



**Horizon Europe**  
**EUROPEAN COMMISSION**  
**European Climate, Infrastructure and Environment Executive Agency (CINEA)**  
**Grant agreement no. 101160684**



## Use of open-source P2P energy sharing platforms for energy Democratization

### Deliverable D 2.3 P2P trading matching and energy sharing models

**Document Details**

<b>Due date</b>	31-12-2025
<b>Actual delivery date</b>	30-12-2025
<b>Lead Contractor</b>	KU Leuven
<b>Version</b>	1.0
<b>Prepared by</b>	Yucun Lu (KU Leuven), Erik Delarue (KU Leuven), Jelle Meus (KU Leuven), Salomé Aubri (Artelys), Nicolas Fatras (Artelys), Michaël Gabay (Artelys), Rémi Simon (Artelys), Victoria Deichmann (INESC-ID), Diogo Pinto Ferreira (INESC-ID), Tomás Glória (INESC-ID), Alena Kostalova (INESC-ID), Hugo Morais (INESC-ID), Wicak Ananduta (VITO), Hossein Fani (VITO), Anibal Sanjab (VITO), Jure Vulinovic (VITO)
<b>Teams involved</b>	Thomas Heylen (Klimaan), Steven Laurijssen (Klimaan)
<b>Reviewed by</b>	Gilles Deleuze (Exaion), Antonio Grilo (INESC-ID), and Soosan Naderi (Exaion). Glenn Reynders (KU Leuven) as the scientific coordinator
<b>Dissemination Level</b>	Public

### Project Contractual Details

<b>Project Title</b>	Use of open-source P2P energy sharing platforms for energy democratization
<b>Project Acronym</b>	U2Demo
<b>Grant Agreement No.</b>	101160684
<b>Project Start Date</b>	01-09-2024
<b>Project End Date</b>	29-02-2028
<b>Duration</b>	42 months

### Document History

<b>Version</b>	<b>Date</b>	<b>Contributor(s)</b>	<b>Description</b>
0.1	1/12/2025	Yucun Lu et al.	Version for internal review
0.11	17/12/2025	Gilles Deleuze et al.	Internal reviews available
0.2	19/12/2025	Yucun Lu et al.	Version for scientific coordinator review
0.22	21/12/2025	Glenn Reynders	Scientific coordinator review available
1.0	24/12/2025	Yucun Lu et al.	Final report

**Disclaimer**

This document has been produced in the context of the U2Demo project<sup>1</sup>. Views and opinions expressed in this document are however those of the authors only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither the European Union nor the granting authority can be held responsible for them.

**Acknowledgment**

This document is a deliverable of U2Demo project. U2Demo has received funding from the European Union's Horizon Europe programme under grant agreement no. 101160684.



**Funded by  
the European Union**

---

<sup>1</sup><https://u2demo.eu/>

## Executive summary

---

This deliverable presents the outcomes of Task 2.3 of the U2Demo project. It presents analytical models (from conceptualization to mathematical formulations) that evaluate and quantify the implications of various local energy sharing and trading models. These models capture how allocation rules, pricing approaches, and clearing and matching algorithms affect outcomes at the individual and community levels within local energy communities.

This deliverable makes three main contributions. First, it introduces a structured classification of local energy sharing and trading mechanisms. This classification distinguishes between collective and individual arrangements, as well as centralized and distributed configurations. This framework identifies six fundamental model types that capture the diversity of implementations observed in practice and proposed in the literature.

Second, the deliverable develops mathematical formulations for the four model types requiring explicit market tooling to enable the local sharing and trading of energy: (i) allocation of capacity, energy, and revenues from collective assets, (ii) centralized individual energy sharing through internal pricing, (iii) auction-based centralized individual trading, and (iv) pool-based distributed peer-to-peer trading.

Third, these four models are applied to a common case study based on the Dutch Scheveningen pilot. This case study represents a real-world energy community comprising participants with collective and individual assets and heterogeneous profiles. We apply the models to different test cases by altering the pilot's system configuration. As such, we can examine the outcomes under various conditions. We evaluate the outcomes using a set of KPIs that cover the community's procurement costs, as well as fairness and sustainability metrics.

Results indicate that both **centralized and decentralized collective allocation models** provide substantial cost savings and improve self-sufficiency relative to a baseline without energy sharing or trading. Theoretical allocation methods, such as the optimal excess method and the Shapley value, ensure efficiency and individual rationality, though they are computationally demanding. Heuristic methods, particularly multi-round static sharing keys, are a practical alternative for larger communities with flexible assets.

**Internal pricing mechanisms**, such as the mid-market rate and the supply-demand ratio, also deliver substantial cost reductions relative to the baseline without energy sharing. This particularly holds for communities dominated by individual participants that are facing fixed retail contracts. Indeed, internal pricing mechanisms require careful handling of collective assets and negative price conditions to avoid inefficiencies.

Although **auction-based mechanisms** can provide additional flexibility in how energy is allocated within a community, their effectiveness depends heavily on the participants' bidding behavior. In our case study, the incremental benefit over internal pricing or collective management was minimal. This suggests that the additional complexity and participant involvement may not always be justified. Nevertheless, this finding is highly system-specific, and the decision to implement auction-based mechanisms should be evaluated on a case-by-case basis.

**Pool-based distributed peer-to-peer trading** reliably lowers total costs but distributes benefits unevenly due to individual transaction prices, creating potential equity concerns. Although these mechanisms are effective at reducing the total energy bill of the community, they may require additional fairness measures to ensure community members' satisfaction.

Overall, centralized and decentralized energy management schemes and internal pricing mechanisms closely approximate the community's best achievable outcome, at least in the considered case study. Auction-based and distributed P2P approaches offer additional flexibility and customization but introduce complexity, participant engagement requirements, and potentially distributional trade-offs.

## Table of Contents

---

Executive summary . . . . .	5
Table of contents . . . . .	8
List of figures . . . . .	9
List of tables . . . . .	10
Keywords, acronyms . . . . .	11
Nomenclature . . . . .	12
1 Introduction . . . . .	14
1.1 Background and motivation . . . . .	14
1.2 Contributions of the deliverable . . . . .	14
1.3 Relationship with other deliverables . . . . .	16
1.4 Structure of the deliverable . . . . .	17
2 Overview and classification of energy sharing and trading models . . . . .	18
2.1 Structure and classification . . . . .	18
2.2 Six representative models . . . . .	18
2.2.1 Collective energy sharing . . . . .	19
2.2.2 Individual energy sharing – centralized . . . . .	19
2.2.3 Individual energy sharing – distributed . . . . .	21
2.3 Mapping of energy community initiatives and pilot activities . . . . .	21
2.4 Focus of U2Demo modeling activities . . . . .	22
3 Numerical case study and setup . . . . .	24
3.1 Test case description . . . . .	24
3.1.1 The Scheveningen pilot . . . . .	24
3.1.2 Case overview . . . . .	26
3.1.3 Data and processing . . . . .	27
3.2 General assumptions . . . . .	28
3.3 Key performance metrics . . . . .	29
3.3.1 Total energy invoice . . . . .	29
3.3.2 Individual cost saving . . . . .	29
3.3.3 Self-consumption ratio . . . . .	29
3.3.4 Self-sufficiency ratio . . . . .	30
3.4 Baseline results . . . . .	30
3.4.1 Total energy invoice . . . . .	30
3.4.2 Self-consumption and self-sufficiency ratios . . . . .	31
4 Capacity, energy, and revenue allocation models . . . . .	34
4.1 Day-ahead scheduling models . . . . .	34
4.2 Cost and revenue allocation mechanisms . . . . .	35
4.2.1 Shapley values . . . . .	36
4.2.2 Optimal excess . . . . .	36
4.2.3 Hybrid prorated allocation . . . . .	37
4.2.4 Cost allocation with revenue from collective assets . . . . .	37
4.3 Heuristic allocation mechanisms . . . . .	38
4.3.1 Static sharing keys . . . . .	38
4.3.2 Dynamic sharing keys . . . . .	40
4.3.3 Multi-round sharing keys . . . . .	41
4.3.4 Alternative sharing keys . . . . .	42

---

4.3.5	Surplus after allocation	43
4.3.6	Allocated costs and revenues	44
4.4	Model particularities	44
4.4.1	Model-specific assumptions	44
4.4.2	Model-specific KPIs	44
4.5	Results	45
4.5.1	Total energy invoice	46
4.5.2	Self-consumption and self-sufficiency ratios	47
4.5.3	Efficiency of allocation mechanisms	49
4.5.4	Daily cost saving	50
4.5.5	Stability of allocation mechanisms	52
4.5.6	Computational time of allocation mechanisms	52
5	Internal energy pricing models	54
5.1	Methodology	54
5.1.1	Decision-making model by individual consumers	55
5.1.2	Mid-market rate	56
5.1.3	Supply-demand ratio	57
5.1.4	Implementation algorithm	57
5.2	Model particularities	59
5.2.1	Model-specific assumptions	59
5.2.2	Model-specific KPIs	59
5.3	Results	59
5.3.1	Total energy invoice	60
5.3.2	Self-consumption ratio	60
5.3.3	Self-sufficiency ratio	62
5.3.4	Individual cost saving	63
6	Auction-based local energy trading model	66
6.1	Methodology	66
6.1.1	Order generation by market participants	66
6.1.2	Market clearing algorithm	67
6.1.3	Mathematical formulation	67
6.2	Model particularities	69
6.2.1	Model-specific assumptions	69
6.2.2	Baseline	70
6.3	Results	71
6.3.1	Case 1 results	71
6.3.2	Case 2 results	71
6.3.3	Case 3 results	73
7	Peer-to-peer energy trading models	75
7.1	Methodology	75
7.1.1	Retailer	75
7.1.2	Peers	76
7.1.3	Batteries	76
7.1.4	Model variables, sets and inputs	76
7.1.5	Mathematical formulation	77
7.2	Model particularities	79
7.2.1	Model-specific assumptions	79
7.2.2	Description of the baseline simulation test	79



7.2.3	Description of P2P simulation tests . . . . .	80
7.3	Results . . . . .	80
8	Discussion . . . . .	84
8.1	Assessment within the four fundamental mechanisms . . . . .	84
8.2	Assessment across the four fundamental mechanisms . . . . .	86
8.3	Limitations and suggestions for further research . . . . .	87
9	Conclusion and recommendations . . . . .	89
10	References . . . . .	90
	APPENDIX A: Decentralized and centralized energy management problems . . . . .	94

## List of Figures

---

Figure 1.1	Linkages with other deliverables within the U2demo project. . . . .	16
Figure 2.1	Distinction between individual and collective energy sharing. . . . .	19
Figure 2.2	Collective energy sharing models. . . . .	20
Figure 2.3	Centralized individual energy sharing models. . . . .	21
Figure 2.4	Distributed individual energy sharing models. . . . .	22
Figure 3.1	Entities involved in the Scheverningen pilot. . . . .	25
Figure 3.2	Self-consumption ratio under the baseline model . . . . .	33
Figure 3.3	Self-sufficiency ratio under the baseline model . . . . .	33
Figure 4.1	The decentralized energy management scheme . . . . .	35
Figure 4.2	The centralized energy management scheme . . . . .	35
Figure 4.3	Annual energy invoice of centralized and decentralized schemes . . . . .	46
Figure 4.4	Daily energy invoices of centralized and decentralized schemes . . . . .	47
Figure 4.5	SCR for the different energy management schemes . . . . .	48
Figure 4.6	SSR for the different energy management schemes . . . . .	49
Figure 4.7	Box plots of inefficiencies for all tested allocation mechanisms in all cases. . . . .	50
Figure 4.8	Daily cost saving index of Pavilion 1 . . . . .	51
Figure 4.9	Daily cost saving index of Pavilion 2 . . . . .	51
Figure 4.10	Daily cost saving index of Harbor control . . . . .	51
Figure 4.11	Box plots of worst excess for all tested allocation mechanisms in all cases. . . . .	52
Figure 4.12	Computational time of cost/revenue allocation methods . . . . .	53
Figure 5.1	Internal energy buying and selling price vs. supply-demand ratio. . . . .	57
Figure 5.2	Self-consumption ratio under the MMR mechanism . . . . .	61
Figure 5.3	Self-consumption ratio under the SDR mechanism . . . . .	61
Figure 5.4	Self-sufficiency ratio under the MMR mechanism . . . . .	63
Figure 5.5	Self-sufficiency ratio under the SDR mechanism . . . . .	64
Figure 5.6	Cost saving index (CSI, expressed as a percentage relative to the baseline) . . . . .	65
Figure 6.1	Volumes and prices cleared on local market for three representative days under Case 2. . . . .	72
Figure 7.1	Percentual reduction of the total energy bill compared to the baseline case. . . . .	81
Figure 7.2	Percentage increase in the self-consumption ratio to the baseline case. Negative results indicate a decrease in self-consumption, positive results show an increase in self-consumption. . . . .	82
Figure 7.3	Percentual reduction of the total energy bill compared to the baseline case. . . . .	83

## List of Tables

---

Table 3.1	Solar PV capacity [kWp] for the three system configurations. . . . .	26
Table 3.2	Battery (dis)charging power [kW] and energy capacity [kWh] for the three system configurations. . . . .	26
Table 3.3	Annual total energy invoice of the community of the baseline model for all six cases. . . . .	31
Table 3.4	Weighted average daily self-consumption and self-sufficiency ratios of the baseline model. . . . .	32
Table 4.1	Simulated energy management schemes. . . . .	45
Table 4.2	Tested allocation mechanisms. . . . .	45
Table 4.3	Annual average SCR and SSR for all case studies [%]. . . . .	47
Table 4.4	Individual rationality . . . . .	50
Table 5.1	Total annual energy invoice and total cost savings . . . . .	60
Table 5.2	Weighted average daily self-consumption ratios and improvement . . . . .	62
Table 5.3	Weighted average daily self-sufficiency ratios and improvement . . . . .	63
Table 5.4	Jain's fairness index of six cases under both pricing rules . . . . .	65
Table 6.1	Reference scenario assumptions for the auction-based local energy trading model. . . . .	70
Table 6.2	Annual total energy invoice of the community of the baseline [€]. . . . .	70
Table 6.3	Case 1 results under the auction-based energy trading model. . . . .	71
Table 6.4	Case 2 results under the auction-based energy trading model. . . . .	73
Table 6.5	Invoice saving percentages per household due to the local market (under Case 2). . . . .	73
Table 6.6	Case 3 results under the auction-based energy trading model. . . . .	74
Table 7.1	Total energy bill of the community [€]. . . . .	80
Table 7.2	Self-consumption ratio of the community [%]. . . . .	82

## Keywords, Acronym

---

ADMM	Alternating Direction Method of Multipliers
BESS	Battery Energy Storage Systems
BRP	Balance Responsible Party
CSI	Individual Cost Saving Index
DER	Distributed Energy Resource
DSO	Distribution System Operator
EC	Energy Communities
EV	Electric Vehicle
HEMS	Home Energy Management System
KPI	Key Performance Indicator
MMR	Mid-Market Rate
P2P	Peer-to-Peer
PV	Photovoltaic
SCR	Self-Consumption Ratio
SDR	Supply-Demand Ratio
SSR	Self-Sufficiency Ratio
SV	Shapley Value
TEI	Total Energy Invoice

## Nomenclature

---

### Sets

- $\bar{\mathcal{G}}$  Set of trading participants, excluding batteries, that can sell energy in the P2P market.
- $\bar{\mathcal{L}}$  Set of trading participants, excluding batteries, that can buy energy in the P2P market.
- $\mathcal{D}$  Set of representative days.
- $\mathcal{G}$  Set of trading participants that can sell energy in the P2P market.
- $\mathcal{I}$  Set of energy sharing/P2P trading participants.
- $\mathcal{L}$  Set of trading participants that can buy energy in the P2P market.
- $\mathcal{T}$  Set of time steps in one day.

### Parameters

- $\Delta\tau$  Time step [h].
- $\eta$  Charging/discharging efficiency of the BESS [-].
- $\lambda_{d,t}^{inj}$  Retail electricity injection price at hour  $t$  on day  $d$  [€/kWh].
- $\lambda_{d,t}^{off}$  Retail electricity offtake price at hour  $t$  on day  $d$  [€/kWh].
- $C$  Cost curve of a participant in the P2P market [€].
- $C_i^{PV}$  Solar PV capacity of participant  $i$  [kW].
- $C_i^s$  BESS energy capacity of participant  $i$  [kWh].
- $D_{d,t,i}$  Non-controllable electricity demand of participant  $i$  at hour  $t$  on day  $d$  [kW].
- $N_b$  Number of batteries in the community [-].
- $N_g$  Number of generation entities in the P2P model [-].
- $N_l$  Number of load entities in the P2P model [-].
- $N_t$  Number of time steps in the P2P model [-].
- $P_i^s$  Maximum charge/discharge power of the BESS of participant  $i$  [kW].
- $P_{g,t}^{\max, \text{gen}}$  Maximum power generation limit of generator entity  $g$  in time step  $t$  [kW].
- $P_{g,t}^{\max, \text{load}}$  Maximum power consumption limit of load entity  $l$  in time step  $t$  [kW].
- $P_{g,t}^{\min, \text{gen}}$  Minimum power generation limit of generator entity  $g$  in time step  $t$  [kW].
- $P_{g,t}^{\min, \text{load}}$  Minimum power consumption limit of load entity  $l$  in time step  $t$  [kW].
- $P_i^{PV}$  Maximum available PV power for participant  $i$  at time  $t$  [kW].
- $u$  Matrix indicating hard constraints on allowed P2P energy exchange [-].
- $w_d$  Weight of representative day  $d$  [-].

### Variables

- $\lambda_{d,t}^{buy}$  P2P electricity offtake price at hour  $t$  on day  $d$  [€/kWh].
-

$\lambda_{d,t}^{sell}$	P2P electricity injection price at hour $t$ on day $d$ [€/kWh].
$\Pi_i$	Total annual energy invoice of participant $i$ [€].
$\pi_{d,i}$	Daily cost allocation of participant $i$ [€].
$\varepsilon$	Excess of a subcoalition (the gap between aggregated allocated costs and the optimal cost of that subcoalition) [€]
$b$	Annual energy bill of the community [€].
$E_b^{init}$	Initial state-of-charge of battery $b$ [kWh].
$E_b^{max}$	Maximum state-of-charge of battery $b$ [kWh].
$E_b^{min}$	Minimum state-of-charge of battery $b$ [kWh].
$E_{b,t}^{store}$	State-of-charge of battery $b$ in time step $t$ [kWh].
$e_{d,t,i}$	Storage energy content of participant $i$ at hour $t$ on day $d$ [kWh].
$g_{d,t,i}^{pv}$	Solar PV generation of participant $i$ at hour $t$ on day $d$ [kW].
$P_{l,g,t}^{buy}$	Power bought by load entity $l$ to generator entity $g$ in time step $t$ [kW].
$P_b^{ch, max}$	Maximum power charge value of battery $b$ [kW].
$P_{b,t}^{ch}$	Power charged by battery $b$ in time step $t$ [kW].
$P_b^{dch, max}$	Maximum power discharge value of battery $b$ [kW].
$P_{b,t}^{dch}$	Power discharged by battery $b$ in time step $t$ [kW].
$P_{g,l,t}^{sell}$	Power sold by generator entity $g$ to load entity $l$ in time step $t$ [kW].
$P_{d,t,i}^{ch}$	Storage charging of participant $i$ at hour $t$ on day $d$ [kW].
$P_{d,t,i}^{dc}$	Storage discharging of participant $i$ at hour $t$ on day $d$ [kW].
$P_{d,t,i}^{inj}$	Electricity injection of participant $i$ at hour $t$ on day $d$ [kW].
$P_{d,t}^{Inj}$	Total electricity injection of the community at hour $t$ on day $d$ [kW].
$P_{d,t,i}^{off}$	Electricity offtake of participant $i$ at hour $t$ on day $d$ [kW].
$P_{d,t}^{Off}$	Total electricity offtake of the community at hour $t$ on day $d$ [kW].
$v$	Optimal value of a scheduling problem [€]

## 1 Introduction

---

This deliverable presents the results of Task 2.3 of the U2DEMO project. This task involves developing analytical models that evaluate and quantify the implications of different market clearing and matching methodologies for consumer-centric, Peer-to-Peer (P2P) energy trading and sharing. These models enable us to evaluate how various allocation rules, pricing approaches, and matching and clearing algorithms shape outcomes for consumers and energy communities. The remainder of this introduction first provides the necessary context and motivation for this work (Section 1.1). Section 1.2 subsequently details the scientific contribution of the deliverable and provides a brief overview of the energy trading and sharing mechanisms under consideration. Section 1.3 highlights the relationship with other U2DEMO deliverables and Section 1.4 describes the document's structure.

### 1.1 Background and motivation

---

The U2DEMO project aims to support P2P energy sharing and trading. It develops innovative, consumer-centric energy management strategies that support equitable and democratic access to sustainable energy resources. The project focuses on designing open, interoperable, and scalable tools that empower active consumers to participate in local energy markets and energy communities (ECs). These tools and methodologies are tested across four diverse EC pilot programs located in Italy, Portugal, Belgium, and the Netherlands.

A clear understanding of the range of possible designs for energy trading and sharing, as well as their expected outcomes, is essential to develop these tools. To this end, Work Package 2 focuses on the fundamental development of frameworks, models, and methodologies that enable consumer-enabled P2P energy trading and sharing. Task 2.3 specifically contributes by focusing on the design and evaluation of market-clearing and matching methodologies for P2P trading and energy sharing.

### 1.2 Contributions of the deliverable

---

To meet the objective of Task 2.3, this contribution is organized into three parts. First, we present a structured classification of all common forms of local energy sharing and trading currently implemented in practice, tested in demonstration projects, or suggested in academic literature. This classification first distinguishes between mechanisms tied to collective investments and those centered on individual energy sharing, which are not necessarily mutually exclusive. Within the individual category, we further differentiate between centralized individual sharing and trading arrangements, in which a coordinating entity manages allocation, and distributed arrangements, which rely on direct exchanges between participants. These dimensions yield six fundamental models of local energy sharing and trading. A review of existing energy communities and EU demonstration initiatives shows that all observed configurations can be mapped onto one of these models.

The second contribution involves developing methods and models to evaluate various energy-sharing and -trading mechanisms. Of the six identified models, two do not require a dedicated matching or pricing mechanism. Indeed, one of them corresponds to cooperative arrangements without energy sharing, and the other relies on fully distributed, voluntary bilateral trades between participants. Therefore, our methodological work concentrates on the four models that

require an algorithmic or mathematical formulation. Each of these four models is taken up by one of the project's modeling partners and is briefly introduced below.

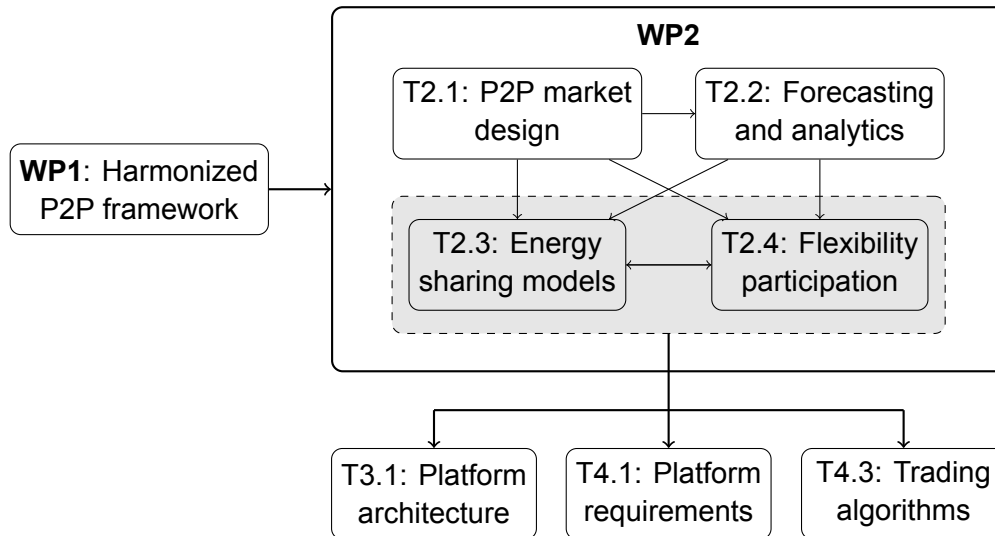
The first model addresses the **allocation of capacity, energy, and revenues from collective assets**. In this model, members invest in a shared resource and seek to distribute its benefits fairly. VITO has developed a model that accommodates hybrid configurations in which collective and individual assets can coexist. There are two operational modes: one in which individual members optimize their own assets while the community manager optimizes the collective ones, and another in which the community manager optimizes both the collective and individual assets centrally. Regardless of the operational mode, the allocation of collective benefits is then determined using game-theoretic cost-allocation methods and predefined partitioning keys.

The second model, developed by KU Leuven, addresses **centralized individual energy sharing through an internal pricing framework**. In these types of schemes, participants make their excess energy production available to the community and meet (part of) their energy needs from shared local resources. The central challenge, then, is to define the internal prices used to value these exchanges. We analyze two pricing mechanisms. The first is the mid-market rate, where the community price is set as an average of retail off-take and injection prices. The second is the supply–demand ratio mechanism, which adjusts the internal price according to the relative availability of local generation. This provides stronger incentives to align consumption with local supply.

The third model, developed by Artelys, focuses on **auction-based centralized individual energy sharing**. In this framework, community members submit explicit price-quantity bids for their surplus or deficit energy to a local market platform. The market clearing algorithm then clears the market, resulting in an efficient allocation of energy among participants. In contrast to the implicit internal pricing mechanism, where all excess electricity is automatically transferred to the community, this auction-based model hence requires explicit control by the community's participants. The developed clearing algorithm operates through two optimization rounds. The first round is designed to maximize overall social welfare, and the second round is designed to maximize redistributive effects among members. This ensures both efficiency and fairness in the allocation process.

The fourth model, developed by INESC-ID, addresses **pool-based distributed, individual energy sharing**. In this distributed setting, each peer can trade directly with multiple other peers by submitting a single bid, i.e., a pair of energy volume and price, or a cost curve, i.e., a lower and higher volume trading limits and the corresponding prices, to a central processing entity (assumed to be the community manager) that also accounts for additional constraints associated with buying from or selling to specific partners. Based on the bids made for each trading interval, the central entity solves the P2P market by maximizing the social welfare of the community, ensuring that all constraints are satisfied and that transactions remain reciprocal. Though the underlying concept is fully distributed, the model developed in this task uses a centralized approximation to determine matching. This enables tractable optimization while representing member-specific trading preferences, enabling peers to influence not only how much they trade but also their willingness to participate in the market and with whom, through bilateral trading choices. The result of this optimization is the amount of energy traded between members, the retailer, and the price for each trade.

The third contribution of this deliverable is the application of all four models (and variants thereof) to a common case study based on the Dutch pilot program. We rely on the set of Key Perfor-



**Figure 1.1 – Linkages with other deliverables within the U2demo project.**

mance Indicators (KPIs) defined in Task 2.3 to evaluate the outcomes of the different models. We pay particular attention to community-level revenues and costs, distributional effects (e.g., individual cost savings), and sustainability metrics (e.g., self-consumption and self-sufficiency). Where appropriate, we add model-specific KPIs to capture features unique to a given design. The goal is to provide as fair a comparison as possible across the different market designs. Nonetheless, fundamental differences between the models sometimes necessitate specific assumptions when applying them to the case study. While every effort has been made to maintain consistency, deviations from a perfectly uniform setup are unavoidable and are explicitly highlighted wherever they occur. For instance, the auction-based model necessitates additional assumptions about participants' bidding strategies. In contrast, the pool-based distributed model is the only one that incorporates trading preferences, which translate with whom peers want to trade energy. Cases that consider various bidding behaviors and preferences are evidently not directly comparable. Nevertheless, the common case study remains valuable because it provides a setting in which to assess how all these various practical features shape the outcomes of local energy sharing and trading mechanisms.

These three components make up this deliverable's contribution: a conceptual framework for local energy sharing and trading; four fully developed algorithmic models (and submodels) representing the main designs found in practice and literature; and a comparative evaluation of these models using a practical case study. The scope of our modeling endeavors is rather unique and of interest to academics, community managers, and policymakers alike. They also lay the groundwork for subsequent work within the U2Demo project, which we turn to next.

### 1.3 Relationship with other deliverables

Task 2.3 is closely connected to several preceding and subsequent tasks within the project and Figure 1.1 provides an overview. This deliverable builds upon the overview of coordinating mechanisms developed in WP1, particularly drawing on the insights of Task 1.2 to inform the design of the common case study. T2.1 contributed to establishing the structured classification of common forms of local energy sharing and trading. Most importantly, this deliverable vastly benefited from the methodological advancements developed in T2.2. The decision-support

models informed our consumer models, and the data analytics framework guided the selection and definition of the common KPIs.

Note that the scope of this work does not include the provision of ancillary services. This topic is covered in Task 2.4, which is closely related to this task. The models developed in this deliverable will serve as building blocks, which Task 2.4 will then extend to include the provision of flexibility services.

Finally, Task 2.3 plays a central role in informing the overall P2P trading platform. The outputs support activities within WP3 and especially WP4. Our modeling work informs T3.1 by helping to define information exchange requirements. It contributes to T4.1, where our recommendations guide the design of the algorithms. Most importantly, it contributes to T4.3, which uses the modeling bricks from T2.3 and T2.4 to develop the integrated P2P trading platform.

## 1.4 Structure of the deliverable

---

The structure of this report largely follows that of the three previously mentioned contributions. **Section 2** introduces the classification of local energy and trading models. It first provides the approach and dimensions used to structure the various models, which leads to six distinct model types. It subsequently discusses the operating principles of each model type. The section proceeds with a review of existing energy communities and pilot initiatives within the EU and demonstrates that all of these real-world implementations can be mapped onto one of the six model categories that were introduced. The section ends by motivating the decisions to focus on four of the six models for the remainder of the report.

**Section 3** introduces the case study setup leveraged to evaluate the outcomes of the selected models. First, it describes the Scheveningen pilot and particularly focuses on the participating community members and their distributed energy resources. It also outlines how multiple test cases are constructed by varying the system configuration. The section proceeds by highlighting a set of general modeling assumptions applicable to all model types, as well as a set of general KPIs that will be used to evaluate the modeling outcomes. Importantly, this section presents outcomes for the baseline case, which represents a situation without energy sharing or trading. In this case, each consumer individually schedules their appliances solely in response to retail prices, with no additional coordination mechanism.

**Sections 4 - 7** are respectively dedicated to: (i) capacity, energy, and revenue allocation models, (ii) internal energy pricing models, (iii) auction-based local energy trading models, and (iv) pool-based P2P matching models. Each section follows a common structure. First, it outlines the methodology and mathematical formulation. Then, it highlights model-specific particularities. Indeed, certain models require additional assumptions that were not covered in Section 3. These assumptions and their implications for comparability are explicitly stated. Finally, each section provides detailed results for the corresponding model variants.

**Section 8** synthesises the modeling outcomes across the four energy trading and sharing mechanisms. Specifically, it compares their performance and offers insights into when each type of mechanism may be most appropriate. It furthermore reflects on the practical implications for real-world implementation and on the limitations of this study.

**Section 9** concludes and offers recommendations.

## 2 Overview and classification of energy sharing and trading models

---

In this section, we introduce the six main local energy sharing and trading models, which constitute the basis and provide a classification for all common forms of local energy sharing and trading which are implemented in practice, being piloted in demonstration activities, or proposed in the academic literature. Section 2.1 introduces the structure and defines the dimensions used to classify the different models. Section 2.2 provides an overview of the six representative models that span this design space. Section 2.3 reviews the literature and demonstrates that these models encapsulate the mechanisms currently being tested or implemented in European energy communities and pilot initiatives. Finally, Section 2.4 motivates the decision to focus on four of the six models for the remainder of the report.

### 2.1 Structure and classification

---

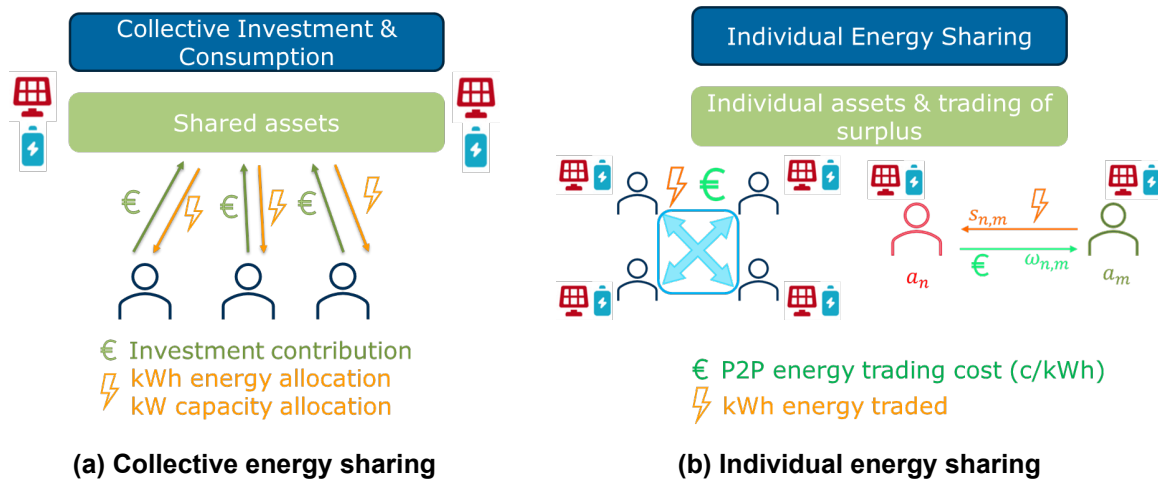
The first step in the classification of local energy sharing and trading models is to capture whether the focus is on collective investment and consumption or an individual energy sharing setting (see Figure 2.1). In the case of *collective investments* and consumption captured in Figure 2.1a, energy community members collectively invest in shared assets, e.g., a large-scale Photovoltaic (PV) installation or Battery Energy Storage Systems (BESS), from which they can all benefit via an implemented capacity, energy, or revenue allocation scheme. On the other hand, in an *individual energy sharing* setting captured in Figure 2.1b, each individual has its own potential energy production, storage, and consumption assets, wherein each individual user aims to sell or transfer energy to the community during periods of surplus to benefit others, or receive energy from the community (i.e., from members who have a surplus) during periods of shortage. Note that these collective and individual schemes do not need to be mutually exclusive, as energy communities can include a situation in which collective and individual energy generation and storage assets concurrently exist, wherein both types of assets can be part of the local energy sharing activities. In fact, this will be exactly the case study investigated in this report.

Within the individual energy sharing scheme, we differentiate between two settings: *centralized individual energy sharing and trading* and *distributed individual energy sharing and trading*. In the centralized case, users with surplus energy transfer or offer that surplus to the community, while members with energy shortage draw energy from the community. As such, no bilateral peer-to-peer trading takes place, constituting a setting of peer-to-pool/pool-to-peer energy exchange. In the distributed individual energy sharing and trading schemes, peers are rather matched bilaterally creating explicit exchanges between pairs of peers, thus constituting an explicit form of peer-to-peer trading. This P2P matching/trading then enables peers to set different preferences for trading with other individual peers (also including different prices), an aspect that is not readily possible in peer-to-pool/pool-to-peer schemes.

### 2.2 Six representative models

---

The dimensions defined in the prior section are the basis for defining the six fundamental local energy sharing and trading models. In what follows, Section 2.2.1 first present two representative models within the collective investment setting: the cooperative model without energy sharing, and the energy and revenue allocation models. We subsequently move to individual energy sharing and trading, which, as mentioned, can be further disaggregated into centralized



**Figure 2.1 – Distinction between individual and collective energy sharing.**

and distributive settings. Section 2.2.2 covers the centralized setting by presenting internal energy pricing models and auction-based local energy trading models. Section 2.2.3 covers the distributed setting and presents continuous P2P-trading and pool-based P2P matching.

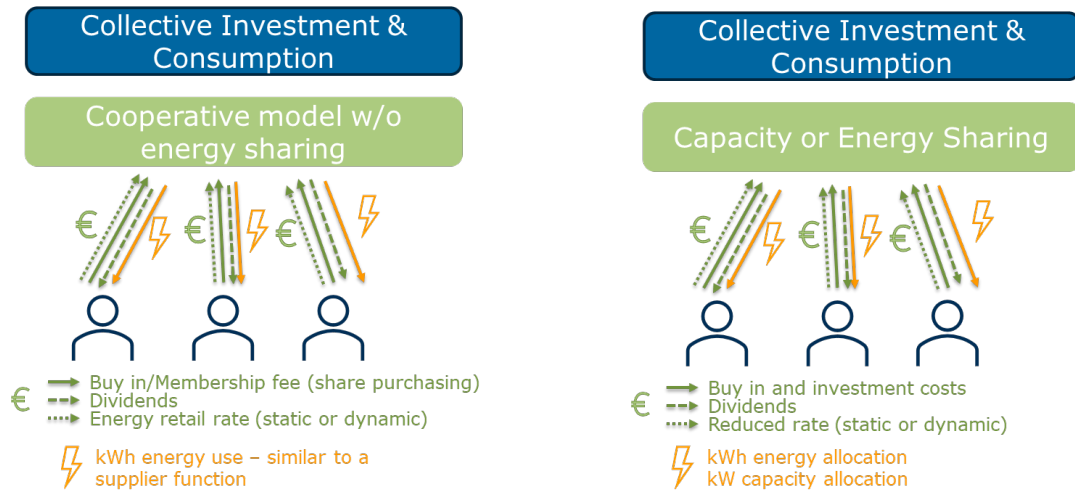
## 2.2.1 Collective energy sharing

The first model of collective investment and consumption corresponds to the energy cooperative model widely adopted in different EU member states. In this energy cooperative model depicted in Figure 2.2a, members typically contribute a buy-in to join the community/cooperative and potentially receive dividends in returns. However, importantly, no energy sharing takes place between the members. The cooperative rather acts as a form of supplier to its members, wherein, the cooperative sources energy from the wholesale market and supplies it to its members (typically at supported rates). This, hence, does not entail explicit energy sharing, but the collective contributions by all members are used to collectively source energy for the energy community.

In the second model of collective investment and consumption captured in Figure 2.2b, which rather includes energy sharing, the members collectively invest in shared assets and aim at sharing the benefits/outcomes therefrom. Members can still potentially receive dividends, but the goal is to share the capacity, the generated energy, or the generated revenues from the collectively owned assets. As such, this model of energy sharing focuses on the design of allocation schemes/allocation keys to split the shared assets' energy or capacity among the community members.

## 2.2.2 Individual energy sharing – centralized

We now focus on the setting of individual energy sharing, where we present two models of centralized sharing and two models of decentralized sharing/P2P energy trading. In the centralized setting, peers do not bilaterally trade energy, but rather offer their surplus (or cover their shortage) from the community as a collective, hence creating a setting of peer-to-pool/pool-to-peer. In the distributed energy sharing setting, peers trade energy with one another, creating a peer-to-peer trading setting.



**(a) Cooperative model without energy sharing (b) Capacity, Energy, and Revenue Allocation Models**

**Figure 2.2 – Collective energy sharing models.**

The first model of individual energy sharing in a centralized setting, captured in Figure 2.3a, focuses on designing predefined pricing mechanism for pricing internal energy sharing. Indeed, in individual energy sharing schemes, each user makes their surplus available to the community and cover their shortages (at least partially) from the community. In this model, the focus is on defining internal pricing mechanisms for such internal energy sharing/flows. Such pricing schemes for internal energy sharing would be defined by the community manager, wherein the collective surplus is priced and used by the community members who require it. This creates a form of implicit energy sharing focusing on defining pricing methods to share the collective surplus.

In the next model, depicted in Figure 2.3b, we focus on explicit energy sharing where surpluses are explicitly offered and shortages are explicitly asked to be covered at user-defined prices via submitted bids. This model still focuses on individual energy sharing in a centralized scheme. Instead of implicitly trading electricity via defined internal prices, however, each community manager must submit sell (in case of a surplus) or buy (in case of a shortage) orders, e.g., by price-quantity bids to a local energy market. The market is then cleared by the centralised market clearing algorithm, resulting in an explicit energy allocation among the members. As the auction process is digitalised, the operation of the market clearing algorithm does not require a dedicated energy community manager, but this can be decided by the community. The level of information access regarding other participants' bids can be decided by the community, based on the level of trust within the community: full exposure of bid information allows participants to better understand how energy is being shared within the community, while restricting accessibility avoids sharing potentially sensitive information.

In this auction mechanism, even though energy is shared (or even traded) explicitly, no one-to-one matching between peers takes place, but rather the surpluses of the users are offered to the community pool and then disaggregated among the members in need of energy. We next focus on two models of distributed, explicit peer-to-peer energy trading.

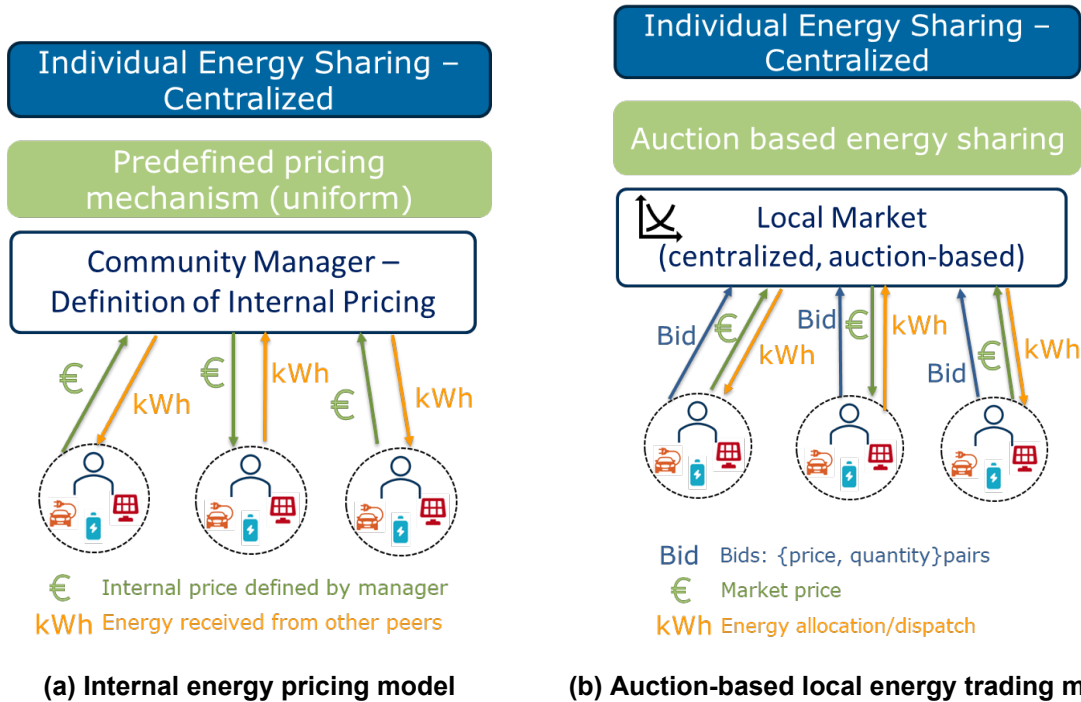


Figure 2.3 – Centralized individual energy sharing models.

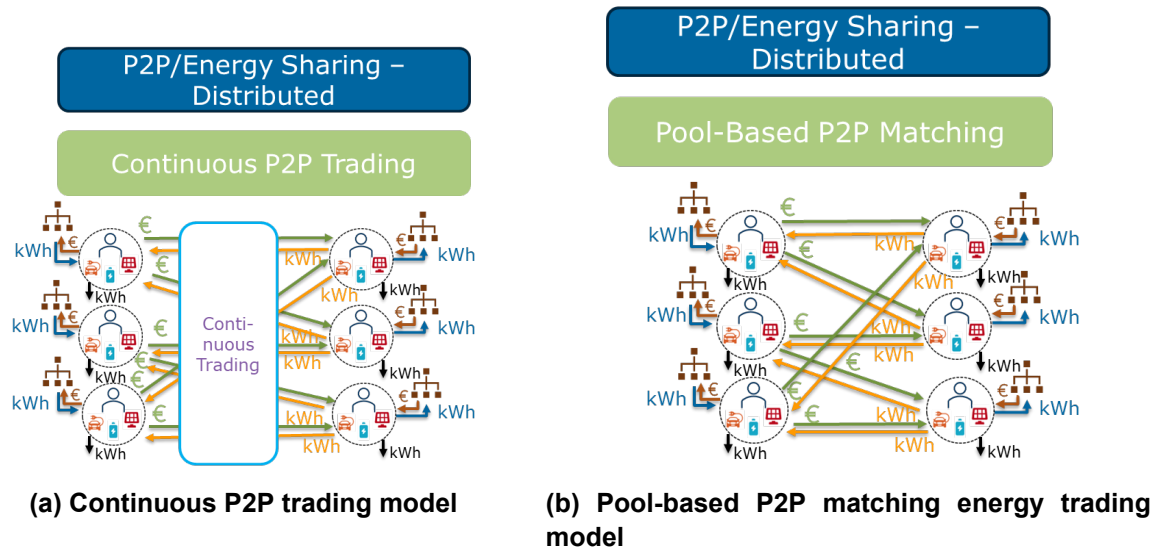
### 2.2.3 Individual energy sharing – distributed

In the next two models we focus on peer-to-peer energy trading. The first, depicted in Figure 2.4a, is a form of continuous peer-to-peer trading, in which a P2P trading platform is set up wherein peers place sell offers and buy bids (price-quantity pairs) to sell their surplus or cover their energy shortage, respectively. Peers can then decide via the platform to match with another peer (to cover their shortage or sell their surplus) on a first come, first served basis. No matching algorithm is required, as the matching choice is made by the peers themselves. Each transaction in this model is bilateral.

This last model, depicted in Figure 2.4b, focuses on algorithmic P2P matching for P2P trading. Each peer has options to trade with other peers, and thus defines the price, quantity, and other forms of preferences for trading with other peers. Then, in light of the different P2P offers (where a peer can submit offers to trade with multiple other peers) an algorithm creates a matching between the peers abiding by their indicated constraints and preferences and ensuring trade reciprocity, i.e., the volume a peer  $i$  is willing to sell to another peer  $j$  should be equal to the volume peer  $j$  is willing to buy from  $i$ . This typically gives rise to a game-theoretic setting. As such, the matching algorithm aims to find a P2P matching that constitutes an equilibrium of the game – i.e., a matching specifying the energy volume to be sold/bought from/to each of the other peers and the defined prices – from which no player would be incentivized to unilaterally deviate [45, 54, 55].

## 2.3 Mapping of energy community initiatives and pilot activities

This set of models span the spectrum of local energy sharing and trading possibilities that have been applied in practice, investigated in demo activities, or analyzed in the academic literature.



**Figure 2.4 – Distributed individual energy sharing models.**

A review of existing energy communities and EU pilot initiatives across Europe reveals that, despite their diversity, they can all be classified within the six models described above. A significant number of communities fall within the category of Cooperative Models Without Energy Sharing, including Brixton Energy [2], Coopernico [4], Ecopower [5], Edinburgh Community Solar Co-operative [6], Energiecoöperatie WPN [8], Jurascic [12], MegaWattPuur [14], and Som Energia [21]. These cooperatives focus on collective ownership while maintaining conventional grid-based consumption. Numerous energy communities and demonstration sites implement Capacity, Energy, and Revenue Allocation Models, applying predefined rules to distribute generation or revenues among participants. Examples include Sunshare [24], Greenbizz.energy [9], HospiGREEN [10], Illuminons notre quartier [11], and l'association Partag'élec [16], among others. Several community-based energy sharing platforms, such as Bolt Energy [1], om nieuwe energie [15], Energie VanOns [7], Vandebroen [25], Powerpeers [18], and SonnenCommunity [22], fall within the Internal Energy Pricing Model, making use of internal tariffs to promote collective self-consumption. More advanced testbeds, such as Quartierstrom project in Switzerland [20], demonstrate the practical feasibility of the Centralized Auction-Based Local Energy Trading Model, enabling competitive and transparent matching of local supply and demand. Distributed approaches include SunContract [23], which falls under the Continuous P2P Trading Model supporting bilateral dynamic exchanges, as well as the Pebbles pilot [17], which falls under the Pool-Based P2P Matching Model coordinating trades through shared preference-based mechanisms. Collectively, these cases indicate that the six models provide a comprehensive framework covering the mechanisms tested or operational across European energy communities and pilot initiatives.

## 2.4 Focus of U2Demo modeling activities

This section has presented the six fundamental forms of local energy sharing and trading. The focus of the U2Demo project (and primarily that of WP2 of which the task behind this report is a part) is to define algorithms and develop the tools for enabling local energy sharing and trading. As such, we focus next on the four models from the presented six which require algorithmic and mathematical model development, namely: (i) Capacity, Energy, and Revenue Allocation

Models, (ii) Internal energy pricing models, (iii) Auction-based local energy trading models, and (iv) Pool-based P2P matching energy trading models.

### 3 Numerical case study and setup

---

This section introduces the numerical case study leveraged to evaluate the selected energy sharing and trading models and explains its structure. The case study focuses on the Scheveningen pilot, which will be covered in Section 3.1. We will also outline how we translate the real-world system into three different test cases by varying the system configuration. Section 3.2 highlights the general modeling assumptions common to all model types. Section 3.3 subsequently presents the KPIs used to evaluate the model outcomes. Importantly, we present the results of the baseline cases in Section 3.4. This baseline represents the situation without energy sharing or trading. In this case, each consumer schedules their appliances in response to retail prices only, without additional coordination mechanisms.

#### 3.1 Test case description

---

The numerical case study is based on the Scheveningen pilot in The Hague, the Netherlands, where entrepreneurs and public entities are engaged in an ongoing cooperative energy initiative. We opted for the Dutch case because (i) granular data was readily available, and (ii) the initiative combines individual and collective assets and participants with heterogeneous profiles. This makes it an interesting setting in which to evaluate various local energy sharing and trading models. A third benefit is that all community participants are located behind the same feeder. This is not necessarily the case in other pilots and presents interesting opportunities for flexibility services, which will be the topic of Deliverable 2.4. What follows is a brief introduction to the pilot. Note that we pay particular attention to the entities and their assets because this is critical for the modelling endeavours. More information, including the pilot's specific objectives, can be found in Deliverable 1.2 of the U2DEMO project. Section 3.1.2 subsequently motivates and introduces the three main case studies that will be used throughout the remainder of this report. Finally, Section 3.1.3 covers the data and processing.

##### 3.1.1 The Scheveningen pilot

---

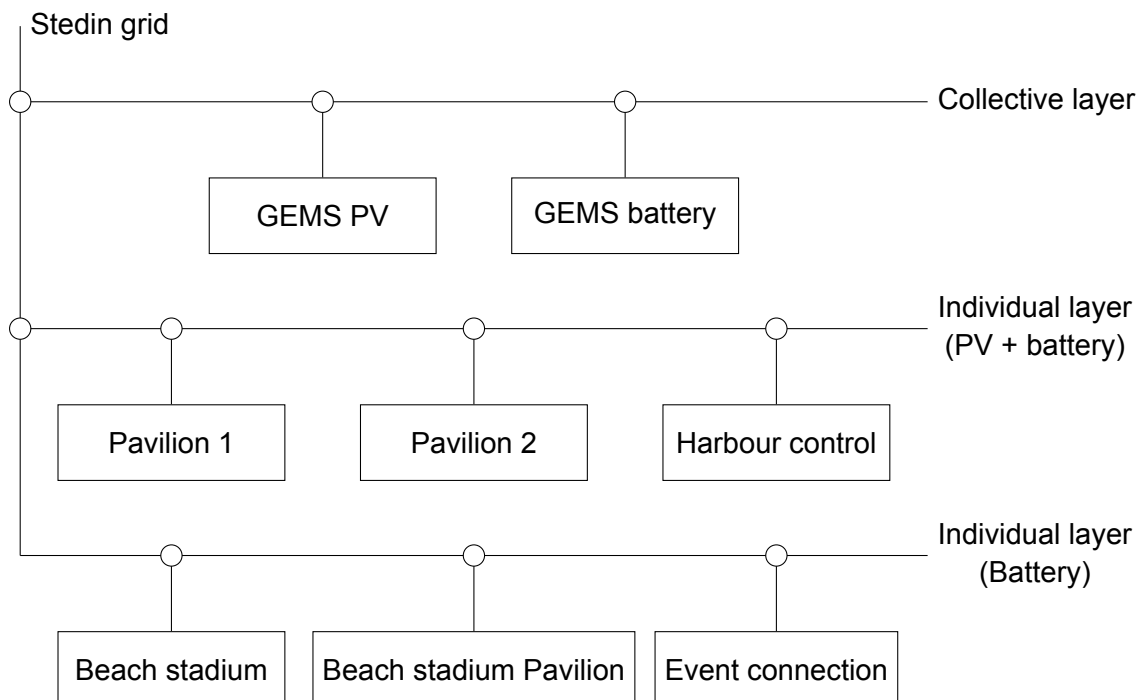
This study focuses on the situation prevailing from summer 2024 to summer 2025, for which an overview is provided in Fig. 3.1. During most of this period, the community consisted of two collective assets: a 9 kWp PV installation and a large battery with an energy capacity of 425 kWh and a (dis)charging power of 200 kW. It furthermore engaged 6 individual parties, reflecting both privately and publicly owned operations:

- Privately operated entities:
  - Pavilion 1 (Aloha): a beach bar & restaurant that also acts as a surf school. It is a consumption-only participant without distributed assets.
  - Pavilion 2 (the Shore): another beach bar and surf school that operates a 9 kWp PV system complemented by a small plug-in battery of 1.5 kWh energy capacity.
- Publicly operated entities:
  - Harbour control: the municipality's control centre responsible for the port of Scheveningen. It is a large consumer that hosts 29 kWp solar PV capacity along with four 11 kW Electric Vehicle (EV) chargers.

- Beach stadium: a stadium that hosts sporting events, mostly during summer. It is a consumption-only participant without distributed assets.
- Beach stadium pavilion: a seasonal pop-up pavilion that hosts a range of activities, such as fitness and yoga classes. It is only active during the summer months and is a consumption-only participant without distributed assets.
- Event connection: an additional connection that supplies electricity for temporary events, replacing the need for diesel generators. It is a consumption-only participant without distributed assets.

Due to data limitations, our test case deviates slightly from the current state of the pilot. First, it omits participants and assets that were recently added. For example, Hito, a privately owned restaurant with a sizable PV installation, recently joined, as did an additional collective PV plant. These developments are not incorporated in the base case because all models rely on historical time-series data that is unavailable for these entities. As will be discussed below, a second case has been constructed to better reflect the pilot’s current configuration.

The second difference concerns the treatment of flexible assets. Although the harbour control building hosts four 11 kW EV chargers, they are not separately metered, so their consumption cannot be distinguished from the building’s general load. Consequently, we do not consider their EV flexibility and assume that the harbour control’s measured demand remains inflexible. Furthermore, the collective battery is currently operated for grid management purposes to avoid exceeding the community’s maximum allowed peak offtake. Throughout our cases, however, we vary the size of the collective battery to demonstrate the impact of operating it more actively.



**Figure 3.1 – Entities involved in the Scheverningen pilot.**

### 3.1.2 Case overview

**Table 3.1 – Solar PV capacity [kWp] for the three system configurations.**

Entity	Type	Case 1	Case 2	Case 3
GEMS	Collective	9	45	45
Pavilion 1	Individual	0	9	9
Pavilion 2	Individual	9	9	9
Harbour control	Individual	29	29	29
Beach stadium	Individual	0	0	0
Beach stadium Pavilion	Individual	0	0	0
Event connection	Individual	0	0	0

**Table 3.2 – Battery (dis)charging power [kW] and energy capacity [kWh] for the three system configurations.**

Entity	Type	Case 1		Case 2		Case 3	
		Power	Energy	Power	Energy	Power	Energy
GEMS	Collective	200	425	20	42.5	200	425
Pavilion 1	Individual	0	0	22	66	22	66
Pavilion 2	Individual	0.8	1.5	0.8	1.5	15	30
Harbour control	Individual	0	0	0	0	30	70
Beach stadium	Individual	0	0	0	0	2	4
Beach stadium Pavilion	Individual	0	0	0	0	2	4
Event connection	Individual	0	0	0	0	10	20

Our goal is to examine the performance of different energy sharing and trading mechanisms under varying system configurations. To this end, we have constructed six cases by cross-combining three different system configurations and two retail pricing schemes. Starting with the former, the three main test configurations progressively expand the pilot’s scope by adjusting the size of distributed energy assets. Tables 3.1 and 3.2 respectively provide an overview of solar PV and battery capacities. The first case reflects the situation that largely prevailed from summer 2024 to summer 2025, using actual consumption, PV generation, and battery characteristics without synthetic adjustments. The second case adapts this configuration to approximate the pilot’s current state by mimicking recent expansions and storage operations. Specifically, the collective PV capacity increases because of the recently added collective PV plant, Pavilion 1 is assigned a PV installation and battery to mimic Hito’s recent connection, and the collective battery is downsized to align with its primary purpose of limiting the community’s maximum offtake. The third case deviates substantially from the real-world setup by significantly increasing battery capacities throughout the system. Though hypothetical, this configuration allows us to examine how P2P energy sharing/trading models behave in a setting where participants have far greater flexibility than is currently available.

The two pricing schemes are based on the assumption that consumers face either a fixed retail contract or a dynamic, hourly one<sup>2</sup>. The fixed scheme applies constant prices for offtake

<sup>2</sup>Note that one model relaxes this assumption, see Section 3.2.

and injection, while the dynamic scheme follows wholesale prices. The latter reflects the actual pilot situation, in which the community manager procures electricity from a Balance Responsible Party (BRP) offering prices indexed to the day-ahead market. Nonetheless, including a fixed-price scenario offers additional insights as we can evaluate the performance of various energy-sharing and trading mechanisms in different pricing environments. Indeed, it is important to investigate both mechanisms because the prevalence of fixed or dynamic contracts varies significantly across Member States.

### 3.1.3 Data and processing

---

All PV production and consumption time series used in the simulations are taken directly from the pilot and span a full year, from August 2024 to July 2025, at hourly resolution. For privacy reasons, we refrain from reporting actual profiles. The original time series suffered from the common data quality issues and underwent pre-processing procedures. Small gaps were filled using linear interpolation and larger gaps (e.g. one day) were reconstructed using data from the preceding week. An exceptionally long outage (i.e. over a month) in the PV measurements of Pavilion 2 required the use of synthetic, irradiance-based PV data sourced from [50], which was subsequently slightly corrected by the collective PV installation's observed production. Finally, consumption was obtained by subtracting metered PV production from measured offtake when necessary.

Modifications to the community's configuration (see Tables 3.1 and 3.2) require a few additional assumptions. When PV sizes differ from those in the pilot program, the corresponding production profiles are scaled proportionally. For example, this is the case for the collective PV installation in cases two and three. The newly introduced PV system at Pavilion 1 adopts Pavilion 2's production profile. Battery modeling relies on maximum charging and discharging power, energy capacity, and round-trip efficiency. The first two parameters are reported in Table 3.2, where we assume that maximum charging and discharging power are equal. We take a uniform round-trip efficiency of 85% for all batteries, which is consistent with empirical data from the storage units operated within the pilot.

Retail prices are based on day-ahead electricity prices during the same period. Offtake prices include the volumetric transmission network tariff and applicable taxes, while injection prices are exempt from both. The values of the network tariff and taxes are based on data from Statistics Netherlands [57]. Note that we used values for non-residential households, which are slightly lower and aligned with the pilot. Most retail contracts impose a small fixed fee, which we exclude from the analysis because it does not affect consumers' incentives or the main results. Under the flat retail contract, the resulting offtake price is 0.257 €/kWh, while the injection price amounts to 0.091 €/kWh.

Although a full year of empirical data is available, the computational burden of several models makes full-year, hourly simulations infeasible. For this reason, all cases are evaluated using a set of thirty representative days, which are selected according to the methodology described in [51]. Even the algorithms capable of solving the entire year use the same selection of days to ensure consistency. Using representative days is a common method in energy system analyses and may only introduce slight inaccuracies, depending on the case at hand [58]. Note that we hence still consider a full year (and seasonal effects), but 'cluster' similar days together to reduce modeling complexity. In doing so, we lose the chronology of days and therefore assume that all batteries start and end the day with a half charge.

## 3.2 General assumptions

---

This section serves to be explicit about the general assumptions common to all model types. Note that fundamental differences between the models sometimes necessitate additional assumptions when applying them to the case study. Any of these model-specific assumptions required will be clearly stated in their respective sections. The following assumptions apply to all models:

- The provision of ancillary services is not considered. This is the topic of Task 2.4.
- Every household signs the same contract with one energy supplier to ensure consistent internal price determination. In other words, all households either face fixed prices or dynamic prices. Mixed contractual settings are mostly not considered. Allowing for a mixed setting would introduce strong arbitrage opportunities, causing participants to trade opportunistically based on contract differences rather than system conditions. This is nevertheless interesting to investigate and, as such, the auction-based centralised individual mechanisms will serve as the exception and does investigate a mix of retail contracts (Section 6).
- Households in the community are exempt from transmission network charges and taxes for energy shared within the community, as is common practice. This is implicitly modeled as they can avoid the offtake price (which incorporates these elements) when procuring electricity locally.
- Households can optimally react to the price signals or system conditions that they face. In practice, this would likely imply that each household is equipped with a Home Energy Management System (HEMS) which helps optimize its energy usage. In addition, a smart meter is installed in every household which measures energy production and consumption during every time step. Note that we assume perfectly rational household behavior throughout this deliverable. In practice, however, households may react imperfectly, a topic partially explored when examining auction-based individual mechanisms (Section 6).
- Households are generally assumed to focus solely on minimizing their energy bills. However, the peer-to-peer energy trading models consider heterogeneous trading preferences and bid structures, which relaxes this assumption (Section 7).
- A community manager is responsible for managing all market transactions and determining internal prices. This role may be fulfilled by an algorithm-driven virtual platform or a traditional intermediary.
- All participants operate with perfect foresight regarding demand, PV production, and local energy prices. Note that, for certain mechanisms, this can be a strong assumption. That said, we aim to compare the energy trading and sharing mechanisms in a first-best setting and we will reflect upon the implications in Section 8.
- All participants behave as price-takers, i.e. we model a competitive setting where no participant can manipulate the local market.
- The system operates at an hourly resolution, and the time steps are identical for all modeled processes. One would expect the benefits of energy trading and sharing mechanisms to be slightly overestimated compared to a 15-minute setting. There will indeed be somewhat more local trade opportunities when averaging over one hour than when having to

abide by a 15-minute window.

### 3.3 Key performance metrics

This section presents the key performance metrics used in our case study to evaluate the outcomes of each model. Most metrics follow those proposed in Section 4 (“Data Analytics Methods”) of Deliverable 2.2, with minor adaptations to better align with the specifics of our case study.

#### 3.3.1 Total energy invoice

The Total Energy Invoice (TEI) is calculated as the sum of all members’ ( $i \in \mathcal{I}$ ) annual electricity bills ( $\Pi_i$ ) over one year, expressed in €. A member’s annual bill is computed by taking the difference between the electricity offtake ( $P_{d,t,i}^{off}$ ), valued at the momentarily offtake price ( $\lambda_{d,t}^{off}$ ), and the electricity injected ( $P_{d,t,i}^{inj}$ ), valued at the momentarily injection price ( $\lambda_{d,t}^{inj}$ ).

$$TEI = \sum_{i \in \mathcal{I}} \Pi_i = \sum_{i \in \mathcal{I}, d \in \mathcal{D}, t \in \mathcal{T}} w_d \cdot (\lambda_{d,t}^{off} \cdot P_{d,t,i}^{off} - \lambda_{d,t}^{inj} \cdot P_{d,t,i}^{inj}), \quad (3.1)$$

where  $w_d$  is the weight of the representative day  $d$ ,  $d \in \mathcal{D}$  and  $t \in \mathcal{T}$  are time indices, with  $d$  referring to days and  $t$  to hours.

#### 3.3.2 Individual cost saving

Individual cost savings (CS) in an energy community quantify how much a member reduces their electricity expenditure by participating in energy sharing or P2P trading, compared to the baseline without these coordination mechanisms. For member  $i$ , the individual cost savings  $CS_i$  are expressed in € and defined over a one-year horizon:

$$CS_i = \Pi_i^{base} - \Pi_i^{P2P} \quad (3.2)$$

From this, one can also derive the relative cost savings, or Individual Cost Saving Index (CSI), expressed as a percentage:

$$CSI_i = \frac{\Pi_i^{base} - \Pi_i^{P2P}}{|\Pi_i^{base}|} \times 100\% \quad (3.3)$$

#### 3.3.3 Self-consumption ratio

The Self-Consumption Ratio (SCR) measures the share of electricity generated within the community that is consumed locally rather than exported to the main grid. It is defined over a given time period (e.g., day, month, or year) and is expressed as a dimensionless value between 0 and 1. In our case study, the SCR is computed on a daily basis.

$$SCR_d = \frac{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} g_{d,t,i}^{PV} - \sum_{t \in \mathcal{T}} \max\{P_{d,t}^{Inj} - P_{d,t}^{Off}, 0\}}{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} g_{d,t,i}^{PV}} \quad (3.4)$$

Higher SCR values indicate greater community autonomy and better utilization of local renewable generation. A higher SCR is typically associated with increased consumer savings, as locally consumed electricity avoids retail tariffs and reduces grid fees. It also generally has a positive impact on the distribution grid since a higher self-consumption ratio reduces loading on the network and mitigates reverse power flows.

### 3.3.4 Self-sufficiency ratio

The Self-Sufficiency Ratio (SSR) measures the share of electricity consumption within an energy community that is supplied by local generation rather than imported from the main grid. It is defined over a given time horizon (e.g., day, month, year) and is expressed as a dimensionless ratio between 0 and 1. In our case study, the SSR is again computed on a daily basis.

$$SSR_d = 1 - \frac{\sum_{t \in \mathcal{T}} \max\{P_{d,t}^{Off} - P_{d,t}^{Inj}, 0\}}{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} (P_{d,t,i}^{ch} + D_{d,t,i})} \quad (3.5)$$

A higher SSR indicates greater community autonomy (i.e., less import) and better utilization of local renewable generation. It is often associated with higher savings, as reduced imports lower electricity procurement costs.

## 3.4 Baseline results

With an overview of the case study, as well as the various KPIs that are considered, we can now move to the results of the baseline case. This is an important case, as it will be used as reference for three of the four energy trading and sharing models under consideration: (i) capacity, energy, and revenue allocation model (Section 4), (ii) internal energy pricing models (Section 5), and (iii) auction-based local energy trading models (Section 6). The fourth model, i.e. peer-to-peer energy trading (Section 7), relies on a set of fundamentally different assumptions and cannot directly be compared to this baseline.

The baseline model represents a situation without energy sharing or trading. In this case, each consumer schedules their appliances in response to retail prices only, without additional coordination mechanisms. The collective PV installation and the collective battery are each treated as an individual household, i.e. they are also scheduled based on retail prices. As such, we can avoid having to assume allocation keys that may distort the results. We have obtained the results below using the model that will be presented in Section 5. That being said, the models presented in Sections 4 and Sections 6 have also been tested on the baseline and produce the same outcomes. Put differently, the three models are consistent.

In what follows, we present the results of the baseline model, focusing on three of the key performance indicators introduced in Section 3.3: the total energy invoice, and the self-consumption and self-sufficiency ratios.

### 3.4.1 Total energy invoice

The total energy invoice of one year of the whole community without energy sharing or P2P trading is shown in Table 3.3. Under the fixed retail contract, the total energy invoice decreases

**Table 3.3 – Annual total energy invoice of the community of the baseline model for all six cases.**

Case	Total energy invoice [€]
Case 1 - Fixed	75898
Case 2 - Fixed	70343
Case 3 - Fixed	70341
Case 1 - Dynamic	78651
Case 2 - Dynamic	74605
Case 3 - Dynamic	72206

in Case 2 and Case 3 primarily due to higher solar PV adoption. The shift from Case 2 to Case 3 yields only marginal additional savings, as the installed household battery capacity in Case 2 already enables PV-equipped households to make efficient use of nearly all of their self-generated electricity. This leaves limited scope for further improvements from additional flexibility, which is also reflected in the self-consumption ratios reported in Section 3.4.2.

Under the dynamic contract, the total energy invoice decreases across Case 2 and Case 3 for two reasons: (i) increased solar PV installations reduce net imports from the grid (Case 2), and (ii) higher flexibility enables members to perform price arbitrage by strategically charging and discharging their batteries in response to hourly price variations (Case 3).

### 3.4.2 Self-consumption and self-sufficiency ratios

The self-consumption ratio and self-sufficiency ratio of every representative day are calculated and plotted in Figure 3.2 and 3.3, respectively. Under the fixed contract, the self-consumption ratio decreases as more solar PV is installed. A larger PV capacity, especially from the collective installation, makes it more difficult for the community to self-consume all generated electricity. Note that the collective battery is not incentivized to operate under the fixed retail price because it faces identical buy and sell prices and therefore there is no arbitrage value. The self-consumption ratios of Case 2 closely resemble those of Case 3, indicating that the individual batteries installed in Case 2 are already sufficient for members to use most of their self-generated electricity. As a result, the additional flexibility introduced in Case 3 offers little further improvement in efficiency. Under the dynamic contract, the hourly varying price signals lead to two distinct battery operating patterns that influence the self-consumption ratio. First, batteries store PV surplus during low-price hours and for later use. This behavior will increase the self-consumption ratio, as can be seen in Case 2. Second, batteries engage in price arbitrage by charging when prices are low and discharging when prices are high. This increases the amount of electricity exported to the main grid, which in turn reduces the self-consumption ratio, as reflected in Case 3.

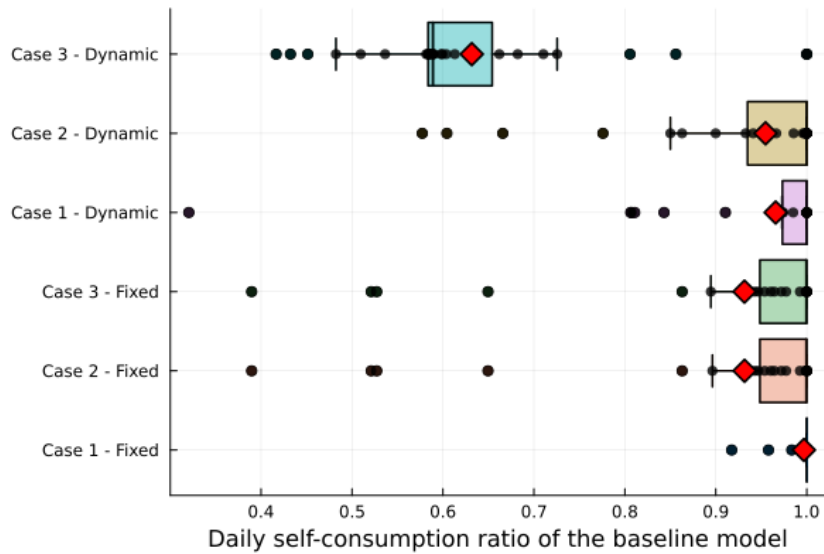
Under the fixed contract, the self-sufficiency ratio increases when moving from case 1 to cases 2 and 3 due to higher solar PV adoption. With more PV capacity installed, a larger share of household demand is met by self-generated electricity, raising self-sufficiency in both Case 2 and Case 3. Similar to the self-consumption ratios, the self-sufficiency ratios of Case 2 and Case 3 are also nearly identical, for the same reasons as discussed earlier. Under the dynamic contract, the two battery operating modes also affect the self-sufficiency ratio. First, storing PV surplus increases self-sufficiency, since a greater portion of locally generated electricity is used

to meet local demand (Case 1). Second, price-arbitrage operation reduces self-sufficiency, because charging the battery during low-price hours increases electricity imports from the grid, thereby lowering the share of demand met by local generation (Case 3).

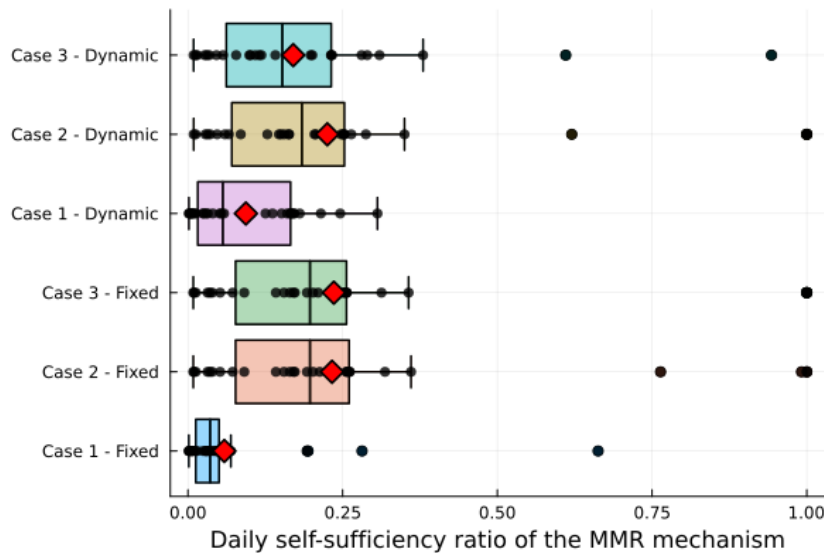
The weighted average daily self-consumption and self-sufficiency ratios for all six cases are also summarized in Table 3.4 to showcase the exact numerical values underlying the trends discussed above.

**Table 3.4 – Weighted average daily self-consumption and self-sufficiency ratios of the baseline model.**

Case	Self-consumption ratio	Self-sufficiency ratio
Case 1 - Fixed	0.997	0.180
Case 2 - Fixed	0.932	0.300
Case 3 - Fixed	0.932	0.300
Case 1 - Dynamic	0.987	0.168
Case 2 - Dynamic	0.973	0.302
Case 3 - Dynamic	0.946	0.344



**Figure 3.2 – Self-consumption ratio under the baseline model. Daily ratios are plotted in black dots while the weighted average daily ratios of each case are plotted in red diamonds.**



**Figure 3.3 – Self-sufficiency ratio under the baseline model. Daily ratios are plotted in black dots while the weighted average daily ratios of each case are plotted in red diamonds.**

## 4 Capacity, energy, and revenue allocation models

In this section, we discuss the energy sharing and scheduling models in an energy community where the community members have individual and collectively invested assets (Section 4.1). Subsequently, we present the revenue or cost allocation mechanisms of the energy community (Sections 4.2–4.3), i.e., how the revenue obtained by forming an energy community can be distributed to all the members.

### 4.1 Day-ahead scheduling models

We consider that each community member does not only have inflexible loads but might also have inflexible generation (e.g., from solar panels) and a set of flexible assets (e.g., home batteries, heat pumps, electric vehicles, and shiftable loads) that can be scheduled. Furthermore, we also consider that the community can have a set of collectively owned generation units (e.g., solar panels) and flexible and dispatchable assets, such as batteries, operated by a community manager. To optimally schedule the flexible and controllable assets as well as the energy sharing, we consider two energy management schemes, namely decentralized and centralized management. Note that we assume the computed schedules are daily, and the scheduling is performed day-ahead with perfect forecasts of inflexible loads and generation<sup>3</sup>.

In a decentralized energy management scheme, shown in Figure 4.1, each community member optimizes individually the schedule of its flexibility assets with the objective of minimizing its own energy cost and considering the operational constraints of the assets. Then, the community members send the resulting energy profiles (net production/consumption profiles) to the community manager, which will take these energy profiles into account when optimizing the schedule of the collective, flexible assets. To optimize the schedule of the collective assets, the community manager considers the objective of minimizing the energy cost of the community, which is the summation of the energy cost of the members<sup>4</sup>.

Differently, in a centralized scheme (Figure 4.2), the schedules of all (individual and collective) assets are optimized by the community manager. Thus, it solves a central energy management problem, which takes into account the operational constraints of all assets and inflexible consumption and generation profiles of all members. As in the decentralized scheme, the objective of this optimization problem is to minimize the energy cost of the community.

For concreteness, the optimization problem formulations of the decentralized and centralized energy management schemes are provided in Appendix A. Let us denote the optimal value (cost) of the day-ahead scheduling optimization problem (regardless of the scheme used) by  $v_d(I)$ , i.e.,

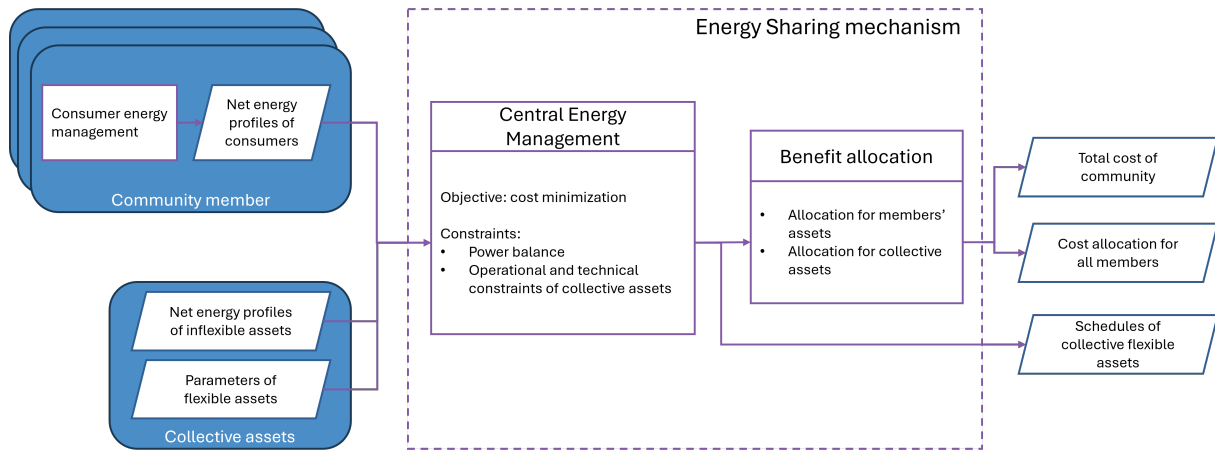
$$v_d(I) := \sum_{i \in I} \sum_{t \in T} \lambda_{d,t}^{off} \hat{P}_{d,t,i}^{off} - \lambda_{d,t}^{inj} \hat{P}_{d,t,i}^{inj}, \quad (4.1)$$

where  $\hat{P}_{d,t}^{off}$  and  $\hat{P}_{d,t,i}^{inj}$ , respectively, denote the offtake and injection schedules of member  $i \in I$  obtained from a solution of the scheduling problems (see Problem (A.2) or (A.3) in Appendix A). Note that since  $v_d(I)$  reflects the cost, revenue is obtained when  $v_d(I)$  is negative, which occurs when there is a surplus of generation and the community injects this surplus to the grid.

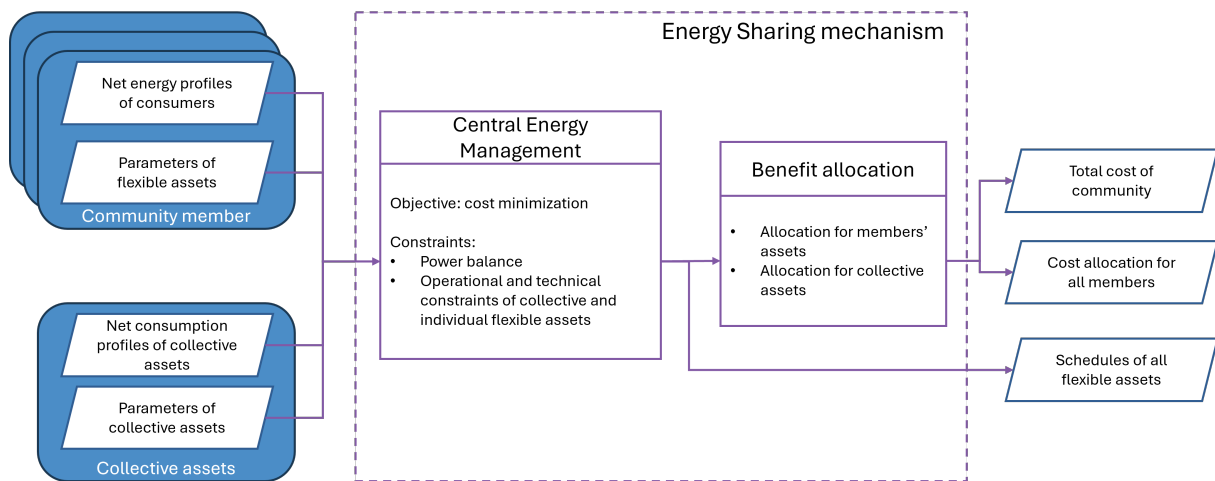
The decentralized energy management scheme is seen to be more practical than the centralized

<sup>3</sup>The treatment of uncertainties of the loads and generation is out of the scope of this work

<sup>4</sup>A community manager may consider a different objective, such as maximizing the self-consumption ratio.



**Figure 4.1 – The decentralized energy management scheme. All members submit their energy profiles and the community manager optimally schedules the collective assets and subsequently calculates the cost allocation for all members.**



**Figure 4.2 – The centralized energy management scheme. The community manager optimally schedules the collective as well as the individual assets, and subsequently calculates the cost allocation for all members.**

one since individual assets are locally controlled by their owners as opposed to by a third-party (the community manager). The centralized scheme indeed requires community members to share possibly sensitive and private information of their assets, which may not be desirable in practice. However, from the optimization point of view, the centralized management scheme provides a better schedule in terms of energy cost, i.e., the schedule obtained from the decentralized scheme can be suboptimal (less cost-efficient than the centralized one).

## 4.2 Cost and revenue allocation mechanisms

The objective of a cost and revenue allocation mechanism is to distribute the energy cost  $v(I)$  in Eq. 4.1 to the community members<sup>5</sup>. In the following, we denote by  $\pi_i$  the daily cost or

<sup>5</sup>In this section (and Section 4.3), the value (or cost) considered is a daily value and we drop the day index  $d$  for brevity of the notation.

revenue allocated to member  $i \in I$ , and  $\pi = \text{col}((\pi_i)_{i \in I})$  is a concatenation of these individual daily costs. We consider cooperative game-theoretic approaches, namely the Shapley Value (SV) [52] and the optimal excess [27], as well as a cost allocation method based on individual offtake/injection of the participants. Furthermore, to fairly distribute the revenue obtained by the collective assets, they will first be considered as an additional fictitious community member, which gets some allocation of the community cost/revenue. Afterward, this cost/revenue from the collective assets is redistributed to all community members according to their shares in the assets.

### 4.2.1 Shapley values

The SV is essentially the average of the marginal costs that a player (community member) incurs over all possible subcoalitions (subsets of the energy community with the same energy sharing capabilities). Let  $\mathcal{S}(i) \subseteq I_+$ <sup>6</sup> denote a subcoalition that contains player  $i$  and  $v(\mathcal{S})$  denote the value of subcoalition  $\mathcal{S}$ , i.e., the optimal value of the scheduling problem considering only a subset of community members in  $\mathcal{S}$ . The SV of player  $i \in I_+$  is given by:

$$x_i^{\text{SV}} = \sum_{\mathcal{S}(i) \in 2^{I_+}} \frac{(|\mathcal{S}(i)| - 1)! (|I_+| - |\mathcal{S}(i)|)!}{|I_+|!} (v(\mathcal{S}(i)) - v(\mathcal{S}(i) \setminus \{i\})), \quad (4.2)$$

where the operator  $|\cdot|$  denotes the set cardinality, the operator  $(\cdot)!$  denotes the factorial operator, and  $2^{I_+}$  denotes the power set of  $I_+$ . Operatively, one can execute Algorithm 1 to calculate the cost allocation based on Shapley values.

---

#### Algorithm 1 Shapley value computation

---

- 1: Generate all possible subcoalitions, i.e., members of the power set  $2^{I_+}$ .
  - 2: Calculate the value (cost) of each subcoalition,  $v(\mathcal{S})$ ,  $\forall \mathcal{S} \subseteq I_+$ .
  - 3: For each community member, compute its Shapley value by Eq. 4.2.
- 

Cost allocation based on Shapley values is guaranteed to be efficient, i.e., the community cost  $v(I)$  is fully allocated to the members,

$$v(I) = \sum_{i \in I_+} x_i^{\text{SV}}, \quad (4.3)$$

and individually rational, i.e., the allocated cost  $\pi_i$  is at most equal to the cost incurred by each member had it scheduled itself individually (without energy sharing),

$$\pi_i \leq v(\{i\}).$$

### 4.2.2 Optimal excess

For a subcoalition  $\mathcal{S}$ , the excess ( $\varepsilon(\mathcal{S})$ ) is the difference between the optimal cost (value) of  $\mathcal{S}$  ( $v(\mathcal{S})$ ) and the aggregated allocated cost ( $\sum_{i \in \mathcal{S}} \pi_i$ ), i.e.,

$$\varepsilon(\mathcal{S}) = v(\mathcal{S}) - \sum_{i \in \mathcal{S}} \pi_i. \quad (4.4)$$

---

<sup>6</sup>The set  $I_+$  includes all the community members and the fictitious player representing the collective assets.

An allocation mechanism is then called *stable* if the worst-case excess (the minimum excess over all possible subcoalitions) is non-negative, implying that no community member has any incentive to quit the energy community and form a subcoalition, as they cannot perform better by doing so. By considering this condition, one can optimize worst-case excess to derive an allocation mechanism. Specifically, one has to solve the following linear programming problem:

$$x^{\text{OE}} \in \begin{cases} \operatorname{argmax}_{x \in \mathbb{R}^{|I_+|}, \varepsilon \in \mathbb{R}} & \varepsilon \\ \text{s.t.} & v(\mathcal{S}) - \sum_{i \in \mathcal{S}} \pi_i - \varepsilon \geq 0, \quad \forall \mathcal{S} \subset I_+, \\ & v(I) - \sum_{i \in I_+} \pi_i = 0, \\ & v(\{i\}) - \pi_i \geq 0, \quad \forall i \in I_+. \end{cases} \quad (4.5)$$

Note that to be able to formulate the optimization problem, we first have to compute the value of all possible subcoalitions, as in the SV approach. By construction (see the last two constraints in Problem (4.5)), this allocation is efficient and individually rational. Furthermore, when  $\varepsilon$  is non-negative, this allocation is *stable*.

### 4.2.3 Hybrid prorated allocation

A dynamic cost allocation based on the offtake and injection of each member can be defined as:

$$x_i^{\text{HP}} = \begin{cases} \frac{\hat{P}_{t,i}^{\text{off}}}{\sum_{j \in I_+} \hat{P}_{t,j}^{\text{off}}} v(I), & \text{if } v(I) > 0, \\ \frac{\hat{P}_{t,i}^{\text{inj}}}{\sum_{j \in I_+} \hat{P}_{t,j}^{\text{inj}}} v(I), & \text{otherwise} \end{cases} \quad (4.6)$$

where the community cost is assigned proportionally to the offtaking members whenever it is positive and conversely to the injecting members whenever it is negative.

### 4.2.4 Cost allocation with revenue from collective assets

Denoting by  $\alpha_i \in [0, 1]$  the share of member  $i$  in the collective assets ( $\sum_{i \in I} \alpha_i = 1$ ), the daily cost allocated to each community member  $i \in I$ , taking into account the distributed revenue from the collective assets, is computed as:

$$\pi_i = x_i^j + \alpha_i x_{\text{coll}}^j \quad (4.7)$$

where  $j$  indicates the choice of cost allocation mechanism, i.e.,  $j \in \{\text{SV}, \text{OE}, \text{HP}\}$ , where SV, OE, and HP refer to the SV, optimal excess, and hybrid prorated allocation methods, respectively.

The papers [27, 42, 53] have shown that, in some energy communities (those with renewable generation and batteries) and under some price assumptions (uniform offtake and injection prices as well as offtake prices being higher than injection prices), the optimal excess method is stable. Meanwhile, the SV allocation is not stable under these settings. Nevertheless, both mechanisms potentially suffer from an intractability issue since their calculations require computing the optimal costs of all possible subcoalitions (solving an optimal scheduling problem for each subcoalition), and the number of subcoalitions grows exponentially with the number of community members.

## 4.3 Heuristic allocation mechanisms

---

In the framework of energy communities, the concept of sharing/repartitioning keys defines the methodological basis for allocating injected energy among participating members according to transparent, fair, and replicable criteria. Repartitioning keys serve as the linking mechanism between physical energy flows and the virtual allocation of energy rights, costs, and benefits within the community. They ensure that the distribution of injected energy reflects both the technical performance of generation assets and the contractual participation rules established among members.

The repartitioning process operates on the aggregated energy injected into the local grid or community platform. Injected energy, denoted by  $P_t^{inj}$ , refers to the surplus electricity produced by distributed generation units, such as photovoltaic systems or other renewable sources, that exceeds local consumption and is exported to the communal or distribution network. Repartitioning keys determine how this collective injection is divided among members for accounting, settlement, and remuneration purposes, i.e.:

$$P_t^{Inj} = \sum_{i \in I_+} P_{t,i}^{inj}$$

Conceptually, the repartitioning keys are derived from predefined parameters such as installed capacity, ownership share, metered production, or contribution to investment costs. In some configurations, dynamic keys are applied based on the, in most cases, energy consumption of each settlement interval. Regardless of the chosen formulation, the keys must maintain consistency with the regulatory framework and metering accuracy requirements, ensuring traceability between physical injections and the corresponding virtual energy shares. In the following sections, we review existing sharing keys that are available in practice and considered as heuristic allocation methods.

### 4.3.1 Static sharing keys

---

Static (fixed) sharing keys refer to pre-determined, static (fixed) allocation coefficients used to distribute shared energy among members of an energy community. These keys remain constant over a defined period (e.g., monthly or annually) and are independent of the consumption profiles of individual participants.

The principle of fixed sharing is based on proportionality and transparency, enabling each member's share of collective generation to be defined ex-ante, according to agreed criteria such as ownership, installed generation capacity, total self-generated energy, financial contributions, or may simply follow an equal split among members.

The fixed sharing key also has notable limitations. It often leads to the creation of energy surplus, meaning that a significant portion of the locally generated energy is not consumed by participants. This occurs because the allocation percentages remain fixed regardless of actual demand. As a result, surplus energy may be exported to the grid even when some consumers within the community could have absorbed it, reducing the overall efficiency of local energy use.

Computation of fixed sharing keys typically follows a contractual or administrative procedure established at the creation of the energy community. The key values (e.g. percentages or ratios) are determined through a sharing matrix that reflects each participant's entitlement within the community.

Formally, a fixed key  $k_i$  is assigned to each member  $i \in I$ , with

$$\sum_{i \in I} k_i = 1 \quad (4.8)$$

and each  $k_i$  remaining constant throughout the defined period.

The allocation of shared energy  $E_{share,i}$  to member  $i$  is thus

$$P_{t,i}^{shr} = k_i \cdot \hat{P}_t^{Inj} \quad (4.9)$$

where  $E_{total}$  represents the total aggregated shared energy.

Fixed sharing keys are introduced in regulation or facilitated by the DSOs in several countries, including Belgium (Flemish Region [39], Walloon Region [31], and Brussels-Capital Region [56]), France [34, 36], Portugal [37], Spain [48], and Austria [30].

In the Flemish Region, instead of pooling all injected energy and distributing it collectively among all members, the energy injected by each participant is redistributed among the remaining members, excluding the injecting member, according to each member's individual fixed key. In addition, there is a special form of fixed key in which the redistribution takes into account the injecting member's individual fixed key (percentage). This percentage is redistributed to the remaining participants in proportion to the initial coefficients. Then the allocation of the energy injected by the injecting member is redistributed to the remaining members based on the newly recalculated keys.

In Portugal, fixed keys are introduced in Regulation No. 815/2023, of 27 July, under Article 29 [37]. The regulation stipulates that the managing entity must inform the DSO in advance of the fixed coefficients assigned to each participating installation, and that, in the event of missing or invalid coefficients, the DSO shall apply the consumption-based keys instead.

Pursuant to Royal Decree 244/2019 of 5 April [48], members of an energy community in Spain may adopt any criteria for energy sharing, provided that such criteria are agreed upon by all members and that the corresponding coefficients sum to one for each hourly period. The Institute for the Diversification and Saving of Energy published a Collective self-consumption guide [44] where a few examples are listed, such as keys based on the contracted power, by percentage of participation in the homeowners' association, and by percentage of participation in the installation costs.

In France, fixed keys are rarely used in collective self-consumption schemes, as it is considered the least efficient method which often generates significant virtual surplus. As a result, energy may be exported or wasted even when some consumers could have absorbed it. It was used in a few early collective self-consumption projects in 2018, primarily because it was the simplest to implement. However, due to its inefficiency, most of those projects later transitioned to the "default dynamic allocation key", which better matches production with real consumption [36]. One such example is the Partag'elec initiative [16] which initially applied a fixed key to distribute photovoltaic generation among participating consumers. The project demonstrated the administrative simplicity of fixed allocation but also revealed its limitations in optimising local consumption and reducing virtual surplus. Following the first operational phase, the initiative migrated to a variable (dynamic) sharing key, enabling alignment between production and demand and improving the overall self-consumption rate within the community. Data from the

French DSO Enedis suggest that, in August 2023, there were 8 collective self-consumption communities using a fixed sharing key [35].

### 4.3.2 Dynamic sharing keys

---

Variable (dynamic) sharing keys allocate shared energy based on data that varies over time. In practice, consumption-based dynamic keys are the most commonly applied, as they most directly reflect actual energy use within the community and eliminate or reduce the surplus. Unlike fixed sharing keys, variable consumption-based keys continuously adjust the allocation of shared energy according to the individual consumption of each time interval and it is calculated ex-post. This method provides an adaptive allocation but requires advanced metering infrastructure and digital systems for reliable data collection and processing. However, the consumption-based distribution key also has certain limitations: because energy is allocated in proportion to consumption, participants with higher demand receive a larger share of the locally generated electricity. In mixed configurations, such as those including an industrial consumer and several households, the industrial participant may absorb most of the available shared energy, leaving smaller consumers with only a limited portion of local production.

For each settlement interval  $t$ , the variable coefficient  $k_{t,i}$  for member  $i$  is calculated as the ratio of their instantaneous consumption relative to the community's total:

$$k_{t,i} = \frac{\hat{P}_{t,i}^{off}}{\sum_{j \in I} \hat{P}_{t,j}^{off}} \quad (4.10)$$

where  $P_i(t)$  represents the measured consumption of member  $i$  at time  $t$ . The portion of shared energy attributed to each member during that interval is subsequently given by:

$$P_{t,i}^{shr} = k_{t,i} \cdot \hat{P}_t^{Inj}, \quad (4.11)$$

where  $k_{t,i}$  is based on Eq. 4.10. Variable (dynamic) sharing keys have been introduced in several European countries as part of the regulatory frameworks for collective self-consumption and energy communities. These schemes enable the allocation of shared energy based on time-varying data, typically reflecting members' actual consumption. One of the countries allowing these keys are Belgium (Walloon Region [31] and Brussels-Capital Region [56]), France [34, 36], Portugal [37], Spain [48], and Austria [30].

In France, in addition to the consumption-based variable key, there are two other forms of dynamic allocation. The first is the "simple" dynamic allocation key, in which the shared production is distributed according to the community manager's chosen criteria at each time interval. The second is the "full dynamic" distribution key, which allows the allocation of shared production by individual producer-consumer pair [34, 36].

In Portugal, under the dynamic sharing [37, 33], the community manager allocates shared energy among participants based on real consumption and production data provided daily by the DSO. Community managers define time-varying sharing coefficients for each producer-consumer pair and submit them to the DSO for validation and billing. If the community manager fails to send valid coefficients within the allowed time, the DSO will apply a default sharing mode using coefficients proportional to each member's consumption. Each month, the DSO performs calculations on a set billing date, allows a defined revision period for the community manager to

update coefficients, and then finalizes energy allocation and billing using validated data. Currently, the dynamic sharing is only possible by participating in the DSO E-REDES pilot project scheme.

Examples of energy communities currently applying consumption-based sharing keys include Les Petits Riens [13] in Brussels and Ville de Hannut [26] in Wallonia Region. Furthermore, according to data from the French DSO Enedis, as of August 2023, 204 collective self-consumption communities were using a consumption-based sharing key [35]. There were also 34 collectives using the “simple” dynamic allocation key. In Portugal, the energy regulator ERSE approved the DSO E-REDES Pilot Project on energy sharing models in self-consumption in September 2022 [32]. Since then, six projects have been approved for dynamic energy sharing [38].

### 4.3.3 Multi-round sharing keys

Multi-round sharing keys allocate shared energy through successive distribution rounds within a single settlement interval. After the initial allocation, any remaining unassigned energy is redistributed among participants whose consumption has not yet been fully covered. This iterative process continues until either all available shared energy is allocated, or all participants’ demand is satisfied. Compared to single-round allocation, multi-round allocation improves the utilization of local generation and reduces virtual surplus. However, it also introduces additional administrative and computational complexity. Each distribution step requires additional data handling and validation, which can complicate settlement and auditing. The calculation of this energy allocation method is presented in Algorithm 2.

---

#### Algorithm 2 Multi-round sharing keys

---

- 1: Define  $P_{t,i}^{\text{net}} \leftarrow \hat{P}_{t,i}^{\text{off}}$ ,  $P_{t,i}^{\text{shr}} \leftarrow 0$  for all  $i \in I$ ,  $P_t^{\text{Shr}} \leftarrow \hat{P}_t^{\text{Inj}}$ , and  $\ell \leftarrow 1$ .
  - 2: **while**  $P_{t,i}^{\text{net}} > 0$ ,  $\forall i \in I$ , **and**  $\ell \leq \ell_{\text{max}}$  **and**  $P_t^{\text{Shr}} > 0$  **do**
  - 3:     **for**  $i \in I$  **do**
  - 4:         Calculate allocated energy at round  $\ell$ :  $P_{t,i}^{\text{alo}} = \min\{k_i \cdot P_t^{\text{Shr}}, P_{t,i}^{\text{net}}\}$
  - 5:         Calculate net energy after allocation at round  $\ell$ :  $P_{t,i}^{\text{net}} = P_{t,i}^{\text{net}} - P_{t,i}^{\text{alo}}$
  - 6:     **end for**
  - 7:     Calculate remaining shared energy:  $P_t^{\text{Shr}} \leftarrow P_t^{\text{Shr}} - \sum_{i \in I} P_{t,i}^{\text{alo}}$
  - 8:      $\ell \leftarrow \ell + 1$
  - 9: **end while**
  - 10: **Output:**  $P_{t,i}^{\text{shr}} = \hat{P}_{t,i}^{\text{off}} - P_{t,i}^{\text{net}}$ , for all  $i \in I$ .
- 

Multi-round sharing keys are introduced in Flemish Region [39], Walloon Region [31], and Brussels-Capital Region [56] in Belgium. In Flemish and Brussels-Capital Region, the iterations continue until either the entire injection has been fully distributed, or the total consumption has been completely balanced. The use of fixed keys is required in both regions. In the Walloon Region, the number of iterations is limited to three, allowing combinations of different allocation keys. For instance, two fixed keys (equal and specific) followed by a dynamic key proportional to consumption for the remaining volume. When the same fixed key is applied over multiple iterations, the allocation percentages must remain identical in each iteration to ensure consistency within the computational process. One example of multi-round sharing keys used in practice is the Klimaan energy community in Flanders, Belgium.

### 4.3.4 Alternative sharing keys

We also find two alternative sharing keys, which are variants of the previously discussed sharing keys.

**Hybrid sharing keys.** Hybrid sharing method applies a two-stage energy distribution process combining fixed and variable allocation keys. The first distribution round uses static sharing keys, limited by the offtake of each participant. Any remaining injected energy not used in the first round is then redistributed during a second round with dynamic keys based on the remaining consumption that is not covered by the shared energy from the first round.

The allocated energy ( $P_{t,i}^{\text{shr}}$ ), for each  $t \in T$ , for each member  $i$ , using these sharing keys are defined by:

$$P_{t,i}^{\text{shr},1} = \min(k_i \hat{P}_t^{\text{Inj}}, \hat{P}_{t,i}^{\text{off}}), \quad (4.12a)$$

$$P_{t,i}^{\text{shr},2} = \begin{cases} 0, & \text{if } \hat{P}_t^{\text{Inj}} - \sum_{i \in I} P_{t,i}^{\text{shr},1} = 0, \\ \frac{\hat{P}_{t,i}^{\text{off}} - P_{t,i}^{\text{shr},1}}{\sum_{j \in \mathcal{I}} \hat{P}_{t,j}^{\text{off}} - P_{t,j}^{\text{shr},1}} \left( P_t^{\text{shr}} - \sum_{i \in I} P_{t,i}^{\text{shr},1} \right), & \text{otherwise} \end{cases} \quad (4.12b)$$

$$P_{t,i}^{\text{shr}} = P_{t,i}^{\text{shr},1} + P_{t,i}^{\text{shr},2}. \quad (4.12c)$$

One of the regions where a hybrid sharing key is available is the Brussels-Capital Region, implemented by the DSO Sibelga [56]. In the Walloon Region, it is likewise possible to apply a fixed key in the first round, followed by a consumption-based key in the subsequent allocation step [31]. In both regions, with the approval of the relevant authority, energy communities can propose sharing keys other than those currently in place [56, 49]. Hybrid sharing keys are currently applied in several energy communities, such as Quartier Chomé [19], Illuminons notre quartier [11], and Communauté D'énergie Terdelt [3] in Brussels-Capital Region.

**Hierarchical sharing keys.** Hierarchical sharing method defines a structured approach to allocate renewable generation among multiple participants connected to the same distribution grid segment. The method operates in two sequential iterations and requires the participants to be divided into groups. In the first, locally generated energy is distributed exclusively among installations at the group level. In the second iteration, any aggregated surplus from those groups is redistributed across all participating consumption points that still have unmet demand. Each group consists of one or more consumption and generation points that share a common physical, contractual, or management relationship. The definition and composition of groups are the responsibility of the community manager, which communicates them to the Distribution System Operator (DSO). Grouping enables modular control of internal energy allocation before collective-level redistribution, reflecting real-world structures such as buildings, facilities, or clusters of prosumers. Energy distribution follows rules defined by the community manager through two sharing modes: static sharing keys as in Eq. 4.9, and consumption-based dynamic sharing keys as in Eq. 4.11. These modes apply both within groups (intragroup sharing) and between groups (intergroup redistribution of surpluses).

In Portugal, a pilot project to test hierarchical (and dynamic) sharing model was proposed by E-REDES, the main DSO in Portugal. Energy regulator ERSE (*Entidade Reguladora dos*

*Serviços Energéticos*”) approved the pilot in September 2022, and six projects are currently operating under this framework [32]. Regulation No. 815/2023 subsequently incorporated these models into the national regulatory framework (Articles 31 and 32) [37] providing only high-level guidance, and leaving ERSE to assess pilot results and approve the final methodologies. Under Article 46, adoption of these models is only permitted through participation in the mentioned pilot.

### 4.3.5 Surplus after allocation

---

After the allocation of shared energy within an energy community, any portion of locally generated energy that remains unconsumed will be an energy surplus (i.e. community energy surplus) that is injected into the grid. This surplus typically arises when using single-round fixed keys and part of the available energy is left unallocated, even though some members could still have used it, or when the total generation exceeds the aggregated consumption of the community during a given settlement interval.

Depending on national regulations and the community’s contractual arrangements, the surplus may be exported to the public grid, credited to a collective account, or remunerated at a pre-defined feed-in tariff or market price. Surplus management ensures that no locally produced energy is lost from an accounting perspective and that all flows are properly recorded for settlement with the DSO or relevant market entity.

How surplus energy is managed depends on national and regional regulations. In the Flemish Region, energy allocation and surplus management are performed together in three steps [39]. In the first step, the energy injected by each participant is redistributed among the remaining members, excluding the injecting member, according to each member’s individual fixed key. This can result in a surplus, as the injected energy is not shared with the producer. In the second step, the individually allocated energy from the first round is compared with each member’s gross consumption. If a member receives more energy than they consume, an additional surplus is generated. In the final step, the surplus energy from the first step is returned to the respective producers, while the surplus energy from the second step is redistributed to the producers in proportion to their individual injected energy.

In the Walloon Region, the surplus of energy can be managed in one of two ways. It may either be redistributed among other participants whose consumption has not yet been fully covered, through a second allocation round, or it may be sold on the market. In the latter case, the surplus injection is reported back to the producers and allocated to them proportionally to their individual energy injections [31].

In the Brussels-Capital Region, according to the draft sharing agreement prepared by Brussels Environment [29], a regional administration under the Brussels-Capital Government, a price is set between the community and the energy-producing member for the injected energy. Consequently, the community effectively purchases all the energy produced by that member. In this case, any surplus from the producer’s perspective is financially compensated through the agreed purchase price.

In our study, we suppose that the surplus of energy is distributed to the community members

proportionally to their energy injection  $\hat{P}_{t,i}^{inj}$ :

$$P_{t,i}^{\text{surplus}} = \frac{\hat{P}_{t,i}^{inj}}{\sum_{j \in I_+} \hat{P}_{t,i}^{inj}} \left( \hat{P}_t^{Inj} - \sum_{j \in I} P_{t,i}^{\text{shr}} \right).$$

### 4.3.6 Allocated costs and revenues

Upon the allocation of aggregated injected energy based on the aforementioned heuristic methods, the allocated cost or revenue of each community member can then be calculated by:

$$\pi_i = \sum_{t \in T} \lambda_t^{\text{off}} \max \left\{ \hat{P}_{t,i}^{\text{off}} - P_{t,i}^{\text{shr}} - P_{t,i}^{\text{surplus}}, 0 \right\} + \lambda_t^{\text{inj}} \min \left\{ \hat{P}_{t,i}^{\text{off}} - P_{t,i}^{\text{shr}} - P_{t,i}^{\text{surplus}}, 0 \right\}, \quad \forall i \in I. \quad (4.13)$$

## 4.4 Model particularities

In the numerical simulation study based on the test case described in Section 3, we consider some specific assumptions and KPIs in addition to those described in Section 3.

### 4.4.1 Model-specific assumptions

- The share of collective assets of each community member is equal. This implies that any revenue obtained from collective assets will be shared equally among the community members.
- In both centralized and decentralized energy management schemes, all necessary information to compute optimal schedules, including asset parameters of each community member for the centralized scheme, is available.

### 4.4.2 Model-specific KPIs

The key performance metrics considered for the different allocation mechanisms are as follows:

- *Inefficiency*, which measures how (in-)efficient an allocation mechanism is and is defined by:

$$\eta_d^{\text{ineff}} = \frac{\sum_{i \in I} \pi_{i,d} - v_d(I)}{|v_d(I)|}, \quad \forall d \in D \quad (4.14)$$

where  $\pi_{i,d}$  denotes the allocated cost of member  $i$  on day  $d$  based on an allocation mechanism and  $v_d(I)$  denotes the optimal cost of the community. If the inefficiency  $\eta_d = 0$ , then the allocation mechanism is efficient (see Eq. 4.3).

- *Daily cost saving index*, which measures the revenue obtained by each community member by joining the energy community and sharing energy as compared to individually optimizing its schedule without sharing energy, i.e.,

$$\eta_{i,d}^{\text{profit}} = \frac{v_d(\{i\}) - \pi_{i,d}}{|v_d(\{i\})|}, \quad \forall i \in I, d \in D \quad (4.15)$$

where  $v_d(\{i\})$  denotes the optimal cost of individual scheduling without energy sharing.

- *Individual rationality.* An allocation mechanism is individually rational if the profits  $\eta_{i,d}^{\text{profit}}$ , for all  $i \in I$  and  $d \in D$ , are non-negative.
- *Worst excess,* which measures the worst-case difference between the optimal cost of a subcoalition and the aggregated allocated cost for all members in that subcoalition, i.e.,

$$\eta_d^{\text{excess}} = \min_{\mathcal{S} \in 2^I} \varepsilon_d(\mathcal{S}), \quad \forall d \in D \quad (4.16)$$

where  $\varepsilon_d(\mathcal{S})$  is the excess of subcoalition  $\mathcal{S}$  (see Eq. 4.4).

- *Stability.* An allocation mechanism is stable if it is efficient, individually rational, and has non-negative worst excess, for all  $d \in D$ .
- *Computational time,* which indicates the time needed to perform the cost allocation in every simulated day. It measures the computational complexity of an allocation mechanism.

## 4.5 Results

In this section, the results of the energy and revenue allocation models for the defined case studies are presented. Specifically, we simulate the combinations of the energy management schemes in Table 4.1 and the allocation mechanisms in Table 4.2 for all the three cases with fixed and dynamic prices, which are explained in Section 3.

**Table 4.1 – Simulated energy management schemes.**

Energy management scheme	Reference
Decentralized	Figure 4.1, Equations A.1–A.2
Centralized	Figure 4.2, Equation A.3

**Table 4.2 – Tested allocation mechanisms.**

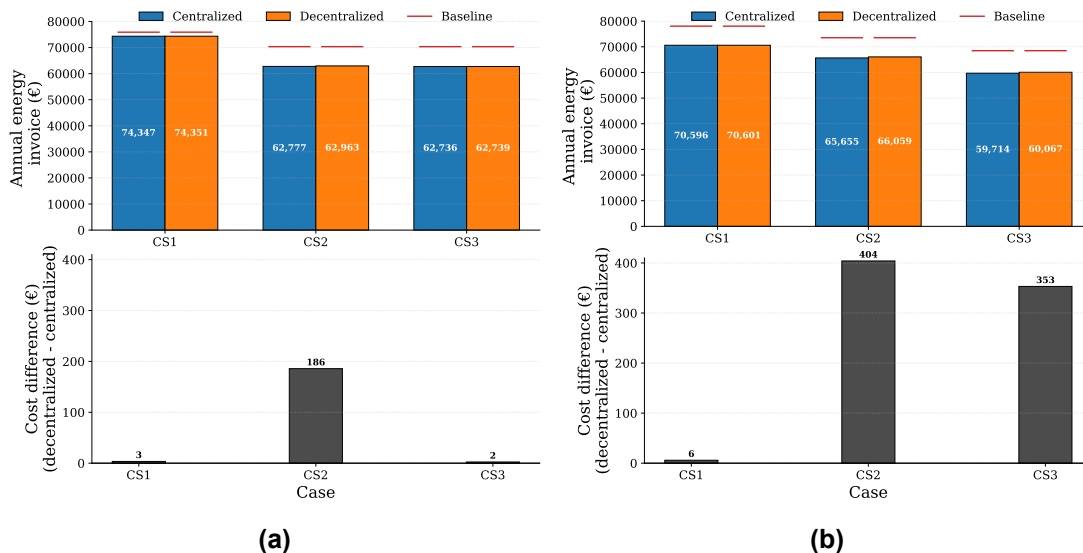
Allocation mechanism	Type	Reference	Note
Shapley value	cost allocation	Eq. 4.2 and 4.7	
Optimal excess	cost allocation	Eq. 4.5 and 4.7	
Hybrid prorated cost allocation	cost allocation	Eq. 4.6 and 4.7	
Static sharing keys	heuristic	Eq. 4.9 and 4.13	equal keys
Dynamic sharing keys	heuristic	Eq. 4.10, 4.11, and 4.13	based on individual offtake
Hybrid sharing keys	heuristic	Eq. 4.12 and 4.13	static then dynamic
Multi-round sharing keys	heuristic	Algorithm 2 and Eq. 4.13	equal keys

Note that for direct cost allocation mechanisms (the first three in Table 4.2), the redistribution of revenue from collective assets is applied (see Eq. 4.7). Furthermore, for all heuristic allocation mechanisms, the energy surplus/injection to the grid after energy sharing is allocated to the community members proportionally to the quantity of injected energy. Additionally, we do not test the hierarchical sharing keys, which require grouping of members due to the low number of community members.

First, we discuss the results of the total energy invoice, and the self-consumption and self-sufficiency ratios for the day-ahead energy management schemes, i.e., the centralized and decentralized approaches, comparing them with each other and with the baseline cases, where there is no energy sharing among the members (Section 3.4). This is followed by the analysis of the outcomes for the allocation mechanisms based on the KPIs in Section 4.4.2.

## 4.5.1 Total energy invoice

To evaluate the effectiveness of the proposed energy sharing schemes, Figure 4.3 presents the total annual invoice (cost) for the entire community, including individual members and shared assets, for both the centralized and decentralized energy management schemes, along with the differences between them. Results are shown for the three cases (CSs). Figure 4.3a illustrates the outcomes under fixed retail prices, whereas Figure 4.3b presents the results under dynamic prices.

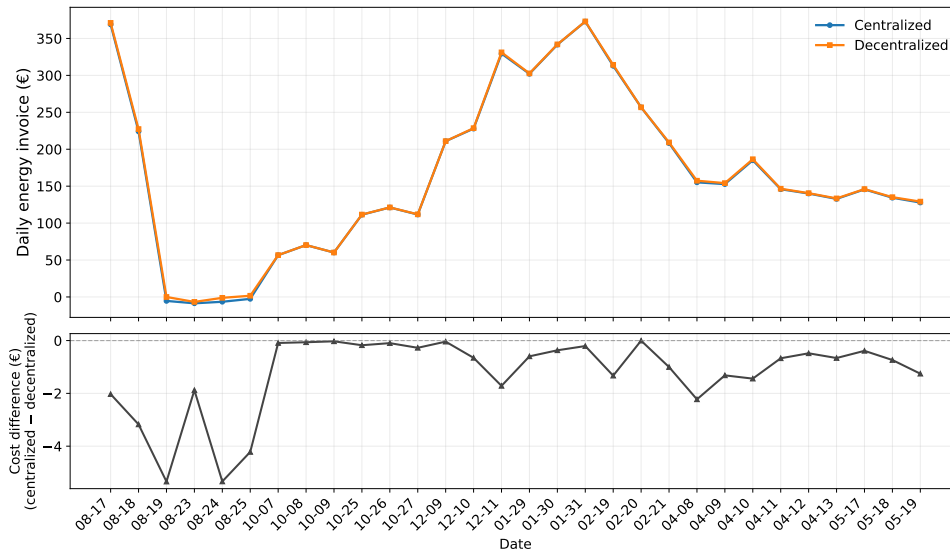


**Figure 4.3 – Annual energy invoice (top) and differences between centralized and decentralized energy management schemes (bottom) under: (a) Static and (b) dynamic retail prices.**

As shown in Figure 4.3, the energy management schemes reduce the annual energy invoice compared to the baselines (red lines). However, the differences between the centralized and decentralized schemes are minimal for CS1 under both price structures, while more noticeable differences appear in CS2 and CS3. As explained earlier, CS1 has limited PV surplus and a smaller battery installations compared to CS2 and CS3; therefore, the energy management schemes have less flexibility to exploit, resulting in smaller cost reductions. Due to the case particularities, it is not possible to draw a broad conclusion about how much the centralized scheme can improve energy costs relative to the decentralized scheme. However, the results do indicate that energy-sharing schemes reduce the annual invoices compared to having no energy management mechanism (the baseline cases), and that the centralized approach generally performs better.

To illustrate the short-term performance of the energy-sharing schemes, the daily energy invoices for the 30 identified representative days are shown in Figure 4.4. The results are presented only for CS2 under dynamic prices, since this case exhibits more pronounced differences between the energy management schemes compared to the other cases as observed in the annual invoice analysis.

As illustrated in Figure 4.4, the daily energy invoices are lower during the summer period when PV surplus is high, and higher during the winter period due to limited PV generation. The centralized energy management scheme also shows more improvements during summer, as the larger PV surplus and battery flexibility can be dispatched more among community members.



**Figure 4.4 – Daily energy invoice (top) and the difference (bottom) for the energy management schemes for CS2 under dynamic prices.**

In contrast, such flexibility and power surplus is more constrained in the decentralized scheme. However, the extent to which the centralized approach reduces daily costs compared to the decentralized scheme cannot be generalized, as it strongly depends on the specific parameters of each case study.

### 4.5.2 Self-consumption and self-sufficiency ratios

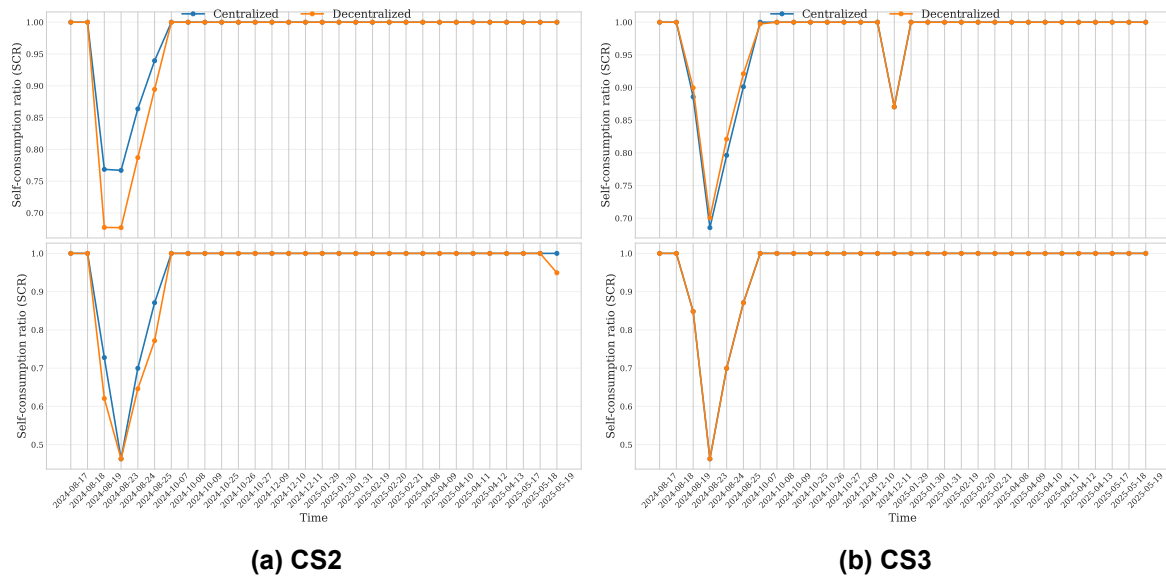
In this section, the SCR and SSR results for the different case studies are presented. As shown in Table 4.3, both the centralized and decentralized energy management schemes improve the average SCR and SSR for all cases compared to the baseline since locally generated energy from PVs can be used not only by their owners but also by others within the community. The differences between the two energy management schemes are not substantial, and the results under dynamic prices are slightly better than those under static prices. The underlying reasons for these observations are further elaborated in the discussion of the daily SCR and SSR results.

**Table 4.3 – Annual average SCR and SSR for all case studies [%].**

Cases	Self-consumption ratio (SCR)			Self-sufficiency ratio (SSR)		
	Centralized	Decentralized	Baseline	Centralized	Decentralized	Baseline
Case 1-Static	100.0	100.0	99.7	18.2	18.2	18.0
Case 2-Static	97.1	96.3	93.2	33.1	32.4	30.0
Case 3-Static	97.4	97.4	93.2	33.3	33.3	30.0
Case 1-Dynamic	100.0	100.0	98.7	33.7	33.7	16.8
Case 2-Dynamic	98.5	97.8	97.3	37.8	37.3	30.2
Case 3-Dynamic	97.9	98.0	94.6	46.8	46.9	34.4

As mentioned earlier, CS1 has no substantial PV surplus; therefore, for both the centralized and decentralized energy management schemes, under either fixed or dynamic prices, the SCR is close to one and the SSR is close to zero. This indicates that the limited PV generation is fully consumed internally within the community. Consequently, the daily SCR and SSR results are presented only for CS2 and CS3.

The SCR results, calculated using Eq. 3.4, for the centralized and decentralized energy management schemes under dynamic and fixed (static) prices are presented in Figure 4.5. The results show that, for both schemes and across both price signals, the SCR is lower than one during the summer period, as some PV surplus is injected into the grid. In contrast, during the winter period, all PV generation is consumed internally, resulting in an SCR equal to one for most days. Furthermore, the SCR under dynamic prices is higher than under static prices. This is because, with dynamic pricing, the batteries tend to charge from the grid when the offtake price is low; otherwise, they are charged using PV generation. Consequently, less PV power is injected into the grid under dynamic prices, leading to a higher SCR.

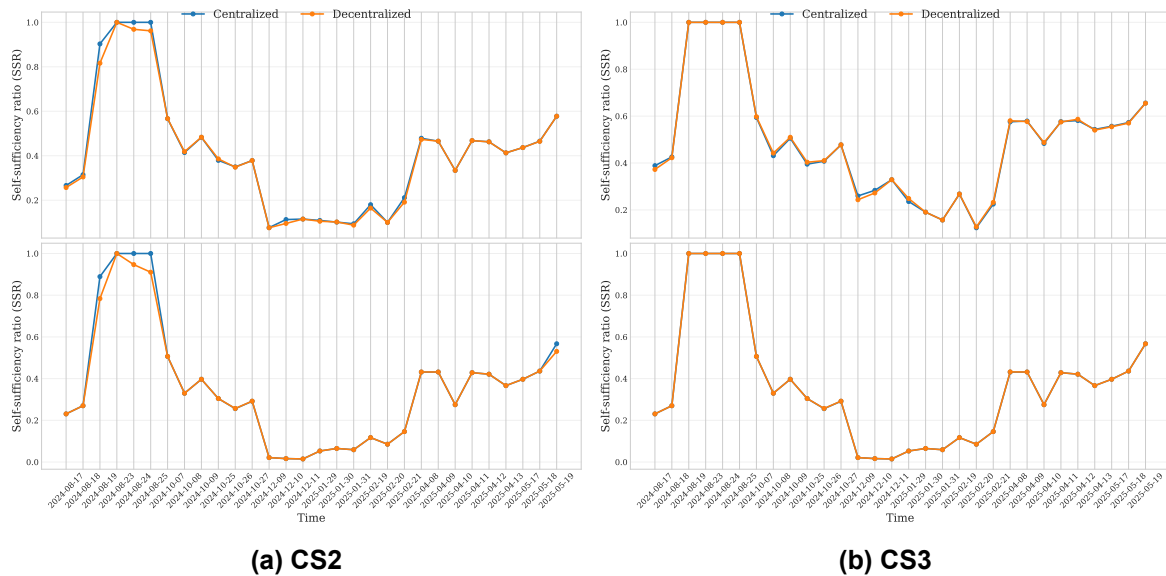


**Figure 4.5 – SCR for the different energy management schemes under dynamic (top) and static (bottom) prices for: (a) CS2 and (b) CS3.**

The SCR results for CS2 and CS3, which include larger PV capacities and more flexible assets, are presented in Figures 4.5a and 4.5b, respectively. In CS2, the centralized energy management scheme results in a higher SCR compared to the decentralized scheme. However, in CS3, the decentralized scheme performs better in terms of SCR. This is because CS3 has a larger shared battery capacity and more members equipped with individual batteries compared to CS2, providing greater flexibility to absorb internal PV generation. Overall, the SCR performance of the different energy management schemes is highly dependent on the characteristics of the community and the assets they own.

The SSR results, calculated using Eq. 3.5, are presented in Figure 4.6 for the centralized and decentralized energy management schemes under both dynamic and static price signals. The results show that both schemes achieve higher SSR values during the summer period, while the lowest values occur in winter. This indicates that, in summer, a larger share of the community’s total consumption is supplied internally by PV generation, whereas in winter, limited PV availability leads the community to import energy from the grid on certain days, resulting in an SSR that is close to zero.

Similar to the SCR results, the SSR under dynamic pricing is higher than under static pricing. The SSR results for CS2 and CS3 are shown in Figures 4.6a and 4.6b, respectively. For CS2, the centralized scheme performs better than the decentralized approach, whereas in CS3, the decentralized mechanism slightly outperforms the centralized one on some days. However,



**Figure 4.6 – SSR for the different energy management schemes under dynamic (top) and static (bottom) prices for: (a) CS2 and (b) CS3.**

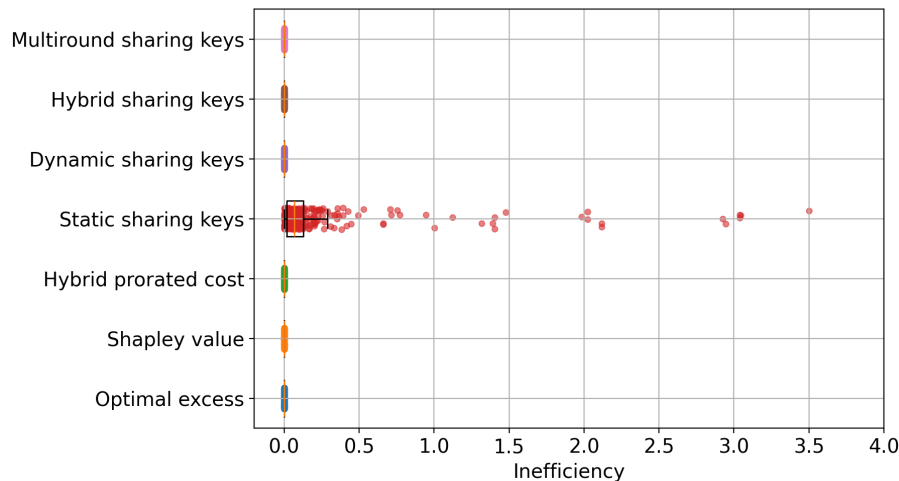
these differences are not substantial. Overall, the SSR is also sensitive to the specific case parameters for each energy management scheme.

### 4.5.3 Efficiency of allocation mechanisms

The efficiency of an allocation mechanism is crucial as it ensures that the community cost is fully allocated to the community members (Eq. 4.3 holds). The (daily) inefficiencies (Eq. 4.14) of the tested allocation mechanisms in all cases are shown in Figure 4.7. As can be seen in this figure, all allocation mechanisms, except for the static sharing keys, are efficient. Static sharing keys can result in suboptimal sharing of locally generated energy, leading to a higher aggregated total cost. The inefficiency of the static sharing keys is aligned with the observation in the literature, as reported in Section 4.3.1. Meanwhile, the efficiency results of the other heuristic allocation mechanisms provide a positive argument to choose these mechanisms over the static sharing keys. Note that the optimal excess and the Shapley value approaches are efficient by design.

The daily cost-saving index per community member (Eq. 3.3) measures the benefit that a member obtains by sharing energy in the community and depends on the cost allocation scheme used. Thus, the daily cost savings for each member differ for different allocation mechanisms, e.g., as can be seen in Figures 4.8, 4.9, and 4.10, which show the daily cost saving indices for three members with dynamic prices and the centralized energy management scheme. In the analysis of the daily cost-saving index, we use CS2 with dynamic prices as an example, although our observations in this case also mostly hold for other cases. Additionally, from the daily cost-saving index, we can infer the individual rationality of an allocation mechanism, i.e., if the daily cost-saving index is negative, then the allocation mechanism is not individually rational. Table 4.4 provides the summary of the individual rationality of all tested allocation mechanisms.

Cost allocation methods based on the Shapley values and the optimal excess are individually rational by design, as validated in this numerical study (see the first two rows of Table 4.4). Thus, all members obtain non-negative daily cost savings in every case and price scheme. From Figures 4.8, 4.9, and 4.10, we can also observe that the daily cost saving dynamical



**Figure 4.7 – Box plots of inefficiencies for all tested allocation mechanisms in all cases.**

**Table 4.4 – The occurrence of the tested allocation mechanisms producing individually rational allocated costs in all cases.**

Case	case 1				case 2				case 3			
	dynamic		static		dynamic		static		dynamic		static	
EM scheme	Cent.	Decent.	Cent.	Decent.	Cent.	Decent.	Cent.	Decent.	Cent.	Decent.	Cent.	Decent.
Optimal excess	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Shapley value	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Hybrid prorated cost allocation	10%	10%	90%	100%	23%	10%	50%	50%	7%	13%	50%	53%
Static sharing keys	10%	10%	100%	100%	30%	27%	97%	100%	20%	33%	100%	100%
Dynamic sharing keys	10%	10%	90%	100%	27%	17%	53%	60%	10%	20%	53%	53%
Hybrid sharing keys	10%	10%	90%	100%	27%	17%	53%	60%	10%	20%	53%	53%
Multiround sharing keys	10%	10%	100%	100%	27%	17%	53%	60%	10%	20%	53%	53%

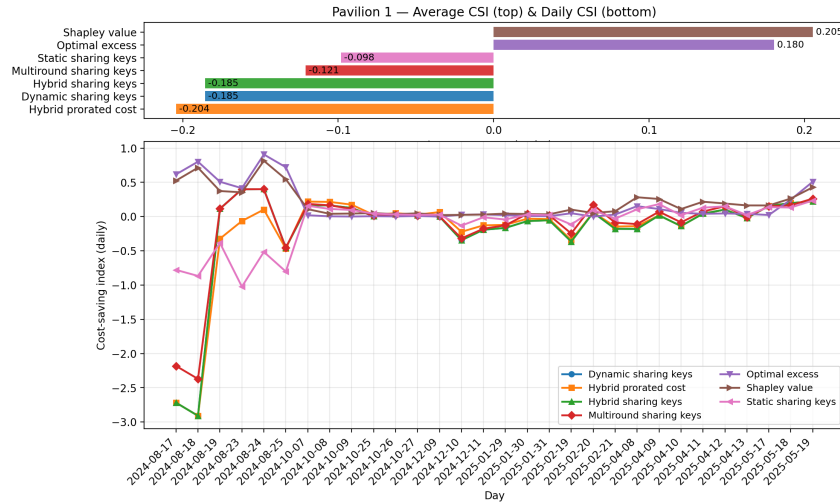
patterns of these two allocation mechanisms are similar, showing closeness in the allocated daily costs from these two approaches.

The other cost allocation method, i.e., the hybrid prorated allocation, is not individually rational. Negative cost-saving indices can be observed for Pavilion 1 and Pavilion 2 in Figures 4.8 and 4.9. Indeed for Pavilion 1, particularly in CS2 with dynamic prices, this allocation method provides the worst cost-saving index on average. Meanwhile on the other hand for Harbor Control, which is a significantly larger offtaker than Pavilion 1, this method provides the second-best cost-saving index.

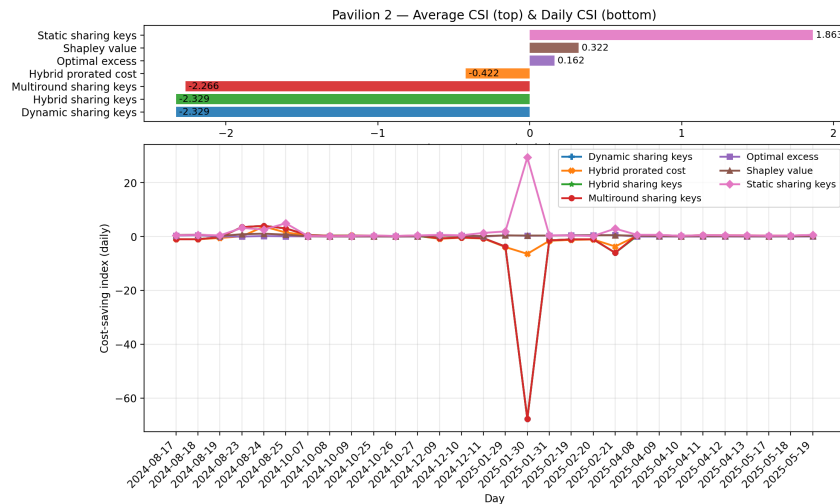
#### 4.5.4 Daily cost saving

Similar to the hybrid prorated cost allocation method, all heuristic allocation methods are not individually rational. Furthermore, their cost-saving index patterns, except for the static sharing keys, observed in the bottom plots of Figures 4.8, 4.9, and 4.10 are close to each other but rather different from the Shapley value and optimal excess approaches. Furthermore, heuristic allocation mechanisms typically overcompensate offtakers, e.g., the Harbor Control.

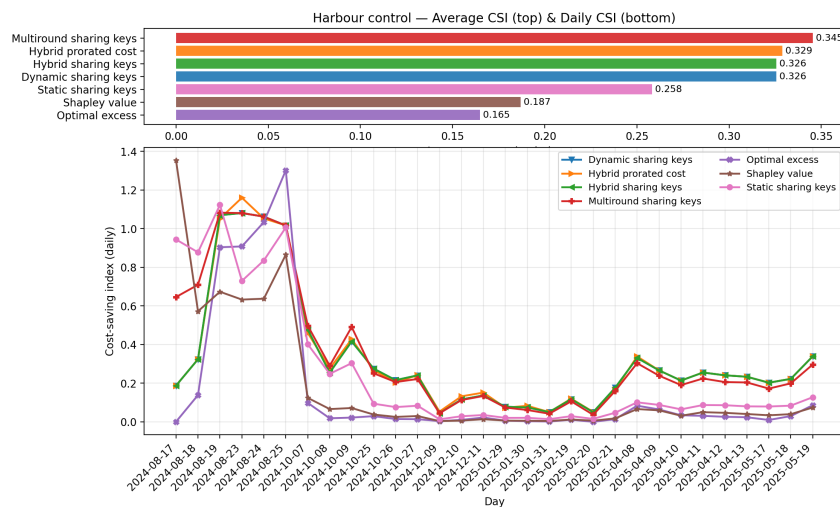
There are no differences in the performances of the hybrid and dynamic sharing keys in all cases. As dynamic sharing keys are simpler to implement than the hybrid sharing keys, the equal performance indicates that dynamic sharing keys can be preferred over the hybrid ones. The multi-round sharing keys, on the other hand, perform better than the dynamic and hybrid sharing keys as they provide higher cost-saving values for all community members as compared



**Figure 4.8 – Daily cost saving index of Pavilion 1 in CS2 with dynamic prices and the centralized energy management scheme.**



**Figure 4.9 – Daily cost saving index of Pavilion 2 in CS2 with dynamic prices and the centralized energy management scheme.**

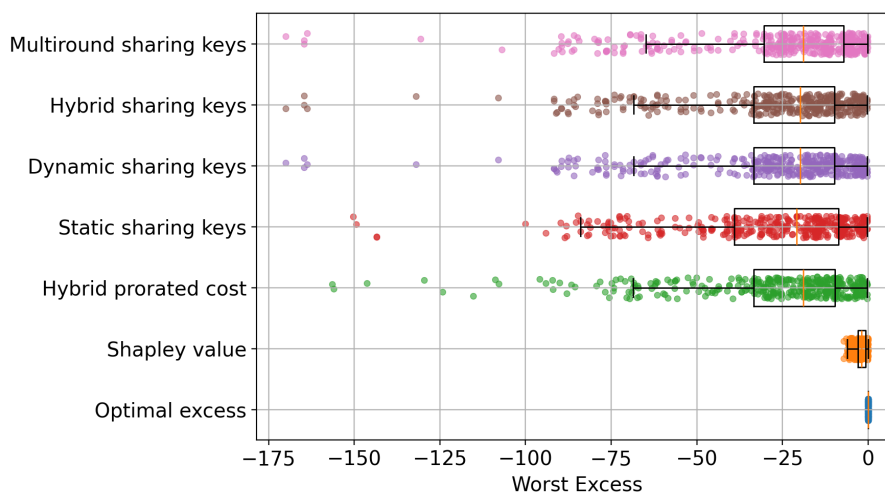


**Figure 4.10 – Daily cost saving index of Harbor control in CS2 with dynamic prices and the centralized energy management scheme.**

to those of the dynamic and hybrid sharing keys. Finally, the static sharing keys perform the best among the heuristic allocation methods in the individual rationality measure (Table 4.4), especially when static prices are used. In terms of the cost-saving index, among the heuristic allocation mechanisms, the static sharing keys provide the closest average value to those of the Shapley value and optimal excess approaches for Harbor Control, which is the largest offtaker in the community, and the highest average values for other members. Despite a better performance in this KPI from the static sharing keys, the inefficiency of this method is a significant disadvantage.

#### 4.5.5 Stability of allocation mechanisms

The stability of an allocation mechanism indicates that community members are better off by staying in the community as compared to creating a (smaller) sub-community to perform energy sharing. To assess stability, we first evaluate the worst excess (Eq. 4.16), as presented in Figure 4.11. From this figure, we observe that, except for the optimal excess approach, all allocation mechanisms have negative worst excess values in most simulated days and cases. When the worst excess value is negative, there exist subcoalitions where (some) community members can aggregatively gain larger cost savings. Differently, the optimal excess achieves non-negative worst excess in all simulated days and cases. This fact means that this cost allocation method ensures that each community member gains the highest profit by being in the community. Considering the individual rationality and efficiency results, we can conclude that only the optimal excess mechanism is stable.

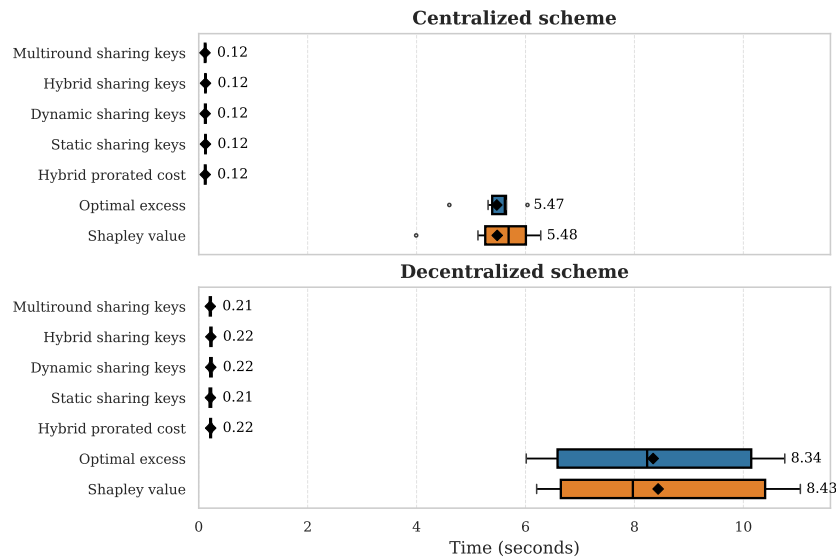


**Figure 4.11 – Box plots of worst excess for all tested allocation mechanisms in all cases.**

#### 4.5.6 Computational time of allocation mechanisms

In this section, the computational time required to simulate the cost/revenue allocation methods for the centralized and decentralized energy management schemes is presented in Figure 4.12. The simulations were executed on an Intel(R) Xeon(R) Gold 5120 CPU @ 2.20 GHz, using Python 3.13 and the HiGHS 1.12.0 solver.

The results shown in Figure 4.12 indicate that the computational times of the Shapley value and worst-excess optimization allocation methods are significantly higher than those of the other mechanisms (approximately around 40-50 times higher). This is because both approaches



**Figure 4.12 – Computational time of cost/revenue allocation methods for the centralized (top) and decentralized (bottom) energy management schemes.**

require solving a large number of optimization problems to compute the costs (values) of all possible sub-coalitions.

Although the optimal excess and Shapley value methods are the superior methods based on other KPIs, their computational loads raise a concern about their practicality. Since the number of sub-coalitions increases exponentially with the number of community members, the Shapley value and optimal excess methods can quickly become computationally intractable for larger communities. The cost/value calculation of all sub-coalitions requires solving optimization problems when flexible assets must be optimally scheduled. Under the decentralized scheme and when there is no collective flexible assets, the calculation becomes inexpensive. Although predictably, it is still computationally more expensive than the other mechanisms, these two approaches can still be tractable, even when the number of community members is large under the previously mentioned setting.

In addition, Figure 4.12 shows that the computational time of the cost/revenue allocation methods is higher for the decentralized scheme than for the centralized one. This is because, in the decentralized approach, to calculate the values of subcoalitions, multiple optimization problems must be solved, one for each community member in the first stage (individual scheduling) and another one in the second stage to optimally schedule the collective assets, and this is done sequentially, resulting in a higher computational time. Meanwhile, in the centralized approach, a single optimization problem is solved for computing the cost of each subcoalition. We note that parallelization could help improve the computational time of the Shapley value and the optimal excess methods, particularly during the process of calculating the values of all subcoalitions.

## 5 Internal energy pricing models

---

Internal energy pricing models fall within the category of centralized individual energy sharing, in which peers do not trade energy bilaterally, but rather offer their surplus (or cover their shortage) to the community. The system is designed so that every participant automatically makes their surplus available to the community, and automatically consumes from the community if surplus is available. Note, however, that each consumer is still able to individually schedule their flexible appliances. For instance, they can still determine when to discharge a battery. The central question then becomes how to establish an efficient pricing rule that remunerates these internal exchanges in a way that incentivizes consumers to behave according to the needs of the local system.

Common pricing mechanisms are mid-market rate pricing [43], supply-demand ratio pricing [46], and auction based pricing [59]. The former two will be the topic of this section, and the latter is left for Section 6. The Mid-Market Rate (MMR) sets the internal energy price as the simple average of the retailer's offtake and injection prices. The Supply-Demand Ratio (SDR) is more involved, but aims to adjust prices such that participants are better incentivized to consume when local electricity is available. It was first introduced by [46], and is now commonly implemented in local energy markets [60, 41]. There are a few studies that have attempted to compare these mechanisms [47, 60, 41]. Generally speaking, these studies have shown that SDR models can achieve similar cost reductions than MMR models, albeit with different distributional consequences. The SDR mechanisms, for instance, provides greater benefits to electricity buyers, whereas auction-based pricing mostly favors electricity sellers.

Our study makes two contributions to this field of research. First, all of these previous studies pair local pricing mechanisms with a flat retail price. While this approach is applicable to many practical pilots, it does not apply to all. For instance, the community manager of the Scheveningen pilot is exposed to dynamic prices. Therefore, we evaluate the different mechanisms under both fixed and dynamic prices to assess whether they still perform adequately. Second, and more importantly, the models in the preceding and subsequent sections are compared using a common case study. This allows us to compare not only the performance of different pricing mechanisms, as in the case for the references above, but also to compare them to fundamentally different local energy and trading arrangements.

The remainder of this section is structured similarly to Sections 4, 6, and 7. Section 5.1 presents the methodology, Section 5.2 presents the model particularities and specific assumptions, and Section 5.3 presents the results.

### 5.1 Methodology

---

Recall that internal energy pricing models allow consumers to schedule their appliances as desired, and steer that behavior through internal price signals. Our methodology follows a game-theoretic framework that hence needs to comprise two elements: the decision-making model of individual consumers (i.e. how they act based on prices), and the internal price formation. In what follows, Section 5.1.1 describes the decision-making model. Sections 5.1.2 and 5.1.3 respectively discuss the MMR and the SDR price formation models. Section 5.1.4 ties these elements together and explains how the resulting market equilibrium is being computed.

### 5.1.1 Decision-making model by individual consumers

The consumer decision model functions as a HEMS that optimizes and schedules household energy use. The same model is applied under different internal pricing rules; however, the varying price signals lead to different operational behaviors. The objective function, input parameters, and decision variables are detailed below.

**Objective** The objective of the consumer decision model is to minimize the annualized electricity bill by optimally managing Distributed Energy Resources (DERs), namely solar PV and BESS, when available. The optimization problem is formulated as:

$$\min : \sum_{d \in \mathcal{D}, t \in \mathcal{T}} \lambda_{d,t}^{off} \cdot P_{d,t}^{off} - \lambda_{d,t}^{inj} \cdot P_{d,t}^{inj} \quad (5.1)$$

**Input parameters** The input parameters fall into four main categories:

- Price parameters: internal injection & offtake prices ( $\lambda^{inj}$  &  $\lambda^{off}$ ) seen by consumers
- Load parameters: uncontrollable household demand ( $D$ )
- PV parameters: maximum potential PV generation ( $P^{PV}$ )
- BESS parameters: battery capacity ( $C^s$ ), charge/discharge efficiency ( $\eta$ ), and maximum charge/discharge power ( $P^s$ )

**Decision variables** The optimization determines the following decision variables:

- Grid interactions: offtake ( $P^{off}$ ) and injection ( $P^{inj}$ )
- PV operation: actual PV generation ( $g^{PV}$ ) after possible curtailment.
- BESS operation: charging ( $P^{ch}$ ), discharging ( $P^{dc}$ ), and state of charge ( $e$ )

**Constraints formulations** The decision-making model includes constraints for energy balance, PV generation, and battery operation.

- Individual energy balance constraint:

$$P_{d,t}^{off} - P_{d,t}^{inj} = D_{d,t} - g_{d,t}^{PV} + P_{d,t}^{ch} - P_{d,t}^{dc} \quad (5.2)$$

The behind-the-meter energy balance for each consumer is determined by Constraint 5.2, linking hourly net offtake with consumer's demand ( $D_{d,t}$ ), electricity charged ( $P_{d,t}^{ch}$ ) or discharged ( $P_{d,t}^{dc}$ ) from storage, and PV generation ( $g_{d,t}^{PV}$ ).

- PV operation constraint:

$$g_{d,t}^{PV} \leq P_{d,t}^{PV} \quad (5.3)$$

The actual PV generation ( $g_{d,t}^{PV}$ ) is limited by constraint 5.3, ensuring PV generation cannot exceed available irradiance potential.

- Battery operation constraints:

$$e_{d,t} = e_{d,t-1} + \eta \cdot P_{d,t}^{ch} - \frac{1}{\eta} \cdot P_{d,t}^{dc}, \quad (5.4)$$

$$e_{d,1} = \frac{1}{2}C_i^s + \eta \cdot P_{d,1}^{ch} - \frac{1}{\eta} \cdot P_{d,1}^{dc}, \quad (5.5)$$

$$e_{d,\text{end}} = \frac{1}{2}C^s, \quad (5.6)$$

$$C^s - e_{d,t} \geq 0, \quad (5.7)$$

$$P_{d,t}^{ch}, P_{d,t}^{dc} \leq P^s \quad (5.8)$$

Constraint 5.4 updates the battery's state of charge considering efficiency losses. Cyclic boundary conditions are imposed by Constraints 5.5–5.6. Capacity and power limits are enforced by Constraints 5.7–5.8.

The complete decision-making problem consists of Objective 5.1 subject to Constraints 5.2–5.8.

## 5.1.2 Mid-market rate

In the MMR mechanism, the internal energy price at a given moment is computed ex-post as the simple average of the retailer's offtake and injection prices:

$$\lambda_t^{P2P} = \frac{\lambda_t^{off} + \lambda_t^{inj}}{2} \quad (5.9)$$

However, not all electricity can necessarily be exchanged within the community. As a result, consumers typically engage in two types of transactions: local trading within the community, and trading the residual offtake or injection with the retailer. The two transactions are priced differently. Electricity bought or sold to a retailer is respectively valued at the offtake price ( $\lambda^{off}$ ) or the injection price ( $\lambda^{inj}$ ), while internal energy transactions are valued at the internal energy price ( $\lambda^{P2P}$ ). Since some pricing rules do not allow a clean separation between local and retail volumes, making direct comparisons across mechanisms difficult, we define a weighted average buying and selling price. These reflect the effective prices consumers face, accounting for the proportions of electricity traded locally versus with the retailer:

$$\lambda_t^{buy} = \lambda_t^{P2P} \cdot x^{off,P2P} + \lambda_t^{off} \cdot x^{off,ret} \quad (5.10)$$

$$\lambda_t^{sell} = \lambda_t^{P2P} \cdot x^{inj,P2P} + \lambda_t^{inj} \cdot x^{inj,ret} \quad (5.11)$$

where  $x^{off,P2P}$  and  $x^{off,ret}$  denote the fractions of offtake purchased locally and from the retailer, respectively (analogously for injection). For example, when local production is insufficient ( $P_t^{Off} > P_t^{Inj}$ ), consumers must procure part of their demand from the retailer ( $x^{off,ret} > 0$ ), resulting in an average buying price above  $\lambda_t^{P2P}$ . All injection can be consumed locally ( $x^{inj,ret} = 0$ ) such that the average selling price equals the internal market price.

Following the conventions defined above, one can compute the consumer's average buying and selling price depending on whether the local market experiences a surplus or a deficit:

$$\lambda_t^{buy} = \begin{cases} \frac{\lambda_t^{off} + \lambda_t^{inj}}{2} & P_t^{Off} \leq P_t^{Inj} \\ \frac{Inj_t}{Off_t} \cdot \frac{\lambda_t^{off} + \lambda_t^{inj}}{2} + (1 - \frac{Inj_t}{Off_t}) \cdot \lambda_t^{off} & P_t^{Off} > P_t^{Inj} \end{cases} \quad (5.12)$$

$$\lambda_t^{sell} = \begin{cases} \frac{Off_t}{Inj_t} \cdot \frac{\lambda_t^{off} + \lambda_t^{inj}}{2} + (1 - \frac{Off_t}{Inj_t}) \cdot \lambda_t^{inj} & P_t^{Off} \leq P_t^{Inj} \\ \frac{\lambda_t^{off} + \lambda_t^{inj}}{2} & P_t^{Off} > P_t^{Inj} \end{cases} \quad (5.13)$$

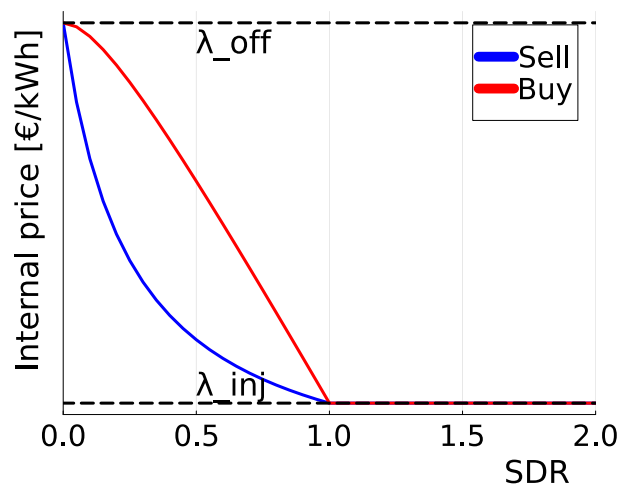
### 5.1.3 Supply-demand ratio

This SDR pricing rule's central principle is that internal energy prices should reflect the local energy balance, incentivizing participants to consume when local electricity is available. To achieve this, the average buying and selling price<sup>7</sup> depends on the local supply to demand ratio ( $SDR_t = Inj_t / Off_t$ ). The internal buying and selling price can be computed as:

$$\lambda_t^{sell} = \begin{cases} \frac{\lambda_t^{off} \cdot \lambda_t^{inj}}{(\lambda_t^{off} - \lambda_t^{inj}) \cdot SDR_t + \lambda_t^{inj}}, & \text{if } 0 \leq SDR_t \leq 1, \\ \lambda_t^{inj}, & \text{else.} \end{cases} \quad (5.14)$$

$$\lambda_t^{buy} = \begin{cases} \lambda_t^{sell} \cdot SDR_t + \lambda_t^{off} \cdot (1 - SDR_t), & \text{if } 0 \leq SDR_t \leq 1, \\ \lambda_t^{inj}, & \text{else.} \end{cases} \quad (5.15)$$

The internal buying and selling prices with respect to the supply-demand ratio are presented in Figure 5.1. The figure shows that when the SDR is low, i.e. when local injection is scarce, the selling price approaches the retail offtake price and consumers are encouraged to inject more. On the other hand, when local injection is abundant, the buying price falls to the retail injection price and the system hence encourages more consumption (while reducing the value of injection). As for the MMR approach, a community manager can calculate the consumer's buying and selling prices ex-post using their offtake and injection data.



**Figure 5.1 – Internal energy buying and selling price vs. supply-demand ratio.**

### 5.1.4 Implementation algorithm

We model the interactions between consumers and the community manager as a non-cooperative game, where participants are rational price takers with perfect foresight. Each consumer acts as an independent decision-maker who minimizes their annual electricity bill by optimally operating their DERs. The central community manager, which could function either as an algorithm-driven virtual platform or as a traditional intermediary, manages all transactions, sets the internal energy price according to the defined pricing rules, and interacts with the retailer to trade any

<sup>7</sup>We would like to emphasize that we are referring here to the buying and selling price, see above. This is one of the pricing rules where it is not easy to distinguish between the local price and the retail price.

residual electricity surplus or deficit. We seek a Nash equilibrium in which no consumer can improve their outcome given the decisions of others.

The simulation is based on a deterministic setup, meaning internal energy prices and traded quantities are determined simultaneously and assumed to be known with certainty. In practice, however, prices would need to be communicated to consumers in advance to guide their operational behavior. The practical implementation of internal pricing models is beyond the scope of this deliverable and will be further addressed in Deliverable 4.1.

The Nash equilibrium is computed through an iterative algorithm inspired by the Alternating Direction Method of Multipliers (ADMM), a dual decomposition method for convex optimization [28]. However, given that we assume the electricity retailer can always balance any electricity surplus or deficit within the community, the coupling constraint typically required for equilibrium is inherently satisfied. In each iteration, every consumer optimizes their objective based on the governing prices. Given the resulting offtake and injection profiles, the community manager (re)computes the internal energy prices following the pricing rules. Consumers subsequently re-optimize their decisions based on updated prices, and so on. The process continues until the consumer's decisions and the governing internal prices are consistent, i.e. until the Nash equilibrium is reached. An overview of the algorithm structure is presented in Algorithm 3.

---

**Algorithm 3** Iterative algorithm for computing a Nash equilibrium of the non-cooperative game

---

**Require:** All parameters belonging to all consumers' optimization problems (5.1)-(5.8)

**Ensure:** Nash equilibrium solution to the game

```

1: Define  $\rho_{off}, \rho_{inj}, \epsilon_{dual}, iter_{max}$ 
2: Initialize Internal energy prices  $\lambda_{d,t}^{buy}$  &  $\lambda_{d,t}^{sell}$ 
3:  $conv \leftarrow \text{False}$ 
4:  $iter \leftarrow 0$ 
5: while  $conv = \text{False}$  and  $iter \leq iter_{max}$  do
6:   Solve consumers' decision-making problems (5.1)-(5.8)
7:   Compute dual residuals  $r_{dual}$ 
8:   Update Internal energy prices based on pricing rules (5.12)-(5.13) OR (5.14)-(5.15)
9:    $conv \leftarrow \|r_{dual}\| \leq \epsilon_{dual}$ 
10:   $iter \leftarrow iter + 1$ 
11: end while

```

---

The process begins by defining penalty rates for consumers' offtake and injection decisions ( $\rho_{off}, \rho_{inj}$ ), tolerances for dual residuals ( $\epsilon_{dual}$ ), and a maximum iteration limit ( $iter_{max}$ ). We then initialize the convergence status and the internal prices ( $\lambda^{buy}$  and  $\lambda^{sell}$ ). These prices are iteratively updated based on the pricing rules introduced in Section 5.1.3 and 5.1.2 to guide the agents towards an equilibrium. In each iteration, updated prices are announced to all consumers, who then optimize their individual objectives as detailed in Section 5.1.1. After all agents complete their optimization, we calculate dual residuals by comparing current and previous injection or offtake values. The algorithm repeats until convergence which represents a Nash equilibrium of the game described by Equations 5.1 - 5.8.

## 5.2 Model particularities

---

The framework presented above requires additional assumptions, in addition to the general ones presented in Section 3.2, that are made explicit in Section 5.2.1. Section 5.2.2 furthermore introduces an additional KPI that serves to assess the fairness of the various mechanisms.

### 5.2.1 Model-specific assumptions

---

We require two additional model-specific assumptions, specifically:

- The P2P trading process is modeled as a non-cooperative game where all households optimize simultaneously. The Nash equilibrium is sought using an iterative algorithm.
- The market coordinator holds a passive role: it observes the aggregated offtake and injection after consumers optimize and then computes the corresponding P2P price. It neither matches individual trades nor makes strategic decisions. Any residual imbalance is automatically handled through the retailer.

### 5.2.2 Model-specific KPIs

---

The general KPIs introduced in Section 3.3 serve to evaluate the overall performance of energy sharing mechanisms at the community level. However, community-level metrics do not reveal how benefits are distributed among individual members. Understanding individual gains is crucial, as the perceived fairness of benefit allocation strongly influences participants' willingness to join and remain in an energy-sharing community. Therefore, in the following section, we shift focus to individual outcomes by analyzing both the cost savings achieved by each member and the fairness of benefit distribution under the two internal pricing rules.

To evaluate the fairness of benefits allocation, we apply Jain's fairness index and calculate it based on the individual cost saving index (CSI, defined in Section 3.3):

$$FI = \frac{(\sum_{i \in I} CSI_i)^2}{|I| \cdot \sum_{i \in I} CSI_i^2} \quad (5.16)$$

where  $|I|$  is the number of participants in the community set  $I$ .

Jain's index reflects a "fair share" perspective, that is, whether all members benefit equally from participation in the community. The index takes values between 0 and 1: an index close to 1 indicates highly equitable benefit distribution (all members achieving similar CSI values), whereas lower values signal increasing disparity in how benefits are shared.

## 5.3 Results

---

In this section, we present the results of the internal energy pricing models for the defined case studies. As introduced in Section 5.1, two internal pricing rules are examined: the MMR and the SDR. For both pricing mechanisms, we report the outcomes across the five key performance metrics introduced in Sections 3.3 and 5.2.2: the total energy invoice, the self-consumption and self-sufficiency ratios, individual cost savings, and the fairness metrics.

### 5.3.1 Total energy invoice

We begin by presenting the total annual energy invoice and the corresponding reduction relative to the baseline (no–energy-sharing) model in Table 5.1. Overall, energy sharing consistently reduces the community’s annual energy invoice, with savings reaching up to 10% across the different cases. As flexibility increases, primarily through higher levels of BESS installation, the cost savings also rise. This is clearly visible when comparing Case 1 and Case 2, where the additional flexibility in Case 2 yields a substantial improvement in savings. By contrast, further increasing flexibility in Case 3 delivers little additional benefit. This is because the primary advantage of energy sharing comes from utilizing self-generated electricity locally. Once (almost) all locally produced electricity is already efficiently consumed, additional flexibility offers limited incremental value.

In general, the MMR mechanism yields slightly higher cost savings than the SDR mechanism. Under the fixed retail tariff, however, this difference is almost negligible. This suggests that when operating under fixed prices, as long as consumers are incentivized to use locally generated renewable electricity efficiently, the collective benefits of energy sharing can be achieved regardless of whether MMR or SDR is applied. However, when energy sharing operates under dynamic retail prices, the MMR delivers noticeably greater cost savings than the SDR.

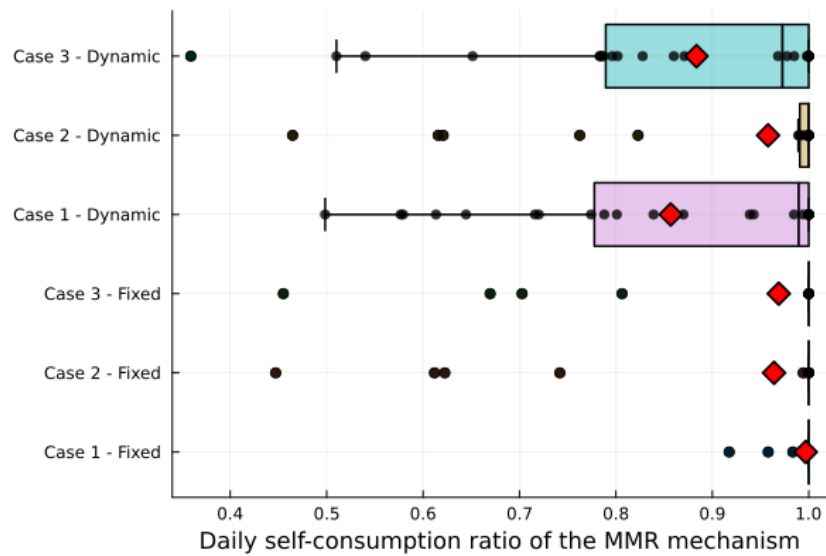
### 5.3.2 Self-consumption ratio

Next, we analyze the self-consumption ratio and its improvement relative to the baseline model. Figures 5.2 and 5.3 show the daily self-consumption ratios across the modeled 30 representative days for the MMR and SDR mechanisms, respectively. Table 5.2 summarizes the weighted average self-consumption ratios and their improvements compared to the baseline model.

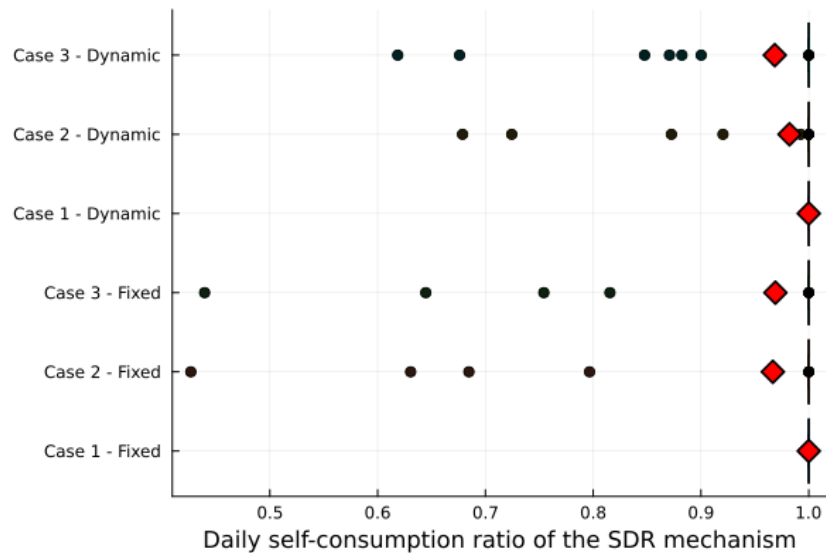
**Table 5.1 – Total annual energy invoice and total cost savings, (relative to the baseline model, under the MMR and SDR mechanisms.**

	MMR		SDR	
	Total Invoice [€]	Cost saving [%]	Total Invoice [€]	Cost saving [%]
Case 1 - Fixed	74373	2.01	74356	2.03
Case 2 - Fixed	63201	10.15	63443	9.80
Case 3 - Fixed	63558	9.65	63842	9.24
Case 1 - Dynamic	74266	5.58	74816	4.88
Case 2 - Dynamic	66270	11.18	68473	8.22
Case 3 - Dynamic	62921	12.86	65862	8.78

Overall, energy sharing increases self-consumption under the fixed retail contract. By providing internal price signals, both pricing mechanisms encourage members to better align their demand with locally available generation, leading to more efficient use of distributed PV resources. Under the dynamic contract, however, self-consumption decreases under the MMR mechanism relative to the baseline. This occurs for two main reasons. First, negative retail prices in the baseline (without energy sharing) create incentives for curtailment during low-price hours. With the MMR mechanism, however, internal selling prices remain positive even when retail prices are negative, removing this curtailment incentive and resulting in more PV injection, and therefore a lower self-consumption ratio. Second, under the MMR, producers with surplus



**Figure 5.2 – Self-consumption ratio under the MMR mechanism. Daily ratios are plotted in black dots while the weighted average daily ratios of each case are plotted in red diamonds.**



**Figure 5.3 – Self-consumption ratio under the SDR mechanism. Daily ratios are plotted in black dots while the weighted average daily ratios of each case are plotted in red diamonds.**

**Table 5.2 – Weighted average daily self-consumption ratios and improvement, relative to the baseline model, under the MMR and SDR mechanisms.**

	MMR		SDR	
	Self-consumption ratio	Improvement	Self-consumption ratio	Improvement
Case 1 - Fixed	0.997	+0.000	1.00	+0.003
Case 2 - Fixed	0.964	+0.032	0.967	+0.035
Case 3 - Fixed	0.969	+0.037	0.969	+0.038
Case 1 - Dynamic	0.856	-0.130	1.00	+0.013
Case 2 - Dynamic	0.958	-0.015	0.982	+0.009
Case 3 - Dynamic	0.884	-0.062	0.968	+0.022

energy gain an incentive to arbitrage across hours. Rather than storing PV surplus for later self-consumption, they prioritize injecting directly when retail prices are high, which increases injection to the grid and lowers self-consumption.

Comparing the two pricing mechanisms, the SDR consistently delivers larger improvements in self-consumption than the MMR. This is evident in the improvements reported in Table 5.2 and in Figure 5.3, where most representative days under SDR achieve self-consumption ratios close to 100%. This can be attributed to two factors. First, internal prices under SDR are directly tied to the local energy balance: consuming locally during surplus hours is rewarded with lower prices, while exporting is discouraged through lower remuneration. This strong alignment between price signals and local conditions effectively steers participants toward maximizing the use of community-generated renewable energy. Second, when combined with the dynamic retail contract, negative or zero wholesale prices also translate into negative or zero internal selling prices under SDR. In such hours, exporting PV surplus becomes unattractive, and curtailment becomes the rational choice, which increases the calculated self-consumption ratio. In contrast, under the MMR mechanism, internal selling prices remain positive even when retail prices are negative, encouraging more injection and lowering self-consumption.

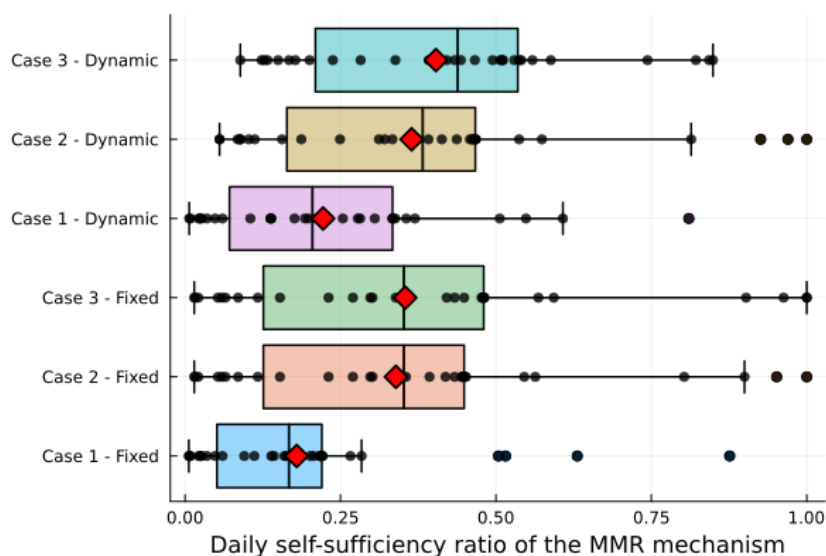
### 5.3.3 Self-sufficiency ratio

Next, we look at the self-sufficiency ratio and its improvement relative to the baseline model. As done before for the self-consumption ratio, Figures 5.4 and 5.5 show the daily self-sufficiency ratios across the modeled 30 representative days for the MMR and SDR mechanisms, respectively. Table 5.3 also summarizes the weighted average self-sufficiency ratios and their improvements compared to the baseline model.

The patterns observed for self-sufficiency closely mirror those of self-consumption, and most findings can be explained by the same underlying mechanisms. Overall, energy sharing increases self-sufficiency across all cases, as internal price signals encourage members to rely more on locally generated electricity rather than imports from the grid. Under the fixed retail contract, the SDR mechanism yields higher self-sufficiency, reflecting its strong alignment with the local energy balance: SDR prices incentivize members to maximize the use of community-generated renewable energy and reduce reliance on external supply. Under the dynamic retail contract, however, the trend reverses. The MMR mechanism achieves higher self-sufficiency ratios than the SDR because PV production is frequently curtailed under SDR in hours with zero or negative retail prices (which translates into zero or negative internal selling prices). In

**Table 5.3 – Weighted average daily self-sufficiency ratios and improvement, relative to the baseline model, under the MMR and SDR mechanisms.**

	MMR		SDR	
	Self-sufficiency ratio	Improvement	Self-sufficiency ratio	Improvement
Case 1 - Fixed	0.179	+0.003	0.182	+0.005
Case 2 - Fixed	0.339	+0.044	0.352	+0.032
Case 3 - Fixed	0.354	+0.047	0.365	+0.035
Case 1 - Dynamic	0.222	+0.067	0.228	+0.085
Case 2 - Dynamic	0.364	+0.086	0.328	+0.028
Case 3 - Dynamic	0.404	+0.156	0.379	+0.178

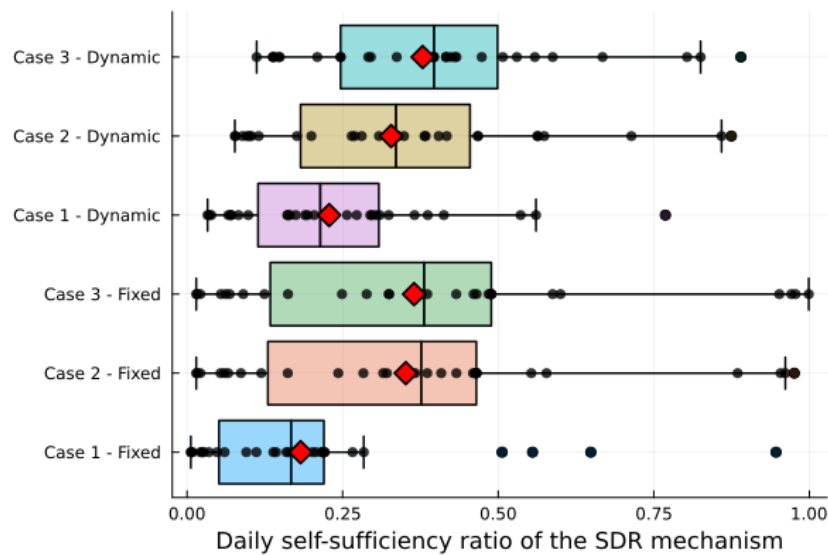


**Figure 5.4 – Self-sufficiency ratio under the MMR mechanism. Daily ratios are plotted in black dots while the weighted average daily ratios of each case are plotted in red diamonds.**

contrast, the MMR maintains positive internal selling prices even during such hours, leading to less curtailment and therefore more locally generated electricity being used, resulting in higher self-sufficiency ratios.

### 5.3.4 Individual cost saving

In the previous sections, we evaluated the performance of energy sharing at the community level by examining total energy invoices, overall cost savings, and indicators such as the self-consumption and self-sufficiency ratios, both of which reflect how effectively local generation is utilized. However, community-level metrics do not reveal how benefits are distributed among individual members. Understanding individual gains is crucial. This is why we introduced the Jain’s index in Section 5.2.2. Recall that the index reflects a “fair share” perspective, that is, whether all members benefit equally from participation in the community. The index takes values between 0 and 1: an index close to 1 indicates highly equitable benefit distribution, whereas lower values signal increasing disparity in how benefits are shared.



**Figure 5.5 – Self-sufficiency ratio under the SDR mechanism. Daily ratios are plotted in black dots while the weighted average daily ratios of each case are plotted in red diamonds.**

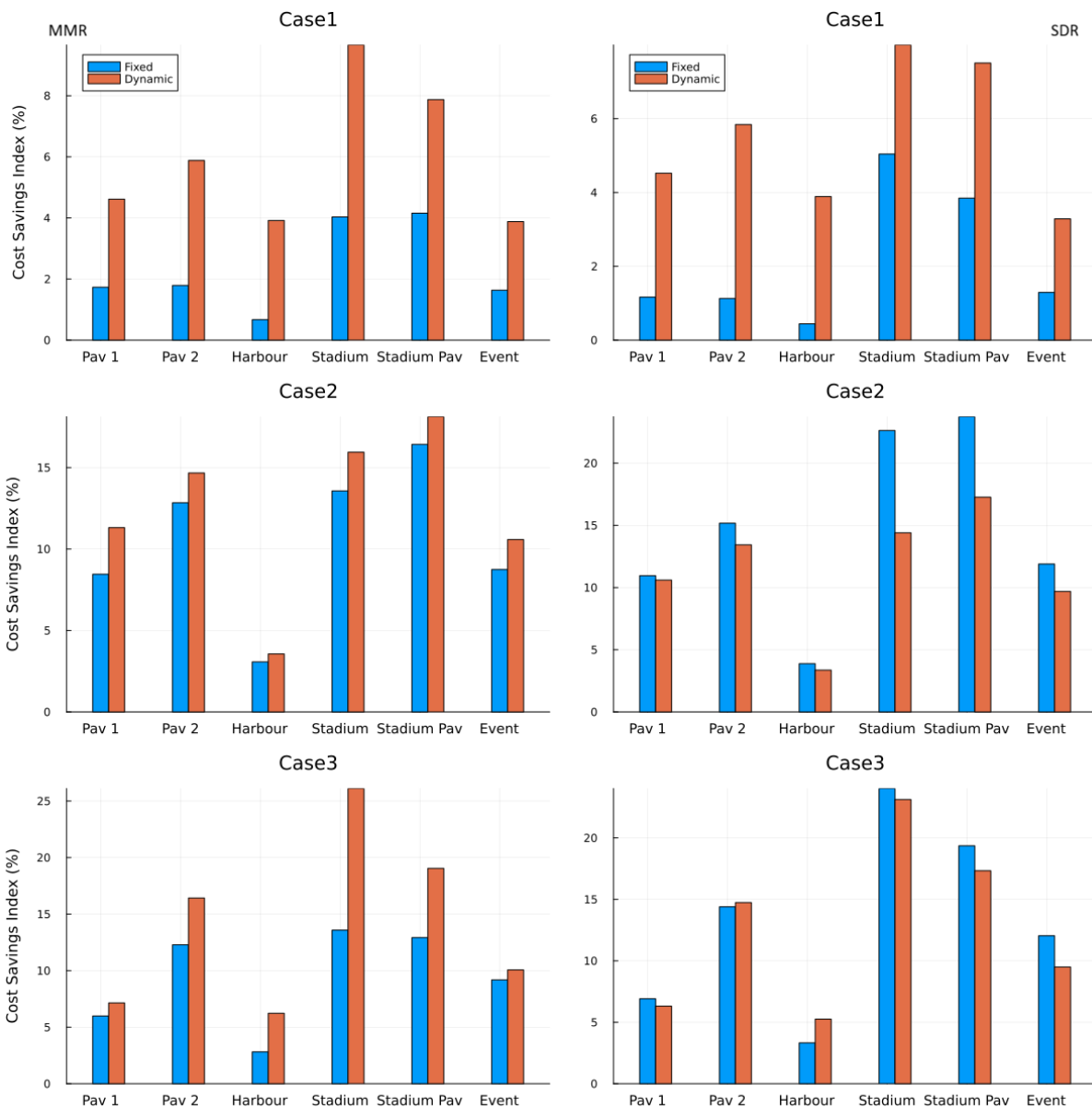
The CSI results for all cases under both pricing rules are shown in Figure 5.6. Overall, the trends are consistent across cases. The cost saving index under the dynamic retail contract is generally higher than under the fixed contract, as dynamic prices offer more opportunities for price arbitrage. The only exception is the SDR combined with dynamic prices, where PV curtailment (as explained earlier) reduces the achievable savings.

Across individual members, the beach stadium and beach stadium pavilion show the highest CSI values. This is mainly because their electricity demand is very low compared to other members. While their percentage savings appear high, the absolute savings amount to only a few tens of euros per year. Based on the CSIs,

Table 5.4 presents the Jain’s fairness index. We observe that the cost benefits of energy sharing are allocated in an almost equitable manner across most cases, with all fairness index values above 0.8. The only exception is Case 1, where fairness is noticeably lower. This is because Case 1 offers very limited flexibility, meaning that cost savings depend almost entirely on individual consumption patterns. As a result, benefits are distributed more unevenly, leading to a lower fairness score. It is also interesting to observe that the fairness index decreases in Case 3 compared to Case 2. This decline is more pronounced under the dynamic contract. The reduction in fairness is driven by the increased flexibility available in Case 3, which provides all members with greater opportunities for price arbitrage, especially when wholesale prices vary hourly under the dynamic contract. As a result, members with relatively low electricity demand and sufficient battery capacity (such as the beach stadium and the beach stadium pavilion) can cover their consumption during low-price hours. Their cost savings increase substantially compared to other members, which leads to a lower fairness index. Nonetheless, the fairness index remains close to 0.8, suggesting that the benefit allocation remains fairly robust as long as members possess enough flexibility to actively engage in energy sharing. Comparing the two pricing rules, the MMR generally performs better under fixed retail prices, while the SDR achieves a higher fairness score when combined with dynamic retail prices.

**Table 5.4 – Jain’s fairness index of six cases under both pricing rules. Index close to 1 indicates more equitable benefits allocation.**

	Fairness Index	MMR	SDR
Case 1 - Fixed	0.764	0.622	
Case 2 - Fixed	0.855	0.821	
Case 3 - Fixed	0.852	0.784	
Case 1 - Dynamic	0.885	0.906	
Case 2 - Dynamic	0.873	0.872	
Case 3 - Dynamic	0.800	0.801	



**Figure 5.6 – Cost saving index (CSI, expressed as a percentage relative to the baseline) for each community member across all cases. Left: results under the MMR mechanism; Right: results under the SDR mechanism.**

## 6 Auction-based local energy trading model

---

### 6.1 Methodology

---

The centralized market clearing represents an auction-based mechanism, which clears orders submitted by community members. Community members are used interchangeably with the term market participant in this section.

The orders submitted by community members consist of curves of volume-price pairs per timestep, submitted simultaneously over all time steps of the market clearing horizon. Volumes correspond to the energy which members are willing to share with / buy from the community, while prices correspond to the value at which they are willing to sell / buy this volume.

The clearing horizon of the market is in principal not fixed and could span from a whole day (or even a few days) to only a few hours), based on the use case and the information which participants have access. In practice, we assume the market only runs once a day for the 24 hour of the next day. This avoids over-complexifying the operational scheduling process which community members are exposed, while having access to relatively accurate load and weather data to make the bids without too much uncertainty.

#### 6.1.1 Order generation by market participants

---

Order values are determined by each community member before running the centralized market clearing algorithm, by solving the decision-making model at the individual level introduced in Section 5.1.1. The individual optimisation algorithm of each household is run based on forecasted consumption and production time series, and the energy supplier tariffs corresponding to each community member. The volume submitted to the market corresponds to the net volume export/import found by the individual optimization problem, while the price submitted to the market is computed in post-process of the individual optimization. Price calculation is based on the notion of *market aggressiveness*, indicating the aggressiveness of households' strategies when bidding on the local market. A consumer taking an aggressive posture would lower its prices compared to its offtake prices with the hopes of purchasing cheaper electricity locally. Conversely, a producer with an aggressive strategy would increase its prices compared to its injection prices with the hopes of selling to a higher price its production locally. Both actors have higher risks of not being cleared.

Each participant builds order steps which are step curves of price-volume values.

- First step is at injection (respectively offtake) price for producers (resp. consumers).
- The rest of the volume is divided into steps between the injection and offtake prices.
- The volume share of the first step is determined by the *market aggressiveness* of consumers. While this share is very dependent on members' preferences, indicative values have been used for the rest of this study. Values were chosen to represent large enough differences between member behaviours and see the impact of aggressiveness on market results. The different aggressiveness levels with their corresponding volume share of the first step are shown below:
  - Low aggressiveness: 80% of volume at first step,
  - Medium aggressiveness: 50% of volume at first step,

- High aggressiveness: 20% of volume at first step.

These order steps are then aggregated into curves, which can span across one or multiple timesteps. The set of curves over all timesteps considered in the market clearing horizon represent the order of a certain community member.

## 6.1.2 Market clearing algorithm

---

The market clearing algorithm is based on a lexicographic approach, where two rounds of optimization are performed before achieving the final solution, each round with a distinct objective function. The first objective is the maximization of social welfare. In a second phase, rejected volumes are minimized. The goal is to reduce redistribution inequalities. For instance, it is particularly relevant in case some members are bidding more competitively than others.

Additional constraints are added to model market rules and specific bid types requirements. In the current version, only simple bids (fully divisible, divisible and indivisible) are implemented. In a latter version, complex bids such as block orders will be available to the participants.

Orders generated and submitted by each market participant within the community are sent to the algorithm. After execution, the algorithm returns the cleared volume of each order step submitted. The clearing price is taken as the average of the marginal consumption bid and the marginal production bid, to include the impact of consumer's pricing strategy on market prices.

## 6.1.3 Mathematical formulation

---

### Sets & indexes

- $T$ : Set of timesteps
- $O$ : Set of all orders
- $O_t$ : Set of orders active at timestep  $t \in T$
- $S_{o,t}$ : Set of price-volume curve steps for order  $o \in O$  at timestep  $t \in T$
- $\mathcal{D}$ : Set of demand orders,  $\mathcal{D} \subseteq O$
- $\mathcal{S}$ : Set of supply/offer orders,  $\mathcal{S} \subseteq O$

### Parameters

#### Order parameters

- $p_{o,t,s}$ : Price of step  $s$  for order  $o$  at timestep  $t$  (€/kWh)
- $v_{o,t,s}^{\min}$ : Minimum volume of step  $s$  for order  $o$  at timestep  $t$  (kWh)
- $v_{o,t,s}^{\max}$ : Maximum volume of step  $s$  for order  $o$  at timestep  $t$  (kWh)
- $\Delta t$ : Timestep duration in hours (default: 1.0)

#### Sign convention

$$d_o = \begin{cases} +1 & \text{if order } o \in \mathcal{D} \text{ (demand)} \\ -1 & \text{if order } o \in \mathcal{S} \text{ (supply/offer)} \end{cases}$$

### Price caps & floors

- $P_{\max}^{\text{offer}}$ : Offer price cap, set to 10,000 €/kWh
- $P_{\max}^{\text{demand}}$ : Demand price cap (VoLL), set to 30,000 €/kWh
- $P_{\min}^{\text{offer}}$ : Offer price floor set to 0 €/kWh
- $P_{\min}^{\text{demand}}$ : Demand price floor set to 0 €/kWh

### Optimization Parameters

- $\epsilon$ : Numerical tolerance (default  $10^{-6}$ )
- $\lambda_{\text{obj}}$ : Objective preservation slack (default 1.0)

### Decision Variables

#### Binary Variables

- $a_{o,t,s}$ : Acceptance of step  $s$  for order  $o$  at timestep  $t$

#### Continuous Variables

- $v_{o,t,s}$ : Cleared volume of step  $s$  for order  $o$  at timestep  $t$  (kWh)
- $V_{o,t}$ : Total cleared volume for order  $o$  at timestep  $t$  (kWh)

### Lexicographic Hierarchy

In general, a lexicographic (hierarchical) optimization follows the structure outlined below:

1. Optimize primary objective to find  $\text{Obj}_1^*$
2. Add constraint:  $\text{Obj}_1 \geq \lambda_1 \cdot \text{Obj}_1^*$
3. Optimize secondary objective to find  $\text{Obj}_2^*$
4. Add constraint:  $\text{Obj}_2 \geq \lambda_2 \cdot \text{Obj}_2^*$
5. Continue for all objectives in priority order

While the presented model is capable of implementing as many objective functions as desired, the rest of this report will focus on a two-part lexicographic approach, based on the two objective functions presented in 6.1.2.

**First formulation** The first optimization is formulated as follows:

$$\max \quad SW = \sum_{t \in T} \sum_{o \in O_t} \sum_{s \in S_{o,t}} d_o \cdot v_{o,t,s} \cdot p_{o,t,s} \cdot \Delta t \quad (6.1a)$$

$$\text{s.t.} \quad v_{o,t,s}^{\min} \cdot a_{o,t,s} \leq v_{o,t,s} \leq v_{o,t,s}^{\max} \cdot a_{o,t,s} \quad \forall o \in O, t \in T, s \in S_{o,t} \quad (6.1b)$$

$$\sum_{o \in O_t} \sum_{s \in S_{o,t}} d_o \cdot v_{o,t,s} = 0 \quad \forall t \in T \quad (6.1c)$$

$$V_{o,t} = \sum_{s \in S_{o,t}} v_{o,t,s} \quad \forall o \in O, t \in T \quad (6.1d)$$

$$a_{o,t,s} \in \{0, 1\} \quad \forall o \in O, t \in T, s \in S_{o,t} \quad (6.1e)$$

$$v_{o,t,s} \geq 0 \quad \forall o \in O, t \in T, s \in S_{o,t} \quad (6.1f)$$

$$V_{o,t} \geq 0 \quad \forall o \in O, t \in T \quad (6.1g)$$

The objective function (Eq. 6.1a) maximizes social welfare. In Eq. 6.1b, the accepted order step volume is bounded by its minimum and maximum volumes. Eq. 6.1c ensures the balance

of the accepted order steps. Demand orders contribute positively ( $d_o = +1$ ) while supply orders contribute negatively ( $d_o = -1$ ). Timestep volume aggregation is ensured by Eq. 6.1d where the total cleared volume of each timestep equals the sum of all cleared step volumes. Finally, domain validity of each variable is enforced in Eqs. 6.1e - 6.1g.

**Second formulation** Then, a second optimization is executed:

$$\max - \sum_{t \in T} \sum_{o \in O_t} \left( \frac{V_{o,t} - V_{o,t}^{\max}}{V_{o,t}^{\max}} \right)^2 \quad (6.2a)$$

$$\text{s.t. Market constraints (6.1b) - (6.1g)} \quad (6.2b)$$

$$SW \geq \lambda \cdot SW^* \quad (\text{after 1st optimization}) \quad (6.2c)$$

The objective of the second optimization minimizes the rejected volumes in Eq. 6.2a. The same market constraints as in the first optimization are applied (Constraints 6.1b – 6.1g). Finally, the preservation of the first objective function is enforced in Constraint 6.2c, where a slack variable is introduced to allow for a small deviation from the optimal value of the first optimization. The market clearing price is computed in post-processing.

## 6.2 Model particularities

---

### 6.2.1 Model-specific assumptions

---

- The collective battery and collective PV are modeled as two distinct households, enabling the community to benefit from offers submitted by PV production to the market.
- In this study, members only submit two-step bids, with the first step volume determined by the market aggressiveness assigned to each participant, and the second step corresponding to the leftover net position. The price of the second step is the weighted value of the injection (respectively offtake) and offtake (respectively injection) prices for producers (respectively consumers), where weights correspond to the market aggressiveness share and the leftover share.
- To enable the collective battery to optimise its operations based on its own contract before submitting a bid, an additional contract type is introduced specifically for the collective battery. This tariff applies the retail offtake price to both injection and withdrawal volumes. As injection prices in this study are always below offtake prices, keeping separate prices for the battery would otherwise effectively force it to stand still, as it would unavoidably lose money by charging and discharging. This additional contract, referred to as *Energy Market*, incorporates network tariffs, taxes, and the energy component price itself. This symmetric contract for offtake and injection prices effectively corresponds to being directly exposed to market prices, with network tariffs and tax costs in addition.
- To evaluate the impact of different modeling assumptions, the following scenarios are introduced:
  - **Reference case:** Baseline assumptions are presented in Table 6.1. In the reference case, only the first objective function is applied to the market clearing algorithm, without redistributive relaxation.
  - **High aggressiveness:** This scenario tests the bidding strategy by setting all households to high risk aggressiveness.

**Table 6.1 – Reference scenario assumptions for the auction-based local energy trading model.**

Household	Market aggressiveness	Contract type
GEMS battery	High	Energy Market
GEMS PV	High	Fixed
Pavilion 1	Low	Fixed
Pavilion 2	Medium	Dynamic
Harbour control	Medium	Fixed
Beach Stadium	Low	Fixed
Beach Stadium Pavilion	Low	Fixed
Event connection	Low	Fixed

**Table 6.2 – Annual total energy invoice of the community of the baseline [€].**

Study Case	Fixed	Dynamic
Case 1	75852	78878
Case 2	70348	74836
Case 3	70341	73159

- **Flexible contract:** All contracts use flexible tariffs, except for the collective battery, which maintains the specific tariff described above.
- **Redistributive relaxation:** As detailed in Section 6.1, the market clearing algorithm follows a lexicographic approach that first maximizes social welfare, then minimizes rejected volumes. In this scenario, the second optimization can deviate by up to 20% from the first optimization’s social welfare ( $s_1 = 0.8$ ). In the reference case, this value is set to 1, meaning no redistribution is permitted after the first optimization.

## 6.2.2 Baseline

In the baseline scenarios described in previous sections, participants are assigned either fixed or dynamic contract types. When applying these contract configurations to the developed model, the results presented in Table 6.2 are obtained, which align consistently with the values from subsection 3.4. However, under these conditions, the collective battery has minimal incentive to charge or discharge, remaining largely idle. For the model implemented in this study, this was considered too conservative a behavior as batteries operating without energy sharing in a community will instead focus on self-profit maximization. Moreover, the battery strategy significantly influences the auction-based model outcomes, and a comparison with a baseline with an idle battery might overestimate the impact of the local auction-based mechanism. Therefore, an alternative baseline is adopted for this section: the collective battery operates under the *Energy Market* tariff defined previously. Therefore, the community energy invoice without local market represents a baseline where each household independently optimizes their grid transactions using the contract types specified in the reference scenario, while the collective battery responds to market price signals through its dedicated contract type.

## 6.3 Results

### 6.3.1 Case 1 results

Results for Case 1 are presented in Table 6.3. Several observations can be made:

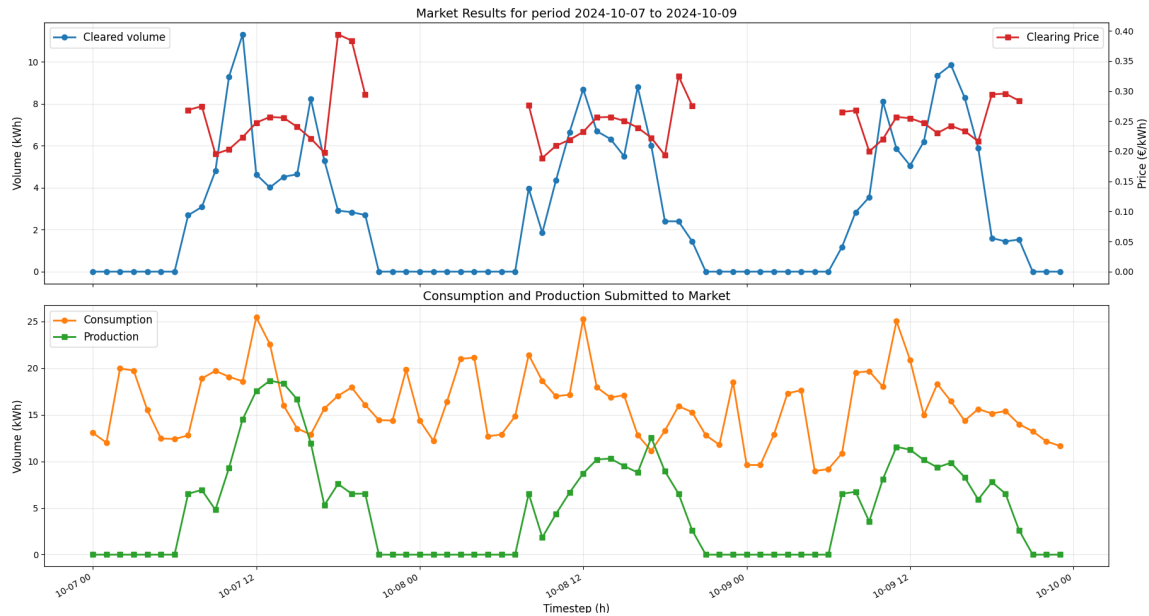
- The high aggressiveness scenario demonstrates that overly aggressive bidding strategies reduce cleared volumes, limiting the potential benefits of market participation.
- The flexible contract scenario enables higher cleared volumes but paradoxically results in lower overall savings, suggesting that increased market activity does not necessarily translate to improved economic outcomes, clearing prices might in those cases be too close to the retail offtake prices.
- The redistributive relaxation scenario achieves higher cleared volumes with relatively smaller profit losses compared to the other alternative scenarios, indicating that allowing some deviation from strict social welfare maximization can facilitate market participation without substantially compromising economic benefits.
- Overall, the auction-based model yields limited improvements to the community invoice in Case 1, with cost savings ranging between only 2% and 2.7%. This modest performance can be attributed to insufficient cleared volumes, which results from the community's limited production capacities. The auction-based market mechanism requires adequate local generation to create significant trading opportunities and deliver substantial economic benefits. Without sufficient production assets within the community, the potential for cost reduction through local energy trading remains constrained.

**Table 6.3 – Case 1 results under the auction-based energy trading model.**

KPI	Scenarios			
	Reference	High aggressiveness	Flexible contract	Redistributive relaxation
Collective self-consumption ratio	0.98	0.94	0.98	0.99
Collective self-sufficiency ratio	0.02	0.02	0.02	0.03
Exchanged volume (kWh)	12 587	10 418	41 783	18 770
Community energy invoice with local market (€)	66 563	66 756	70 449	66 666
Community energy invoice without local market (€)	68 436	68 436	71 860	68 436
Community cost savings due to local market (€)	1 873	1 680	1 410	1 770
Community cost savings due to local market (%)	2.7%	2.5%	2.0%	2.6%

### 6.3.2 Case 2 results

Volumes submitted to the local market and cleared as well as the corresponding market clearing prices are displayed for a representative period of three days in Figure 6.1. Batteries modify the overall production profile and allow for some volume to be cleared early in the morning and at the end of the day. The cleared volumes peaks are avoiding the clearing price peaks. Prices are generally higher when the production only relies on batteries. The price peaks during times of lower consumption can be interpreted based on two drivers: on one side, participants' mar-



**Figure 6.1 – Volumes and prices cleared on local market for three representative days under Case 2.**

ket aggressiveness, which cause less volumes to be cleared and the market equilibrium to be higher up the demand curve; on the other side, the use of the average marginal price as market price, making high-priced demand push up the clearing price. Higher prices therefore reflect the community’s inability to find an agreement, either due to physical shortage (for example when using batteries) or due to too aggressiveness bidding strategies.

The results for Case 2 are presented in Table 6.4. The main key points are as follows:

- The self-consumption ratio is slightly lower than in Case 1 due to increased PV production and reduced flexibility. In contrast, the self-sufficiency ratio is approximately multiplied by 5, almost proportionally to the expansion of the photovoltaic capacity.
- The high aggressiveness scenario demonstrates that when all members adopt aggressive bidding strategies to push prices in their favor (lower consumption prices, higher production prices), paradoxically no member benefits, as they clear fewer volumes overall. This overly aggressive approach decreases the self-sufficiency ratio proportionally. Additional scenarios based on game theory would be needed to investigate the behavior when individual members, rather than all participants simultaneously, attempt to influence prices. However, this is not within the scope of this study.
- The flexible contract scenario enables higher cleared volumes while slightly lowering the level of savings in the community.
- The redistributive relaxation scenario yields higher profits through increased cleared volumes. The redistribution mechanism increases participation volumes, even though this additional volume is suboptimal from a social welfare perspective. Table 6.5 compares benefit distribution between households in the reference and redistributive relaxation scenarios. As expected, the results reveal improved redistribution in the latter scenario, where most households achieve significant savings from market participation. Both collective assets sacrifice some profit to benefit individual households, with the battery reaching an

**Table 6.4 – Case 2 results under the auction-based energy trading model.**

KPI	Scenarios			
	Reference	High aggressiveness	Flexible contract	Redistributive relaxation
Collective self-consumption ratio	0.85	0.72	0.93	0.90
Collective self-sufficiency ratio	0.12	0.08	0.11	0.14
Exchanged volume (kWh)	34 415	23 138	42 107	46 142
Community energy invoice with local market (€)	63 843	65 638	68 643	63 512
Community energy invoice without local market (€)	69 402	69 402	74 134	69 402
Community cost savings due to local market (€)	5 559	3 765	5 491	5 891
Community cost savings due to local market (%)	8.0%	5.4%	7.4%	8.5%

**Table 6.5 – Invoice saving percentages per household due to the local market (under Case 2).**

Household	Reference scenario	Redistributive relaxation
GEMS battery	4.7%	-69.7%
GEMS PV	96.4%	59.8%
Pavilion 1	5.1%	13.9%
Pavilion 2	10.1%	13.4%
Harbour control	0.6%	2.3%
Beach Stadium	10.3%	28.5%
Beach Stadium Pavilion	9.6%	33.2%
Event connection	2.7%	8.8%

extreme point where it loses by participating in the local market. The results also indicate that volume redistribution can have economic benefits to the community members, despite the lower social welfare. This paradox could be explained by the maximization of social welfare in the algorithm's objective function, rather than the minimization of procurement cost in the objective function of the market clearing algorithm. Changing the objective function in the first step could potentially reduce the bill of community members even further. This questions the relevance of social welfare maximization as a primary objective in a local context, where the concept of marginal cost of orders is less clear. This point should therefore be investigated in further work.

- Overall, the auction-based model yields modest improvements to the community invoice, with cost savings ranging between 5.4% and 8.5%.

### 6.3.3 Case 3 results

Results for Case 3 are presented in Table 6.6. The main takeaways are:

- Despite a substantial increase in storage capacity, the self-consumption ratio remains nearly unchanged compared to Case 2. This limited impact may be attributed to the definition of self-consumption, which focuses solely on PV production utilization.

**Table 6.6 – Case 3 results under the auction-based energy trading model.**

KPI	Scenarios			
	Reference	High aggressiveness	Flexible contract	Redistributive relaxation
Collective self-consumption ratio	0.85	0.74	0.93	0.91
Collective self-sufficiency ratio	0.09	0.07	0.09	0.10
Exchanged volume (kWh)	34 173	23 758	47 851	51 876
Community energy invoice with local market (€)	56 996	58 679	60 552	56 640
Community energy invoice without local market (€)	62 535	62 535	66 142	62 535
Community cost savings due to local market (€)	5 539	3 856	5 590	5 895
Community cost savings due to local market (%)	8.9%	6.2%	8.5%	9.4%

- Cleared volumes show slight improvements relative to Case 2, though only in the flexible contract and redistributive relaxation scenarios.
- Overall, the observations align with those from Case 2, with community savings remaining relatively similar across both cases.

These findings suggest that the auction-based market model is only relevant in contexts where consumption, production, and storage are adequately balanced and of comparable magnitude. When this condition is met, market benefits appear consistently and significantly positive across all scenarios, with only minor variations. This consistency indicates a certain robustness of the auction market implementation to different operational contexts and modeling assumptions.

## 7 Peer-to-peer energy trading models

---

### 7.1 Methodology

---

The proposed model describes a P2P centralized energy trading framework designed to optimize energy exchanges in a local energy market. The model assumes the presence of a central entity (assumed to be the community manager) that receives bids from the energy community members to buy or sell energy based on their generation and consumption forecasts. Each bid consists of a pair (energy volume, price) to buy or sell in the P2P market. Based on the bids made for each trading interval, the central entity clears the P2P market by maximizing the social welfare of the community. The result of this optimization is the amount of energy traded between EC members, community assets, and the retailer, and the price for each trade. The proposed methodology has been included in PyECom tool allowing the use for research purposes [40].

For each trading interval, market participants can either be understood as producers or consumers, depending on their net injection value after self-consumption being positive or negative. Market participants include:

- EC members: these peers submit a bid for each trading interval to buy or sell energy for a certain price. For modeling purposes, each member is modeled as a generation entity and a load entity in the P2P market. Depending on the net injection value of each peer, either the generation entity or the load entity is active;
- batteries: these peers can buy and sell from/to the other P2P market participants in each trading interval. For modeling purposes, each battery is modeled as a generation entity and a load entity in the P2P market. The load entity is used to model the charging of the battery, while the generator entity is used to model its discharging. In the optimization problem it is ensured that in each trading interval, each battery is only used as either a load or a generator;
- a retailer: this peer can buy and sell energy from/to the other P2P market participants at each trading interval. For modeling purposes, the retailer is modeled as a generation entity and a load entity in the P2P market. The load entity buys energy from the other market participants, while the generator entity sells energy to the other market participants.

In the following, the modeling of each of the market participants is further detailed.

#### 7.1.1 Retailer

---

The retailer is represented in the model by a generation entity and a consumption entity. The maximum generation and consumption values are set to the contractual limits and the cost curve of the retailer entities can be expressed as follows:

- consumption entity:  $C(P) = \lambda_{d,t}^{inj} P$ , with  $P$  being the amount of energy sold by an entity to the retailer and  $\lambda_{d,t}^{inj}$  the price to sell energy to the retailer at hour  $t$  of day  $d$ ;
- generation entity:  $C(P) = \lambda_{d,t}^{off} P$ , with  $P$  being the amount of energy bought by an entity from the retailer and  $\lambda_{d,t}^{off}$  the price to buy energy from the retailer at hour  $t$  of day  $d$ .

## 7.1.2 Peers

---

For each of the peers, the net injection is computed for each time step, based on their generation and consumption forecast. In the time steps with a positive net injection, the peer is considered to act as a producer, while in time steps with a negative net injection, the peer is considered to act as a consumer. Each peer submits a bid to the market depending on whether the peer acts as a consumer or a producer. These bids are either in the form of a single bid (which is a pair of energy volume and price), or a cost curve (consisting of lower and higher volume trading limits and the corresponding prices). In both cases, the cost submitted by a peer takes on the general form  $C(P)$ , where  $P$  is the amount of energy this peer is buying or selling. The peers submit the following information.

- In the case of the peer acting as a consumer:
  - the maximum load and the minimum load it is willing to consume;
  - the cost function for this consumption, meaning the price the peer is willing to pay for being able to consume for a certain amount of energy.
- In the case of the peer acting as a generator:
  - the maximum and minimum generation it can produce for each time interval,
  - the cost function for this generation, meaning the price the peer is willing to sell a certain amount of energy for.

By convention, the power injected into the system by a peer is considered positive ( $P > 0$ ), while the power consumed from the system is considered negative ( $P < 0$ ).

## 7.1.3 Batteries

---

For each of the  $N_b$  batteries, a generation and a consumption entity exist in the model. The maximum generation and consumption values for these entities are set to the maximum charge and discharge values of the batteries. The batteries are excluded from the cost function of the optimization problem, they are thus not associated with cost curves.

## 7.1.4 Model variables, sets and inputs

---

**Sets** The sets  $\mathcal{G}$  and  $\mathcal{L}$  are used to denote all generators and loads in the P2P market, respectively. On the other hand, the sets  $\bar{\mathcal{G}}$  and  $\bar{\mathcal{L}}$  denote the generator and load entities corresponding only to the retailer and the peers, excluding those corresponding to the batteries.

**Inputs** The inputs to the optimization problem are the bids of the peers (power values and cost functions), the technical limits of the batteries, the contractual constraints of trade with the retailer (power values and prices) and constraints on the trade between members of the community.

The following variables describe the power limits of the  $N_g$  generation entities and the  $N_l$  consumption entities:

- $P^{\min, \text{gen}} \in \mathbb{R}^{N_g \times T}$ : minimum power generation limits in each time interval (kW)
- $P^{\max, \text{gen}} \in \mathbb{R}^{N_g \times T}$ : maximum power generation limits in each time interval (kW)

- $P^{\min, \text{load}} \in \mathbb{R}^{N_l \times T}$ : minimum power consumption limits in each time interval (kW).
- $P^{\max, \text{load}} \in \mathbb{R}^{N_l \times T}$ : maximum power consumption limits in each time interval (kW).

In addition to the power constraints, the peers submit their load curves  $C(P)$  to the central coordinator.

The technical constraints of the  $N_b$  batteries are indicated by:

- $E^{\min} \in \mathbb{R}^{N_b}$ : minimum state-of-charge (kWh)
- $E^{\max} \in \mathbb{R}^{N_b}$ : maximum state-of-charge (kWh)
- $P^{\text{dch}, \max} \in \mathbb{R}^{N_b}$ : maximum power discharge value (kW)
- $P^{\text{ch}, \max} \in \mathbb{R}^{N_b}$ : maximum power charge value (kW)
- $E^{\text{init}} \in \mathbb{R}^{N_b}$ : initial state-of-charge (kWh)
- $\eta$ : efficiency of the battery

The parameters defining the constraints of the trade within the community are given in

- $u \in \mathbb{R}^{N_g \times N_l}$ : Binary variable indicating if a trade between generator  $g$  and consumer  $l$  is allowed or not.

**Decision variables** The following variables describe the decision variables of the optimization problem. The amount of energy exchanged between the generation entities and the consumption entities is given by

- $P^{\text{sell}} \in \mathbb{R}^{N_g \times N_l \times T}$ : the power sold by each generator  $g$  to each load  $l$  during each time interval (kW).
- $P^{\text{buy}} \in \mathbb{R}^{N_l \times N_g \times T}$ : the power bought by each load  $l$  from each generator  $g$  during each time interval (kW).

For the model of the batteries, the following variables are used:

- $P^{\text{ch}} \in \mathbb{R}^{N_b \times T}$ : the charging power of each battery at each time instant (kW).
- $P^{\text{dch}} \in \mathbb{R}^{N_b \times T}$ : the discharging power of each battery at each time instant (kW).
- $E^{\text{store}} \in \mathbb{R}^{N_b \times T}$ : the state of charge of the battery in each time instant (kWh).

The discharging and charging power of the batteries are connected to the matrices  $P^{\text{sell}}$  and  $P^{\text{buy}}$  through  $P_{g,l,t}^{\text{sell}} = P_{b,t}^{\text{dch}}$  for the index of the generator  $g$  in  $P_{g,l,t}^{\text{sell}}$  denoting the battery  $b$  and through  $P_{l,g,t}^{\text{buy}} = P_{b,t}^{\text{ch}}$  for the index of the load  $l$  in  $P_{l,g,t}^{\text{buy}}$  denoting the battery  $b$ .

## 7.1.5 Mathematical formulation

The optimization problem is formulated over a time horizon with  $N_t$  time steps. In the simulations performed, the time horizon is set to one day with hourly time steps.

The objective function of the optimization problems takes into account the generation costs and the consumption costs given by the cost curves of the generation entities and consumption entities of the retailer and the peers. The battery entities are excluded from the cost function.

In the following, the positive cost functions  $C_g(P)$  denotes the cost of generation entity  $g$  to sell the certain amount  $P$ . The negative cost function  $C_l(P)$  on the other hand denotes the cost of consumer  $l$  to buy a certain amount  $P$ .

The mathematical formulation of the optimization problem is as follows:

$$\min_{P^{sell}, P^{buy}} \sum_{t=0}^{N_t} \left( \sum_{g \in \bar{\mathcal{G}}} C_g \left( \sum_{l \in \mathcal{L}} P_{g,l,t}^{sell} \right) + \sum_{l \in \bar{\mathcal{L}}} C_l \left( \sum_{g \in \mathcal{G}} P_{l,g,t}^{buy} \right) \right) \quad (7.1)$$

with the constraints:

$$\sum_{l \in \mathcal{L}} P_{g,l,t}^{sell} \leq P_{g,t}^{\max, gen} \quad \forall g, t \quad (7.2)$$

$$\sum_{l \in \mathcal{L}} P_{g,l,t}^{sell} \geq P_{g,t}^{\min, gen} \quad \forall g, t \quad (7.3)$$

$$\sum_{g \in \mathcal{G}} P_{l,g,t}^{buy} \leq P_{l,t}^{\min, load} \quad \forall l, t \quad (7.4)$$

$$\sum_{g \in \mathcal{G}} P_{l,g,t}^{buy} \geq P_{l,t}^{\max, load} \quad \forall l, t \quad (7.5)$$

$$P_{g,l,t}^{sell} + P_{l,g,t}^{buy} = 0 \quad \forall g, l \text{ with } u_{g,l} = 1 \quad (7.6)$$

$$P_{g,l,t}^{sell} = P_{l,g,t}^{buy} = 0 \quad \forall g, l \text{ with } u_{g,l} = 0 \quad (7.7)$$

$$E_{b,0}^{store} = E_b^{init} - \frac{\frac{P_{b,0}^{dch}}{\eta} + \eta P_{b,0}^{ch}}{N_t/24} \Delta\tau \quad \forall b \quad (7.8)$$

$$E_{b,t}^{store} = E_{b,t-1}^{store} - \frac{\frac{P_{b,t}^{dch}}{\eta} + \eta P_{b,t}^{ch}}{N_t/24} \Delta\tau \quad \forall b, t > 0 \quad (7.9)$$

$$P_{b,t}^{dch} P_{b,t}^{ch} = 0 \quad \forall b, t \quad (7.10)$$

$$E_{b,t_{end}}^{store} = E_b^{init} \quad \forall b \quad (7.11)$$

$$E_b^{\min} \leq E_{b,t}^{store} \leq E_b^{\max} \quad \forall b, t \quad (7.12)$$

$$0 \leq P_{b,t}^{dch} \leq P_b^{dch,max} \quad \forall b, t \quad (7.13)$$

$$P_b^{ch,max} \leq P_{b,t}^{ch} \leq 0 \quad \forall b, t \quad (7.14)$$

with  $\Delta\tau$  being the length of a time step. Equations (7.2) to (7.5) show that the amount sold/bought has to be within the limits specified in the contract with the retailer or the bids of the peers, (7.6) ensures that the amount sold by one generator to a load is equal to the amount bought by the load from the generator and (7.7) ensures that only trade complying with the constraints on the EC internal trade happen. Equations (7.8) to (7.14) model the characteristics of the batteries, showing the dynamic equation of the state-of-charge in (7.8) for the first time step and in (7.9) for the following ones, the mutually exclusive behavior of charging and discharging in (7.10) and the constraint of the initial state-of-charge coinciding with the final state-of-charge

in (7.11). The constraints in (7.12), (7.13) and (7.14) ensure that the state-of-charge and the charging and discharging values of each battery are always within the allowed limits.

## 7.2 Model particularities

---

### 7.2.1 Model-specific assumptions

---

In the following simulations, the cost curves of the peers are assumed to be linear functions in the amount of energy bought or sold by the peer.

### 7.2.2 Description of the baseline simulation test

---

For the retailer, each member and each battery, a generator entity and a consumer entity is created in the model.

**Power constraints** For the generation and consumption entities corresponding to the retailer, the maximum power generation and maximum power consumption limits are set to the limits set in the contract with the retailer. The minimum limits for both entities are set to zero.

For each one of the peers, the net injection is computed from the data set for each time step. In the time steps with negative net injection, this peer is considered to be a consumer. The negative net injection is set as the maximum power consumption limit of the entity corresponding to this member, and the maximum generation limit is set to zero. On the other hand, in time steps with a positive net injection, this peer acts as a generator. Thus the the maximum power generation of the entity corresponding to this member is set to the net injection value and the maximum power consumption value of the consumer entity of this peer is set to zero. In the baseline case, the consumption and generation of the members are not allowed to be curtailed. For each entity, the maximum and minimum limits thus coincide.

For the batteries, the maximum limits of consumption and generation are set to the battery constraints of charging and discharging and the minimum limits are set to zero.

**Cost curves** The generation and consumption cost of the retailer member correspond to the price of buying energy from the retailer and the price to sell energy to the retailer, given in the data set. The generation and consumption cost of the member entities on the other hand are submitted to the central coordinator in the bidding process. In this baseline case, the generation cost of each peer is set to be lower than the generation cost of the retailer, and the consumption cost is set to be higher than the consumption cost of the retailer. The generation and consumption cost of the battery entities is excluded from the cost function and thus does not have to be set.

**Trading constraints** In the baseline case, no EC internal trade is allowed. Each member can only trade with their own battery and with the retailer. The common PV installation and the common battery can exchange energy with each other, as they are seen as belonging to the same member.

### 7.2.3 Description of P2P simulation tests

**P2P with single bids** In the P2P simulation, the power constraints and the cost curves are set as in the baseline case. However, EC internal P2P trade is allowed, so there are no constraints on the trading options between the members.

**P2P with bid curves** The P2P simulation with bid curves is conducted as the P2P simulation with single bids, but with the additional option of curtailing the consumption and the generation. The members thus now submit bidding curves to the P2P market by indicating their maximum and minimum generation and consumption, along with the cost coefficient for their linear cost function. For the generation entities, the minimum generation is set to zero for all members, while the consumption of each entity can be curtailed up to 30% of the original consumption value.

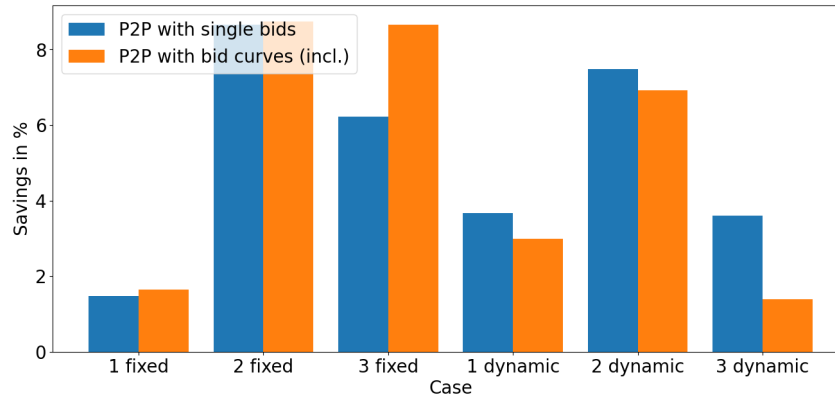
**P2P with bid curves including curtailed power supplied by the retailer (P2P with bid curves (incl.))** This case is an extension of the P2P simulation with bid curves. As the loads can be curtailed in the P2P simulation with bid curves, a reduction in the total energy bill may be due to the reduction of the load, making it difficult to assess the effect of the EC internal P2P trade. Therefore, the price for buying the curtailed load at retailer prices is computed and added to the total bill of each member. This allows to exclude the effect of curtailing the loads from the analysis.

## 7.3 Results

**Total energy bill** Table 7.1 shows the annual total energy bill of the community for each of the 6 cases and the different simulation methods. In the P2P simulation with bid curves, the total energy bill of the community is significantly lower than in the P2P simulation with single bids. This can be attributed to the community internal trade, as well as to the option of reducing the consumption. This motivates the analysis of the case P2P with bid curves (incl.) in which the amount of curtailed consumption is bought from the retailer, to exclude the influence of curtailed consumption from the total energy bill.

**Table 7.1 – Total energy bill of the community [€].**

Study Case	Fixed	Dynamic
Case 1 - Baseline	75905	78241
Case 2 - Baseline	70346	73674
Case 3 - Baseline	70509	69158
Case 1 - P2P with single bids	74784	75367
Case 2 - P2P with single bids	64258	68171
Case 3 - P2P with single bids	66126	66667
Case 1 - P2P with bid curves	51984	52597
Case 2 - P2P with bid curves	43913	47749
Case 3 - P2P with bid curves	43780	46982
Case 1 - P2P with bid curves (incl.)	74661	75898
Case 2 - P2P with bid curves (incl.)	64202	68587
Case 3 - P2P with bid curves (incl.)	64406	68194



**Figure 7.1 – Percentual reduction of the total energy bill compared to the baseline case.**

To compare the simulation results to the baseline case, the percentual reduction  $\Delta b_i$  of the energy bill for a case  $i$  to the baseline case is calculated according to

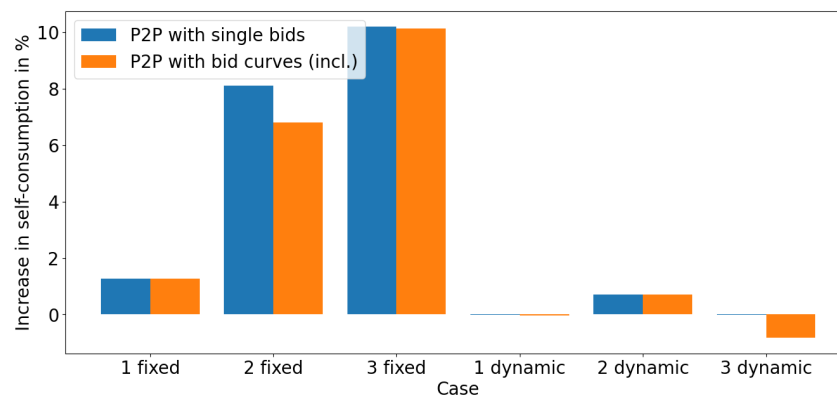
$$\Delta b_i = \frac{100}{b_0} (b_0 - b_i) \quad (7.15)$$

where  $b_0$  denotes the bill in the baseline case and  $b_i$  the bill in the case to be analyzed. The results of comparing the percentual reduction of the total energy bill of the community in the P2P simulation with single bids and in the P2P simulation with bid curves (incl.) are shown in Figure 7.1. In all simulations the total energy bill of the community was reduced. There are however significant differences over the cases, as the amount of batteries, their technical limitations and the PV production are different in the cases. As the cost function optimized in this approach is not the total energy bill but the sum over the consumption and generation costs, the optimal solution with respect to the cost function is not necessarily the solution with the lowest total energy bill for the community. This effect can be observed in the results of the simulations of Case 3 fixed. Even though the trading solution of the P2P simulation with bid curves (incl.) is part of the solution space of the P2P simulation with single bids, the total energy bill of the P2P simulation with single bids is higher than of the P2P simulation with bid curves (incl.).

**Self-consumption ratio** The self-consumption ratio of the community is shown in Table 7.2. The percentual increase of the self-consumption ratio in the P2P simulation with single bids and the P2P simulation with bid curves, calculated similarly as the savings on the energy bill in Eq. 7.15 with respect to the baseline case, are shown in Figure 7.2. Positive values correspond to an increase in self-consumption, while negative values show that the self-consumption decreased. The results show that the self-consumption ratio was increased in all cases in the fixed pricing scheme. The results of the P2P simulation with single bids and the P2P simulation with bid curves are quite similar, but those of the P2P simulation with single bids are slightly higher. The highest percentual increase in self-consumption was achieved in case 3 fixed. In the dynamic pricing scheme on the other hand, the self-consumption ratio was only slightly increased in case 2, while a small decrease in self-consumption ratio is observed in the other cases.

**Table 7.2 – Self-consumption ratio of the community [%].**

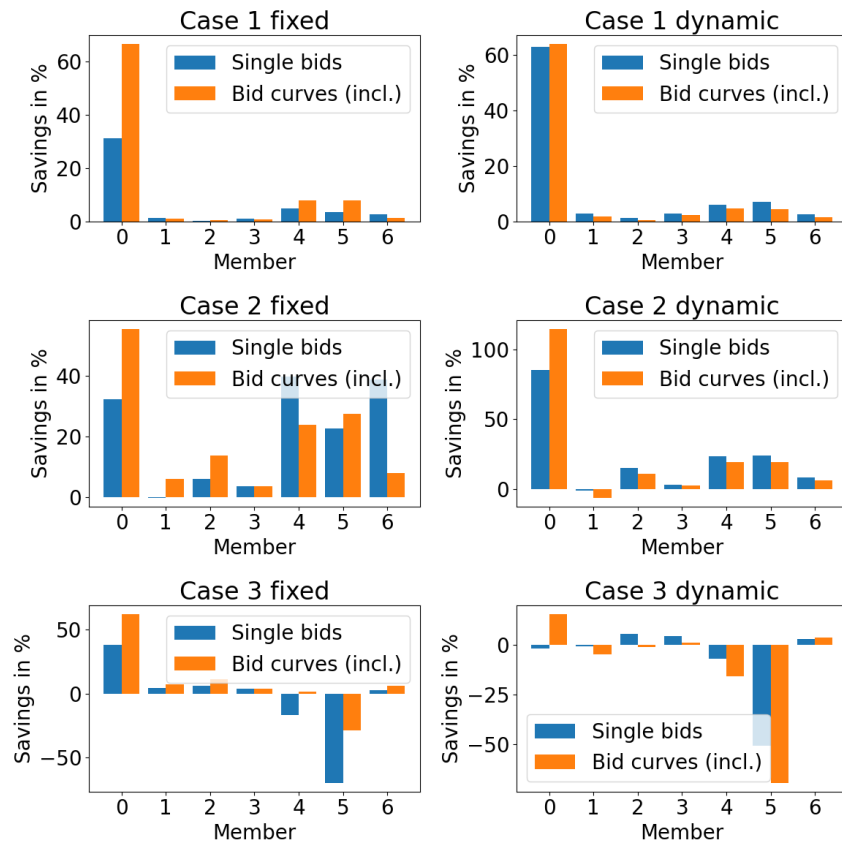
Study Case	Fixed	Dynamic
Case 1 - Baseline	98.7	100.0
Case 2 - Baseline	88.6	95.4
Case 3 - Baseline	88.6	98.9
Case 1 - P2P with single bids	100.0	100.0
Case 2 - P2P with single bids	95.8	96.1
Case 3 - P2P with single bids	97.7	98.9
Case 1 - P2P with bid curves	100.0	100.0
Case 2 - P2P with bid curves	94.6	96.1
Case 3 - P2P with bid curves	97.6	98.1



**Figure 7.2 – Percentage increase in the self-consumption ratio to the baseline case. Negative results indicate a decrease in self-consumption, positive results show an increase in self-consumption.**

The savings on the total energy bill and the change in self-consumption of the community vary significantly over the different cases, as the cases assume different assets in the community. It can thus not be concluded which case is best for the community, as the investment costs associated with the assets have to be taken into account too. In general, it can be concluded that in the dynamic pricing scheme, case 2 shows the highest savings and self-consumption, while in the fixed pricing scheme cases 2 and 3 show the highest savings and self-consumption.

**Bill per member** In the following, the energy bill of each member is analyzed to assess the benefits for each member individually. Figure 7.3 shows the savings on the annual energy bill for each member. The index 0 in the figure stands for the community PV installation and the community battery. The rest of the numbering follows the order [Pavilion 1, Pavilion 2, Harbour control, Beach stadium, Beach stadium Pavilion, Event connection], always including the trades made by their respective batteries. Each one of the bar plots shows one of the cases, the cases with the fixed pricing scheme on the left and those with the dynamic pricing scheme on the right. Positive values indicate that the simulation type is favorable for the entity (i.e. the entity receives more money or pays less with respect to the baseline), while negative values show that the simulation type is less favorable for this entity (i.e. the entity receives less money or pays more with respect to the baseline). In cases 1 and 2, the P2P simulations with single bids and the P2P simulations with bid curves (incl.) are favorable for all members, with the exception



**Figure 7.3 – Percentual reduction of the total energy bill compared to the baseline case.**

of a small increase in the bill for Pavilion 1 in case 2 dynamic. With the exception of case 2 fixed, the benefit in cases 1 and 2 is significantly higher for the common assets than for the other community members. This indicates, that the distribution mechanism of the benefit of the common assets over the the community members is important to assess the benefit for each member. A clear advantage of one of the simulation methods over the other one is not visible. It depends highly on the member and on the case and the pricing scheme. Case 3 on the other hand shows a different behaviour. In case 3 fixed, the Beach stadium and the Beach stadium Pavilion have a higher energy bill in the P2P simulation with single bids than in the baseline case, while in the P2P simulation with bid curves (incl.) only the Beach stadium Pavilion has a higher energy bill. In case 3 dynamic, in the P2P simulation with the single bids, the common assets, the Beach stadium and the Beach stadium Pavilion are at a disadvantage compared to the baseline case. In the P2P simulation with bid curves (incl.), Pavilion 1 and Beach stadium and Beach stadium Pavilion have a higher energy bill than in the baseline case.

In conclusion, the benefits for each member vary significantly over the cases, the pricing scheme and the simulation method. In case 1 and case 2 the members in general all benefit from the P2P trading scheme, while this is not the case in case 3. The distribution mechanism of the community benefits is important to further assess the benefits for each member.

## 8 Discussion

---

This section discusses the results of the four energy sharing and trading models developed in Task 2.3. First, we summarize the main insights obtained within each model type, providing an overview of how the various submodels perform in the common case study. Second, we briefly compare the general energy trading and sharing mechanisms to each other. Lastly, we discuss the models' limitations and outline avenues for further research.

Note that the quantitative results presented in the preceding sections are case-specific and should be interpreted with caution. Therefore, the findings are not intended to be universally generalizable. That said, the analysis systematically explored multiple configurations by varying key system characteristics, such as retail price structures and system configurations. This structured variation allows us to draw insights into how different mechanisms will likely perform under various conditions. However, the precise numerical outcomes depend on the specific context in which they are applied.

### 8.1 Assessment within the four fundamental mechanisms

---

The analysis of **capacity, energy, and revenue allocation models (Section 4)** shows that performing energy sharing in an energy community, either through the proposed centralized or the decentralized energy management scheme, provides considerable total cost savings at the community level. Both mechanisms furthermore provide an increase in self-consumption and self-sufficiency. The decentralized scheme typically produces slightly higher community costs than the centralized one, but the differences observed for this specific case study are minor. On the other side, the decentralized scheme showcases a higher practical impenetrability potential as it limits the control of individual assets to the community member to whom they belong.

This section furthermore contributes to answering the central question of how to allocate the costs and revenues of collective assets. Various allocation mechanisms were tested based on three criteria: individual rationality (each member should benefit from joining the community), efficiency (costs and revenues are fully allocated to members), and stability (members have no incentive to form smaller sub-communities). The analysis showed that the optimal excess method is the best performing allocation method overall because it is efficient, individually rational, and stable. The Shapley value method is a close second: it is efficient and individually rational but not stable. Both methods are superior to the heuristic allocation methods, but they are far more computationally expensive, which challenges their practical implementability. The main benefit of heuristic allocation methods is that they are easy and fast to compute. Among these, the multi-round static sharing keys performed the best, as they are efficient and have a better cost-saving index than the hybrid and dynamic sharing keys. In addition, the computational times of all heuristic methods are similar, showing no disadvantage in this aspect for the multi-round static keys.

Overall, the findings suggest a trade-off between performance and computational feasibility. The optimal excess and Shapley value methods are well-suited for small communities and for larger communities without collective flexible assets and the decentralized energy management scheme. In contrast, heuristic sharing keys (e.g., multi-round static sharing keys) are a scalable alternative for large communities with flexible collective resources where game-theoretic allocation mechanisms are impractical.

The **internal pricing model (Section 5)** examines two implicit pricing mechanisms for central-

ized individual energy sharing: the MMR and the SDR. Both mechanisms deliver substantial cost savings to the community. The magnitude of these benefits increases when participants have sufficient flexibility to adjust their consumption or manage distributed assets. However, once the community can efficiently absorb all locally generated electricity, more flexibility yields only marginal improvements. Both pricing rules furthermore allocate benefits in a broadly equitable manner, provided that participants possess sufficient flexibility to engage in energy sharing.

The performance of the two pricing rules depends on the structure of the retail contract. Both mechanisms perform well under a fixed retail contract. In this setting, the efficient use of locally generated electricity is the main driver of community benefits. Therefore, the community's priorities could guide the choice between the two: the MMR is preferable when the primary objective is to maximize cost savings and ensure an even distribution of benefits, whereas the SDR is best suited for communities that prioritize maximizing self-consumption and self-sufficiency. Under a dynamic contract, however, the trade-offs differ. The MMR interacts poorly with zero or negative wholesale prices, which leads to distorted incentives. Internal prices remain positive despite negative wholesale prices, which encourages the community to inject even when it is system-inefficient. While the MMR still yields higher cost savings for the community, it may compromise the system's overall efficiency without additional measures to handle negative prices.

A second limitation of these mechanisms is how they handle collective assets. Recall that, for consistency purposes, we have exposed the collective PV plant and the collective battery to the same internal prices as the rest of the community. We strongly discourage this approach in practice, as the collective batteries would not operate efficiently. Indeed, the collective BESS is rarely operated when exposed to a fixed retail contract, and is also discouraged from absorbing the community's excess PV production under a dynamic retail contract under the SDR.

In summary, internal pricing mechanisms are appropriate for communities with individual participants and can yield substantial cost savings. They can be readily implemented in situations with fixed retail contracts. However, the MMR would require additional provisions to handle negative prices under dynamic retail contracts. Collective assets, particularly batteries, should either be exposed to different price signals or should be integrated in a different way.

For the **auction-based mechanisms (Section 6)**, the results show that a local auction market can be implemented at the community level while providing most participants with tangible benefits. These benefits are consistently positive across scenarios, though their magnitude varies by case. As in previous models, savings are highest in cases 2 and 3 due to greater self-consumption of local PV production. The minimal difference between cases 2 and 3 suggests that the battery capacity available in case 2 is already sufficient to capture most of the value of local flexibility.

A key finding is that community members' bidding strategies strongly influence outcomes. To examine this, a scenario was introduced in which participants bid more aggressively, i.e. willing to pay less for consumption or having to receive more for production. This behavior reduces the volumes cleared in the auction and significantly diminishes the community's overall benefit. Therefore, participant bidding strategies are an important design consideration, which should be carefully considered.

The results additionally demonstrate that social redistribution objectives can be incorporated by relaxing the primary clearing mechanism, which is solely based on economic efficiency, and adding a secondary redistribution step. Although this additional clearing algorithm slightly re-

duces the benefit to the community as a whole, it does increase the number of households achieving substantial savings.

For the **peer-to-peer trading models and matching algorithms (Section 7)**, the results show that all P2P configurations lead to a reduction in total community costs relative to the baseline without P2P trading. However, these benefits are distributed more unevenly than those of the previously discussed mechanisms. Unlike internal pricing and auction-based models, P2P trading can create substantial differences in benefits between the members. Some peers experience cost savings, while others face higher costs than the baseline. This outcome is a result from the individual bids submitted by the peers, which can differ substantially in the price for the energy. The optimization of the total social welfare of the community does not target individual benefits but benefits for the whole community, which influences bilateral trades in ways that do not necessarily align with individual objectives. This leads to more heterogeneous impacts across the community.

## 8.2 Assessment across the four fundamental mechanisms

---

Using a common case study furthermore allows for comparison of the four different general mechanisms. Before doing so, note that the benchmark scenario, which does not include local energy trading or sharing, serves as a practical upper bound on the community's energy cost. Although a mechanism could theoretically perform worse, such an outcome is highly unlikely and did not appear throughout this analysis. In addition, the centralized coordinated case discussed in Section 4 provides a theoretical lower bound since no mechanism can achieve lower total energy costs than this fully optimized solution. All mechanisms should therefore fall within this range, with some potentially coming closer to the centralized optimum than others.

Both centralized and decentralized energy management schemes, as well as internal pricing mechanisms, perform similarly in reducing the community's energy cost. In our case study, internal pricing mechanisms yield slightly higher costs than decentralized energy management schemes, which remain slightly above the centralized optimum. Put differently, these mechanisms approximate the theoretical optimum rather well. Note that the differences between the models are modest and should be interpreted as case-specific rather than as universal insights. That said, the results do suggest some indicative patterns. Decentralized energy management schemes appear more suitable for communities with large collective assets, given the difficulty of incorporating such assets into internal pricing mechanisms (see above). Conversely, internal pricing mechanisms may be more appropriate for communities composed predominantly of individual participants, where decentralized coordination offers limited additional value.

The auction-based clearing mechanisms leveraged a slightly adjusted benchmark, as they would also have been affected by the inefficient dispatch of collective resources. In particular, collective storage was exposed to different prices, so the results are not directly comparable to those of centralized and decentralized energy management schemes and internal pricing mechanisms. Nevertheless, qualitative discussion is still possible. The performance of auction-based mechanisms is sensitive to participant bidding behavior. In theory, these mechanisms could improve upon the others and even achieve the same outcomes as centralized optimization if all participants submitted optimal bids. In practice, however, this scenario may not hold and performance may be lower, as observed in the case study. Since energy management schemes and internal pricing mechanisms already approximate the centralized optimal community outcome, at least for this case study, any additional gains achievable through auction-based mechanisms

could be small. However, the auction-based model implemented in this study has shown that clearing mechanisms can also have substantial positive benefits apart from economic optimality, such as the redistribution of overall community benefits, achieved by implementing a two-step clearing with different objective functions. From an implementation point of view, auction-based approaches demand significant participant involvement, either through active engagement or algorithmic support, and require a high level of energy literacy. These mechanisms should consequently be reserved for communities where participants can efficiently bid and are motivated to engage with the market, or are willing to automate the bidding process while only keeping a supervisory role. In general, auction-based mechanisms should be reserved for communities where members' independent decision making is highly valued. Whether participants' bids can approach optimality remains an empirical question, though game-theoretic models may provide useful insights (see below).

The distributed P2P trading mechanism is the only one of the models which incorporates bilateral trading choices, which define who each peer wants to engage with in the P2P market. This is an important difference between the auction-based clearing mechanism and the P2P trading mechanism. Another difference between these two models is the definition of the bids as cost curves, which is more versatile and allows for personalized bids of each peer. As a result, the P2P trading mechanism delivers explicit transactions between peers. Each of these transactions has an individual price, allowing trades within the community with heterogeneous prices. A disadvantage of the P2P trading mechanism compared to the other discussed mechanisms is the uneven distribution of benefits among the members of the community, raising distributional concerns. The P2P trading mechanism may therefore be less preferable when fairness is an important consideration in the community.

### 8.3 Limitations and suggestions for further research

---

Although this deliverable provides a first comprehensive overview that compares all major classes of energy sharing and trading mechanisms, several aspects warrant further investigation. First, for the internal pricing mechanisms, it was assumed that collective assets faced the same internal price signals as individual members. As previously discussed, we revealed that this results in undesirable distortions. Future research could therefore focus on developing pricing frameworks that differentiate between individual and collective assets.

Second, the mechanisms were evaluated in a first-best setting that ignored uncertainty. While this allowed us to identify the core properties without any confounding effects, it does not capture uncertain demand and production profiles. This will likely reduce the performance of all mechanisms, though some may be affected more than others. Internal pricing mechanisms are expected to be particularly sensitive because they require communicating internal prices to participants in advance so they can optimize their behavior accordingly. One potential solution is to introduce a community coordinator who announces price signals ahead of time based on predicted volumes. While this restores coordinated behavior, it creates discrepancies between the predicted volumes (on which internal prices are based) and actual volumes. This would likely require an ex-post reconciliation or adjustment step to ensure cost recovery. The design of this process remains an open question.

A third avenue for future research is modeling bidding behavior in auction-based mechanisms under bounded rationality and imperfect information. While the current analysis assumes stylized bidding strategies, real-world participants usually operate with limited information, cognitive

constraints, and heuristic decision-making processes. Incorporating these elements through behavioral game theory, agent-based modeling, or learning-based behavioral rules could provide a more realistic understanding of how local auctions perform in practice.

A fourth aspect concerns the role of bilateral trading choices. In our analysis, only the P2P matching algorithm incorporated such preferences to an extent, in the form of constraints defining which peers are allowed to trade with each other. It remains an empirical question how significant such heterogeneity is in real communities. If preference differences are substantial, mechanisms that do not account for them may lead to inefficiencies or uneven distribution of benefits. Therefore, future research could quantify the extent of preference heterogeneity in practice and assess the amount of efficiency lost when mechanisms rely on simplified or homogeneous preference assumptions.

A fifth limitation is that we did not consider two energy trading and sharing mechanisms because they did not require specific algorithms. Nevertheless, we can provide a qualitative discussion. The cooperative model without energy sharing has the potential to reduce the community's costs, though not to the same extent as other energy sharing and trading mechanisms. In this model, members contribute to a buy-in and potentially receive dividends in return. This model is widely adopted because it is simpler than the other mechanisms. However, it does not include any formal mechanism that improves the incentives of individual consumers. Thus, the efficiency gains explored throughout this deliverable remain largely untapped, and gains in self-consumption are likely to be significantly more modest. When moving to continuous P2P trading, one can expect its performance to be similar to the pool-based P2P matching energy trading model, provided that information requirements are met.

Note that the quantitative values are furthermore case-specific. We did evaluate the models for three different system configurations (in addition to two different retail contracts), but the relative performance of these mechanisms could vary significantly for fundamentally different configurations.

Finally, the potential of energy trading and sharing was only evaluated based on retail price signals. Flexibility and ancillary services could provide an additional value stream, which is the topic of Task 2.4, whose outcomes will be reported in D2.4 of U2Demo.

## 9 Conclusion and recommendations

---

This deliverable presents the results of Task 2.3 from the U2Demo project, which focused on developing analytical models to evaluate peer-to-peer energy trading and sharing mechanisms. The main objectives were to classify different types of local energy sharing and trading arrangements, develop mathematical formulations for those requiring explicit market mechanisms, and evaluate their performance using a common case study based on the Dutch Scheveningen pilot. This case study included a realistic community of participants with collective and individual assets, diverse energy usage patterns, and storage capabilities.

The analysis shows that all four modeled mechanisms, i.e. capacity, energy, and revenue allocation; internal pricing; auction-based centralized trading; and distributed peer-to-peer trading, successfully reduce total community energy costs relative to a baseline without local energy sharing or trading. Those relying on coordinated energy management (whether centralized or decentralized) or internal pricing perform particularly well, approaching the theoretical optimum. Centralized auction-based trading can also perform well, but its efficiency depends on the community participants' bidding behavior.

Second, capacity, energy, and revenue allocation models show that mathematically rigorous allocation rules, such as optimal excess and Shapley value, provide the greatest efficiency and stability, though they may be computationally impractical for large communities. Scalable heuristic methods are a practical alternative for sizable communities with collective assets. Of these methods, multi-round static sharing keys performed best because they are efficient and have a better cost-saving index than hybrid and dynamic sharing keys.

Third, internal pricing mechanisms are an effective solution for communities with predominantly individual participants. However, their performance depends on the underlying retail contract and the design choices made for collective assets. Our results suggest that collective assets should not be subject to the same internal prices as the rest of the community because this results in inefficient dispatch schedules. Additionally, the mid-market rate can provide distorted incentives under a dynamic retail contract. It is important to be aware of these limitations when designing one of these mechanisms.

Fourth, although auction-based mechanisms can yield meaningful benefits, their effectiveness depends heavily on participant bidding behavior. This makes them suitable only when participants can reliably engage. In our case study, the incremental benefits of auction-based mechanisms compared to collective energy management or internal pricing mechanisms were relatively small. This suggests that the additional complexity and participant involvement may not always be justified, unless additional criteria, such as redistributive measures, are also considered, in which case adapted auction-based mechanisms can bring positive benefits to the community. In general, these findings are highly system-specific, and the decision to implement auction-based mechanisms should be evaluated on a case-by-case basis.

Finally, although pool-based distributed peer-to-peer trading reliably reduces total community costs, it distributes benefits unevenly due to the individual bid structure and the individual transaction prices, which could raise equity concerns. While some participants experience significant cost savings, others may see little benefit or even higher costs than in the baseline scenario. Therefore, although P2P trading can lead to reductions in the total energy bill of the community, additional mechanisms or incentives may be necessary to ensure fairness and maintain participant satisfaction within the community.

## 10 References

---

- [1] Bolt energy. <https://www.boltenergie.be/nl> [Accessed: 2025-05-05].
  - [2] Brixton energy. <https://brixtonenergy.co.uk> [Accessed: 2025-05-05].
  - [3] Communauté D'énergie Terdelt. <https://www.terdelt.be/communaut%C3%A9-d-%C3%A9nergie-terdelt/> [Accessed: 2025-10-28].
  - [4] Coopernico. <https://www.coopernico.org> [Accessed: 2025-05-05].
  - [5] Ecopower. <https://www.ecopower.be> [Accessed: 2025-05-05].
  - [6] Edinburgh community solar co-operative. <https://www.edinburghsolar.coop> [Accessed: 2025-05-05].
  - [7] Energie vanons. <https://energie.vanons.org/> [Accessed: 2025-05-05].
  - [8] Energiecoöperatie WPN. <https://energiecooperatiewpn.nl> [Accessed: 2025-05-05].
  - [9] Greenbizz.energy. <https://wesmart.com/en/communautes/greenbizzenergy-6b055b94> [Accessed: 2025-05-05].
  - [10] HospiGREEN. <https://ideta.be/projets/energie-hospigreen-premiere-communaute-denergie-renouvelable-de-consommateurs-publics-en-wallonie/> [Accessed: 2025-05-05].
  - [11] Illuminons notre quartier. <https://www.illuminonsnotrequartier.be/> [Accessed: 2025-05-05].
  - [12] Jurascic. <https://jurascic.com> [Accessed: 2025-05-05].
  - [13] Les Petits Riens. <https://wesmart.com/en/communautes/les-petits-riens-62d0e298> [Accessed: 2025-10-28].
  - [14] Megawattpuur. <https://megawattpuur.be> [Accessed: 2025-05-05].
  - [15] om nieuwe energie. <https://www.samenom.nl/> [Accessed: 2025-05-05].
  - [16] Partag'élec. [https://enogrid.com/collaboration-partagelec-enogrid/?\\_ga=2.59314669.191958298.1761916502-2141661795.1761916501](https://enogrid.com/collaboration-partagelec-enogrid/?_ga=2.59314669.191958298.1761916502-2141661795.1761916501) [Accessed: 2025-05-05].
  - [17] Pebbles. <https://pebbles-projekt.de/en/> [Accessed: 2025-05-05].
  - [18] Powerpeers. <https://powerpeers.nl/> [Accessed: 2025-05-05].
  - [19] Quartier Chomé. <https://www.quartierchome.be/projet/cel/> [Accessed: 2025-10-28].
  - [20] Quartierstrom. <https://quartier-strom.ch/index.php/en/homepage/> [Accessed: 2025-05-05].
  - [21] Som energia. <https://www.somenergia.coop/es> [Accessed: 2025-05-05].
  - [22] Sonnencommunity. <https://sonnen.de/sonnencommunity/> [Accessed: 2025-05-05].
  - [23] Suncontract. <https://suncontract.org/> [Accessed: 2025-05-05].
  - [24] Sunshare. <https://www.ioenergy.eu/sunshare/> [Accessed: 2025-05-05].
-

- [25] Vandebbron. <https://vandebron.nl/> [Accessed: 2025-05-05].
- [26] Ville de Hannut. <https://wesmart.com/en/communautes/ville-de-hannut-b0538f06> [Accessed: 2025-10-28].
- [27] E. Baeyens, E. Y. Bitar, P. P. Khargonekar, and K. Poolla. Coalitional aggregation of wind power. *IEEE Transactions on Power Systems*, 28(4):3774–3784, 2013.
- [28] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein. *Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers*. Now Foundations and Trends, 2011.
- [29] Bruxelles Environnement. Partage d’électricité au sein d’une communauté d’énergie. <https://guidebatimentdurable.brussels/partage-deelectricite-sein-dune-communaute-denergie> [Accessed: 2025-10-28].
- [30] Bundesgesetz. Elektrizitätswirtschafts- und -organisationsgesetz 2010 – EIWOG 2010. <https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=20007045>.
- [31] CWaPE. Liste de clés de répartition standards permettant la répartition des volumes partagés entre les participants à une activité de partage d’énergie au sein d’une communauté d’énergie ou entre des clients actifs agissant collectivement au sein d’un même bâtiment . Technical report, 2023. <https://www.cwape.be/sites/default/files/cwape-documents/2023.04.27-0928-Proposition%20cl%C3%A9s%20de%20r%C3%A9partition%20volumes%20partag%C3%A9s.pdf>.
- [32] E-redes. Projeto-Piloto. Modelos de partilha de energia em Autoconsumo. <https://www.e-redes.pt/pt-pt/modelos-de-partilha-de-energia-em-autoconsumo> [Accessed: 2025-10-28].
- [33] E-redes. Autoconsumo Coletivo – Partilha Dinâmica. Modelo e formato de dados. Technical report, 2023. <https://www.e-redes.pt/sites/eredes/files/2023-08/Autoconsumo%20Coletivo%20-%20Partilha%20Din%C3%A2mica.pdf>.
- [34] Enedis. Autoconsommation collective. Guide pédagogique. Technical report. <https://www.enedis.fr/sites/default/files/documents/pdf/autoconsommation-collective-guide-pedagogique.pdf>.
- [35] Enedis. Observatoire français de la transition écologique. L’autoconsommation collective dans les starting-blocks. <https://observatoire.enedis.fr/article/lautoconsommation-collective-dans-les-starting-blocks> [Accessed: 2025-10-28].
- [36] Enogrid. Les clés de répartition en autoconsommation collective, 2024. <https://enogrid.com/les-cles-de-repartition-en-autoconsommation-collective/> [Accessed: 2025-10-28].
- [37] Entidade Reguladora dos Serviços Energéticos. Regulamento n.º 815/2023, de 27 de julho, 2023. <https://diariodarepublica.pt/dr/detalhe/regulamento/815-2023-216251911>.
- [38] ERSE. Projetos-piloto aprovados ao abrigo do artigo 55.º do Regulamento do Autoconsumo. [https://www.erse.pt/media/kjnks5z1/lista\\_site\\_projetos\\_piloto\\_pt.pdf](https://www.erse.pt/media/kjnks5z1/lista_site_projetos_piloto_pt.pdf) [Accessed: 2025-10-28].

- [39] Fluvius. Protocol energiedelen, persoon-aan-persoonverkoop en verkoop in gebouwen – versie 3.2. Technical report, 2024. <https://partner.fluvius.be/sites/fluvius/files/2024-07/protocol-energiedelen-p2p-verkoop-in-gebouwen-v3-2.pdf>.
- [40] E. Gomes, L. Pereira, A. Esteves, and H. Morais. Pyecom: A python tool for analyzing and simulating energy communities. *SoftwareX*, 24:101580.
- [41] N. Hadiya, F. Teotia, R. Bhakar, P. Mathuria, and A. Datta. A comparative analysis of pricing mechanisms to enable p2p energy sharing of rooftop solar energy. 9 2020.
- [42] L. Han, T. Morstyn, and M. McCulloch. Incentivizing prosumer coalitions with energy management using cooperative game theory. *IEEE Transactions on Power Systems*, 34(1):303–313, 2019.
- [43] H. Huang, S. Nie, J. Lin, Y. Wang, and J. Dong. Optimization of Peer-to-Peer Power Trading in a Microgrid with Distributed PV and Battery Energy Storage Systems. *Sustainability*, 12(3):923, Jan. 2020.
- [44] Instituto para la Diversificación y Ahorro de la Energía (IDAE), Madrid. Guía de autoconsumo colectivo. Technical report, 2024. [https://www.idae.es/sites/default/files/documentos/publicaciones\\_idae/Guia-Autoconsumo-Colectivo/20240709\\_Guia\\_Autoconsumo\\_Colectivo\\_v2.1.pdf](https://www.idae.es/sites/default/files/documentos/publicaciones_idae/Guia-Autoconsumo-Colectivo/20240709_Guia_Autoconsumo_Colectivo_v2.1.pdf).
- [45] H. Le Cadre, P. Jacquot, C. Wan, and C. Alasseur. Peer-to-peer electricity market analysis: From variational to generalized nash equilibrium. *European Journal of Operational Research*, 282(2):753–771, 2020.
- [46] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei. Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers. *IEEE Transactions on Power Systems*, 32:3569–3583, 9 2017.
- [47] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng, and N. Jenkins. Peer-to-peer energy trading in a community microgrid. In *2017 IEEE Power & Energy Society General Meeting*, pages 1–5, July 2017.
- [48] Ministerio para la Transición Ecológica. Real decreto 244/2019, de 5 de abril, 2019. <https://www.boe.es/eli/es/rd/2019/04/05/244>.
- [49] Ores. Energiedelen in de praktijk. <https://www.ores.be/particulieren/in-de-praktijk> [Accessed: 2025-10-28].
- [50] S. Pfenninger and I. Staffell. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. *Energy*, 114:1251–1265.
- [51] K. Poncelet, H. Hoschle, E. Delarue, A. Virag, and W. Drhaeseleer. Selecting Representative Days for Capturing the Implications of Integrating Intermittent Renewables in Generation Expansion Planning Problems. *IEEE Transactions on Power Systems*, 32(3):1936–1948.
- [52] A. E. Roth. *The Shapley value: essays in honor of Lloyd S. Shapley*. Cambridge University Press, 1988.

- [53] A. Safdarian, P. Astero, M. Baranauskas, A. Keski-Koukkari, and A. Kulmala. Coalitional game theory based value sharing in energy communities. *IEEE Access*, 9:78266–78275, 2021.
- [54] A. Sanjab and G. de Almeida Terça. Grid-impact aware p2p trading and implications on flexibility markets. In *IEEE PES Innovative Smart Grid Technologies Europe (ISGT EU-ROPE)*, pages 1–6, 2024.
- [55] I. Shilov, H. Le Cadre, A. Bušić, A. Sanjab, and P. Pinson. Towards forecast markets for enhanced peer-to-peer electricity trading. In *IEEE SmartGridComm*, pages 1–7, 2023.
- [56] Sibelga. Distribution methods. <https://www.sibelga.be/en/connections-meters/renewable-energy/energy-sharing/repartition-methods> [Accessed: 2025-10-28].
- [57] Statistics Netherlands. Prices of natural gas and electricity, Sep 2025.
- [58] H. Teichgraeber and A. R. Brandt. Time-series aggregation for the optimization of energy systems: Goals, challenges, approaches, and opportunities. *Renewable and Sustainable Energy Reviews*, 157:111984.
- [59] B. Zhang, Y. Du, E. G. Lim, L. Jiang, and K. Yan. Design and Simulation of Peer-to-Peer Energy Trading Framework with Dynamic Electricity Price. In *2019 29th Australasian Universities Power Engineering Conference (AUPEC)*, pages 1–6, Nov. 2019.
- [60] Y. Zhou, J. Wu, and C. Long. Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework. *Applied Energy*, 222:993–1022, 7 2018.

## APPENDIX A: Decentralized and centralized energy management problems

---

In this section, we explain the decentralized and centralized scheduling problems that must be solved by an energy community using the energy sharing schemes discussed in Section 4.1.

### Decentralized scheduling problem

---

In the decentralized management scheme, first, each community member optimally schedules their flexible assets taking into account their inflexible loads and generation as well as the operational constraints of their flexible asset. For example, when a community member owns a battery and PV-based generation, the individual scheduling problem of this community member can be formulated as in (5.1) subject to (5.2)–(5.8). In general, this problem can be written as:

$$\min_{\mathbf{u}_i, \mathbf{P}_i^{\text{net}}} \sum_{t \in T} \lambda_{d,t}^{\text{off}} [P_{t,i}^{\text{net}}]_+ + \lambda_{d,t}^{\text{inj}} [P_{t,i}^{\text{net}}]_- \quad (\text{A.1a})$$

$$\text{s.t. } P_{t,i}^{\text{net}} = P_{t,i}^{\text{inflex}} + \mathbf{1}^\top \mathbf{u}_{t,i}, \quad \forall t \in T, \quad (\text{A.1b})$$

$$\mathbf{u}_i \in \mathcal{U}_i, \quad (\text{A.1c})$$

where  $P_i^{\text{net}} = \text{col}((P_{t,i}^{\text{net}})_{t \in T})$  is the net energy positions of member  $i$  over all time period, i.e.,  $P_{t,i}^{\text{net}} = P_{t,i}^{\text{off}} - P_{t,i}^{\text{inj}}$ ,  $P_{t,i}^{\text{inflex}}$  is net position of all inflexible assets (loads - generation), where  $P_{t,i}^{\text{inflex}} > 0$  means that aggregatively the inflexible assets are consuming power and  $P_{t,i}^{\text{inflex}} < 0$  means that the inflexible assets are injecting power. The vector  $\mathbf{u}_i := \text{col}((u_{t,i})_{t \in T})$  denotes the decision of dispatch/schedules of all flexible assets. The set  $\mathcal{U}_i$  in Eq. A.1c represents the constraint set of all flexible assets, which includes operational and technical constraints of the considered assets. For simplicity, we model all constraints of the assets as linear constraints, resulting in polytopic  $\mathcal{U}_i$ . Finally, the operators  $[\cdot]_+ = \max(\cdot, 0)$  and  $[\cdot]_- = \min(\cdot, 0)$  are projections to the non-negative and non-positive orthants.

Denoting an optimal solution to Problem (A.1) by  $\hat{\mathbf{u}}_i, \hat{P}_i^{\text{net}}$ , we can then obtain the community-level energy management problem in this decentralized scheme as follows:

$$\min_{\mathbf{u}^{\text{com}}, \mathbf{P}^{\text{Net}}} \sum_{t \in T} \lambda_{d,t}^{\text{off}} [P_t^{\text{Net}}]_+ + \lambda_{d,t}^{\text{inj}} [P_t^{\text{Net}}]_- \quad (\text{A.2a})$$

$$\text{s.t. } P_t^{\text{Net}} = P_t^{\text{Inflex}} + \mathbf{1}^\top \mathbf{u}_t^{\text{com}} + \sum_{i \in I} P_{t,i}^{\text{net}}, \quad \forall t \in T, \quad (\text{A.2b})$$

$$\mathbf{u}^{\text{com}} \in \mathcal{U}^{\text{com}}, \quad (\text{A.2c})$$

$$P_{t,i}^{\text{net}} = \hat{P}_{t,i}^{\text{net}}, \quad \forall t \in T, \quad (\text{A.2d})$$

where  $P_t^{\text{Net}}$  denotes the net energy position of the community, satisfying Eq. A.2b,  $\mathbf{u}^{\text{com}} = \text{col}((u_t^{\text{com}})_{t \in T})$ ,  $P_t^{\text{Inflex}}$  denotes the net position of the collective inflexible assets,  $\mathbf{u}^{\text{com}}$  is the decision vectors for the schedules of all collectively invested assets, and  $\mathcal{U}^{\text{com}}$  is the constraint set of the flexible assets.

## Centralized scheduling problem

---

In the centralized scheduling problem, all flexible assets within the community are optimally scheduled by solving the following central problem:

$$\min_{\mathbf{u}^{\text{com}}, \mathbf{P}^{\text{Net}}} \sum_{t \in T} \lambda_{d,t}^{\text{off}} [P_t^{\text{Net}}]_+ + \lambda_{d,t}^{\text{inj}} [P_t^{\text{Net}}]_- \quad (\text{A.3a})$$

$$\text{s.t. } P_t^{\text{Net}} = P_t^{\text{Inflex}} + \mathbf{1}^\top \mathbf{u}_t^{\text{com}} + \sum_{i \in I} P_{t,i}^{\text{net}}, \quad \forall t \in T, \quad (\text{A.3b})$$

$$\mathbf{u}^{\text{com}} \in \mathcal{U}^{\text{com}}, \quad (\text{A.3c})$$

(A.1b) and (A.1c) hold.

## Optimal schedules

---

The optimal schedules of the flexible assets, obtained by either solving Problem (A.2) or (A.3) are denoted by  $\hat{\mathbf{u}}_i$ , for all community member  $i \in I$ , and  $\hat{\mathbf{u}}^{\text{com}}$ , for the collectively invested assets. Furthermore, the optimal schedules of the offtake and injection of each community member are denoted by:

$$\begin{aligned} \hat{P}_{d,t,i}^{\text{off}} &= [\hat{P}_{d,t,i}^{\text{net}}]_+, \\ \hat{P}_{d,t,i}^{\text{inj}} &= [\hat{P}_{d,t,i}^{\text{net}}]_-, \end{aligned}$$

for all  $i \in I$ ,  $t \in T$ , and  $d \in D$ .