Deliverable 4.1

Implications for Balancing

The ALEXANDER consortium

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Executive summary

ALEXANDER, *Accelerating Low voltagE fleXibility pArticipation iN a griD safE manner*, develops methods and tools to unlock flexibility from low-voltage (LV) assets for system services in a grid-safe and socially acceptable way. Within this framework, Task 4.1, *Implications for balancing*, analyses how a large-scale deployment of emerging local flexibility mechanisms – as developed in WP2 and WP3 – will affect system balancing and the interaction between regulated and unregulated market players.

Balancing with LV flexibility: focus of Task 4.1
Deliverable 4.1 reports on this analysis. It focuses on the role of energy communities, virtual power plants and aggregators of active prosumers as flexibility service providers (FSPs), and on how their business models, bidding strategies and internal decision-making processes translate into reliable provision of system services. The deliverable explicitly accounts for consumers' preferences and possible bounded rationality, and studies how these behavioural aspects shape the amount, reliability and economic value of LV flexibility.

Deliverable 4.1 starts from the observation that LV flexibility will increasingly be activated through local mechanisms: local energy markets (LEMs) and local flexibility markets (LFMs), dynamic tariffs, connection agreements and community-based coordination schemes. When such mechanisms are deployed at scale, they will influence how much flexibility remains available for system balancing, how predictable and controllable that flexibility is, and how risks and benefits are distributed across actors.

Against this background, Deliverable 4.1 pursues three main objectives:

- to assess how emerging business models (energy communities, aggregators) affect the capability of FSPs to provide reliable balancing services when consumer preferences and bounded rationality are taken into account;
- to analyse how interactions between FSPs at system level should be organised so that operational stability is guaranteed while economic efficiency is maximised;
- to evaluate the operational and financial impact on system operators (TSO and DSOs) of a large deployment of LV flexibility models, and to derive building blocks for an integrated Belgian framework for procurement and activation of LV flexibility, in line with the recommendations from Task 3.3.

Approach and scope of Deliverable 4.1
The deliverable brings together three complementary modelling and analysis strands:

- **Community- and aggregator-level mechanisms.**
  Models of local energy markets and local flexibility markets translate heterogeneous user preferences (financial, comfort, environmental) and technical constraints into net demand baselines and flexibility offers that are meaningful for DSOs and TSOs.
- **TSO–DSO market coordination and strategic interaction.**
  Game-theoretic tools are used to explore how different designs of coordinated flexibility markets (e.g. common, multi-level, fragmented) perform when FSPs behave strategically and when liquidity is limited, highlighting risks for efficiency and operational security.
- **Price-based demand response for balancing under uncertainty.**
  Data-driven, inverse-optimisation methods are developed and tested to learn residential price-response from historical data and to design aggregator participation strategies in balancing services that are robust to behavioural uncertainty, focusing on value for balancing rather than purely on forecast accuracy.

These strands jointly cover the micro-level decisions of end-users and communities, the meso-level strategies of aggregators and FSPs, and the macro-level organisation of system services and coordination between system operators.

Key implications for balancing and for an integrated Belgian framework
From the combined analyses, several cross-cutting insights emerge that are relevant for Belgian balancing arrangements and the future framework for LV flexibility:

- **Business models and actors –** Local flexibility mechanisms enable new roles for energy communities and aggregators, but also redistribute responsibilities and risks. Reliable provision of balancing/flexibility services from LV assets requires that these actors can aggregate diverse resources, manage internal conflicts between comfort and economic incentives, and honour external commitments towards DSOs and the TSO.
- **Market design and coordination –** The way in which TSO and DSOs coordinate procurement and activation of flexibility has a direct impact on system-wide efficiency and on exposure to strategic behaviour. Designs that ensure sufficient competition, avoid fragmentation of liquidity and provide clear priority rules for local versus system needs are essential to safeguard operational stability while making best use of LV flexibility.
- **Consumer behaviour and uncertainty –** The effective balancing potential of LV flexibility is smaller and more uncertain than technical assessments suggest, because households care about comfort and other non-financial motives and do not always respond perfectly rationally to price signals. Modelling preferences and bounded rationality, and using value-oriented learning approaches, improves the robustness of balancing strategies and reduces the risk of over- or under-delivery.
- **System operators and operational impact –** A large deployment of LV flexibility mechanisms will increase the need for grid visibility, forecasting tools and coordinated activation procedures at DSO level, and will change the volume, timing and predictability of flexibility seen by the TSO. While this can reduce the need for conventional reinforcement and central reserves, it also requires clear cost-recovery mechanisms and incentives for DSOs to actively procure and facilitate LV flexibility.
- **Towards an integrated Belgian framework –** Combining the above insights with the recommendations from Task 3.3, the deliverable points to the key building blocks of an integrated Belgian framework for LV flexibility: coherent products for system services that are accessible to LV resources; transparent baselining and verification; harmonised TSO–DSO coordination rules; and clear allocation of roles, responsibilities and incentives between regulated (TSO/DSOs) and unregulated actors (communities, aggregators).

Overall, Deliverable 4.1 shows that the implications of LV flexibility for balancing cannot be understood by looking at technology alone. The way local mechanisms are designed, how consumer behaviour is represented, and how system-level markets are organised jointly determine whether LV flexibility strengthens operational security and delivers economic benefits, or introduces new risks. The findings provide input for the ALEXANDER roadmap and for ongoing regulatory discussions on the future design of balancing and LV flexibility in Belgium.

Table of Contents

List of Figures

List of Tables

Abbrevations and acronyms

Abbreviation	Full term
BRP	Balance Responsible Party
CM	Community Manager
CMF	Comfort-driven (community type)
DA	Day-ahead
DER	Distributed Energy Resource
DSO	Distribution System Operator
DR	Demand Response
DRR	Demand Response Resource
EC	Energy Community
ENV	Environmental-driven (community type)
EV	Electric Vehicle
FCR	Frequency Containment Reserve
FIN	Financial-driven (community type)
FOIO	Forecast-Oriented Inverse Optimisation
FSP	Flexibility Service Provider
HP	Heat Pump
IO	Inverse Optimisation
KER	Key Exploitable Result
LEM	Local Energy Market
LFM	Local Flexibility Market
LV	Low Voltage
MAE	Mean Absolute Error
MIX	Mixed-preference (community type)
MV	Medium Voltage
RTP	Real-Time Pricing
SBVOIO	Scenario-Based Value-Oriented Inverse Optimisation
SMEs	Small and Medium-sized Enterprises
SO	System Operator
TSO	Transmission System Operator
VOIO	Value-Oriented Inverse Optimisation
VPP	Virtual Power Plant
WP	Work Package
BAL	Balanced (community type)

1. Introduction

1.1. Context

Europe's electricity systems are entering a phase in which flexibility becomes as critical as capacity. Rising shares of variable renewable generation, the electrification of heating and mobility, and increasing congestion at distribution level all push system operators to make more active use of demand-side flexibility. A significant part of this flexibility potential is connected at the low-voltage (LV) grid, through assets such as rooftop PV, residential batteries, electric vehicles (EVs) and heat pumps (HPs), often coordinated via energy communities, virtual power plants (VPPs) or aggregators of active prosumers.

In parallel, new local flexibility mechanisms are emerging at LV level. Building on the work of ALEXANDER WPs 2 and 3, these mechanisms include local energy and flexibility markets, dynamic tariffs, non-firm connection agreements and operating envelopes, as well as new community-based coordination schemes. While these instruments are primarily designed to address local network issues and to enable consumer participation, their large-scale deployment will inevitably affect how much LV flexibility is available for system balancing and congestion management, how reliably it can be activated, and how risks and benefits are shared between actors.

Belgium offers a particularly relevant context for this analysis. The coexistence of three regional regulatory frameworks, evolving arrangements for TSO–DSO coordination, and a fast-growing stock of distributed resources mean that LV flexibility will play an increasing role in adequacy and balancing. At the same time, balancing products, prequalification procedures and market rules have historically been shaped around large, centralised resources. Understanding how emerging LV-oriented mechanisms interact with system-level services is therefore essential for designing an integrated Belgian framework for procurement and activation of LV flexibility.

Task 4.1 "Implications for balancing" is positioned at this interface between local mechanisms and system needs. It investigates how large-scale deployment of LV flexibility models, as defined in WP2 and WP3, impacts balancing arrangements, the functioning of system services, and the roles of both regulated and unregulated players.

1.2. Challenges

The integration of LV flexibility into system balancing and congestion management raises several interconnected challenges that go beyond purely technical considerations.

First, **new business models and actors** change how flexibility is organised and offered. Energy communities, VPPs and aggregators bundle small-scale assets and mediate between end-users, DSOs and the TSO. Their internal decision-making, including how they design baselines, share costs and benefits, and manage comfort versus savings, directly affects the volume and reliability of flexibility they can commit to system services. The ability of flexibility service providers (FSPs) to deliver balancing products therefore depends not only on technology, but also on incentives, governance structures and contractual arrangements at community and aggregator level.

Second, the **behaviour of end-consumers** introduces uncertainties. Households value comfort, autonomy and environmental impact alongside financial gains, and they may not respond in a fully rational or perfectly predictable way to price signals or activation requests. If these aspects are ignored, activation strategies may lead to systematic over or under-delivery in balancing/flexibility services. Considering preferences and bounded rationality in quantitative models is thus key to assessing the real contribution of LV flexibility to system stability.

Third, **interactions between FSPs at system level** can create coordination and efficiency issues. As more actors bid LV-sourced flexibility into balancing and other system services, competition and strategic behaviour become important. Market design and TSO–DSO coordination rules influence whether flexibility is used where it has highest system value, or whether fragmentation, double activation and local market power lead to inefficiencies and operational risks.

Finally, there are **operational and financial implications for system operators**. DSOs must ensure grid-safe activation of LV flexibility while dealing with limited observability, data constraints and regulatory obligations. The TSO must secure sufficient, reliable balancing capacity and energy in a context where part of the flexibility is activated locally for congestion management. Both levels need clear procedures and cost-recovery mechanisms if LV flexibility is to become a structural component of balancing rather than an ad-hoc resource.

Task 4.1 addresses these challenges by explicitly modelling the interactions between consumers, communities, aggregators, DSOs and the TSO, and by analysing how different local flexibility mechanisms and market designs perform when behavioural aspects and strategic incentives are taken into account.

1.3. Scope

Deliverable 4.1 reports on the work carried out in Task 4.1 between M24 and M42. In line with the task description, its scope is threefold:

- **Impact of emerging LV business models on system-service provision.** The deliverable examines how energy communities, VPPs and aggregators of active prosumers, operating under the mechanisms developed in WP2 and WP3, affect the ability of FSPs to reliably provide balancing and related system services. Particular attention is paid to how consumer preferences, comfort considerations and bounded rationality influence the flexibility that can be contracted and delivered.
- **Organisation of competition between FSPs for operational services.** Building on game-theoretic and optimisation-based models, the deliverable analyses how interactions between multiple FSPs at system level should be organised to guarantee operational stability while maximising economic efficiency. Different TSO–DSO coordination schemes and market designs are compared in terms of their effectiveness in integrating LV flexibility and their vulnerability to strategic behaviour.
- **Impacts on system operators and contribution to an integrated Belgian framework.** The deliverable assesses how a large-scale deployment of LV flexibility mechanisms affects DSOs and the TSO, both operationally and financially. Based on these insights, and in conjunction with the recommendations from Task 3.3, it identifies key building blocks for an integrated Belgian framework for procurement and activation of LV flexibility, ensuring coherent treatment of LV resources across congestion management, balancing and other system services.

These questions are addressed through three main modelling and analysis strands, each associated with a Key Exploitable Result (KER) of ALEXANDER Task 4.1:

- community-level mechanisms for providing baseline-based flexibility services to DSOs;
- simulation environments for coordinated TSO–DSO flexibility markets and strategic FSP behaviour;

- data-driven frameworks for price-based residential demand response participation in balancing services under behavioural uncertainty.

Rather than presenting these KERs in isolation, Deliverable 4.1 emphasises their combined implications for balancing and their relevance for Belgian stakeholders.

1.4. Organisation

The remainder of this deliverable is structured around three KERs and a concluding section. The first KER section focuses on how communities and aggregators organise LV flexibility and offer it to DSOs, the second on TSO–DSO coordination and competition between flexibility service providers in coordinated markets, and the third on data-driven frameworks for price-based residential demand response participation in balancing. The final section synthesises the implications of these three KERs for system balancing in Belgium and outlines key design principles for an integrated framework for LV flexibility.

2. KER 1: Energy Communities providing flexibility services for Distribution System Operators

2.1. An Innovative Framework for Heterogeneous Energy Communities Providing Baseline Flexibility Services in Distribution Networks [1]

Motivation

The increasing proliferation of distributed energy resources (DERs) such as solar PV, battery storage, and electric heat pumps is reshaping the operational dynamics of modern power distribution networks. While DERs offer promising solutions for decentralization and decarbonization, they also pose significant technical challenges, most notably line congestion and voltage regulation issues at the distribution level. Addressing these challenges traditionally involves grid reinforcement, but such measures are capital-intensive, slow, and inflexible to localized variations. A more adaptive alternative lies in the use of flexibility services, which allow DSOs to manage demand and supply variations using controllable resources across the network.

Energy Communities (ECs) (groups of prosumers and consumers sharing local energy resources) have emerged as promising contributors of such flexibility services. Through coordinated energy trading and DER sharing, ECs can provide demand response capabilities, promote self-consumption, and ease pressure on the grid. However, realizing this potential in practice requires addressing key challenges related to user behavior, market design, and system-level integration.

Objectives and Contributions

This study introduces an innovative framework for enabling heterogeneous ECs to effectively participate in flexibility markets, offering a mechanism through which DSOs can procure flexible services while respecting the internal dynamics of ECs. Unlike capacity limitation models where power consumption caps are imposed, baseline mechanisms define a reference consumption level from which flexibility is measured. While more adaptable, baseline mechanisms are vulnerable to strategic behavior and uncertainty, especially when users have diverging motivations.

The paper addresses several critical gaps in current research and implementation:

1. User Preference Integration: Many existing frameworks lack mechanisms that account for diverse user preferences—financial, environmental, and comfort-related—leading to limited understanding of user behavior.
2. Baseline Manipulation Risk: Without careful design, users may game the system by inflating their historical consumption, increasing baseline values and securing undue compensation.
3. Inadequate Valuation of Flexibility: Flexibility services are often compensated using uniform or cost-based approaches, overlooking users' true marginal contributions to network support.
4. Neglect of Network Constraints: Local voltage and congestion constraints, particularly in LV networks, are frequently omitted, risking grid reliability when implementing distributed flexibility.

Overview of Methodology

To address these challenges, we propose a three-stage methodological framework, combining game theory, bilevel optimization, and power system modeling to deliver a realistic and operationally sound approach.

The structure of EC is depicted in Figure 1. In this framework, Community Manager (CM) is responsible. For coordinating EC including energy exchanges between the members and financial transaction. Retailer supports the EC for energy balancing by purchasing surplus electricity selling deficit power to the CM. The DSO is also responsible for grid safety and coordinates with CM for flexibility service provision.

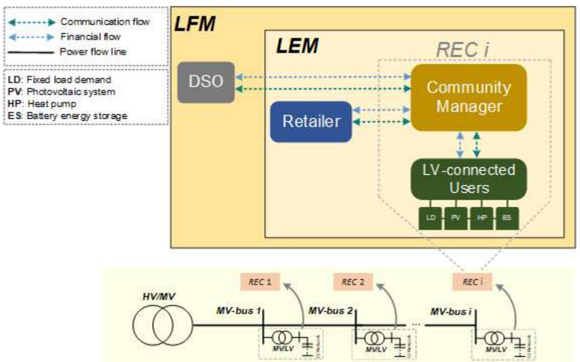

Figure 1: The structure of energy community and interactions with other entities

Stage 1: Local Energy Market (LEM) with Preference-Aware Design

In the first stage, energy transactions within the EC are governed by a Stackelberg game (SG) between the CM and community users. The CM sets internal electricity prices considering retail tariffs, distribution grid fees, and network constraints. In response, users schedule their resource activities based on a personalized utility function that incorporates three weighted preferences:

- Financial savings;
- Environmental impact (based on CO_2 intensity of energy);
- Thermal comfort (modeled via indoor temperature deviation).

This interaction is modeled as a bilevel programming problem, where the CM solves an upper-level optimization to minimize the total cost of imports, exports, and grid usage, while users solve individual lower-level problems to maximize utility. The bilevel model includes:

- Power flow constraints in the radial LV network using LinDistFlow equations;
- Operational limits on battery storage, heat pumps, and energy exchanges;
- Voltage and power constraints at all nodes.

The bilevel formulation is reformulated into a single-level mixed-integer quadratic program using the Karush-Kuhn-Tucker conditions, allowing for tractable computation.

The outcome of this stage includes net demand baseline values and estimated flexibility prices for each EC, which are communicated to the DSO for subsequent planning.

Stage 2: Local Flexibility Market (LFM) with Congestion Management

In the second stage, the DSO uses the submitted baseline power and price data to optimize congestion management across the medium-voltage (MV) distribution network. The object of the problem is to:

- Allocate upward and downward flexibility requests;
- Ensure power balance and voltage limits across all MV buses;
- Minimize overall flexibility procurement costs, including power losses.

Once flexibility needs are identified, the CM coordinates with users to adjust schedules within their available DER capacities, ensuring that the community collectively meets its obligations without violating baseline commitments or local constraints. A penalty mechanism is introduced to discourage deviation from baseline values and mitigate strategic behavior.

Stage 3: Flexibility Valuation and Fair Revenue Allocation
After flexibility services are delivered, financial compensation is allocated using Distribution Locational Marginal Prices. Internally, each CM employs the Shapley value method to distribute rewards among users based on their actual contribution to flexibility provision. This game-theoretic approach ensures:

- Fairness across heterogeneous participants;
- Recognition of users with higher flexibility impact;

Main Findings
This study explores how different types of energy communities—each with distinct user preferences—participate in local energy and flexibility markets. Five community archetypes were modeled: comfort-driven (CMF), financial-driven (FIN), environmental-driven (ENV), balanced (BAL), and mixed-preference (MIX). The initial results demonstrate clear differences in operational behavior, flexibility provision, and economic outcomes across these communities.
In the LEM stage, user preferences strongly influence internal buying and selling prices. Comfort and environmental communities exhibit higher internal buying prices due to their strong non-financial motives, whereas financial community shows lower prices, prioritizing cost efficiency. This directly impacts energy scheduling and resource usage, with CMF community purchasing heavily during low-cost hours to preserve comfort, while FIN and MIX communities strategically time imports and exports for economic gain.
The transition to the LFM highlights how communities adapt their flexible resource schedules (batteries and heat pumps) in response to system-level requests.
According to Tables 1 and 2, cost and revenue analysis shows that FIN achieves the lowest LEM operational costs and the highest LFM revenues, validating the effectiveness of financial-driven strategies. BAL and MIX communities perform moderately across all dimensions, while CMF and ENV face higher costs and lower revenues. The Shapley value is used for fair revenue allocation, rewarding communities proportionally to their flexibility contributions.

Table 1: Operation costs of different EC members participating in LEM

Users	Users Operation Costs in LEM				
	CMF	FIN	ENV	BAL	MIX
User 1	111.10	152.18	162.08	111.32	179.94
User 2	114.44	104.01	114.07	122.22	138.67
User 3	190.98	108.71	128.87	133.55	103.10
User 4	157.87	102.28	146.52	162.75	109.84
User 5	231.04	141.03	135.73	207.35	106.33

Table 2: Revenues of participating in LFM for different EC members

EC Type	Total Revenues	Revenue Allocation Using Shapely Value Method				
		User 1	User 2	User 3	User 4	User 5
CMF	40.95	9.04	8.75	8.99	7.58	6.57
FIN	99.37	28.71	29.60	28.66	26.24	26.22
ENV	47.74	6.93	7.55	7.99	12.75	12.59
BAL	63.58	9.53	13.29	10.19	12.69	17.86
MIX	68.72	10.77	13.73	17.72	7.23	19.25

Next Steps

For the next steps more analysis on physical network constraints including active power flow should be conducted to see impact of various ECs on grid conditions. In addition, the research paper regarding this research should be completed.

3. KER 2: Strategic Behaviour in TSO-DSO coordinated Flexibility Markets

3.1. Strategic behavior in TSO-DSO coordinated flexibility markets: A Nash equilibrium and efficiency analysis [2]

Motivation

Strategic behavior refers to the actions taken by market participants, such as Flexibility Service Providers (FSPs), to maximize profits by leveraging market rules, conditions, or competitors' actions. Accounting for strategic behavior in flexibility market analyses is critical because the assumption that FSPs bid solely at marginal costs oversimplifies market dynamics and fails to reflect the complexities of real-world competition.

Strategic bidding can significantly impact market efficiency, exposing vulnerabilities in market design. Depending on the structure of flexibility markets, FSPs with dominant market shares or access to isolated resources may exploit their positions by bidding aggressively or manipulating prices. For example, fragmented market designs—where markets are separated by service (e.g., congestion management and balancing) or by system operator (e.g., DSOs and TSOs)—can lead to increased costs due to reduced competition and monopolistic behavior by FSPs. Additionally, gaming strategies, such as the "inc-dec" game or exploiting congestion to create local monopolies, can undermine the primary objectives of flexibility markets. By leveraging grid constraints, FSPs can isolate parts of the network, gaining disproportionate pricing power, which directly increases system operators' costs and reduces market fairness.

Even in competitive markets, strategic behavior can create opportunities for market power. In scenarios with low liquidity or insufficient coordination between flexibility buyers, dominant FSPs can influence prices and maximize profits, resulting in suboptimal resource allocation and reduced overall efficiency. These challenges highlight the importance of carefully designed market rules to prevent exploitation and encourage fair competition.

Strategic behavior is not only possible but inevitable in markets involving profit-driven participants. Ignoring this aspect would oversimplify analyses and lead to unrealistic conclusions. Simulating FSP decision-making under realistic conditions—taking into account full or partial information and varying levels of participants' computational capability—ensures a more accurate understanding of market outcomes and provides insights into mitigating potential inefficiencies of certain designs.

Objectives and Contribution

In this work, the strategic behavior of FSPs is analyzed within a duopolistic setting involving the procurement of flexibility by a TSO and a DSO. The study explores three market designs—common, fragmented, and multi-level markets—to investigate how varying levels of resource sharing and coordination affect market outcomes and the potential for gaming by FSPs. In the common market design, all FSPs are pooled together, and the market is jointly cleared by the TSO and DSO, ensuring centralized coordination and access to all available resources. In the fragmented market model, system operators clear their markets independently, with resources being exclusively available to the SO managing the network to which they are connected. Finally, the multi-level market introduces a sequential design, granting DSOs priority access to local resources in the first stage, while any remaining resources are made available to the TSO in the second stage. These designs capture varying degrees of TSO-DSO coordination, providing a framework for assessing the impact of strategic behavior on market efficiency and competition.

Overview of Methodology

A detailed mathematical analysis of strategic bidding in those markets, considering a duopolistic setting, is performed by using tools from game theory. Specifically, the existence of equilibria of this interaction between FSPs and the market and how strategic behaviors impact market efficiencies under the different practical market settings are analyzed. Subsequently, a structured comparison between different TSO-DSO coordination schemes can be derived. A numerical simulation study is also conducted to illustrate and validate the theoretical results. The analytical methodology of this study is summarized in Figure 2-.

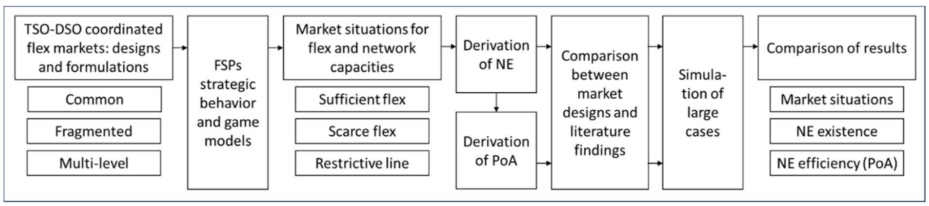

Figure 2:- Methodology of the study

Main findings

Notable differences in market performance across the three designs can be observed from the analysis. The common market emerges as the most efficient, leveraging optimal resource pooling and centralized clearing to minimize inefficiencies and enhance competition. By allowing all resources to compete in a single clearing process, it reduces the opportunities for FSPs to exploit market power. In contrast, the fragmented market demonstrates how the absence of coordination between TSOs and DSOs can amplify inefficiencies. The separation of markets limits competition, enabling FSPs to manipulate prices by exploiting reduced liquidity and localized monopolies.

The multi-level market provides an intermediate level of efficiency. While its sequential structure improves upon the fragmented market by introducing partial resource sharing, it still leaves room for strategic behavior due to the prioritization of DSOs in the first stage. This design allows for some coordination but introduces complexities that can reduce overall market efficiency if not carefully managed. For example, FSPs in local markets may still leverage congestion or limited competition to influence prices, though the second-level access for TSOs mitigates these effects to some extent.

These findings underscore the critical importance of market design in mitigating strategic behavior. This study demonstrates that greater coordination between TSOs and DSOs, as exemplified by the common market, can significantly enhance market efficiency and reduce the risk of gaming. However, the challenges of achieving such coordination in practice highlight the need for innovative solutions to balance decentralized decision-making with the benefits of resource sharing.

3.2. Analyzing the Impact of Flexibility Service Providers Bidding Behavior: a k-level Reasoning Approach

Motivation

Historically, flexibility markets have operated exclusively at the TSO level. Examples include balancing markets for manual frequency restoration reserve (mFRR), automatic frequency restoration reserve (aFRR), and frequency containment reserve (FCR). The emergence of local (DSO-level) flexibility markets as a flexibility mechanism to resolve grid issues in distribution systems, such as congestion, has significantly transformed the flexibility market landscape. The coexistence of TSO- and DSO-level flexibility markets introduces various market coordination schemes between TSOs and DSOs. This study focuses on three general coordinated market schemes: fragmented, sequential/multilevel, and common market schemes.

A critical yet underexplored factor influencing the efficiency of the previously mentioned emerging market models is the strategic behavior of participants and its potential effects on market design and performance. In TSO–DSO coordinated markets, flexibility service providers (FSPs) offering flexibility through bids are likely to adopt bidding strategies aimed at maximizing their expected revenues, an approach referred to here as strategic bidding.

Objectives and Contribution

This work analyzes the strategic behavior of FSPs in TSO–DSO coordinated market models while fully accounting for network constraints. Using a Stackelberg game framework, it evaluates three distinct designs, namely a common market, a fragmented market, and a multi-level market, highlighting differences in resource sharing, market sequencing, and priority access, and assessing their performance under strategic bidding. To better reflect real-world decision-making, the study incorporates a bounded rationality approach through a *k*-level reasoning model, capturing varying complexities in FSP behavior. The methodology is applied to a realistic interconnected TSO–DSO system facing congestion and imbalance, with extensive simulations providing insights into how market design and strategic behavior interact to influence efficiency.

Overview of Methodology

To analyze how FSPs bid strategically and how such behavior affects the flexibility market, we adopt a Stackelberg game-theoretic modeling approach. In this framework, FSPs are modeled as leaders playing a non-cooperative game, each aiming to maximize their individual market profits. The market operator acts as a follower, responding to the collective decisions (i.e., bids) of the FSPs by executing the market-clearing process. This hierarchical interaction between strategic FSPs and the market operator leads to the formulation of a Stackelberg game, which can be translated into an Equilibrium Problem with Equilibrium Constraints (EPEC), capturing the interdependence of FSPs' strategic behavior and the market-clearing outcome. Moreover, we incorporate the notion of bounded rationality in our modeling. Rather than assuming FSPs always compute an exact equilibrium of the EPEC, we allow for approximate reasoning through k-level reasoning. Under this assumption, FSPs do not necessarily find an equilibrium but instead engage in iterative best-response dynamics, where each FSP chooses its strategy based on beliefs about the strategies of others. This approach provides a more realistic representation of decision-making behavior under limited information.

Building on the strategic bidding model described previously, we conducted an extensive set of numerical simulations to evaluate the influence of such behavior across the three flexibility market schemes: fragmented, sequential, and common markets. In addition to the baseline scenarios, two special cases were investigated:

- A low liquidity market scenario, where the number of active market participants is limited.
- An aggregation scenario, in which an FSP controls a pool of resources and can bid them collectively

Main Findings

Our numerical simulation study yielded several key insights:

- *Impact of market fragmentation and liquidity*:

Market fragmentation and low liquidity can amplify the potential for market power, as fewer available resources increase the influence of individual FSPs on market outcomes. Among the examined schemes, the common market scheme demonstrated superior performance in mitigating market power, owing to its more integrated and liquid structure. In contrast, fragmented and sequential schemes were more vulnerable to inefficiencies under low-participation conditions.

- *Congestion-induced market power*:
  Congestion at the TSO–DSO interconnection points can lead to localized market power or even monopolistic conditions, regardless of the coordination scheme employed. This finding highlights the critical role of network constraints in shaping strategic opportunities and underscores the need for market designs that explicitly address congestion management at interconnection points.
- *Effects of resource aggregation*:
  When an FSP aggregates multiple resources, it may exercise price manipulation strategies more effectively. However, the common market scheme proved to be more robust against such manipulation due to its higher liquidity and larger competition pool. This suggests that centralized, co-optimized market designs may offer more resilience to strategic exploitation by large aggregators.

4. KER 3: Price-Based Demand Response Participation in Balancing Services

As Belgium transitions to a carbon-neutral energy system, integrating flexible electricity consumption is becoming essential. The growing share of variable renewable energy sources, such as wind and solar, requires new approaches to balance supply and demand while maintaining grid reliability and controlling costs. Demand Response (DR) programs, which allow consumers to voluntarily adjust their energy usage in response to dynamic conditions or price signals, offer a promising solution. By leveraging distributed demand-side resources, these programs can help balance supply and demand, reduce dependence on fossil fuels, and contribute to a more resilient power system.

In Belgium, small-scale residential assets are expected to play a key role in this transformation. Elia's adequacy study projects that by 2034, the country could see approximately 143,000 home batteries, 930,000 smart-charging electric vehicles, and 300,000 controllable heat pumps participating in grid flexibility. In high-flexibility scenarios, these numbers could exceed 2 million electric vehicles and 1.2 million heat pumps. If well-coordinated, such resources could reduce Belgium's projected capacity gap by up to 1.1 GW—more than double the potential contribution of industrial flexibility alone. Economically, this shift could generate annual system-wide savings of €205 million to €438 million, primarily by reducing the need for reserves and capacity remuneration.

Residential flexible energy assets are typically connected to the low-voltage electricity grid. Individually, these assets are small in scale and often lack the monitoring systems to meet strict technical standards for telemetry, verification, or bidding thresholds required for participating in electricity markets. As a result, a single household cannot typically participate directly in these markets. To overcome this, aggregators play a key role. They group together many residential energy users to form a larger, more predictable resource that can interact with the grid in a meaningful way. Aggregators manage the important tasks of forecasting energy use, tracking consumption (metering), and coordinating responses across the group. This allows aggregated households to provide energy flexibility services just like larger commercial or industrial users.

To manage and influence when and how households use electricity, aggregators generally use one of two coordination strategies: direct control or indirect control. Direct control involves sending specific on/off signals to devices within homes, such as turning off water heaters or reducing battery charging at certain times. While this approach can be effective and precise, it raises concerns about scalability and consumer privacy, since it requires a high level of access and communication with individual devices. Indirect control, on the other hand, influences consumer behavior without direct interference. A common and effective method here is dynamic pricing, where electricity prices vary over time to reflect real-time supply and demand conditions. One of the most notable forms of dynamic pricing is Real-Time Pricing (RTP). Under RTP, electricity prices are updated frequently (e.g. hourly, quarter-hourly, etc.,) based on conditions in the power system. This encourages consumers to adjust their energy use in response to price signals, for example by running appliances when electricity is cheaper. RTP is especially beneficial in systems with a high share of renewable energy, where supply can be variable and less predictable.

However, RTP's effectiveness depends on the ability to accurately predict consumer responses to price signals (hereafter referred to as price-response behavior). Unlike direct control schemes, RTP does not require formal commitments, resulting in voluntary and highly variable participation. This variability is further complicated by consumers' bounded rationality, as consumers may find it difficult to make consistent, cost-effective decisions in response to fluctuating prices. Limited insights into individual or collective preferences and constraints also hinder the ability to model or forecast behavior accurately.

This unpredictability poses financial risks for aggregators. Misestimating consumer behavior can lead to over-activation or under-activation of demand-side flexibility, which could result in missed opportunities or even penalties. To address these challenges, in the first task—detailed in Section 4.1—we investigate state-of-the-art data-driven optimization techniques for estimating how residential consumer groups respond to price signals. Building on this, we introduce a novel model selection framework for consumer response to price signals that integrates the financial consequences of uncertainty into both estimation and decision-making processes. Finally, we evaluate the performance of our proposed method in the context of a balance responsible party (BRP) relying on small-scale consumers as its demand response resources (DRRs), providing implicit reserve to the Belgian single-price imbalance settlement mechanism.

In the second contribution, presented in Section 4.2, we build on previous work by introducing a novel heuristic approach for developing a data-driven, multi-scenario price-response model for DRRs. This model allows the aggregator to consider multiple possible consumer behavior patterns in reaction to price signals during real-time decision-making. The goal is to support a more conservative, uncertainty-aware participation of a BRP managing small-scale consumers under Belgium's single-price imbalance mechanism, thereby facilitating the integration of flexible residential demand into the country's evolving energy system.

4.1. Price-Based Demand Response Participation in Balancing Services: A Value-Oriented Inverse Optimization Framework [3]

Motivation

To develop the price-responsive behavior of DRRs and support price-based DR programs, Inverse Optimization (IO) has emerged as a promising approach for learning such behavior from historical data. IO offers interpretable, decision-compatible models that integrate smoothly into the operational frameworks of aggregators. Unlike black-box machine learning models, IO retains the structural rationale behind consumer behavior, which is essential for optimization-based applications. However, traditional data-driven IO methods typically focus on minimizing forecast errors. This approach can be misleading in practical settings, particularly when inferred consumer flexibility is embedded within an aggregator's decision-making process in electricity markets. This is because not all forecast errors result in equal financial consequences. Recent studies highlight that forecast effectiveness should be evaluated based on ex-post decision value, i.e., the actual profit realized after observing system outcomes. Some forecast errors may have minimal operational impact, while others can lead to significant financial losses, depending on the magnitude of the error, the state of the system, and market conditions. Consequently, there is a growing need for value-oriented learning, where model selection emphasizes minimizing decision-making regret. In this context, regret refers to the difference between the profit actually achieved and the best possible profit that could have been achieved with perfect information. Prioritizing regret minimization over forecast accuracy is essential for making decisions that are more aware of uncertainty and lead to better economic outcomes in real-world conditions.

Objective and Contribution

The main objectives of this research are, first, to implement the aggregate DRRs flexibility model, obtained using IO, into the decision-making problem of a BRP (the aggregating entity in this study), and second, to develop a model selection framework for IO that takes into account the financial impacts of the IO model's forecast errors when implemented in the BRP's decision-making process.

The key innovation lies in shifting the IO model selection process from a forecast-accuracy objective to a decision-making regret-minimization objective, without fully embedding the decision problem into the training phase (which would be computationally prohibitive). Instead, the proposed Value-Oriented IO (VOIO) framework evaluates IO hyperparameters based on their downstream impact on BRP profitability.

To test the effectiveness of the proposed framework, a case study using Belgian market data is conducted. The BRP is assumed to control a portfolio of DRRs and must decide on daily price signals to elicit the desired flexibility. Historical DA prices and DRR consumption data are used to build and validate the models. Performance is assessed in terms of both forecast error and ex-post financial outcomes.

Overview of the methodology

The paper models the BRP's strategic participation in the single-price imbalance market using a bilevel optimization framework (Figure 3) that captures the hierarchical interactions between the BRP, the balancing market, and DRRs. At the upper level, the BRP seeks to maximize its profit by deciding real-time price signals to influence DRR consumption, thereby shaping its imbalance position. This profit depends on both the incentives paid to DRRs and the imbalance prices received from the market. The first lower-level problem models the aggregate price-response behavior of DRRs, using parameters estimated through the proposed IO model selection (Figure 4). The second lower-level problem simulates the system operator's market-clearing process, determining imbalance prices based on aggregate imbalances and reserve activation costs. This bilevel setup enables the BRP to exploit DRR flexibility while accounting for its impact on market prices, creating a closed-loop decision model that reflects real-world operational and market complexities.

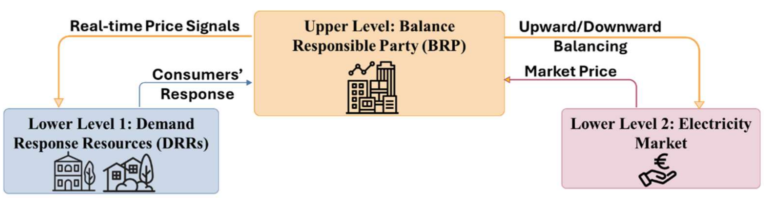

Figure 3:- Bilevel programming model for BRP's decision-making in the single-price imbalance settlement market

On the other hand, Figure 4 presents a high-level flowchart of the proposed value-oriented, data-driven IO framework. The process starts with historical price-consumption data (a) and historical balancing market data (b), which serve as inputs to the IO stage (c). In this stage, various hyperparameter combinations—such as the granularity of DRRs' consumption levels and the number of training days—are explored to build a consumption model that estimates DRRs' aggregate willingness to pay for each consumption level. Each hyperparameter set results in a corresponding DRR model, which is then integrated into the BRP's decision-making process during the validation period. This integration facilitates both the estimation of expected profits and the generation of price signals to be communicated to DRRs. To account for uncertainty in DRR responses to real-time prices, an ex-post profit analysis (e) is conducted using real-time price data generated from each hyperparameter combination. This analysis evaluates actual profits under uncertain conditions. Based on the results, the most effective hyperparameter set is selected for future optimization.

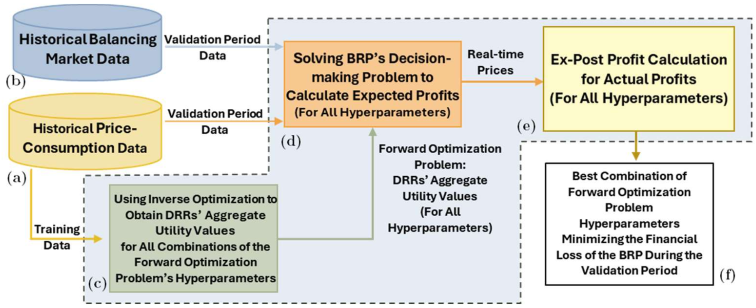

Figure 4-: Overview of the workflow for the proposed Value-Oriented Data-Driven Inverse Optimization Model Selection process (VOIO framework)

Main findings

The empirical evaluation of the VOIO framework yields several key findings:

- **Improved Financial Performance:** Compared to a forecast-optimized baseline (FOIO), the proposed value-oriented method (VOIO) improved BRP ex-post profits by 2.69% on the validation set and 1.94% on the test set, despite having slightly lower consumption forecast accuracy.
- **Forecast Accuracy vs. Value Misalignment:** The statistical correlation between forecast error and ex-post profit was negligible (Pearson r = 0.1, Spearman ρ = -0.02), highlighting that better forecasts do not guarantee better decisions—underscoring the need for value-based model evaluation.
- **Reduced Over-activation Losses:** VOIO yielded more conservative real-time price signals, reducing BRP over-activation of balancing services:
    - 7.68% reduction in extreme over-activation cases that could disrupt the anticipated system imbalance

Next steps

Building on the VOIO framework, the following direction is proposed for future work:

- Multi-Scenario Flexibility Curve Learning: Enhance the BRP's decision-making process by extracting multiple flexibility curves for demand response resources (DRRs) from historical data. This approach aims to represent a range of possible DRR behaviors rather than relying on a single curve derived from the entire dataset. By incorporating multiple scenarios, the BRP can better account for uncertainty in DRRs' price-responsive behavior at the time of decision-making, leading to more robust and informed market participation.

4.2. Price-Based Demand Response Participation in Balancing Services: A Multi-Scenario Inverse Optimization Framework

Motivation

The VOIO approach proposed in Section 4.1 improves the BRP's profits by enabling a more conservative price-response modeling strategy compared to the FOIO benchmark. However, the resulting single price-response model for DRRs remains vulnerable to financial losses due to over- or underestimation of their reactions to real-time prices. This limitation can be addressed by transitioning from a single-scenario model to a multi-scenario approach for modeling DRRs' price responses. While prior research on scenario-based decision-making for DR aggregators has demonstrated both economic benefits and robustness, these methods often depend on a set of predefined scenarios or rely heavily on computationally demanding Monte Carlo techniques. These drawbacks limit their practical deployment in real-time market contexts.

A promising direction is to leverage data-driven methods that can efficiently produce multiple price-response models reflecting a range of plausible DRR behaviors. By accounting for variability—such as by fitting models to different quantiles of historical data—BRPs could make more informed real-time pricing decisions. Such scenarios would enable the BRP to calculate its profit for a given real-time price across a spectrum of DRR responses, from optimistic to pessimistic, and ultimately select a real-time price that remains profitable under all plausible outcomes.

Objective and Contribution

The objective is to develop a Scenario-Based Value-Oriented Inverse-Optimization (SBVOIO) framework that:

- Automatically extracts multiple price-response scenarios of DRRs (e.g., lower- and upper-quantile curves) from historical price-consumption data,
- Embeds these scenarios into a scenario-aware bilevel model for the BRP's participation in the balancing market, and
- Selects IO hyperparameters by maximizing the expected ex-post profit across scenarios (i.e., minimizing multi-scenario regret).

The main contributions of this work are as follows:

- **Heuristic quantile-based algorithm:** A novel approach that adjusts the shape of the flexibility curve by systematically forcing each flexibility scenario to either over- or under-estimate historical consumption at a specified quantile level, in a computationally efficient manner.
- **Scenario-based bilevel BRP model:** A comprehensive formulation in which the upper level maximizes expected profit by considering the DRRs' flexibility scenarios extracted in the previous step. The first lower level captures the DRRs' price-response scenarios, while the second lower level clears the balancing market for each scenario.
- **Scenario-Based Value-Oriented IO (SBVOIO) model-selection framework:** An extension to value-oriented model selection in the previous contribution (Section 4.1) that combines the heuristic algorithm and bilevel model into a hyperparameter grid search. It selects the IO hyperparameters set that yields the highest ex-post profit across scenarios, reducing vulnerability to uncertainty.
- **Case study on the Belgian balancing market:** Demonstrates that the SBVOIO approach reduces the mean absolute error (MAE) of profit compared to the VOIO method, while also reducing losses related to over-activation of services.

Overview of the methodology

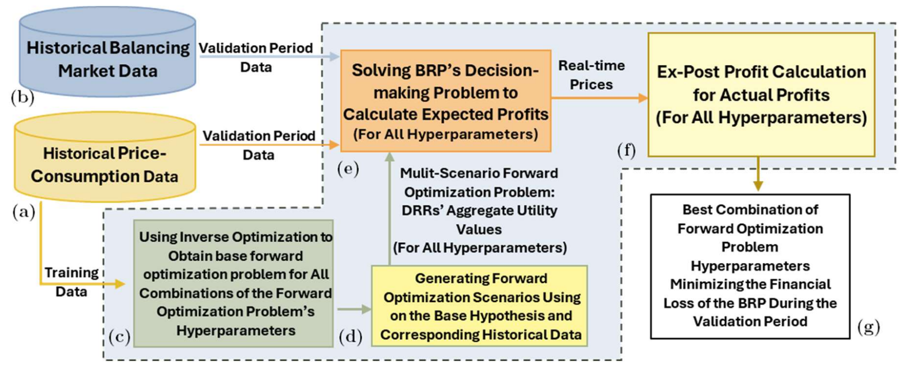

Figure 5: Overview of the workflow for the proposed Scenario-Based Value-Oriented Inverse Optimization (SBVOIO) Model Selection process

Figure 5 outlines the overall framework for selecting an inverse optimization model. The process begins with collecting historical data on price-consumption patterns (a) and balancing market data (b). A grid search is then conducted across different hyperparameter settings to configure the DRRs' price-response model (stages c–f). In stage (c), each hyperparameter combination is used to solve an IO problem that estimates a base single-scenario model capturing how DRRs respond to prices. In step (d), this base model and its corresponding hyperparameters are used to construct multiple DRR price-response scenarios that reflect the uncertainty observed in historical data. These scenarios are incorporated into the BRP's operational strategy and evaluated on a validation dataset to forecast expected profits and generate price signals aimed at influencing DRR behavior. Stage (e) evaluates each hyperparameter combination by performing an ex-post analysis, where DRR responses are perturbed to mimic their uncertain response to real-time prices and the impact on realized profits. Finally, in stage (g), the hyperparameters that deliver the highest realized profit under uncertain DRR behavior are selected for future deployment.

Main findings

In a case study using real-world data from the Belgian balancing market, we demonstrated

- Compared to the VOIO as the baseline, the proposed SBVOIO method improved BRP ex-post profits by 4.7% on the validation set and 4.34% on the test set.
- A noticeable reduction in costly overactivation of DR, demonstrated by a 77% reduction in extreme overactivation cases that could disrupt the anticipated system imbalance.

This means the BRP was able to gain higher profit and better match consumer flexibility with market needs by sending uncertainty-aware real-time prices that were less likely to overactive demand response.

Next steps

Modeling Temporal Dynamics: Extend the DRR behavior model to capture time-dependent features such as delayed or non-instantaneous responses, fatigue effects, and rebound behaviors.

5. Conclusion and outlook

This deliverable has examined how a large-scale deployment of emerging LV flexibility mechanisms affects system balancing, focusing on the interactions between consumers, communities, aggregators, DSOs and the TSO. Building on three KERs, it has shown that the contribution of LV flexibility to balancing cannot be assessed purely from a technical perspective. Instead, it depends on how local mechanisms are designed, how consumer preferences and bounded rationality are reflected in those mechanisms, and how system-level markets and coordination arrangements channel LV flexibility towards the services where it has highest value.

Across the three KERs, a coherent picture emerges. At community and aggregator level, properly designed internal pricing, baselining and revenue-sharing schemes are essential to turn diverse household preferences into reliable flexibility offers for DSOs and, indirectly, for the TSO. At system level, the organisation of TSO–DSO coordination and the design of coordinated flexibility markets strongly influence the efficiency and robustness of balancing when strategic behaviour by flexibility service providers is taken into account. For aggregators relying on price-based demand response, value-oriented and uncertainty-aware learning approaches are needed to translate noisy, behaviourdriven price-response into activation strategies that support balancing without leading to systematic over- or under-delivery.

Taken together, these insights have several implications for the future of balancing with LV flexibility in Belgium. First, they confirm that LV flexibility can make a meaningful contribution to balancing and distribution grid congestion management, but only if local mechanisms, business models and system services are designed consistently. Misalignment between community incentives, DSO needs and TSO products risks fragmenting scarce flexibility, increasing operational complexity and eroding the economic benefits. Second, they underline the importance of explicitly incorporating consumer behaviour and bounded rationality into the assessment of flexibility potential and into the design of activation strategies, to avoid overestimating what LV resources can deliver in practice. Third, they highlight that the rules governing competition and coordination between FSPs must be robust to strategic behaviour and limited liquidity, otherwise the efficiency gains of coordinated markets may not materialise.

The outlook of this work is twofold. On the one hand, the models and insights developed in Task 4.1 provide concrete building blocks for an integrated Belgian framework for procurement and activation of LV flexibility, to be further refined together with regulatory and operational stakeholders. This includes the articulation between local flexibility mechanisms and balancing products, the definition of transparent baselining and verification procedures that are compatible with consumer heterogeneity, and the clarification of roles and incentives for DSOs and aggregators in supporting system services. On the other hand, the work points to several directions for future research and development: extending behavioural models to capture longer-term learning and temporal dynamics; improving observability and data flows between LV grids, aggregators and system operators; and testing the proposed mechanisms in pilots and regulatory sandboxes to validate their performance under real-world conditions.

6. References

Commented [WA1]: The numbering in this list must be updated

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