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Energy Sharing Under Uncertainty

A Long-Term Stochastic Multi-Criteria Assessment of Allocation Mechanisms in Renewable Energy Communities

Erasmus Mundus Joint Master on Smart Cities and Communities (SMACCs)

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ABSTRACT:

Renewable Energy Communities (RECs) face a defining governance decision at creation: selecting the Key of Repartition (KoR) — the rule that determines how shared renewable generation is allocated among members at each settlement period.
This thesis evaluates five sharing mechanisms applied to Guzmán Renovable, a 14-member, 30.3 kWp collective self-consumption community in Burgos, Spain. Performance is assessed across six criteria covering efficiency (self-consumption ratio), individual sufficiency (self-sufficiency ratio), economic value (bill savings), distributional equity (Gini coefficient), flexibility demand (Energy to Shift), and environmental impact (CO_2 avoided). Rather than relying on a single observed year, outcomes are characterized across several scenarios (years) generated by seasonal block bootstrap resampling of a 21-year historical solar record (2004–2025) and a six-year consumption record (2020–2025), capturing the inter-annual variability a community faces.
No KoR dominates across all criteria. Dynamic KoRs achieve a higher self-consumption ratio compared to static KoRs, they also avoid more emissions. The communities implemented KoR has the worst equity and ranks last on every criterion. Adding a shared 30 kWh / 15 kW battery raises self-consumption ratio for dynamic KoRs while leaving equity rankings unchanged. Critically, the stochastic framing reveals that equity outcomes are far more sensitive to inter-annual variability than efficiency.

KEYWORDS: Renewable energy communities, key of repartition, energy sharing mechanisms, stochastic simulation, seasonal block bootstrap, multi-criteria assessment, self-consumption rate, distributional equity, battery energy storage.

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1 Introduction

The growing deployment of distributed photovoltaic generation at the community scale is reshaping electricity supply from the demand side. Renewable Energy Communities (RECs) have emerged as a legally recognized vehicle for this transition: collective entities through which groups of consumers and prosumers share locally generated electricity, reduce their dependence on the grid, and capture economic and environmental benefits. A defining governance decision for any REC is the Key of Repartition (KoR) — the rule that determines how the community's shared generation is distributed among members at each settlement period. The KoR directly shapes who benefits making its design the central decision examined in this thesis.

EU member states recognize multiple KoR types but leave selection to individual communities and they differ across countries. Studies comparing sharing mechanisms have predominantly relied on single-year evaluations and a limited set of criteria, leaving a broader multi-criteria and long-term perspective underexplored. This thesis contributes a simulation-based, multi-criteria assessment of alternative sharing mechanisms applied to a real operating community, with particular attention to performance under inter-annual variability.

1.1 Scope

This thesis evaluates five sharing mechanisms for Guzmán Renovable, a Renewable Energy Community in Burgos, Spain. The mechanisms span static and dynamic allocation strategies and are assessed across criteria covering efficiency, equity, economic value, and environmental impact. Performance is evaluated not for a single year, but across a distribution of synthetic scenarios generated by seasonal bootstrap resampling of historical data, capturing the natural variability in solar generation and member consumption over a long planning horizon. The effect of a shared community battery energy storage system is examined as an additional scenario.

1.2 Objective and Paper Organization

The thesis pursues three objectives:

1. Implement and compare five sharing mechanisms for a REC across a multi-criteria performance framework covering efficiency, equity, economic value, and environmental impact.
2. Characterize the distribution of each KoR performance outcomes under inter-annual variability and assess their robustness.
3. Quantify the effect of a shared community battery storage system on each mechanism's performance across all criteria.

These objectives attempt to answer the central research question: what available allocation rules gives the best results for RECs under multiple criteria.

The remainder of this thesis is organized as follows. Chapter 2 provides background on EU energy community definitions and the regulatory frameworks governing sharing mechanisms in Spain, Belgium, and Finland. Chapter 3 reviews the literature on sharing mechanism design and evaluation, and on stochastic modeling in energy communities. Chapter 4 describes the energy community model, the sharing mechanisms evaluated, the stochastic simulation methodology, the performance criteria, and the case study data. Chapter 5 presents the simulation results. Chapter 6 discusses the findings in the context of community decision-making. Chapter 7 summarizes the main conclusions.

2 Background

This section establishes the conceptual and regulatory context for the analysis. It covers the definition and configuration of energy communities, including the role of the Key of Repartition as the central allocation design variable, and the national regulatory frameworks that govern energy sharing in Spain, Belgium, and Finland.

2.1 Energy Community Definition

The growing deployment of distributed energy resources (DERs)— photovoltaic panels, batteries — at the medium and low voltage level has shifted the role of electricity consumers from passive users to active participants in the energy system. Energy communities emerged as a response to this shift and European Union's directive to promote investment in renewable DERs. These are legal entities through which consumers and prosumers collectively produce, consume, and share locally generated renewable energy, without relying on traditional wholesale and retail market platforms. The objective is to deliver economic, social, and environmental benefits to members: bill reductions, social inclusion, and emissions reductions [1], [2].

The EU framework recognizes two distinct community types. Citizen Energy Communities (CECs) are defined under the Electricity Market Directive (2019/944) [2] and are open to any participant, including households, SMEs, and local authorities. Renewable Energy Communities (RECs), introduced under the Renewable Energy Directive (RED II, 2018/2001) [1], apply specifically to renewable generation. In both cases, participation is voluntary and members retain all rights as individual electricity customers (e.g., electricity supplier choice for complementary volumes).

2.2 Energy Community Configuration

Energy community configurations vary significantly in how shared generation is structured and distributed. In behind-the-meter (BTM) arrangements, generation and storage assets are co-located within a shared installation, and members exchange energy directly without grid intermediation. In collective self-consumption (CSC), a shared generation asset feeds into the grid and a DSO actively meters and allocates energy to each member at their individual connection point. Virtual net metering (VNM) follows a similar physical topology but replaces DSO-mediated allocation with virtual billing credits, requiring no physical proximity between members. Figure 1 visualizes these three configurations. The rules governing how energy is split among members at each settlement period also differ: some communities use fixed shares agreed at inception, while others adjust allocations dynamically based on real-time consumption.

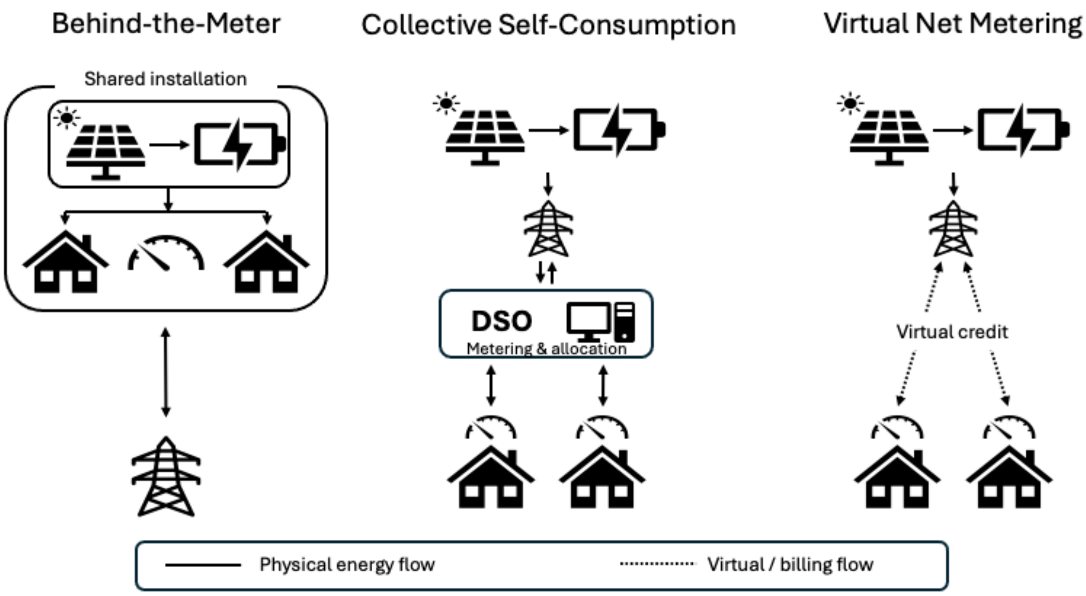

Figure 1. Left: BTM sharing within a single installation. Center: CSC with DSO-mediated metering and allocation. Right: VNM with virtual billing credits and no proximity requirement.

The central concept for characterizing these sharing arrangements is the Key of Repartition (KoR): the rule that governs how community-level generation is allocated across members at each settlement period (Figure 2). A KoR defines a set of coefficients, one per member, that must sum to one at every timestep — ensuring all community production is fully accounted for. The design of this coefficient set determines who benefits from shared production, in what proportion, and under what conditions, making it a primary design variable for an energy community.

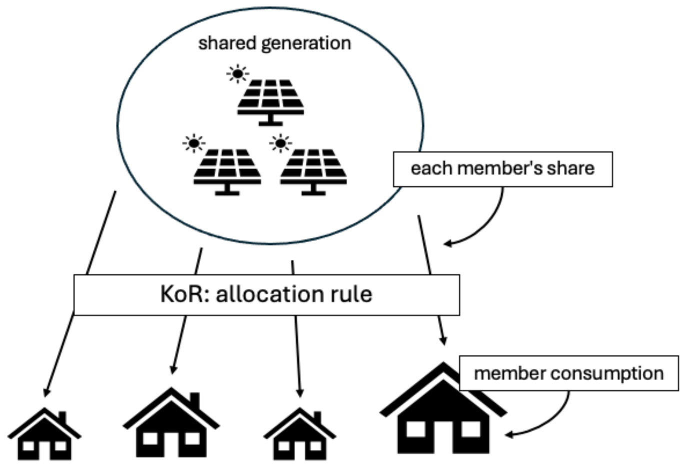

Figure 2. Role of the Key of Repartition (KoR) in the energy community model. Shared PV generation is distributed among members according to the KoR allocation rule.

The case study explored in this thesis, Guzman Renovable, is a Renewable Energy Community in Burgos, Spain, built around a collectively owned 30.3 kWp photovoltaic system with a CSC arrangement. Each of the 14 members contributes to the system cost in proportion to their agreed share of the community generation. Their KoR coefficient reflects both their financial stake and their entitlement to shared production. This structure, where ownership, cost, and allocation are aligned through the KoR, is one of many possible configurations, and motivates the central question of this thesis: the selection of the KoR design.

2.3 EU Regulatory Framework

The legal basis for energy communities in the EU is defined by two directives from the Clean Energy for All Europeans package: the Electricity Market Directive (2019/944) [2], which introduced Citizen Energy Communities, and the Renewable Energy Directive (RED II, 2018/2001) [1], which introduced Renewable Energy Communities. Both required member states to establish an enabling regulatory framework.

The directives define the obligations but leave implementation to member states, resulting in considerable variation across the EU in what sharing mechanisms are permitted and how network costs are recovered. The following sections describe the implementations most relevant to this thesis: Spain, where the case study community operates, as well as Belgium and Finland for comparison.

2.3.1 Spain

Spain regulates collective renewable energy sharing through Royal Decree RD 244/2019 [3], which establishes the conditions for collective self-consumption (autoconsumo colectivo). A group of consumers and prosumers share electricity from a shared renewable generation installation connected to the local low or medium voltage network. The IDAE guide for collective self-consumption (Guia de Autoconsumo Colectivo, 2024) [4] provides operational guidance on how communities register and apply their chosen sharing mechanism.

Four configurations are defined, distinguished by how surplus generation is handled. In configurations without surplus, inverter output is limited so that no energy is exported to the grid. In configurations eligible for compensation, members receive bill credits for unused allocated energy, which can either be redirected to nearby consumers (e.g., credited to another member within the same collective arrangement) or exported to the grid (e.g., compensated at the hourly spot price under Spain's simplified compensation scheme), depending on the configuration . In configurations not eligible for compensation, surplus is sold directly on the market by the generation facility owner.

In all configurations, generation is allocated among members through distribution coefficients (β) that must sum to one at each settlement period. RD 244/2019 grants full freedom in choosing the allocation criterion — consumption, contracted power, ownership share, or any other agreed basis. The IDAE guide distinguishes two permitted forms: a) a constant coefficient, identical for all hours of the year; and b) an hourly fixed coefficient, pre-defined but differentiated across the 8,760 hours of the year, enabling time-of-use discrimination [5]. In both cases, coefficients must be declared and submitted to the DSO at registration and may be modified at most once every four months [5]. If no agreement is submitted, the DSO applies a default scheme proportional to each member's contracted power [3], [5].

2.3.2 Belgium

Energy regulation in Belgium is decided by the regions, resulting in separate frameworks for Wallonia, Flanders, and Bruxelles. These regions have implemented collective self-consumption, but with different regulatory structures and permitted sharing rules.

In Wallonia, the regulatory framework is overseen by the CWAPE (Commission Wallonne pour l'Energie) [6]. Three types of energy sharing rules are recognized [7]: fixed egalitarian key allocates an equal share of production to each member, regardless of consumption. A fixed specific key assigns a predetermined percentage to each member based on an agreed criterion, such as ownership share or investment contribution. A dynamic prorata key allocates generation proportionally to each member's net consumption at each settlement period. Wallonia also permits iterative allocation [7], where distribution is applied over multiple rounds, enabling prioritization among member groups before redistributing any remaining surplus. In practice, communities combine these mechanisms: the Soleil d'Aubange community in the Gaume natural park, for example, uses two rounds of fixed egalitarian allocation followed by a final dynamic prorata round [8].

2.3.3 Finland

Finland transposed the EU energy community framework through the Electricity Market Act, with the Ministry of Economic Affairs and Employment (TEM) coordinating implementation [9].

The allocation of generation among members uses a fixed distribution key agreed by the community. When community generation exceeds total consumption, the treatment of surplus depends on the chosen distribution model. Under the SMA model, surplus electricity and any revenue from its sale are directed back to the production site — typically the housing cooperative that owns the generation asset. Under the SMB model, surplus is distributed to all community members according to the same agreed distribution key, with each member holding their own surplus electricity sales contract. Communities select their distribution model at formation.

3 Literature Review

With the regulatory context and the role of the KoR as a central design variable established, this chapter reviews the academic literature on sharing mechanism design and evaluation. It surveys the KoRs proposed across regulation and research, the criteria used to assess them, and the treatment of uncertainty — building toward the gap that motivates this thesis.

3.1 Sharing Rules: A taxonomy

The Walloon regulator, CWaPE, uses the term clé de répartition [7] to denote how the community generation is allocated to each member—it translates to keys of repartition or simply KoR. For the rule that allocates community generation among members; throughout this thesis the equivalent term key of repartition (KoR) is used. KoRs are defined differently across European countries through national laws and regulatory frameworks [10] and many studies propose alternative approaches that diverge from regulation [11]. Within the three countries reviewed in Section 2, several distinct KoRs are already in regulatory use, with the academic literature adding further variants. Table 1 consolidates the KoRs covered in this thesis, as well as those in literature, grouping them by allocation logic and noting their origin. Ultimately, KoRs can be grouped into static, dynamic, game-theoretic, and optimization based.

Table 1 Keys of repartition (KoRs) by allocation logic and source.

KoR Name	Description	Source
	STATIC KoRs	
Equal	Each member receives an identical fixed fraction of generation (1/N), regardless of consumption or investment.	[11], [12]
Fixed Ownership Share	Fixed coefficients proportional to each member's financial contribution to the shared asset.	[11], [12]
Fixed Annual Consumption	Fixed coefficients proportional to each member's historical annual consumption.	[11], [12]

Fixed Peak Demand	Fixed coefficients proportional to each member's contracted power or peak demand.	[12]
Fixed Production Share	Fixed coefficients proportional to each member's own production relative to total community production. Members without local assets receive nothing.	[11]
	DYNAMIC KoRs	
Consumption Prorata	Generation allocated proportionally to each member's actual consumption at every settlement period.	[10], [11]
Hybrid Equal-Prorata	Two-round allocation: equal split first, then unclaimed surplus redistributed by consumption prorata.	[11]
Cascade	Iterative equal-split rounds; satisfied members are removed each round and their surplus reallocated, converging toward a needs-based distribution.	[11]
	GAME-THEORETIC KoRs	
Shapley Value	Allocates benefits based on each member's average marginal contribution across all possible sub-coalitions. Stable when the game is convex.	[11], [12]
Minimum Variance (MinVar)	Selects the core allocation that minimizes variance of individual payoffs. Unique and always stable when the core is non-empty.	[12]
Nucleolus	Minimizes the maximum unhappiness of any sub-coalition. Always in the core when non-empty; more computationally demanding than MinVar.	[12]
	OPTIMIZATION-BASED KoRs	
Bill Minimization	Dynamic ex-post key minimizing the sum of all members' electricity bills.	[11], [13]
Equity-based (Min. Variance of Allocation)	Long-term planning key minimizing expected variance of annual energy allocation among consumers.	[10]
Equal Bill Saving Ratios	All members are constrained to achieve the same proportional bill reduction relative to their individual baseline.	[11]

Max-Min Savings	Maximizes the minimum individual bill reduction across all members. Prioritizes the worst-off participant.	[11]
Self-Sufficiency Constrained	Bill-minimization optimization with an added minimum self-sufficiency rate (SSR) constraint per member.	[13]

The taxonomy spans from simplicity and regulatory acceptance toward greater efficiency, fairness, and computational sophistication. Static KoRs dominate current regulation because they are transparent and easy to administer, but they ignore the temporal mismatch between generation and consumption that drives self-consumption performance. Dynamic, game-theoretic, and optimization-based KoRs respond to this limitation, yet the literature tends to evaluate them under deterministic conditions—a single year of measured or simulated data—leaving open how each behaves when generation, demand, and prices vary over longer horizons. This gap motivates the two reviews that follow: Section 3.2 surveys the metrics used to evaluate KoR performance, and Section 3.3 examines how uncertainty and stochastic modeling have been treated in the REC literature.

3.2 Performance Evaluation of Energy Sharing Mechanisms

Studies on sharing mechanisms typically select one or two metrics aligned with their design objective, making cross-study comparison difficult.

Economic and efficiency metrics dominate. Self-consumption rate (SCR) and self-sufficiency rate (SSR) are the most reported indicators. Fina et al. use these alongside electricity cost savings and find that dynamic keys achieve roughly 10% higher self-consumption than static KoRs [14]. Gianaroli et al. add a "shared energy assignment" metric to quantify not just how much is shared [15], but who receives it. Rego et al. focus on bill savings in a Portuguese prosumer community, evaluating how the allocation rule redistributes economic gains across members with heterogeneous consumption profiles [16].

Equity metrics form a smaller part of the evaluation. Musilek & Hussain show that dynamic keys can increase community self-consumption while concentrating gains among members whose consumption profile aligns with solar generation, and use equity metrics to expose uneven benefit distribution [17]. Gasca et al. extend this to centralized and decentralized community configurations, finding that cost-sharing strategy substantially redistributes outcomes regardless of the energy management logic [18]. Boccard & Goetz evaluate sharing rules against five normative criteria from cooperative game theory — efficiency, stability, individual rationality, equity, and monotonicity — and find that no standard rule satisfies all five simultaneously [19]. González-Asenjo et al. show that no cost allocation method can satisfy all fairness criteria simultaneously [20].

3.3 Uncertainty and Stochastic Evaluation

There is a significant limitation of studies only using one year of simulated data for a decision with a 20–25 year horizon (typical PV lifetime): a KoR that appears optimal in one year may not be robust to inter-annual variability in PV generation or member consumption.

Zheng et al. review scenario generation methods for wind and PV uncertainty, distinguishing explicit probabilistic methods (parametric distributions, copulas), implicit generative approaches (GANs, VAEs), and historical resampling methods (bootstrap, k-means). They conclude that resampling-based methods are computationally efficient, require no parametric assumptions, and preserve the temporal structure of the original data [21]. For power systems reliability analysis, Shu & Jirutitijaroen demonstrate that Latin Hypercube Sampling substantially reduces the number of scenarios needed to achieve a given variance target compared to Monte Carlo sampling [22].

There are limited studies that characterizes the distribution of KoR performance outcomes across multi-year scenarios or tests whether KoR rankings are robust to inter-annual variability.

4 Methods

This chapter presents the methodology used to evaluate five Keys of Repartition across a multi-criteria performance framework under long-term uncertainty. The analysis is organized around four components, described in Sections 4.1 through 4.4.

The starting point is the energy community model (Section 4.1) which defines the generation and demand inputs on which all KoR evaluations depend. Five allocation mechanisms are then specified in Section 4.2— two static KoRs (the community's current allocation and equal sharing) and three dynamic KoRs (consumption prorata, hybrid equal-prorata, and cascade) — each formulated as a set of coefficients that distribute shared generation among members at every settlement period.

Rather than evaluating these mechanisms against a single observed year, the long-term stochastic simulation described in Section 4.3 generates a distribution of synthetic years from the historical record using seasonal block bootstrapping. This captures the inter-annual variability in solar irradiance and member consumption that a community encounters over a typical 25-year PV lifetime, enabling conclusions that are not contingent on any year's conditions. A shared community battery storage scenario is evaluated within this same framework.

The performance criteria used to assess each KoR across all simulated scenarios are defined in Section 4.4. Six metrics are computed — covering efficiency, individual sufficiency, economic value, distributional equity, flexibility demand, and environmental impact — providing a multi-dimensional view whose outcome distributions are compared to characterize both expected performance and robustness to long-term variability.

The methodology is applied throughout to a concrete case: Guzmán Renovable, a collective self-consumption community in Burgos, Spain, operating a shared 30.3 kWp photovoltaic system across 14 members.

4.1 Energy Community Model

4.1.1 Baseline

The energy community model represents the physical energy flows between the shared PV plant, the community members, and the electricity grid. At each settlement period t

(one hour), the community PV plant produces a total generation $\mathrm{G}(t)$ [kWh], which is distributed among *M* members according to a selected KoR. Let $A_i(t)$ denote the hourly energy allocation assigned to member *i*. The allocation satisfies the following constraints:

$$\mathrm{A_i}(t) \geq 0, \qquad \forall\, i, t \tag{1}$$

$$\sum_i A_i(t) \leq G(t), \qquad \forall\, t \tag{2}$$

The model operates on energy surplus sharing: only the community-level generation surplus is subject to allocation. Each member's self-consumed energy from the community PV plant is limited by both their allocation and their actual consumption $\mathrm{C_i(t)}$:

$$\mathrm{E_i(t)} = \min\big(\mathrm{A_i(t)}, \mathrm{C_i(t)}\big) \tag{3}$$

When a member's allocation exceeds their consumption, the surplus is credited as excedentaria at the network export compensation rate. When their consumption exceeds their allocation, the remaining demand is met by grid import at the member's supply tariff.

Each member's net position at each settlement period is determined by comparing their allocation $A_i(t)$ to their actual consumption $C_i(t)$. The self-consumed community energy $E_i(t)$ is defined by Equation (3). The remaining allocation that the member does not consume — the *excedentaria* — is:

$$X_\mathrm{i}(\mathrm{t}) = \max\big(0, A_i(t) - C_i(t)\big) \tag{4}$$

and is compensated at the network export rate. Any consumption not covered by the allocation is met by grid import:

$$I_i(t) = \max\big(0, C_i(t) - A_i(t)\big) \tag{5}$$

at the member's applicable supply tariff. These three quantities satisfy the member-level energy balance:

$$C_i(t) = E_i(t) + I_i(t) \tag{6}$$

$$A_i(t) = E_i(t) + X_i(t) \tag{7}$$

At the community level, the allocation constraint ensures all generation is accounted for:

$$G(t) = \sum_i E_i(t) + \sum_i X_i(t) \tag{8}$$

4.1.2 Baseline with added BESS

A shared community BESS is evaluated alongside the baseline scenario to quantify the impact of battery storage on each KoR's performance across all metrics. The BESS operates at the community level prior to KoR allocation. Each hour, the battery charges from aggregate PV surplus (generation exceeding total community consumption) and discharges into aggregate deficit. Charge and discharge are mutually exclusive within any hour; the augmented generation $G_{aug}(t)$ available for KoR allocation is:

$$G_{aug}(t) = G_{PV}(t) - P_{charge}(t) + P_{discharge}(t) \tag{9}$$

All KoR rules and metric computations are applied to $G_{aug}(t)$ without modification.

The battery state of charge (SOC) is initialized at zero at the start of each scenario. The community net energy at each hour is defined as:

$$E_{net}(t) = G_{PV}(t) - C_{total}(t) \tag{10}$$

The dispatch algorithm applies a greedy rule-based strategy. When $E_{net}(t) > 0$ (PV surplus), the battery charges:

$$P_{charge}(t) = \min\big(E_{net}(t), P_{max}, E_{cap} - SOC(t-1)\big) \tag{11}$$

$$SOC(t) = SOC(t-1) + P_{charge}(t) \tag{12}$$

When $E_{net}(t) < 0$ (community deficit), the battery discharges:

$$P_{discharge}(t) = \min(E_{net}(t), P_{max}, SOC(t-1)) \tag{13}$$

$$SOC(t) = SOC(t-1) - P_{discharge}(t) \tag{14}$$

Each KoR is evaluated under both the baseline $G_{PV}(t)$ and the BESS-augmented $G_{aug}(t)$ scenarios across the same generated scenarios for a direct comparison.

4.2 Keys of Repartition

A Key of Repartition (KoR) defines the rule by which the community's shared PV generation is allocated among members at each settlement period. KoRs are broadly classified as static, where allocation coefficients are fixed at community creation and do not change over time, or dynamic, where coefficients are recomputed each settlement period based on actual generation and consumption. Dynamic KoRs are included in this analysis as a reference benchmark to assess the theoretical performance ceiling and to characterize the trade-offs associated with the static constraint.

Five KoRs are implemented and evaluated:

4.2.1.1 Static KoRs

Guzmán Specific (GA). The fixed allocation shares registered by the Guzman Renovable community with the Spanish distributor under Royal Decree RD 244/2019. These shares were agreed by the community at creation and represent the current operational baseline:

$$\mathrm{A_i}(t) = s_i \cdot G(t) \tag{15}$$

Equal Sharing (ES). Each member receives an equal fixed fraction of generation at every timestep:

$$\mathrm{A_i}(t) = \frac{G(t)}{M} \tag{16}$$

This is the simplest egalitarian key.

4.2.1.2 Dynamic KoRs

Consumption Prorata (PR). Generation is allocated proportionally to each member's actual consumption at each settlement period:

$$w_i(t) = \frac{C_i(t)}{\sum_j C_j(t)} \tag{17}$$

$$A_i(t) = \min\big(G(t) \cdot w_i(t), C_i(t)\big) \tag{18}$$

This is the relative distribution key described in Belgian regulation [7]. Because allocation shares are proportional to consumption, the fraction $G(t)/\sum_j C_j(t)$ applies equally to all members: when generation falls short of total consumption, every member receives a proportional fraction of their demand and no surplus arises; when generation exceeds total consumption, every member is fully satisfied simultaneously, and the residual is exported as community excedentaria.

Hybrid Equal-Prorata (HEP). The HEP mechanism operates in two successive rounds designed to balance a baseline equity guarantee with a needs-based correction. In the first round, generation is divided equally among all members, and each member receives the lesser of their equal share and their actual demand — ensuring no member is allocated more than they can consume. The surplus left unclaimed by members whose demand falls below the equal share is not wasted: it is pooled and redistributed in a second round proportionally to the remaining unmet demand of members who were not fully satisfied in the first. The mechanism thus provides every member with an equal initial entitlement to shared generation while directing residual energy toward those with the greatest need.

Cascade (CA). An iterative allocation procedure in which, at each round, the equal share among still-active members is computed. Members whose full remaining demand is covered by this equal share are fully satisfied and removed from the active pool; their freed allocation is returned to the pool for the next round. The loop continues until no further members can be fully satisfied, at which point the remaining pool is distributed equally among whoever is still active. This mechanism progressively reallocates unclaimed energy toward members with higher unmet demand, converging toward a needs-based distribution.

4.3 Performance Evaluation Criteria

The performance of each KoR is evaluated using six quantitative metrics covering community-level efficiency, individual sufficiency, economic value, distributional equity, flexibility demand, and environmental impact. Each metric is computed for every scenario and every KoR, producing a distribution of outcomes characterized by its mean and by the P10 and P90 percentiles, which represent the pessimistic and optimistic tails of the outcome distribution respectively.

4.3.1.1 Community Self-Consumption Rate (SCR)

The Self-Consumption Rate measures the fraction of the community's total PV generation that is collectively self-consumed:

$$\mathrm{SCR} = \frac{\sum_{i=1}^{M}\sum_{t=1}^{T}\min\left(G_{alloc,i}(t), C_i(t)\right)}{\sum_{t=1}^{T} G_{PV}(t)} \tag{19}$$

SCR takes values in [0, 1], where 1 indicates that all generated energy was consumed within the community without export. Higher SCR reflects greater temporal alignment between generation and consumption under the applied KoR. SCR is a community-level aggregate and is insensitive to how benefits are distributed across members.

4.3.1.2 Individual Self-Sufficiency Rate (SSR)

The Self-Sufficiency Rate for member *i* measures the fraction of that member's total consumption covered by community PV allocation:

$$\mathrm{SSR}_i = \frac{\sum_{t=1}^{T} \min\left(G_{alloc,i}(t), C_i(t)\right)}{\sum_{t=1}^{T} C_i(t)} \qquad (20)$$

SSR_i takes values in [0, 1]. Unlike SCR, SSR is computed per member and captures the individual benefit of community participation. The distribution of SSR across members under a given KoR reveals whether some members benefit significantly more than others from the same generation pool.

4.3.1.3 Annual Bill Saving per Member

The annual electricity bill saving for member *i* is the reduction in energy cost attributable to community PV participation, calculated as the monetary value of PV allocation that directly offsets the member's grid purchases, valued at the member's time-of-use supply tariff, plus any compensation received for surplus allocation exported to the grid, with taxes applied:

$$BS_i = \left(\sum_{t=1}^{T} G_{sc,i}(t) \cdot p_i(t) + E_{exc,i} \cdot r_{exc,i}\right) \cdot \tau_i \qquad (21)$$

where:

$G_{sc,i}(t) = \min\left(G_{alloc,i}(t), C_i(t)\right)$ is the self-consumed PV energy of member *i* at hour *t* [kWh]

$p_i(t)$ is the time-of-use supply tariff for member *i* at hour *t* [EUR/kWh]

$E_{exc,i} = \sum_{t=1}^{T} \max\left(0, G_{alloc,i}(t) - C_i(t)\right)$ is the total annual excedentaria — surplus PV allocation exported to the grid — for member *i* [kWh]

$r_{exc,i}$ is the excedentaria compensation rate [EUR/kWh]

$\tau_i = \left(1 + \alpha_{IEE,i}\right)\left(1 + \alpha_{VAT,i}\right)$ is the combined tax multiplier, accounting for Spanish electricity excise tax (IEE) and VAT

4.3.1.4 Gini Coefficient of Bill Savings

The Gini coefficient of member bill savings quantifies the inequality in the distribution of economic benefits BS_m across the M community members in a given scenario where *i* and *k* both index community members (*i*, *k* = 1, …, M):

$$\text{Gini} = \frac{\sum_{i=1}^{M}\sum_{k=1}^{M}|BS_i - BS_k|}{2M\sum_{i=1}^{M} Bi} \tag{22}$$

A Gini of 0 indicates perfectly equal savings across all members; a value approaching 1 indicates extreme concentration of savings BS_m in one or a few members.

4.3.1.5 Energy to Shift (ETS)

The Energy to Shift metric quantifies the minimum total demand relocation across all members and all hours that would be required to achieve the theoretical maximum SCR under a given KoR assuming members can reschedule consumption freely within each day. For each member *I* and each calendar day *d*, an optimal intra-day consumption schedule $\widetilde{C_\iota}(t)$ is constructed by redistributing hourly loads to hours of highest allocation, in descending order of $G_{alloc,i}(t)$, subject to the constraint that total daily consumption is preserved:

$$\sum_{t\epsilon d}\widetilde{C_\iota}(t) = \sum_{t\epsilon d} C_i(t) \qquad \forall\, i, d \tag{23}$$

The energy to shift is then the total upward demand movement across all members and hours:

$$ETS = \sum_{i=1}^{M}\sum_{t=1}^{T}\max(0,\ \widetilde{C_\iota}(t) - C_i(t)) \quad [kWh/year] \tag{24}$$

Values near zero indicate that the KoR already allocates energy in close temporal alignment with member consumption — as is the case for dynamic KoRs, which adapt allocation to actual demand each hour. High ETS values indicate a structural mismatch between the allocation profile and consumption patterns, reflecting the demand flexibility that would be required to close the gap to maximum SCR.

4.3.1.6 CO2 Emissions Avoided

The community CO2 emissions avoided by shared PV self-consumption are estimated as:

$$CO2_{avoided} = \frac{1}{10^6}\sum_{t=1}^{T}\left[\sum_{i=1}^{M}\min\left(G_{alloc,i}(t), C_i(t)\right)\right]\cdot(t) \qquad \textbf{(25)}$$

where $\phi(t)$is the hourly grid carbon intensity for the Spanish peninsula [gCO2eq/kWh], sourced from Electricity Maps (zone ES) for the year 2025. Self-consumed energy [kWh] multiplied by $\phi(t)$[gCO2eq/kWh] yields gCO2eq; division by 10^6converts to tCO2eq. The 2025 hourly intensity profile is applied uniformly across all bootstrap scenarios as a fixed reference, reflecting recent Spanish grid conditions. The avoided emissions represent the carbon cost of electricity that members would otherwise have drawn from the national grid in the absence of the community PV plant.

4.3.1.7 KoR Decision Framework

The analysis uses a criteria-informed comparative approach in which KoR performance across all six metrics is examined in depth, with attention to both expected performance and variability under uncertainty. The goal is not to produce a single ranked recommendation, but to highlight the trade-offs between KoRs and to provide the community with actionable insight into which KoR best serves their priorities.

4.4 Long-Term Stochastic Simulation

The performance of a KoR depends on the specific realization of PV generation and member consumption in any given year. To evaluate KoRs under conditions representative of long-term variability rather than a single observed year, a Monte Carlo simulation framework is applied. Many synthetic years are generated by seasonal bootstrap resampling of the historical record. Each KoR is evaluated across all synthetic scenarios, yielding a distribution of performance outcomes that characterizes both the expected performance and the sensitivity to year-to-year variability.

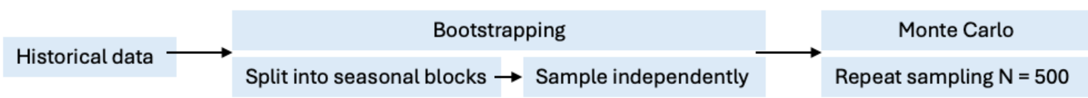

Figure 3. Seasonal block bootstrap Monte Carlo simulation framework.

4.4.1 Historical data

Guzmán Renovable provided information about the Energy Community for the purpose of this thesis. The community has a PV system with 30.3 kWp capacity, the only source of renewable generation at the site, the specifications of the installation are detailed in Table 2. The community is composed of 14 members, most are personal residences, their individual information is provided in Table 3.

Table 2: Guzmán Renovable photovoltaic specifications

Specification	Value
Onsite renewable capacity	30.3 kWp
Number of modules	60
Orientation	50% East, 50% west
Inclination	10°
Model type	LONGI LR5-66HPH505
Investment (CAPEX)	33,951.68 EURO
PV lifetime	25 years

Table 3: Guzmán Renovable community profile

Member	Sector	Average Consumption (2020-2025) (kWh/year)
1	Hospitality	19,702
2	Workshop	8,722
3	Residential	9,156
4	Residential	2,422
5	Residential	3,027
6	Residential	5,673
7	Residential	2,633
8	Residential	2,327
9	Residential	2,507
10	Residential	2,138
11	Residential	2,388
12	Office	3,625
13	Residential	1,620
14	Residential	1,175

The community began producing electricity from their PV panels in 2025, the full year of production is used for this thesis, plotted in Figure 4. There is a period from mid-July to mid-September where the production is degraded, to compensate, this period was excluded and replaced with CAMS-modelled output.

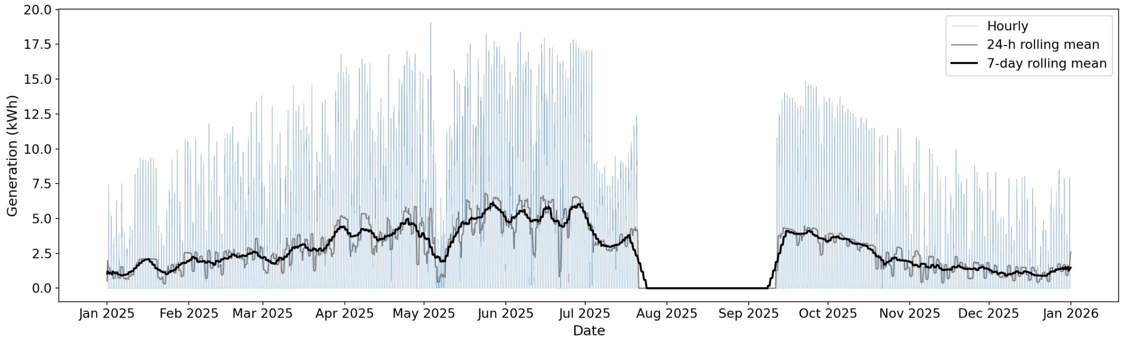

Figure 4: Guzmán Renovable 2025 PV production measured in kWh at the DC-AC inverter

4.4.1.1 Production Data Handling

One year's worth of production data gives an initial impression of the community but is not complete enough to generate future production scenarios. To compensate for the lack of data, historical forecasts datasets. Copernicus Atmosphere Monitoring Services (CAMS) provides historical values (2004 to present) of global (GHI), direct (DNI), and diffuse (DHI) solar irradiation at hourly resolution. The CAMS data, the community specification, along with pvlib, a python toolbox for simulating the performance of PV systems, enables the calculation of the total irradiance. Total plane-of-array irradiance was computed using the Perez transposition model, implemented via the pvlib-python library [23]. To calculate the DC power (P_{DC}) at the panels:

$$P_{DC\_East} = \frac{I_{East}}{1000} \cdot \frac{P_{peak}}{2} \cdot T_{corr} \cdot PR \tag{26}$$

$$P_{DC\_West} = \frac{I_{West}}{1000} \cdot \frac{P_{peak}}{2} \cdot T_{corr} \cdot PR \tag{27}$$

$$P_{DC} = P_{DC\_West} + P_{DC\_East} \tag{28}$$

Where:

	$\frac{I_{tot}}{1000}$	=	Irradiance normalized to STC reference (1000 W/m^2)
	$\frac{P_{peak}}{2}$	=	15.15 kWp, since half of the panels are facing East and the other half West. The peak capacity is 30.3 kWp
	T_{corr}	=	Linear temperature correction factor
	PR	=	Performance ratio

System losses due to soiling, wiring resistance, module mismatch, and other effects were accounted for through a performance ratio PR = 0.60, applied as a fixed derating factor on DC output.

The panels also experience losses due to temperature. Cell temperature was estimated from ERA5 2m air temperature using the Nominal Operating Cell Temperature (NOCT) model, and a linear power correction was applied using the manufacturer's temperature coefficient ($\gamma = -0.34\%$ °C) for the LONGI LR5-66HPH505 panels:

$$T_{cell} = T_{amb} + \frac{NOCT - 20}{800} \cdot I_{tot} \tag{29}$$

$$T_{corr} = 1 + \gamma \cdot (T_{cell} - T_{STC}) \tag{30}$$

Where:

	T_{cell}	=	Temperature of the PV panel cell
	T_{amb}	=	Ambient temperature estimated 2 meters in the air using ERA5 time series
	$NOCT$	=	45 °C nominal operating cell temperature (manufacturer specification)
	T_{corr}	=	Linear temperature correction factor
	γ	=	-0.34 % °C power temperature coefficient
	T_{STC}	=	25° C reference temperature at standard test conditions

DC power was converted to AC power (P_{AC}) using the PVWatts inverter model, implemented via pvlib [23], with a nominal inverter efficiency of $\eta_{inv} = 0.96$.

$$P_{AC} = \eta_{inv} \cdot P_{DC} \tag{31}$$

The historical weather data was calibrated to the existing PV production data to produce expected historical PV production values for the energy community. To validate the model, a comparison was performed: hourly generation estimates against measured production at the Guzmán site for the available period of 2025, excluding the degraded period (4 July – 10 September 2025). The model yielded an annual total of 20,292 kWh against a measured 20,527 kWh (bias of -1.1%), with an RMSE of 2.89 kWh/h and R^2 of 0.57, over 7,896 matched hourly observations. The validated model was subsequently applied to CAMS irradiance inputs spanning 2004–2025, producing 21 years of synthetic hourly generation. This historical series forms the basis for the bootstrap sampling procedure described in the following section. The overlayed series are in Figure 5.

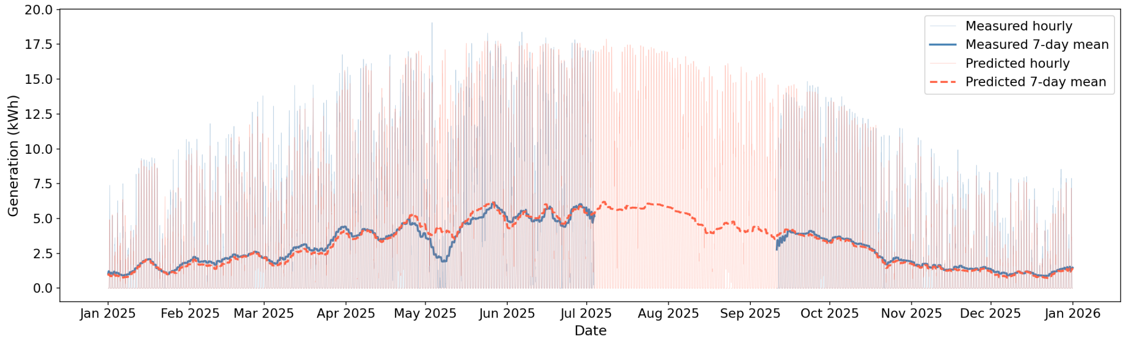

Figure 5: Measured hourly and predicted hourly for 2025.

4.4.2 Monte Carlo Scenario Generation via Seasonal Block Bootstrap

To generate scenarios a seasonal block bootstrap is applied. The seasonal structure preserves the intra-season autocorrelation of both solar irradiance and consumption behavior, while allowing across-season variability to be represented through independent sampling of each seasonal block.

The year is divided into four meteorological seasons following the Northern Hemisphere convention: Winter (December of the preceding year, January, February; 2,160 hours), Spring (March through May; 2,208 hours), Summer (June through August; 2,208 hours), and Autumn (September through November; 2,184 hours). February 29 is excluded from all years to maintain fixed season lengths.

For PV generation, a pool of historical seasonal profiles is constructed from the CAMS-based synthetic generation series spanning 2004 to 2025. Each pool entry is a contiguous seasonal block of the fixed length appropriate to that season. For community consumption, a corresponding pool is constructed from the six-year record (2020-2025), with each pool entry containing all 14 members simultaneously as a matrix of shape (season hours x 14). Retaining all members within the same block ensures that inter-member correlations within each season are preserved across scenarios: if Member 1 consumed heavily in a given winter, Members 2-14 are drawn from that same historical winter.

To generate a single synthetic scenario, one block is drawn at random with replacement independently for each of the four seasons, from the respective generation and consumption pools. The four seasonal blocks are concatenated in Winter-Spring-Summer-Autumn order to produce an 8,760-hour synthetic year. PV generation and community consumption are sampled independently from their separate pools, which cover different historical periods (generation: 2004-2025 from CAMS model output; consumption: 2020-2025 from metered data). This procedure is repeated N_{max} = 500 times.

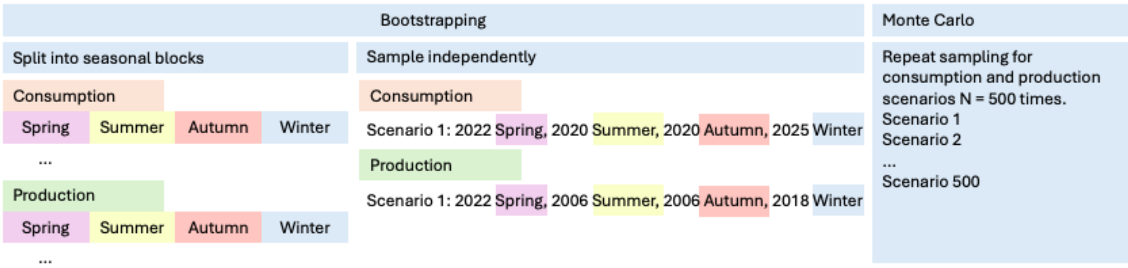

Figure 6: Seasonal block bootstrap procedure for scenario generation.

A maximum of *N* = 500 scenarios are generated upfront from the bootstrap pool. The number of scenarios retained for analysis, *N**, is determined by a convergence criterion rather than fixed arbitrarily. For each KoR and each metric, the half-width of the 95% confidence interval (CI) on the running mean is computed as:

$$\mathrm{h(N)} = 1.96 \cdot \frac{\sigma(N)}{\sqrt{N}} \qquad (32)$$

where σ(*N*) is the standard deviation of the metric across the first *N* scenarios. *N** is defined as the smallest N for which the CI half-width falls below a pre-defined tolerance and remains below that tolerance for at least 20 consecutive values of *N*. *N** is taken as the worst case across all KoRs and across the convergence of evaluated metrics, the case convergence of the metric that results in the greatest number of *N*, determines the actual amount of scenarios used and used as the convergence criterion.

5 Results

This section presents the results of the comparisons of five Keys of Repartition (KoRs) evaluated on the Guzmán Renovable Renewable Energy Community. As a reminder, these keys are the Guzmán Specific (GS), Equal Sharing (ES), Consumption Prorate (PR), Hybrid Equal/Prorate (HEP), and Cascade (CA).

The comparison is held by observing several metrics: community self-consumption, member self-sufficiency, economic savings, fairness in the distribution of bill savings across members, and environmental impact. Then, an analysis of the effect of adding a collective battery energy storage system (BESS) is carried out before discussing the potential for flexibility valorization.

All KoR comparisons are based on the Monte Carlo simulated years.

Throughout, outcomes are reported as the mean across all seasonal bootstrap scenarios together with the interdecile range (P10 to P90). This framing reflects the methodological emphasis on stochastic characterization: rather than reporting a single deterministic year, the analysis reveals the distribution of outcomes a community would experience over a long planning horizon subject to real climatic and consumption variability.

5.1 Multi-criteria KoR Comparison

Table 4 summarizes the KoR performance across five metrics — self-consumption rate (SCR), individual self-sufficiency rate (SSR), annual bill saving, CO_2 emissions avoided, and Gini coefficient of bill savings — reporting, for each metric, the best-performing KoR and its mean value across all simulated scenarios.

Table 4: Multi-criteria performances summary.

Criterion	Metric	Best mean (KoR)	Best mean (value)
Energy efficiency	SCR	PR / HEP / CA	0.788
Cost reduction	Bill saving	HEP	€328
Environmental	CO_2 avoided	PR/HEP/CA	2.166 tCO2eq/yr
Individual benefit	SSR	CA	0.351
Distributional equity	Gini	ES	0.152

The table confirms that no KoR achieves best-in-class performance on all criteria simultaneously. Equal Static dominates on equity but records the worst SCR, CO_2 avoided, and bill savings; it is the appropriate choice only if equity is the overriding community priority and efficiency losses — generation exported to the grid rather than self-consumed locally, despite members having unmet demand — are explicitly accepted. Cascade offers the best combination of mean performance across efficiency, equity, and SSR, making it the recommended allocation mechanism for communities seeking a balanced outcome — its robustness under long-term variability is examined further in Section 5.2. Hybrid Equal/Prorata records the highest mean bill saving at €328 per member, making it the strongest choice for communities where maximizing individual economic return is the primary priority. Consumption Prorata achieves equivalent efficiency and environmental outcomes to CA but with greater equity variability. The Guzmán Specific allocation ranks last or near last on every metric examined — it achieves lower SCR, higher Gini, lower SSR, and lower bill savings. This analysis therefore suggests that alternative allocation mechanisms can improve community outcomes across all evaluated dimensions.

5.1.1 Multi-Criteria Radar Comparison

Figure 7 presents a normalized radar plot with axes corresponding to SCR, mean SSR, mean bill saving, CO_2 avoided, and Gini (inverted). Dynamic KoRs dominate the outer ring on SCR, CO_2, and SSR. ES dominates on the equity (Gini) axis. CA presents the most balanced profile: it occupies the outer ring on efficiency and environmental axes while achieving a better equity position than PR or HEP. GS's profile is notable for its consistently interior position — it achieves neither the efficiency of dynamic KoRs nor the equity of ES.

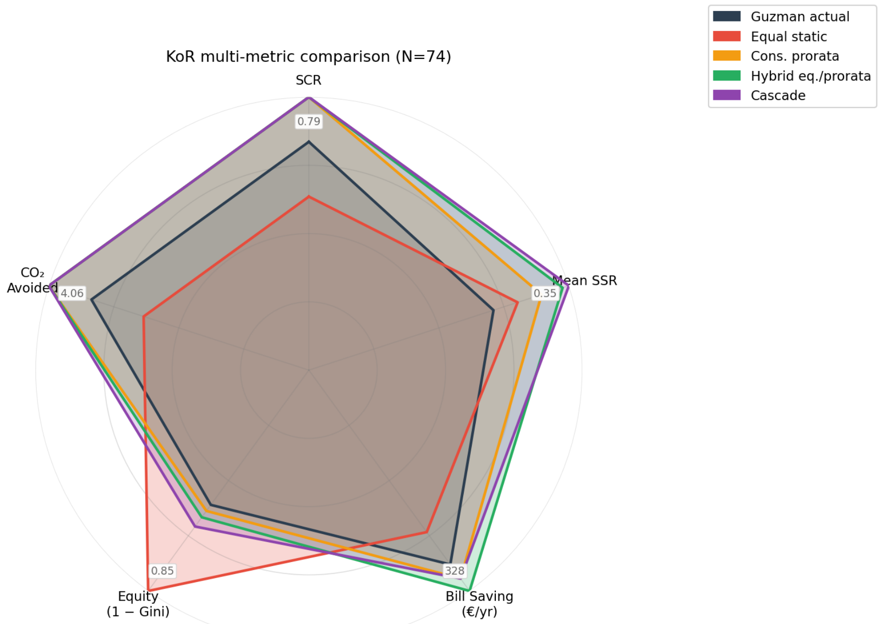

Figure 7: Multi-criteria radar plot comparing GS, ES, PR, HEP, and CA across five normalized performance axes: SCR, mean SSR, mean bill saving, CO2 avoided, and Gini (inverted so that outer = more equal).

Dynamic KoRs (PR, HEP, CA) succeed on SCR, CO_2, and SSR because they reallocate generation at each settlement period to track actual consumption. This minimizes the mismatches over time, typical of static keys. ES dominates the equity axis precisely because its fixed equal shares are consumption-blind: every member receives the same fraction regardless of need, which produces uniform savings but at the cost of systematic efficiency losses. GS's profile is the most revealing: its consistently interior position across all five axes means it makes no favorable trade-off — it achieves neither the efficiency of dynamic KoRs nor the equity of ES.

5.1.2 Simulation Convergence and Computational Cost

Before examining metric-level results, it is necessary to establish that the Monte Carlo sample size is sufficient to draw reliable conclusions. Convergence was assessed by computing, for each metric and each KoR, the smallest number of scenarios N* at which the running mean stabilized within a defined tolerance. The binding constraint across the entire analysis is the Gini coefficient under Consumption Prorata, which requires N*=74 scenarios to converge. All other metric and KoR combinations converge earlier: the Self-Consumption Rate (SCR) stabilizes at N*=59 for GS and N*=52 for the dynamic KoRs (PR, HEP, CA), while Equal Static converges rapidly at N*=11 owing to its lower inter-scenario variability. The Self-Sufficiency Rate (SSR) requires up to N*=52 (PR), and community bill savings converge fastest of all, reaching stability at N*=16 for PR and CA.

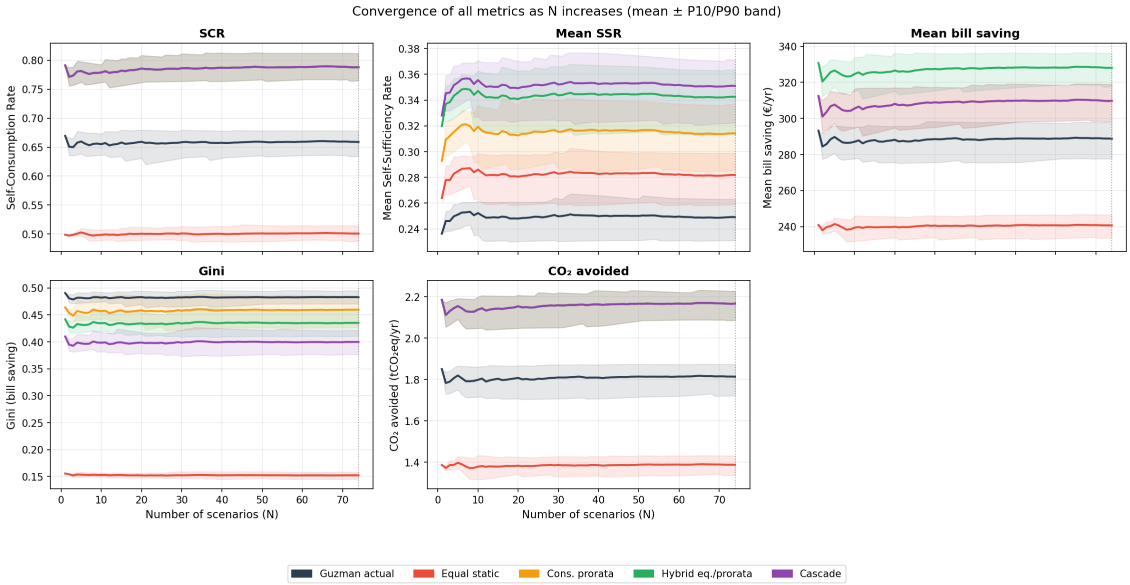

Figure 8: Monte Carlo convergence: 95% CI half-width on the running mean as a function of N, for each metric and KoR. The vertical line marks N*=74, the overall convergence threshold.

The convergence profile is shown in Figure 8. The convergence rates are informative: they indicate that equity outcomes are more sensitive to year-to-year variation than economic outcomes.

5.2 Long-Term Robustness Under Stochastic Variability

This section examines each KoR's outcome distribution — how consistently a KoR delivers its expected performance across the 74 simulated scenarios, and what a community should expect in a ‘poor year’ versus a ‘good one’. This is characterized by the interdecile range — the gap between the 10th and 90th percentile outcomes across simulated years — and used as an uncertainty indicator. Where this range is narrow, a KoR's performance is defined as reliably predictable; where a wide range means that outcomes depend substantially on climatic and consumption variability.

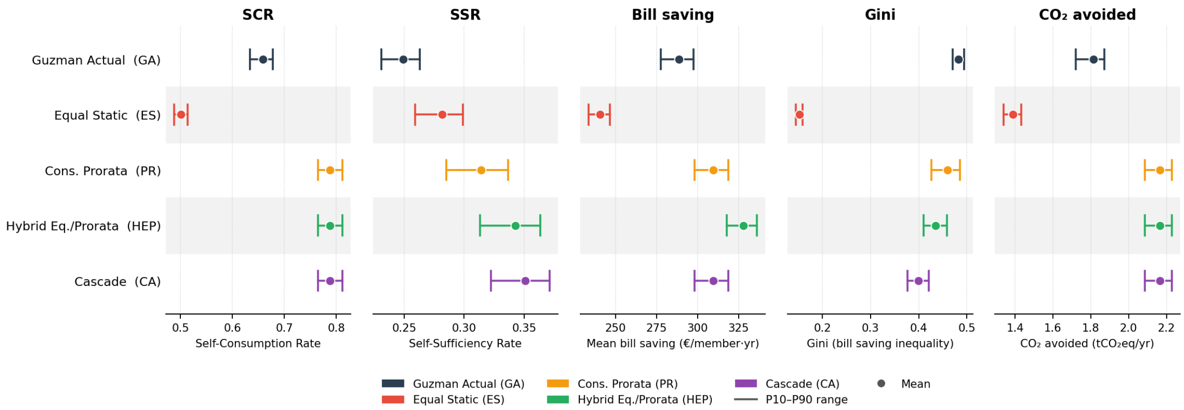

Figure 9: Mean and P10–P90 interdecile range of each KoR across simulated scenarios, for five performance metrics. Dots indicate the mean; whiskers span the 10th–90th percentile range.

Equal Static is the most robust KoR, exhibiting the narrowest P10–P90 bands for SCR (±0.013), SSR, and Gini (±0.007). This predictability arises from its simplicity: because allocation is fixed and symmetric, member-level outcomes track the aggregate generation signal closely and vary little with individual consumption patterns.

Consumption Prorata is the least robust KoR. Its Gini band spans ±0.030 — the widest of any KoR on any metric, and the constraint that determined the N*=74 sample size. Its SSR band is also the widest (±0.050). Under Consumption Prorata, equity outcomes are directly shaped by how consumption is distributed across members in a given year: when demand profiles are heterogeneous, members with higher consumption capture a disproportionate share of generation, widening inequality. Because this distribution shifts from year to year, the realized Gini ranges from 0.427 to 0.486 — a governance concern for communities that have made equity commitments to their members.

Cascade occupies a favorable robustness position. It achieves better mean equity than PR (Gini 0.400 versus 0.460) with a narrower band (±0.022 versus ±0.030), while matching PR on SCR and CO2. Its SSR is the highest of all KoRs. For a community prioritizing a combination of efficiency, moderate equity, and predictable long-term performance, CA presents the strongest evidence-based case.

5.3 Effect of Community Battery Storage (BESS)

Previous results are obtained in a situation where the community only rely on PV production, increasing the need of complementary patterns between the local production and consumption. In this second analysis, a shared 30 kWh / 15 kW BESS is added to the community. With this additional asset, members have the potential to defer the use of PV electricity over the day. Each KoR is applied in this situation to quantify the impact of community battery storage on their performances. The battery charges from community PV surplus and discharges into community deficit, operating as a pure self-consumption maximization device. It does not alter the KoR allocation rule — it augments the generation profile available to the allocator.

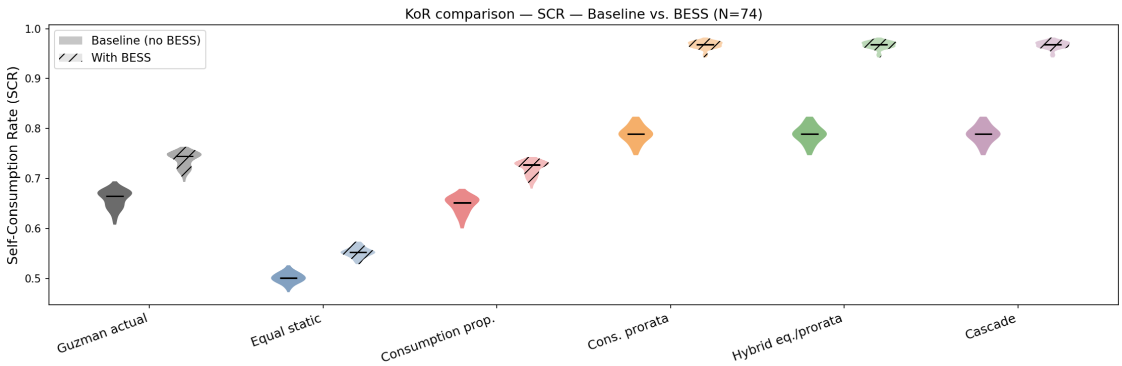

Figure 10: Self-consumption rate (SCR) for each KoR at baseline (no BESS, solid) and with community battery storage (hatched), across simulated scenarios. Each shape represents the outcome distribution; the horizontal bar marks the mean.

BESS improves self-consumption for all KoRs, but the magnitude differs substantially. Dynamic KoRs — PR, HEP, and CA — increase SCR from 0.788 to 0.967, maximizing the self-consumption capacity of the system. The remaining gap of 3.3% reflects generation that exceeds both instantaneous community demand and battery capacity, primarily during peak summer production hours. GS improves from 0.659 to 0.737 and ES from 0.501 to 0.552. The gain is proportionally smaller for static KoRs because their fixed allocation structure introduces a temporal mismatch between generation and member demand that battery storage alone cannot fully resolve.

CO2 avoided increases proportionally with self-consumed energy. Dynamic KoRs with BESS avoid 2.838 tCO2eq/yr, up from 2.166 tCO2eq/yr without storage — a 31% increase. GS rises from 1.813 to 2.170 tCO2eq/yr (+20%) and ES from 1.388 to 1.627 tCO2eq/yr (+17%). The absolute gap between dynamic and static KoRs widens with BESS: the community leaves more environmental benefit on the table by using a static KoR, even with battery storage in place.

Distributional equity is largely unaffected by BESS. Gini coefficients shift by less than 0.025 under all KoRs: GS 0.483 → 0.486, ES 0.152 → 0.145, PR 0.460 → 0.465, HEP 0.435

→ 0.435, CA 0.400 → 0.424. This is expected — the battery operates at the community level and its benefit is distributed according to the allocation rule already in place. Whatever equity imbalance seen by the KoRs remains the same.

The mean ranking of KoRs is unchanged with BESS. However, BESS does alter the variability structure: for dynamic KoRs, the SCR band narrows sharply from ±0.047 to ±0.016 — battery storage absorbs most year-to-year generation variability, making self-consumption highly predictable. Equity bands remain unaffected, and SSR bands widen slightly across all KoRs.

5.4 Demand Flexibility and Operational Guidance

In the previous section, we studied the use of collective BESS as a flexibility solution to improve the performance of the community under different allocation schemes. Another source of flexibility may directly come from member's consumption patterns. Indeed, to retrieve benefits from the local production, they may be tempted to shift part of their consumption to match the PV pattern. In the following, we quantify the energy that could be valorized if shifted at appropriate time.

To this end, we define the Energy to Shift (ETS) metric which measures the minimum total demand relocation that would be required to achieve the maximum SCR given the community's generation and consumption profiles. It quantifies the operational flexibility. A high ETS signals a large valorization opportunity: it represents the energy members could capture as additional self-consumption by shifting demand toward PV production hours. ETS = 0 means the allocation already achieves the theoretical optimum without any behavioral change. This indicator is computed for each KoR.

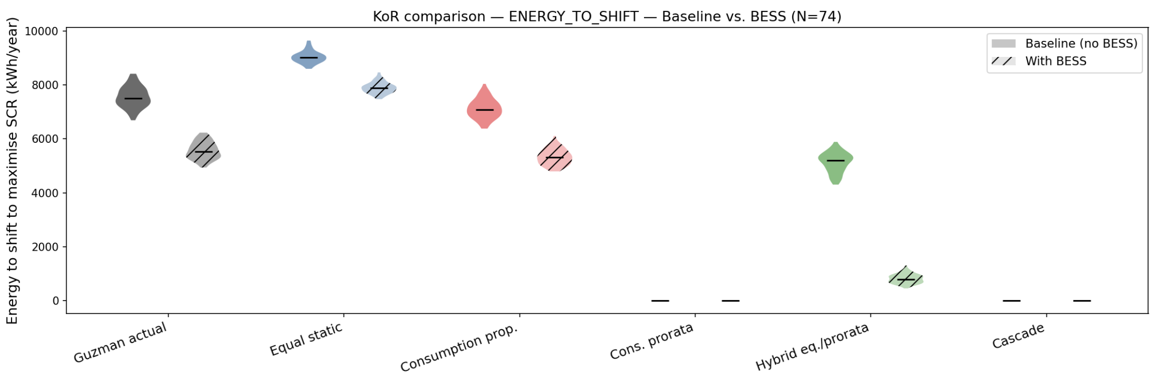

Figure 11: ETS at baseline and with BESS for each KoR

In the scenario without battery storage, PR and CA require zero demand shifting. Because these KoRs allocate generation proportionally to consumption at each hour, the allocation tracks member demand as closely as the generation profile allows — no residual temporal gap exists by construction. HEP retains a residual ETS of 5,129 kWh/yr (P10–P90: 4,551–5,540 kWh/yr) because its equal first-round allocation creates a mismatch for members whose consumption deviates from the equal share. GS requires 7,554 kWh/yr (P10–P90: 7,149–8,053 kWh/yr) and ES requires 9,035 kWh/yr (P10–P90: 8,784–9,347 kWh/yr). These values represent the annual kWh that would theoretically need to be shifted to close the gap between allocated generation and member demand under the given KoR.

With BESS, PR and CA remain at zero — battery storage eliminates any residual gap for these KoRs entirely. HEP drops sharply from 5,129 to 813 kWh/yr: the BESS absorbs most of the temporal mismatch that HEP's equal first-round produces, leaving only a small residual. For GS and ES, the reduction is more modest — to 5,279 and 7,713 kWh/yr respectively. This reflects a structural limitation: their ETS arises from fixed allocation coefficients that do not track actual consumption, and battery storage can smooth the temporal dimension of that mismatch but cannot correct the underlying coefficient mismatch.

The practical implication is direct. Communities adopting PR or CA have no need for demand flexibility programs — their KoR already self-corrects at each settlement period, and BESS eliminates any remaining gap entirely. For HEP communities, a BESS makes demand flexibility largely redundant (813 kWh/yr is a small residual). For GS and ES, the high ETS — even after BESS, 5,279 and 7,713 kWh/yr respectively — represents an opportunity: members who shift consumption toward peak PV production hours could capture that energy as additional community self-consumption rather than drawing from the grid.

6 Discussion

6.1 Interpreting the multi-criteria Trade-off

No single KoR dominates across all criteria. However, the results confirm and sharpen a finding from the literature: dynamic KoRs outperform static mechanisms on efficiency. Fina et al. [14] reported an approximate 10% self-consumption advantage for dynamic allocation; the results here are consistent with that finding.

The trade-off is between efficiency and equity. Equal Sharing achieves the best Gini coefficient (0.152), reflecting equal distribution of economic savings across all 14 members. But this sort of equality, where each member receives the same fraction of generation regardless of their consumption, comes at a cost: generation is inefficiently allocated to members who cannot use it in within that hour. Dynamic KoRs resolve this mismatch by reallocating generation toward members with actual demand, improving collective efficiency. However, this concentrates savings among higher-consumption members, an unequal distribution and therefore higher Gini coefficient.

Equal Sharing provides the same to everyone. Consumption Prorata provides on a needs basis, allocation proportional to demand. Neither in this analysis are superior. But what the results show is the consequence of each choice.

Cascade occupies the most defensible position across criteria. It achieves the same SCR as PR (0.788), the best mean SSR (0.351), and a Gini of 0.400 — better than both PR (0.460) and HEP (0.435). For communities that cannot articulate a single overriding priority, Cascade presents the strongest case for adoption.

6.2 The Guzmán Specific Case: Design, Performance, and Regulatory Context

The most direct result of this analysis is that the Guzmán Renovable community's current allocation mechanism — Guzmán Specific — ranks last or near last on every criterion evaluated. Its SCR of 0.659 trails the dynamic KoRs by 13 percentage points, its Gini of 0.483 is the second worst of all five mechanisms, and its mean bill saving and CO_2 avoided are the lowest in the comparison. It achieves no favorable trade-off: it is neither the most efficient, nor the most equitable, nor the best performing on any criterion.

Member 1 (hospitality sector, 31.0% allocation, 19,702 kWh/yr average consumption) holds a share that reflects their financial commitment but not their hourly demand profile. When that member's consumption is low — on weekday mornings or during lower-activity seasons — their allocated generation is exported to the grid rather than self-consumed, reducing SCR for the entire community. This KoR optimizes for equity of financial contribution at inception, but not for operational efficiency or equity of benefit over time.

Under current Spanish regulation (RD 244/2019, Order TED/1247/2021), only static KoRs are permitted for collective self-consumption communities. The dynamic mechanisms that outperform GS on every metric — Consumption Prorata, Hybrid Equal/Prorata, and Cascade — are not available to Spanish communities without regulatory reform. This is a significant constraint: the results show the dynamic KoRs achieve a 13–29 percentage-point SCR advantage, and BESS amplifies this gap (dynamic KoRs reach SCR 0.967 with storage; GS reaches only 0.737).

Beyond Spain, the regulatory contrast with Belgium is instructive. In Wallonia, CWaPE explicitly recognizes dynamic prorata allocation as a standard sharing key and permits iterative allocation for communities [7]. The infrastructure required for this — hourly metering and DSO-mediated allocation — is the same infrastructure that enables Spanish communities to operate collective self-consumption right now. The performance gap documented in this thesis provides evidence in support of extending Spain's permitted KoR set to include dynamic mechanisms.

6.3 What the Stochastic Framing Reveals

The idea behind a stochastic framing of this thesis is to better approach a decision that has a 20–25 year planning horizon. There is no certainty in whether a KoR's performance is stable or whether it varies substantially from year to year. The stochastic simulation framework applied in this thesis — 74 synthetic years generated via seasonal block bootstrap resampling — makes this variability visible.

The primary finding is that equity outcomes are significantly more variable than efficiency outcomes under inter-annual uncertainty. Self-consumption rate is relatively stable across scenarios: the P10–P90 band for dynamic KoRs is ±0.047, narrowing to ±0.016 with BESS. The Gini coefficient, by contrast, spans ±0.030 for Consumption

Prorata — a range from 0.427 to 0.486 across simulated years. Equal Sharing's Gini band is ±0.007, confirming that its equity performance is highly predictable by design. This asymmetry has a clear explanation: efficiency metrics track PV generation, which is relatively stable year to year; equity metrics track the distribution of consumption across members, which varies with household behavior, occupancy patterns, and economic activity.

For community governance, this result has direct implications. A community that selects Consumption Prorata on the basis of a single observed Gini value is committing to a KoR whose equity performance may differ meaningfully from that reference year. Cascade achieves a better mean Gini (0.400 versus 0.460) with a narrower band (±0.022 versus ±0.030). For communities that have made equity commitments to their members, the predictability of Cascade's equity performance is an argument in its favor.

The convergence analysis also carries a methodological implication for this area of research. The binding constraint across all metrics and KoRs was the Gini coefficient under Consumption Prorata, requiring $N^* = 74$ scenarios to stabilize within the 95% confidence interval. Economic metrics converged at $N^* = 16$; efficiency metrics at $N^* = 59$. This ordering reflects the relative sensitivity of each metric to inter-annual variability and suggests that studies aiming to evaluate equity outcomes of sharing mechanisms require substantially larger scenario sets than those focused on efficiency alone.

6.4 Limitations

Several limitations of this analysis should be acknowledged. First, the case study is a single community — 14 members, 30.3 kWp, predominantly residential, located in Burgos, Spain. The results characterize the performance of five KoRs for this specific configuration; communities with different size, sectoral composition, or climate may exhibit different relative rankings.

Second, the bootstrap simulation draws from the 2004–2025 historical record. Structural shifts — electrification of heating or transport, behavioral change, or climate trends — are not modeled. The six-year consumption record (2020–2025) is relatively short for characterizing long-term variability.

Third, electricity prices are held constant at current tariff levels across all scenarios. Future price trajectories, including changes to time-of-use tariff structures and to the excedentaria compensation rate, affect the absolute bill savings of each KoR and may alter relative rankings on economic criteria.

Fourth, the BESS model is simplified: it operates as a pure self-consumption maximization device with no degradation, and no optimized dispatch strategy.

Finally, the analysis does not model member turnover or strategic behavioral responses.

7 Conclusion

This thesis sets out to evaluate five Keys of Repartition for a operating Renewable Energy Community under long-term uncertainty, using a multi-criteria framework and a seasonal block bootstrap Monte Carlo simulation.

The central finding is that no single KoR is optimal, the choice involves a trade-off between efficiency and equity. The resolution depends on what a community values. Among the mechanisms evaluated, the Cascade KoR presents the most defensible all-round profile: it matches dynamic KoRs on self-consumption and environmental impact while achieving better equity than Consumption Prorata and greater efficiency than Equal Sharing. The community's current mechanism, Guzmán Specific, ranks last on every criterion. Any of the four alternatives would improve outcomes across all dimensions.

The stochastic framing exposes that equity outcomes are far more sensitive to inter-annual variability than efficiency outcomes. A KoR selected because of one year's Gini may perform quite differently over the planning horizon. This finding has direct implications for how communities should choose and commit to allocation mechanisms.

The regulatory constraint that limits Spanish communities to static KoRs is the binding obstacle to capturing the full performance potential shown here. There is a case for regulatory reform, enabling communities to take full advantage of what RECs can provide.

8 Responsible use of AI tools

Addressing the use of AI in this thesis feels incredibly important to me. Because of the time and year in which this thesis is being submitted, it is even more relevant. Every day it felt like there was a new tool available, and this felt like the perfect time to explore using AI — and using it well. However, I think it is important to acknowledge how difficult it was to write a thesis with AI so readily available. It felt like a constant battle of loosening the reins and then taking them back.

For this thesis I paid EUR 21.87/month for a Claude Pro subscription, which gave me access to the main AI tool I used throughout: Claude Code. The first way I used it was to organize my ideas — the thesis structure, the timeline, clarifying the objective and how I was going to achieve it. Once I had this foundation set up, I spent a lot of time going back and forth on my ideas before addressing them with my supervisor. I then did my research and literature review largely without AI, tracking everything I read through Zotero. Though, hoping to find more relevant papers, I did a free trial of ScienceDirect's AI called LeapSpace, which was interesting and helped me find some useful articles.

Once the foundation was laid, I began building my model — the core of this thesis. I spent a lot of time developing the logic myself, and once that was established, I coded it with Claude Code. I had access to it directly through my terminal, so I could edit, review, and write code on my computer by prompting the command line. This was exciting. It felt so easy that I started building more complex models based on papers I was reading — Latin Hypercube sampling, Markov Chain simulations, and I even explored a diffusion model-based time series generation framework called TimeCraft. I was already looking into computing capabilities just to run some of these. This is when I lost the reins: I tried to explain to my advisor how one of these models worked, and I couldn't. So, I went back to the foundation I had laid and the model I had already thought through myself. From that point, AI helped me in a more grounded way: it took my model from a Jupyter Notebook to a standardized project repository, helped me iterate, and helped me stick to a plan.

When it came to processing results, AI was especially helpful for generating figures. I would generate one figure, not like it, and AI could generate ten variations so I could choose how to best communicate my data.

I also got crafty with how I set things up. I connected Notion (my note-taking app), Zotero, my working thesis document, and my GitHub repository to Claude Code via MCP (Model Context Protocol), a standardized protocol that lets the AI interact with external tools directly from the terminal. By doing this I could ask things like: *"Where did I leave off in my last working session?"* or *"Take a look at the notes from my last supervisor meeting — what should I work on next?"* or *"Write a bullet list of everything I've changed in the model."* It made keeping track of a long, complex project much more manageable.

In terms of where AI-assisted content appears in this manuscript: the Python codebase underlying the model in §4 (Methods) was implemented with Claude Code assistance; the figures throughout §5 (Results) were generated and refined with AI help before being selected by me; and the early structural planning predates the written chapters entirely. The literature review (§3), all written sections, the interpretation of results, the discussion (§6), and the conclusions (§7) were written by me without AI-generated text.

As for verification: I reviewed and tested all code against expected outputs before using it. Whenever I could not understand or explain what the AI had built — as with the more complex model variants — I did not use it. That was my check.

The author of the thesis takes full responsibility for the content of the thesis and confirms that all analysis, interpretations, and conclusions were developed by the author.

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Appendix

Algorithm Descriptions

The following pseudocode describes the core algorithms of the energy-sharing simulation model. Notation: M = number of community members; G_t = community PV generation at hour t [kWh]; d_{m,t} = electricity demand of member m at hour t [kWh]; α_{m,t} = PV energy allocated to member m at hour t [kWh]. The complete source code (Python) is available at github.com/msofiaospina/rec-thesis-model.

Algorithm A.1: Seasonal Bootstrap Sampling

Input: H historical hourly profiles (generation and/or consumption), T ≥ 1 complete years

N number of synthetic annual scenarios to generate

Output: N synthetic 8,760-hour annual profiles

```
for each season s ∈ {Winter (Dec–Feb), Spring (Mar–May),
                     Summer (Jun–Aug), Autumn (Sep–Nov)} do
    pool_s  ←  all complete seasonal sub-profiles from H
end for

for i = 1 to N do
    for each season s do
       draw one profile uniformly at random from pool_s  (with replacement)
    end for
    scenario_i  ←  concatenate the four drawn profiles  (8,760 h)
end for

return  { scenario_1 , ... , scenario_N }
```

Algorithm A.2: GuzmanSpecific KoR (Static Baseline)

Input: G_t community PV generation at hour t [kWh]

w_m fixed allocation coefficient for member m (from network operator registration)

Output: α_{m,t} energy allocated to member m at hour t [kWh]

```
for each hour t do
```

```
    for each member m = 1, ..., M do
        α_{m,t}  ←  w_m · G_t
    end for
end for

{Guzman shares w_m (M = 14): 31.0%, 15.6%, 10.0%, 6.0%, 5.7%, 5.7%,
                             4.5%,  4.4%,  4.0%,  3.2%, 3.1%, 2.7%, 2.7%, 1.4%}
```

Algorithm A.3: EqualSharing KoR (Static)

Input: G_t community PV generation at hour t [kWh]

M number of community members

Output: α_{m,t} energy allocated to member m at hour t [kWh]

```
for each hour t do
    for each member m = 1, ..., M do
        α_{m,t}  ←  G_t / M
    end for
end for
```

Algorithm A.4: ConsumptionProrata KoR (Dynamic)

Input: G_t community PV generation at hour t [kWh]

d_{m,t} electricity demand of member m at hour t [kWh]

Output: α_{m,t} energy allocated to member m at hour t [kWh]

```
for each hour t do
    D_t  ←  Σ_m d_{m,t}
    if D_t > 0  then   s_{m,t} ← d_{m,t} / D_t   for all m
    else               s_{m,t} ← 1/M   for all m    {equal fallback}

    for each member m do
        α_{m,t}  ←  min( s_{m,t} · G_t ,  d_{m,t} )
    end for

    S  ←  G_t  –  Σ_m α_{m,t}                {unclaimed surplus}
```

Algorithm A.5: HybridEqualProrate KoR (Dynamic)

Input: G_t community PV generation at hour t [kWh]

d_{m,t} electricity demand of member m at hour t [kWh]

M number of community members

Output: α_{m,t} energy allocated to member m at hour t [kWh]

```
for each hour t do
    ε  ←  G_t / M                             {equal share per member}

  ── Round 1: equal allocation, capped at demand ──

    for each member m do
        α_{m,t}  ←  min( ε ,  d_{m,t} )
    end for

    S  ←  Σ_m ( ε  –  α_{m,t} )           {unclaimed equal-share surplus}

  ── Round 2: redistribute S proportionally to unmet demand ──

    for each member m do
        r_{m,t}  ←  max( d_{m,t}  –  ε ,  0 )   {demand above equal share}
    end for
    R_t  ←  Σ_m r_{m,t}
    if S > 0  and  R_t > 0  then
        for each m with r_{m,t} > 0 do
            α_{m,t}  ←  α_{m,t}  +  ( r_{m,t} / R_t ) · S
        end for
    end if
end for
```

Algorithm A.6: Cascade KoR (Dynamic, Iterative)

Input: G_t community PV generation at hour t [kWh]

d_{m,t} electricity demand of member m at hour t [kWh]

M number of community members

Output: α_{m,t} energy allocated to member m at hour t [kWh]

```
for each hour t do
    A  ←  {1, ..., M}                         {active members}
    P  ←  G_t                                 {remaining energy pool}
    α_{m,t}  ←  0  for all m
    r_{m,t}  ←  max( d_{m,t} , 0 )  for all m   {remaining demand}

    repeat
        ε  ←  P / |A|                          {equal share for active members}
        F  ←  { m ∈ A : r_{m,t}  ≤  ε }        {fully satisfiable members}

        if F = ∅  then
            α_{m,t}  ←  α_{m,t}  +  ε  for all m ∈ A   {split pool equally}
            break
        end if

        for each m ∈ F do
            α_{m,t}  ←  α_{m,t}  +  r_{m,t}         {fully satisfy member}
            P  ←  P  –  r_{m,t}
            A  ←  A \ {m}
        end for
        P  ←  max(P, 0)
    until A = ∅
```

```
end for
```