load can only be shifted throughout a single day as constrained by Equation (7) and only as a proportion of the original load, which means that even with higher DR capacity, the load shape cannot be drastically changed. This is why, even under higher DR capacities, a restricted financial gain is observed. This approach simplifies the diversity of potential shifting behaviors and is rather conservative in scope. However, it can serve as an indication of the potential DR strategies that the households can adopt under the current market conditions.

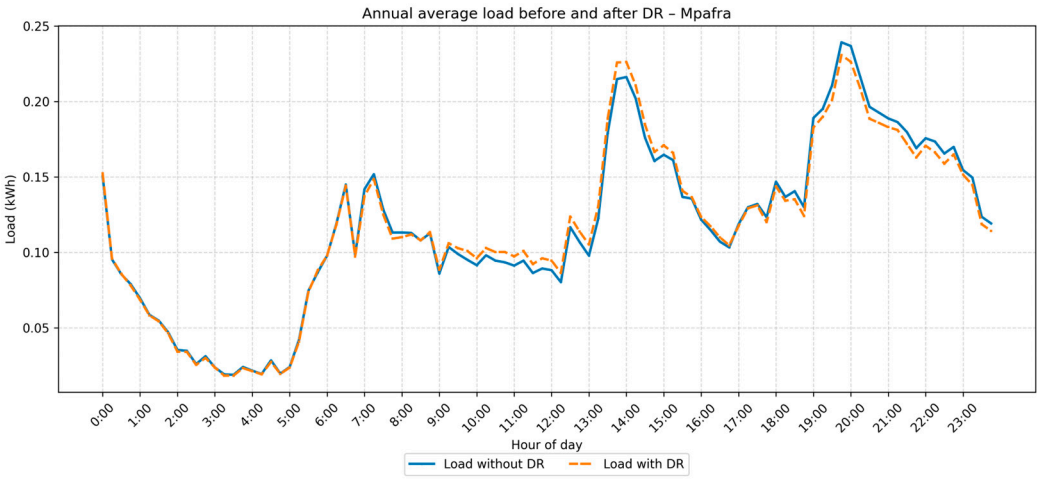


Figure 9. Average DR shifting for the Mpafra house with a DR capacity of 10%.

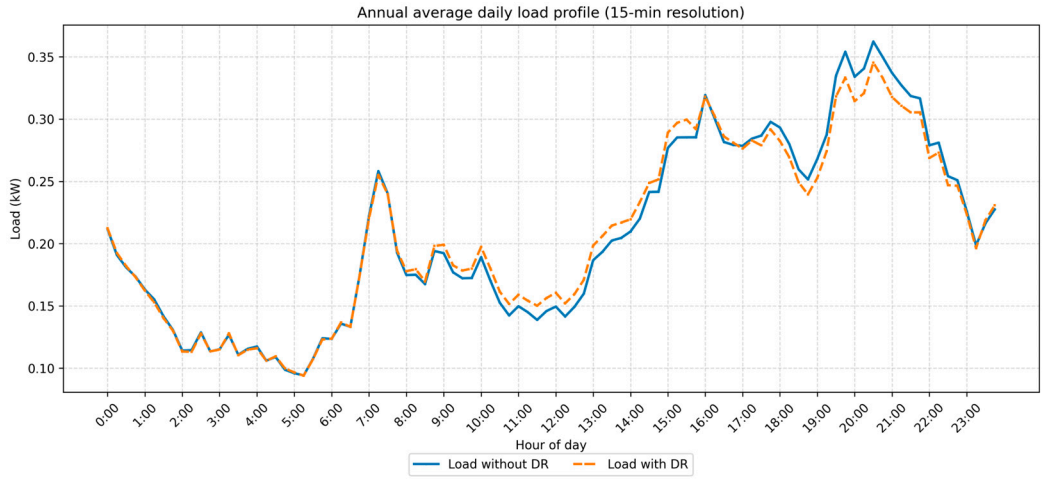


Figure 10. Average DR shifting for the Koutselio house with a DR capacity of 10%.

4. Discussion

Given the current challenges and opportunities that Greek ECs face, the outcomes of this study offer valuable guidance for both policymakers and practitioners. As Greece transitions to the virtual net-billing scheme, where settlements are made every 15 min and surplus generation is less financially rewarding, accurate system sizing becomes crucial. By minimizing net annual costs while maximizing self-consumption, the proposed MILP optimization framework enables ECs to make informed investment decisions that are aligned with the new regulatory and economic conditions.

The sensitivity analyses further reveal that investment viability is strongly influenced by changes in CAPEX and OPEX. In the Mpafra case, net annual costs rise sharply from ~250 €/yr at 500 €/kW to more than 600 €/yr at 1500 €/kW, with optimal PV capacity decreasing below 1 kW at high-cost levels. This indicates that smaller or less energy-intensive households remain economically viable only within a narrow cost envelope. By contrast, the Koutselio case demonstrates greater resilience: PV capacity remains close to 8 kW even at higher CAPEX levels, though net annual costs nearly double (from ~500 €/yr to ~990 €/yr between 500–1500 €/kW). Similarly, increases in OPEX disproportionately affect smaller systems, again narrowing their feasibility range.

From a policy perspective, the results suggest that modest levels of financial support could be decisive. For Mpafra, a 30% CAPEX subsidy would reduce the net annual cost at 1200 €/kW from ~575 €/yr to ~450 €/yr. In Koutselio, a 20% subsidy would be sufficient to keep net costs below 850 €/yr even under high CAPEX. Complementary measures such as reduced VAT on equipment or maintenance cost relief programs tied to EC participation could further stabilize investment outcomes.

In addition to CAPEX and OPEX, the degradation rate of PV systems is another critical factor influencing investment outcomes. The sensitivity analysis shows that increasing degradation from 0% to 2% per year raises the net annual cost by nearly 40% in the Mpafra case and by around 30% in Koutselio. While larger systems remain more resilient, households with modest loads or smaller installations become disproportionately exposed to lifetime performance losses. This underscores the importance of quality standards, warranties, and support schemes that safeguard long-term system performance, while also reinforcing the case for collective citizen participation in the energy system. Ensuring access to durable technologies and maintenance services can therefore complement financial incentives, enhancing both the economic attractiveness and social equity of EC participation.

In addition, the sensitivity to aggregator fees shows moderate but consistent effects: a fivefold increase in fees (from 0.001 to 0.005 €/kWh) raises net annual costs by about 8–10% in both cases. While less critical than CAPEX or OPEX, this highlights the importance of ensuring transparent and fair pricing of aggregation services. As aggregator participation becomes a prerequisite for unlocking demand response flexibility under EU and Greek regulation, safeguarding against excessive fee structures will be key to maintaining the economic attractiveness of energy community participation.

Beyond cost and technical parameters, the analysis also highlights the role of DR. Even under the simplified formulation used here, where per-interval load shifting is capped as a fraction of baseline demand, modest reductions in net annual costs are observed: approximately 6–7% for both households as α increases from 10% to 50%. While the absolute savings are limited, these results indicate that DR can complement PV investments even under conservative assumptions. This suggests that policies and market mechanisms enabling household-level flexibility will be an essential complement to financial incentives in ensuring the viability of energy com-munities under virtual net-billing.

Finally, the results underscore the strategic value of data-driven planning tools to navigate Greece's shifting legislative environment. As ECs are burdened by bureaucratic hurdles and regulatory uncertainty, tools like this can simplify decision-making, reduce investment risk, and foster trust among members. In the context of Law 5074/2024 and the growing complexity of energy market participation, such optimization frameworks can act as enablers, empower local actors and strengthen the legitimacy of grassroots initiatives. Ensuring that the most sensitive cost components are mitigated through targeted support will not only sustain the economic viability of citizen-led ECs but also safeguard compliance

with EU directives on energy democracy, while helping Greece achieve its national targets for decentralized renewable energy deployment.

5. Conclusions

This study presents a high-resolution MILP optimization model for determining the optimal PV sizing and DR actions for a single member of a Greek REC or CEC under the newly implemented virtual net-billing scheme. The model incorporates 15 min resolution data for consumption, production, and market prices, reflecting the dynamic and granular structure of Greece's updated energy regulations. The proposed single-objective formulation offers a practical tool to support citizens and cooperatives in evaluating centralized solar projects under realistic economic constraints.

While the model provides useful insights, it is not without limitations. A central limitation of this study is the absence of battery storage. Shared BESSs, although prevalent in European EC designs, are not currently permitted by the Greek law under the virtual net-billing framework. Consequently, our analysis focused on PV-only scenarios as a first validation step under current national regulation. Future work will extend the framework to include both individual household batteries and hypothetical shared BESS configurations, which are expected to further increase self-consumption, improve economic performance, and align the Greek case with the broader European experience.

Furthermore, the analysis was conducted for a single year and based on two households and serves as an initial validation rather than a basis for national-level generalization. The main contribution of the study lies in developing and testing an optimization framework for the new virtual net-billing model under the current Greek regulatory design. Future research will extend this work by incorporating larger and more diverse datasets—either from the open datasets reviewed in Section 3.2 or from new data collected directly from Greek energy communities through the DR-RISE project (https://dr-rise.eu/).

Looking ahead, the growing deployment of Electric Vehicles (EVs) (installed in properly insulated buildings) is expected to significantly reshape household electricity demand, both in terms of volume and temporal distribution. These technologies not only increase overall consumption but also introduce new flexibility opportunities that can be exploited through DR. Integrating heat pumps and EVs into demand-side management strategies can help flatten demand peaks and enhance system responsiveness [71]. Future work will include multi-day flexibility cycles, behavioral participation models, and appliance-level availability constraints, which are expected to reveal greater savings and strengthen the complementarity between DR and PV in energy communities.

A further limitation of this study is that the optimization is performed at the level of an individual household. Under the current Greek virtual net-billing framework, production and benefits are statically allocated to members, and there is no legal provision for dynamic energy sharing or multi-member collaborative optimization. This restricts the analysis to single-member PV sizing rather than community-level coordination. However, several research studies show that collective optimization and dynamic sharing can unlock higher efficiency and fairness in energy communities [72–74]. We therefore recommend that future regulatory reforms consider enabling such mechanisms, which would allow the presented framework to be extended to community-wide optimization and energy-sharing strategies.

Moreover, the inclusion of stochastic representations of solar generation and load uncertainty could provide a more robust and flexible optimization framework [75]. Such improvements would increase the relevance of the model for policy design and practical deployment across diverse EC settings. Finally, other compensation options for ECs could be considered for surplus production such as fixed tariffs under Power Purchase Agreements (PPAs).

An additional source of uncertainty for the future development of energy communities concerns electricity price dynamics. Price volatility directly affects the economics of virtual net-billing: higher retail prices increase the value of self-consumed PV and shorten payback periods, whereas lower prices weaken the incentive for investment. Beyond average price levels, volatility introduces greater investment risk for households and communities, as future savings become more uncertain. At the same time, fluctuating prices could increase the potential value of demand response, making flexibility a more important complement to PV deployment. These dynamics underline the need to account for electricity price variability in future analyses of energy community viability.

While ECs have demonstrated strong potential across Europe to promote renewable energy, energy democracy, and social equity, their success in Greece is hindered by persistent structural challenges [76]. Moreover, unresolved challenges such as grid access constraints, export curtailments, and a lack of prioritization for community-led initiatives pose significant risks to the long-term viability of the new virtual net-billing scheme. To ensure that RECs and CECs can thrive under this framework, technical optimization must be complemented by robust regulatory support. This includes transparent and equitable capacity allocation, curtailment protections, and policies that elevate social and environmental priorities above purely commercial interests.

Author Contributions: Conceptualization, I.-M.C. and D.K.; methodology, I.-M.C., D.K. and D.A.P.; software, I.-M.C., A.-G.C. and A.X.; validation, I.-M.C., D.K., A.-G.C., G.T.A. and A.X.; writing—original draft preparation, I.-M.C.; writing—review and editing, all; supervision, G.T.A. All authors have read and agreed to the published version of the manuscript.

Funding: The research was funded by the European Union (Grant Agreement No 101104154). Views and opinions expressed are, however, those of the authors only and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the granting authority can be held responsible for them.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Acknowledgments: Results presented in this work have been produced using the Aristotle University of Thessaloniki (AUTh) High Performance Computing Infrastructure and Resources.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CECs	Citizen Energy Communities
RECs	Renewable Energy Communities
ECs	Energy Communities
PV	Photovoltaic
BESS	Battery Energy Storage System
DR	Demand Response

A. Indices and Sets

t, T	Index and set of time intervals (15 min resolution)
d, D	Index and set of days
m, M	Index and set of months

B. Parameters

$D_{d,t}$	Baseline demand at day d and time t (kWh)
$P_{d,t}$	Normalized PV production at day d and time t

$\lambda_{d,t}^{WM}$	Day Ahead Market price at day d and time t (€/kWh)
λ^{R}	Fixed electricity import retail price (€/kWh)
λ^{A}	Aggregator′s charge on surplus energy (€/kWh)
λ_{m}^{N}	Monthly charge on netted energy (€/kWh)
P^{max}	Maximum capacity allowed by law (kW)
c^{cp}	Acquisition and installation cost per kwp (€/kW)
c^{op}	Maintenance cost per kwp for each y (€/kW)
r	Discount rate for cost calculation (%)
N	number of years for the assessment (years)
α	Demand response flexibility limit as a fraction of load
η	PV system degradation rate (%)

C. Variables

P^{sh}	Member′s PV share (kW)
$E_{d,t}^{EXP}$	Energy exported to the grid at day d and time t (kWh)
$E_{d,t}^{IMP}$	Energy imported from the grid at day d and time t (kWh)
$E_{d,t}^{N}$	Energy netted at day d and time t (kWh)
$E_{d,t}^{DR}$	Energy shifted at day d and time t (kWh)
$X_{d,t}$	Binary variable indicating whether the prosumer imports $(X_{d,t} = 1)$ or exports $(X_{d,t} = 0)$ energy at day d and time t

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