National Technical University of Athens
School of Electrical and Computer Engineering
Division of Electric Power

Welfare Benefits of Co-Optimization of Energy and Reserve with Battery Storage in Belgium

Diploma Thesis

Kopitas Chrysostomos

Supervisor: Prof. Anthony Papavasiliou
NTUA

Athens, June 2025

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Περίληψη

Η παρούσα διπλωματική εργασία εξετάζει τις επιπτώσεις στην κοινωνική ευημερία από τη συνεκτιμώμενη εκκαθάριση των αγορών ενέργειας και εφεδρειών στο ηλεκτρικό σύστημα του Βελγίου, εστιάζοντας ειδικά στον ρόλο των Συστημάτων Αποθήκευσης Ενέργειας με Μπαταρίες (BESS). Αναπτύσσεται λεπτομερές μοντέλο εκκαθάρισης αγοράς επόμενης ημέρας, βασισμένο σε μικτού τύπου ακέραιο γραμμικό προγραμματισμό (MILP), το οποίο ενσωματώνει τη δέσμευση μονάδων, την ανάθεση εφεδρειών, περιορισμούς αυξομείωσης ισχύος, κόστη εκκίνησης/διακοπής και τη δυναμική των μπαταριών. Η συνεκτιμώμενη διαμόρφωση συγκρίνεται με διαδοχική εκκαθάριση (reserve-first), όπου τα BESS λειτουργούν αποκλειστικά για ενεργειακό arbitrage.

Αναλύονται οκτώ αντιπροσωπευτικοί εποχιακοί τύποι ημερών· η συνεκτίμηση μειώνει το ετήσιο κόστος συστήματος έως 1.3 (μέση μείωση 10.01 %) και βελτιώνει τόσο την παροχή εφεδρειών όσο και την αξιοποίηση των BESS. Μελέτες ευαισθησίας ποσοτικοποιούν τον ρόλο της σταθερής δέσμευσης, του εύρους συμμετοχής μπαταριών και της τιμολόγησης εφεδρειών στα τελικά αποτελέσματα.

Λέξεις-κλειδιά: συνεκτίμηση αγοράς, εφεδρείες, BESS, MILP, ανάλυση ευημερίας

Abstract

This thesis investigates the welfare implications of co-optimising energy and reserve markets in the Belgian electricity system, with a specific focus on Battery Energy Storage Systems (BESS). A detailed day-ahead market-clearing model is developed using mixed-integer linear programming (MILP). The co-optimised formulation is benchmarked against sequential clearing (reserve-first), where BESS operate purely for energy arbitrage. Eight representative seasonal day types are examined to approximate full-year operation. Co-optimisation reduces annual system cost by up to 1.3 (average 10.01 %) while improving reserve deliverability and BESS utilisation. Sensitivity studies quantify how fixed commitment, battery participation scope and reserve pricing affect welfare. The findings motivate integrated market design and highlight the value of storage under different clearing architectures.

Keywords: energy-reserve co-optimisation, reserve scheduling, battery storage, MILP, welfare analysis

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Chrysostomos Kopitas
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Περιεχόμενα

Κατάλογος σχημάτων

Εκτενής Περίληψη

Η παρούσα διπλωματική εργασία εξετάζει αναλυτικά τα οφέλη ευημερίας που προκύπτουν από την κοινή – ή συνεκτιμώμενη – εκκαθάριση των αγορών ενέργειας και εφεδρειών στο βελγικό ηλεκτρικό σύστημα, δίνοντας ιδιαίτερη έμφαση στον ρόλο που διαδραματίζουν τα Συστήματα Αποθήκευσης Ενέργειας με Μπαταρίες (Battery Energy Storage Systems, BESS). Για τον σκοπό αυτό αναπτύσσεται ένα υψηλής ανάλυσης μοντέλο εκκαθάρισης αγοράς επόμενης ημέρας, βασισμένο σε μικτού τύπου ακέραιο γραμμικό προγραμματισμό (Mixed-Integer Linear Programming, MILP). Το μοντέλο ενσωματώνει: (i) δέσμευση θερμικών και πυρηνικών μονάδων, (ii) ανάθεση εφεδρειών δύο κατηγοριών, (iii) περιορισμούς αυξομείωσης ισχύος και ελάχιστου χρόνου λειτουργίας, (iv) κόστη εκκίνησης/διακοπής, καθώς και (v) πλήρη δυναμική φόρτισης-εκφόρτισης των μπαταριών, συμπεριλαμβανομένων απωλειών στρογγυλού κύκλου και ορίων κατάστασης φόρτισης (State of Charge).

Για τη βαθμονόμηση του μοντέλου υιοθετούνται πραγματικά τεχνικο-οικονομικά δεδομένα από τον διαχειριστή συστήματος Elia: καμπύλες κόστους παραγωγής, ονομαστικές ισχύς, διαθεσιμότητες ανανεώσιμων πόρων και ιστορικά προφίλ ζήτησης δεκαπενταλέπτου. Ο ετήσιος ορίζοντας προσεγγίζεται μέσω οκτώ αντιπροσωπευτικών εποχιακών τύπων ημερών (AutumnWD, WinterWE κ.λπ.), οι οποίοι επιλέγονται βάσει ομοιότητας κλιματικών και ζυγισμένων στατιστικών συνθηκών. Για κάθε τύπο προσομοιώνονται δύο βασικές αρχιτεκτονικές αγοράς:

1. **Συνεκτίμηση (Co-optimised)** – ταυτόχρονη εκκαθάριση ενέργειας-εφεδρειών, όπου τα BESS δύνανται να προσφέρουν τόσο ισχύ/ενέργεια όσο και εφεδρική ικανότητα.

2. **Διαδοχική εκκαθάριση (Sequential)** – αρχικά κατανομή εφεδρειών και στη συνέχεια κατανομή ενέργειας· τα BESS περιορίζονται σε καθορισμένο σενάριο συμμετοχής.

Εξετάζονται επιπλέον τρία σενάρια συμμετοχής μπαταριών: (α) αποκλειστική συμμετοχή στο στάδιο της ενέργειας, (β) σταθερή προ-δέσμευση (fixed dispatch) και (γ) περιορισμένο εύρος (20/80 split). Τα σενάρια αυτά επιτρέπουν την ποσοτικοποίηση της αξίας ευελιξίας των BESS υπό διαφορετικούς κανονισμούς.

Κύρια αποτελέσματα

* **Μείωση κόστους συστήματος:** Η συνεκτίμηση οδηγεί σε ετήσια εξοικονόμηση μέχρι 1.3 (μέση μείωση $10.01\,\%$ έναντι της διαδοχικής εκκαθάρισης), κυρίως μέσω αποτελεσματικότερης ανάθεσης εφεδρειών και άρσης ενεργειακών περιορισμών που επιβάλλει η σταθερή δέσμευση μονάδων.

* **Αξιοποίηση BESS:** Στο συνεκτιμημένο σενάριο, οι μπαταρίες επιτυγχάνουν $18\,\%$ υψηλότερο συντελεστή χρησιμοποίησης (cycle throughput) και $25\,\%$ μεγαλύτερη συνεισφορά σε ανοδικές εφεδρείες σε σχέση με το καθαρά ενεργειακό σενάριο.

* **Ανθεκτικότητα σε αβεβαιότητα ΑΠΕ:** Η κοινή εκκαθάριση μειώνει τα σφάλματα πρόβλεψης αιολικής και ηλιακής παραγωγής έως $15\,\%$.

Συμπεράσματα και προτάσεις πολιτικής

Τα αποτελέσματα καταδεικνύουν ότι:

* Η μετάβαση από διαδοχική σε συνεκτιμημένη εκκαθάριση δικαιολογείται οικονομικά, ακόμη και σε ώριμες αγορές με σχετικά περιορισμένη διείσδυση ΑΠΕ.

* Η διπλή συμμετοχή των BESS (ενέργεια *και* εφεδρεία) βελτιώνει σημαντικά την αποδοτικότητα επενδύσεων σε αποθήκευση και ενισχύει την ασφάλεια εφοδιασμού.

* Η εφαρμογή δυναμικής τιμολόγησης εφεδρειών συνιστάται, ώστε το σήμα αγοράς να αντικατοπτρίζει επαρκώς το οριακό κόστος ευελιξίας.

Μελλοντική έρευνα μπορεί να επεκτείνει το πλαίσιο σε ενδοημερήσιες αγορές, πολυζωνικά σχήματα και υβριδικές λύσεις (π.χ. BESS + υδρογόνο ή V2G στόλοι), προκειμένου να επιβεβαιωθεί η γενικευσιμότητα των συμπερασμάτων.

Κεφάλαιο 1

Introduction

1.1 Context and Motivation

The European electricity landscape is undergoing a fundamental transformation, driven by decarbonisation goals, rapid renewable deployment, and evolving patterns of electricity consumption. In pursuit of the EU's climate neutrality target by 2050, member states are accelerating the phase-out of fossil-based generation while promoting clean energy technologies. Belgium is undergoing similar shifts, rapidly expanding its renewable energy fleet—particularly through large-scale offshore wind farms and distributed solar photovoltaics (PV) across residential and commercial sectors. In parallel, the electrification of transport and heating—fueled by policy incentives and technology cost declines—is increasing both the volume and variability of electricity demand.

This energy transition introduces significant challenges to power system operation. The rise in variable renewable energy sources (VRES) such as wind and solar leads to increased forecast uncertainty, larger intra-day imbalances, and reduced system inertia. These challenges make system flexibility a central pillar of modern electricity markets. Flexibility is required both in real-time balancing operations and in day-ahead market commitments. The efficient use of flexible resources—such as peaking gas units, demand response, and battery storage—is crucial for ensuring reliable, cost-effective operation in this new paradigm.

Historically, Belgium and most of continental Europe have adopted a sequential market design. Under this structure, reserve procurement (for services such as FCR, aFRR, and mFRR) occurs in advance or separately from the day-ahead energy market. The two markets are cleared independently, which may prevent the market from accounting for the opportunity cost of resources that could provide both energy and reserves. For instance, a flexible generator or storage unit may be scheduled to provide upward reserve without considering its value in meeting peak energy demand, resulting in inefficiencies such as excessive reserve procurement or avoidable generator start-ups.

In contrast, co-optimised market clearing—as used by North American system operators such as PJM, MISO, and CAISO—integrates the scheduling of energy and reserve capacity into a single optimisation problem. Co-optimisation allows the system operator to simultaneously consider technical constraints (such as ramping and state-of-charge limits) and system needs across both services. This leads to more efficient resource allocation and overall welfare gains. There are several studies supporting the operational and economic benefits of co-optimisation in high-renewable systems [17][69].

However, implementation of co-optimisation in Europe remains limited. European markets are governed by national and regional regulatory frameworks that often prohibit or restrict joint optimisation of multiple services. While the EU's Clean Energy Package and the evolving

Target Model support greater market integration and flexibility provision, institutional inertia and cross-border coordination challenges have slowed the adoption of co-optimised clearing. Belgium, through its transmission system operator (TSO) Elia, continues to procure reserve products through dedicated auctions and platform-based mechanisms (e.g., PICASSO and MARI for aFRR and mFRR, respectively), with limited interaction between these and energy markets.

Within this evolving context, Battery Energy Storage Systems (BESS) have emerged as a promising technology for grid flexibility. BESS can provide a wide range of services: they can shift energy consumption through arbitrage, provide upward and downward reserve capacity, and deliver fast frequency response. Their rapid response times, scalability, and modularity make them well suited to complement the intermittency of wind and solar. However, in sequential market designs, BESS participation is often limited to a single service—either energy or reserves—which may not fully utilise their capabilities [70]. Moreover, without co-optimisation, storage dispatch may be based on predefined participation strategies that are unable to adapt to real-time price signals or system needs, resulting in lower utilisation and less efficient operation [70].

By contrast, co-optimised markets enable so-called *value stacking*, where storage resources participate in multiple services within the same dispatch interval. This integrated participation increases system flexibility and improves the financial viability of BESS assets [71]. Studies have found that co-optimisation frameworks can significantly improve the net revenue and welfare contribution of storage resources compared to sequential market designs [17].

For Belgium, where both decarbonisation and system adequacy are high on the policy agenda, understanding the economic role of BESS under different market arrangements is crucial. Elia has already integrated storage into reserve capacity qualification frameworks, and pilot projects are exploring dynamic participation of batteries in aFRR and mFRR products. Still, quantitative assessments of how market design influences the value of BESS—and more broadly, how co-optimisation compares to the current sequential setup in welfare terms—remain limited in the Belgian context.

This thesis is therefore motivated by a dual objective. First, to contribute by modelling and comparing the welfare impacts of sequential and co-optimised market clearing in Belgium, with explicit attention to battery participation. Second, to provide empirical and policy-relevant evidence for stakeholders such as Elia and CREG, supporting decisions on future market design, storage incentives, and the integration of flexibility resources in a high-renewable system.

1.2 Problem Statement

This thesis addresses the unexplored economic and operational benefits of co-optimising energy and reserve markets, as well as the role of battery energy storage in enhancing system flexibility by developing a comprehensive, Belgium-specific simulation framework to assess the system-wide welfare impact of integrating battery storage under different market-clearing paradigms. In particular, it focuses on three core dimensions:

1. **Market Design Comparison**: It contrasts the welfare outcomes of *sequential* versus *co-optimised* clearing of energy and reserves in the Belgian electricity system. These scenarios are evaluated under historical load and renewable generation profiles representative of seasonal and intra-week variability.

2. **Battery Storage Modelling:** It incorporates multiple BESS participation strategies, including energy-only dispatch, reserve-only provision, and fully co-optimised energy-reserve coordination. These configurations are tested using detailed operational constraints, such as state-of-charge tracking and round-trip efficiency.

3. **Expanded Welfare Metrics**: It evaluates welfare not only in terms of total production cost, but also by analysing start-up events, ramping requirements, reserve over-procurement, and fixed costs. This multidimensional perspective offers a more nuanced understanding of how BESS and cooptimisation affect overall system efficiency.

By simulating these alternatives on a set of representative day-types (weekday and weekend scenarios across all four seasons), the thesis provides a robust, data-driven basis for assessing whether co-optimisation and more flexible BESS integration can unlock measurable welfare benefits in the context of Belgium's evolving electricity system.

1.3 Research Objectives

The overarching goal of this thesis is to evaluate how market design and battery storage participation models affect the social welfare of the Belgian electricity system. This is achieved by simulating and comparing sequential and co-optimised clearing of energy and reserves, under realistic operational constraints and representative system conditions.

The study is guided by the following central research questions:

Q1 What is the system-wide welfare impact of transitioning from sequential to co-optimised market clearing in the electricity market of Belgium?

Q2 How do different models of battery energy storage system (BESS) participation, such as energy-only, reserve-only, and co-optimised configurations, affect the magnitude of welfare gains under each market paradigm?

Q3 How sensitive are these welfare outcomes to key factors such as battery size, round-trip efficiency, allocation strategy, seasonal load profiles, and renewable generation patterns?

To answer these questions, the specific research objectives of the thesis are as follows:

- To develop a mixed-integer linear programming (MILP) unit-commitment and dispatch model of the Belgian power system that endogenously determines energy schedules and reserve allocations, while incorporating generator-specific operational constraints and reserve requirements.
- To implement a suite of BESS integration methodologies, including:
  - **Energy-only participation**: BESS can charge/discharge based solely on energy arbitrage.
  - **Energy and reserve allocation**: BESS is allocated to either energy or reserve in a static fashion.
  - **Fully co-optimised dispatch**: BESS dynamically allocates state-of-charge to energy and reserve simultaneously based on marginal system value.
- To simulate system performance across a diverse set of temporal profiles that capture seasonal and intra-week variability. Eight representative days are selected: four weekdays (one from each season) and four weekends (also seasonally distributed).
- To calculate and compare multiple welfare-related performance metrics under each scenario, including:

– Total system production cost,

– Number of thermal generator start-ups,

– Ramping and reserve deployment levels,

– No-load fuel consumption and reserve over-procurement.

By systematically varying both the market design and the BESS configuration across these scenarios, the thesis aims to provide quantitative insights into how improved coordination and storage flexibility can support more efficient, resilient, and cost-effective system operation in the Belgian context.

1.4 Methodological Overview

To evaluate the welfare implications of different market-clearing paradigms and battery storage configurations in the Belgian electricity system, this thesis develops a detailed power system optimization model based on a unit-commitment and economic-dispatch formulation. The model is implemented in `Python` and solved using the commercial solver `Gurobi`, which enables the efficient handling of large-scale mixed-integer linear programming (MILP) problems.

Two alternative market-clearing designs are simulated:

1. **Sequential clearing**: In this paradigm, reserve procurement is performed in a preliminary stage based on predefined requirements (covering upward and downward aFRR and mFRR), and often reflects agents' expectations of future energy prices. These reserve-cleared capacities are treated as fixed inputs in the subsequent day-ahead energy market clearing, which minimizes energy production cost subject to unit and system constraints. The reserve-cleared capacities are treated as fixed inputs in the subsequent day-ahead energy market clearing, which minimizes energy production cost subject to unit and system constraints.

2. **Co-optimised clearing**: Here, energy and reserve capacity decisions are made simultaneously within a single optimization problem. The model jointly allocates generation capacity for energy supply and ancillary services, internalizing opportunity costs, reserve substitution effects, and physical coupling constraints such as ramp rates and minimum up/down times. In this configuration, reserve procurement reacts endogenously to the prevailing energy price signal, enabling the model to capture trade-offs between energy and reserve provision in real time.

In both paradigms, the participation of battery energy storage systems (BESS) is modelled under multiple strategies, reflecting the diversity of technical configurations and market rules. These include:

- **Energy-only participation**: BESS can charge or discharge to maximize energy arbitrage value, but is not eligible to provide reserve capacity.

- **Reserve-only or energy-prioritised configurations**: BESS capacity is statically assigned to either energy or reserve provision before optimization, mimicking existing sequential constraints in real markets.

- **Hybrid allocation (sequential case)**: BESS participation is manually balanced between energy and reserve functions, with fixed limits on each service.

- **Fully co-optimised participation**: The allocation of battery energy and reserve capacity is determined endogenously as part of the co-optimised clearing model, allowing for dynamic value stacking and optimal use of flexibility.

The model includes detailed technical and economic constraints:

- Reserve requirements are based on Elia's Adequacy and Flexibility Study, while generator technical parameters are compiled from public reports, academic literature, and representative assumptions consistent with Belgian system characteristics.
- Storage constraints include state-of-charge tracking, round-trip efficiency, power and energy limits, and degradation-penalised cycling.
- System constraints enforce demand balance, spinning reserve coverage, and reserve product substitution rules.

Eight representative simulation days are selected to capture seasonal and intra-week temporal variation: four weekdays and four weekends, one from each meteorological season. Each simulation is treated as an independent optimization run to avoid assumptions about inter-day storage operation or forecast recourse.

Key input data are sourced from publicly available reports and datasets:

- Generator technical characteristics and reserve requirements are based on Elia's *Adequacy and Flexibility Study*.
- Historical fuel prices, CO_2 emission cost estimates, and renewable generation time series are obtained from Belgian market operators and ACER reports.
- Demand and renewable production profiles are constructed using historical hourly data, filtered and aggregated by season and day type.

The simulation outputs include not only system-wide production costs but also operational indicators such as the number of generator start-ups, ramping frequency, reserve activation patterns, and storage utilization metrics. These outputs allow for a comprehensive welfare comparison across market designs and storage participation strategies.

Κεφάλαιο 2

Literature Review

2.1 Market Background and Motivation

2.1.1 Structure of European Electricity Markets

European electricity markets are organized in a sequence of timeframes, from long-term forward contracts to day-ahead and intraday trading, and finally real-time balancing. The day-ahead market consists of a single pan-European auction held at noon each day for the 24 hours of the next day, with all accepted bids paid the marginal clearing price [1]. This day-ahead market is coupled across nearly all EU countries through the Single Day-Ahead Coupling (SDAC), which implicitly allocates cross-border transmission capacity to maximize overall welfare [1]. In practice, each bidding zone (usually corresponding to a country) is treated like a copper-plate, and trades between zones are facilitated by market coupling algorithms that match offers and bids across borders, subject to network constraints. After the day-ahead market is cleared, a continuous intraday market opens, allowing participants to adjust their positions closer to real time as new information (like updated renewable forecasts or plant outages) becomes available [1]. These coupled day-ahead and intraday markets ensure a high level of regional coordination, as electricity is routinely traded across European borders, making use of available interconnection capacity in an efficient, transparent manner. Following the close of intraday trading, the system enters the balancing phase managed by the Transmission System Operators (TSOs). Each TSO is responsible for maintaining the real-time balance of supply and demand in its control area, which in Europe typically corresponds to a national grid [2]. To do so, TSOs procure various reserve products (also known as balancing services) that can be activated on short notice to correct any imbalance. These reserves are generally classified into three main categories in line with EU definitions [3]:

- **Frequency Containment Reserve (FCR)**: Also called primary reserve (R1), which acts to stabilize the system frequency immediately after a disturbance. FCR is triggered automatically and delivered within seconds (full response within 30 seconds) to counteract frequency deviations and prevent system collapse [3]. All TSOs of the synchronous European grid collectively maintain FCR; each TSO carries an obligation to procure a share of the total FCR for the grid. For example, Belgium's FCR requirement is on the order of 80–90 MW (93 MW in 2024, slightly decreasing to 86 MW in 2025), a volume determined at the European level and then shared among countries. FCR is a symmetric reserve (providers must handle both upward and downward frequency deviations) and is procured on a regional or European basis to take advantage of diversity and cost efficiency. Since July 2020, Elia (the Belgian TSO) has participated in a joint FCR procurement auction with neighboring TSOs, replacing earlier national auctions. This common auction allows cross-border competition for FCR provision, though current rules require that at least 30% of Belgium's FCR need be procured from resources located inside Belgium [4].

- **automatic Frequency Restoration Reserve (aFRR)**: Also known as secondary reserve (R2), which restores the balance and frequency to nominal by autonomously adjusting generator output or demand within minutes. In Belgium, aFRR is centrally controlled by Elia's automated generation control system. Reserve providers must be able to ramp up or down to their full contracted aFRR power within 5 minutes, and the TSO continuously sends set-point signals (every few seconds) to track the desired output, allowing precise regulation of the system's balance [3]. Historically, Belgium maintained a static aFRR requirement around 140 MW of upward reserve capacity (with an equal 140 MW downward capacity) [5]. This volume was deemed sufficient to handle normal supply–demand mismatches and was mainly provided by a few large gas-fired units in the past [5]. In recent years, Elia has moved to a more dynamic sizing of aFRR needs. For 2023, the aFRR capacity needed in Belgium was about 117 MW (upward) on average, based on a probabilistic methodology covering 99% of imbalance situations. This requirement is expected to increase as the penetration of renewable energy rises, since a more variable system will need more balancing reserves. Notably, because aFRR activations adjust output continuously, it is considered the most critical balancing resource for the Belgian system to maintain control of frequency. Until recently, aFRR was procured exclusively from large power plants, but this has changed with new market design measures (see below).

- **manual Frequency Restoration Reserve (mFRR)**: Also called tertiary reserve (R3), which provides slower backup power to replace or supplement aFRR in case of sustained large imbalances. mFRR is activated by the TSO via dispatch instructions (manual triggering) and must be fully deliverable typically within 15 minutes of activation notice [3]. It is used to handle major contingencies or prolonged shortages and to restore the aFRR buffer (i.e. release capacity of aFRR that might be saturated) [3]. In practice, mFRR in Belgium serves as the "last resort" reserve to resolve significant deviations and can remain activated for extended durations (minutes to hours) if needed. The volume of mFRR that Elia procures is determined as part of the total FRR (Frequency Restoration Reserve) requirement (aFRR + mFRR) needed to cover the country's worst-case imbalance scenarios. This can amount to several hundred megawatts of reserve capacity depending on system conditions (for instance, to cover the sudden loss of a large power plant or an HVDC interconnector). Since 2013, Belgium has progressively opened the mFRR market to a broader range of technologies and participants. Initially, mFRR was mainly an obligation on large thermal units, but reforms allowed smaller generation, demand response, and aggregated resources to participate [5]. As a result, the mFRR market became quite competitive: by 2017, over 1100 MW of mFRR capacity was being offered by various providers, which was 250–500 MW more than what Elia typically needed to procure at that time [5]. This oversupply indicates a well-developed market with ample flexibility resources for tertiary reserves.

In summary, the European market structure separates energy trading (day-ahead/intraday) from balancing services, but coordinates these layers through clear timelines and coupling mechanisms. Long-term and day-ahead markets handle the bulk of energy scheduling, while balancing markets ensure real-time stability through reserves like FCR, aFRR, and mFRR. Each TSO operates its balancing mechanism according to common EU rules, but with some national specifics in procurement and product design. The Electricity Balancing Guideline (EBGL) issued by the EU in 2017 provides a harmonized framework for integrating these balancing markets across Europe, aiming to foster competition and cross-border exchange of balancing services [6]. Under this framework, European TSOs are establishing platforms for sharing balancing energy (e.g. the PICASSO platform for aFRR and MARI for mFRR), further enhancing regional coordination. Indeed, Belgium's TSO recently joined the PICASSO platform in November 2024, enabling the exchange of aFRR balancing energy with other countries and access to a wider, more cost-efficient pool of balancing resources [7].

2.1.2 Separation of Energy and Reserve Markets

Traditionally, European market design has separated the procurement of energy and reserve capacity, clearing them in a sequential process rather than jointly. In most European countries, reserves (balancing capacity) and energy are traded in independent markets, often in a fixed sequence (e.g. reserve auctions held either shortly before or after the day-ahead energy auction), without a unified optimization of the two products [8]. This sequential market clearing means that generators and other market players decide on reserve offers and energy bids in isolation, taking the other market's outcome as given or uncertain. For example, a generator might secure a contract to hold 50 MW for aFRR (reserve) in a morning capacity auction and later adjust its day-ahead energy bid to account for that reserved capacity. Conversely, if it sells energy in the day-ahead market, it may have less headroom to offer reserves. Under the current paradigm (prevalent in Europe), there is no single algorithm that co-optimizes these decisions – instead, market participants and TSOs manage the linkages through administrative processes and opportunity cost pricing. This sequential clearing is in contrast to many North American power markets, where centralized unit commitment algorithms co-optimize energy and reserves together in the day-ahead market [8].

The separation of energy and reserve markets can lead to several inefficiencies due to the lack of joint optimization. First, treating energy and reserve procurement independently fails to capture the physical interdependency: both products often come from the same capacity on flexible generators or controllable loads. Clearing them separately may yield an outcome that is globally suboptimal – for instance, a power plant might be scheduled to generate energy in day-ahead even though its capacity would have been more valuable providing reserve, or vice versa. Academic studies have shown that a sequential approach tends to result in higher total system costs compared to a co-optimized approach. In a case study of the Central Western Europe region, Van den Bergh and Delarue found that the sequential energy-reserve market clearing incurred greater operating costs than a joint clearing, primarily because the sequential model could not fully account for generators' technical constraints and opportunity costs across markets [8]. These extra costs are attributed to the "missing" co-optimization: for example, some generators might be committed out-of-merit in the energy market just to ensure sufficient reserves are available, or expensive last-minute adjustments might be needed if reserve capacity winners turn out to be unavailable for energy they had sold earlier. Furthermore, under sequential designs, fixed costs and start-up costs of units are often misrepresented in bids: generators bid reserves at an opportunity cost assuming a certain energy market outcome. If that assumption is wrong (e.g. the unit doesn't clear energy but assumed it would), the result can be an inefficient commitment or dispatch of units. An official analysis by the Agency for the Cooperation of Energy Regulators (ACER) underscores these inefficiencies: energy and balancing capacity markets are "strongly interdependent" and separating them can lead to suboptimal outcomes, such as unnecessary unit commitments and higher overall costs.

One notable inefficiency arises from the need to adjust schedules after the fact. In sequential clearing, once the day-ahead energy market is run, TSOs might have to make significant changes (through intraday adjustments or extra reserve activation) because the day-ahead schedule didn't account for reserve needs. If intraday markets cannot fully accommodate these adjustments, the cost savings that could have been achieved via co-optimization are effectively lost, or even negative (since correcting the schedules can be costly). In essence, the sequential model might dispatch the system one way in the energy market, only to redispatch it in part to meet reserve requirements – a redundant and costly shuffle.

These concerns have motivated proposals to move toward joint optimization of energy and reserves in Europe. Co-optimizing means that the day-ahead market algorithm would clear energy and reserve capacity simultaneously, ensuring that the opportunity cost of providing reserves (not generating energy) is explicitly considered in the clearing of energy, and vice versa. Recent studies commissioned by regulators indicate huge potential benefits from such an approach. A 2024 consultancy study for ACER quantified the welfare gain of co-optimizing day-ahead energy and balancing capacity at roughly €1.3 billion per year for the EU, compared to the status quo sequential design [6]. Even an intermediate step – a sequential "market-based allocation" of cross-zonal capacity for reserves (used in the Nordic region) – yields far smaller benefits (€160 million/year), highlighting that only full co-optimization captures the majority of efficiency gains. The study also noted that under sequential arrangements, market participants are forced to speculate on energy prices when bidding for reserve contracts (since those are decided before energy market clears in some designs), which can lead to inaccuracies and risk premiums. If co-optimization is implemented, participants no longer need to separately forecast the energy market outcome in their reserve bids, removing a layer of uncertainty. Overall, the findings are that co-optimization would improve system efficiency by optimizing both the fixed and variable costs of generation in one step, yielding a more economically efficient commitment and dispatch of resources. As a result, interest is growing in reforming European markets to integrate energy and reserve clearing. However, this represents a significant design change – the aforementioned study and other researchers note that adopting joint clearing in Europe would require overcoming regulatory and computational challenges, and thus it may not materialize immediately [8]. In the interim, improvements like better reserve sizing methods and cross-border reserve sharing are being pursued to mitigate some inefficiencies [8]. Nonetheless, the motivation to reduce the inefficiencies of the status quo is clear: a more integrated market design promises enhanced reliability and lower costs as Europe's power system evolves.

2.1.3 Belgian Market Context

Elia's Role and System Characteristics: Belgium's electricity system is operated by Elia, the sole transmission system operator (TSO) responsible for high-voltage electricity transmission and real-time system balancing. Elia operates about 19,300 km of high-voltage lines and 800 substations, supplying power to all of Belgium and connecting roughly 30 million end-users (including those via its 50Hertz subsidiary in Germany) [9]. The Belgian control area is part of the large continental European synchronous grid, which is the most extensive synchronized power network in the world (spanning 26 countries with approximately 860 GW of generation) [9]. This means Belgium's grid is tightly interconnected with its neighbors (France, the Netherlands, Germany, and via HVDC to Great Britain), and cross-border flows are significant. Elia is at the crossroads of this network, making Belgium a critical hub for international power exchange and a beneficiary of regional grid cooperation [9].

Within its control area, Elia's core responsibility is to maintain the balance between electricity generation and consumption at all times. By law and grid code, every market participant (generator, supplier, large consumer, etc.) is financially incentivized to be balanced on a 15-minute basis –

this is done via Balancing Responsible Parties (BRPs) that must ensure their portfolio's injections and offtakes match in each quarter-hour interval [2]. Despite these efforts, real-time imbalances inevitably occur (e.g. a sudden surge in demand or an unforeseen drop in a power plant's output). Elia continuously monitors system frequency and the overall imbalance of the Belgian control zone. Any remaining net imbalance (after BRPs' self-balancing and any imbalance netting with other zones) is corrected by Elia through the activation of balancing power (reserve energy) [2]. To have this ability, Elia procures balancing capacity in advance – a set amount of generation (or controllable demand) that stands ready to adjust output on the TSO's request. By contracting reserves ahead of time in dedicated balancing markets, Elia ensures the necessary resources are available to maintain system stability [2]. Providers of these reserves are known in European terminology as Balancing Service Providers (BSPs). Elia remunerates BSPs for being available (capacity payment) and for any energy actually delivered during activations (energy payment), as explained below.

Reserve Requirements in Belgium (FCR, aFRR, mFRR): Belgium's reserve dimensioning is designed in compliance with ENTSO-E and EU rules, aiming to cover the country's typical imbalances and largest potential power contingencies with high probability (at least 99% reliability for FRR sizing, per EU guidelines). The reserve products used are the same primary, secondary, and tertiary reserves described in Section 2.1.1, but here we detail their current requirements and use in the Belgian context:

- **FCR (R1)**: As part of the synchronous European system, Belgium contributes to the collective frequency containment reserve. The required FCR capacity for Belgium is determined annually based on the ENTSO-E methodology (proportional to the control area's load and generation). As of 2024, Belgium must procure roughly 85–95 MW of FCR capacity for normal operation. This volume can be covered by domestic resources or via cross-border procurement within the FCR cooperation framework. In practice, Elia participates in a regional FCR procurement cooperation with neighboring countries (such as France, Germany, the Netherlands, etc.), holding joint auctions where FCR providers from across the region compete. Belgium must secure at least a minimum "local FCR share" (around 25–30% of its requirement) from units located in Belgium, to ensure some domestic response in case of islanding [4]. FCR in Belgium is fully symmetric (providers must deliver both upward and downward frequency response) and is activated automatically via frequency deviations, requiring no direct TSO control once contracted.

- **aFRR (R2)**: Elia's automatic FRR requirement is sized to handle the bulk of intra-period imbalances that are too large or persistent for primary control alone. Historically set at 140 MW upward (and 140MW downward) for many years [5], the aFRR requirement has been refined by probabilistic analysis in recent years. In 2023 the required aFRR capacity was about 117 MW upward (with a similar magnitude downward), reflecting efficiencies gained through dynamic dimensioning and the introduction of fast-responding resources like batteries. Elia's aFRR is procured on a daily basis and must be able to fully respond within 5 minutes of activation, with the AGC (automatic generation control) system continuously adjusting the output of contracted units every 4 seconds to maintain the control area's interchange at its scheduled value [3]. Notably, aFRR is considered the most crucial balancing reserve for Belgium because it fine-tunes the balance and corrects the residual control error after FCR action. For a long time, only a few large gas-fired units from two or three companies provided all aFRR in Belgium (hence it was a very concentrated market) [5]. Recognizing this, Elia and the regulator (CREG) took steps to open up the aFRR market to more participants and new technologies. After pilot projects, a major redesign was implemented in 2020: aFRR capacity is now procured via a two-step auction that allows new entrants (like aggregators of smaller units, renewables, and demand response) to compete [5]. This has increased competition and diversity in aFRR provision, helping to reduce costs and improve resource adequacy. By 2021, Elia began seeing new providers offering aFRR, and the product is no longer exclusively the domain of large power plants.

- **mFRR (R3)**: The manual FRR requirement covers the remaining imbalance needs beyond what aFRR can manage. Typically, the sum of aFRR + mFRR is sized to cover the reference incident (often the tripping of a large generating unit or import line). In Belgium, the largest single generation unit is around 1 GW (a nuclear unit), but it is neither necessary nor economical to hold that entire volume as spinning reserve at all times. Instead, Belgium's mFRR procurement is a balance between ensuring sufficient contingency coverage and relying on shared reserves or emergency measures for extremely rare events. In practice, Elia tends to procure on the order of a few hundred megawatts of mFRR capacity daily, with the exact volume varying by day and hour (dynamic sizing). For example, if 117 MW of aFRR is required, the remaining upward FRR might be supplied by roughly 300–500+ MW of mFRR to reach the total FRR need (this total could be around 400–600 MW, depending on system conditions and risk level). The mFRR product in Belgium comes in two forms: mFRR Standard (full activation in 15 minutes, sustainable for hours) and mFRR Flex (a shorter-duration product introduced to increase participation, though its usage has been evolving). Since the market liberalization, mFRR has seen significant reforms. In 2013, Elia opened mFRR provision to decentralised resources, allowing distribution-connected generation (e.g. CHP units, emergency generators) and demand response to participate [5]. This led to a rapid growth in the pool of mFRR providers. By 2017, the volume of mFRR offered by the market (over 1100 MW) far exceeded the volume Elia actually needed to contract (typically 600–850 MW at that time), indicating healthy competition [5]. mFRR is used when there are large or prolonged imbalances – for instance, a sudden loss of generation that exceeds aFRR capacity, or when aFRR has been heavily deployed for several minutes and needs relief. mFRR activations are instructed by Elia's control room operators and can last as long as needed to restore system balance and reserves. If a severe deficit occurs, mFRR resources will be activated in merit order, and they can support frequency control over an extended period, effectively backing up the faster reserves [3].

Current Procurement and Activation Processes: Elia procures its reserves through dedicated capacity auctions and then utilizes them through a merit-order activation in real time. The procurement (also known as the balancing capacity market) and activation (balancing energy market) are distinct but linked processes [3]. Key characteristics of the Belgian approach include:

- **Capacity Procurement:**: For each reserve product (FCR, aFRR, mFRR), Elia determines the required volume (capacity need) in advance – historically this could be yearly or monthly for FCR, weekly or daily for aFRR/mFRR, but since recent changes, procurement is moving to shorter intervals (e.g. daily auctions for next-day reserves) to improve efficiency and alignment with forecast conditions. Elia then solicits bids from pre-qualified BSPs to supply that capacity. The auctions are competitive, and bids typically specify a capacity price in €/MW for being available. Elia contracts the lowest-priced offers until the requirement is filled (merit order selection) [3]. All contracted reserve providers receive a capacity payment (availability remuneration) for the contracted period. For example, FCR capacity might be procured in a weekly auction for each upcoming week, whereas aFRR and mFRR capacity are procured through daily auctions for the next day's needs (following the implementation of dynamic dimensioning). Elia's auctions calendar shows weekly and monthly tenders, indicating that some mFRR needs are still procured with slightly longer lead times as of now. The trend, however, is toward short-term procurement to better match reserve sizing with actual system conditions (daily dynamic procurement for both aFRR and mFRR is expected to become the norm). All reserve products (FCR, aFRR, mFRR) in Belgium presently receive a capacity payment to ensure they are ready to respond [3].

- **Activation and Energy Remuneration:**: When an imbalance occurs, Elia activates reserves by calling off energy from the contracted BSPs (and potentially non-contracted resources if available). For aFRR and mFRR, BSPs must submit balancing energy offers (in €/MWh) indicating at what price they are willing to actually increase or decrease generation if activated. The contracted aFRR and mFRR providers are obliged to offer their reserved capacity as energy bids in the real-time balancing market (at or below a price cap), but additional "free bids" from non-contracted units can also be offered to the TSO [3]. These free bids are unfettered capacity that was not paid in advance, yet they can participate in the energy market to compete with contracted reserves. When balancing is needed, Elia sorts all available energy bids (contracted and free) in order of price – this forms the balancing merit order for upward regulation (and similarly for downward regulation if reducing output is needed). Elia then activates the cheapest bids first to meet the imbalance, paying those providers the agreed energy price (typically "pay-as-bid" for mFRR in Belgium, and a form of marginal pricing for aFRR energy under the new design). Notably, FCR differs in that it has no separate energy payment – FCR response is automatic proportional to frequency deviations, and FCR providers are compensated only via capacity payments. aFRR and mFRR providers, on the other hand, receive both the capacity fee and an energy payment for any MWh activated [3]. The activation is coordinated via the international TSOs' systems as well – for example, if imbalance netting can reduce the activation need (counteracting imbalances with a neighbor), that is done before calling up reserves. After activation, any energy delivered is settled at the applicable balancing energy price, and the resulting imbalance price is passed on to BRPs that were short or long, thus incentivizing them to help restore balance.

In summary, Belgium's reserve procurement and activation process mirrors the general European approach: procure sufficient reserve capacity through competitive auctions to guarantee availability, then activate the least-cost resources in real time to handle imbalances. Over the past decade, Belgium (through Elia and CREG) has significantly evolved its balancing market design – opening it to new technologies (like batteries and aggregated demand), harmonizing products with European standards, and joining cross-border platforms for reserve exchange. These efforts in the Belgian market context aim to ensure security of supply and economic efficiency, providing the necessary reserves (FCR, aFRR, mFRR) at minimal cost while integrating the Belgian system into the broader European balancing framework. The ongoing transition toward joint European platforms (e.g. PICASSO for aFRR, which Elia connected to in 2024) will further shape Belgium's balancing operations, allowing for even more regional optimization and sharing of reserves across borders, a practical response to the inefficiencies of strictly separated markets and a step toward the future target model of integrated energy and reserve markets.

2.2 Co-Optimization of Energy and Reserves

2.2.1 Definition and Modeling of Co-Optimization

Co-optimization refers to the simultaneous joint optimization of multiple interdependent products (here, energy and reserve services) within a single clearing mechanism. Unlike separate markets, a co-optimized market explicitly models the coupling constraints between energy and reserves, recognizing that the same generator capacity cannot be used to supply both at once. In other words, any reserve capacity provided by a generator reduces the energy it can produce, and vice versa – an inverse relationship that tightly links the two commodities [11]. For example, a typical formulation will include constraints such as $P_i + R_i \leq P_i^{\max}$ for each generator i, ensuring that its energy output P_i and reserve provision R_i together do not exceed its capacity [11]. All resources are thus optimized together to meet both energy demand and reserve requirements concurrently, rather than in separate sequential steps.

From a formulation perspective, co-optimization is usually implemented as a single optimization problem with a unified objective. The market operator minimizes the total production cost (or maximizes social welfare) by simultaneously clearing energy and reserve schedules. A simplified formulation can be written as a cost minimization:

$$\min_{\{P_i,R_i\}} \sum_i \left(C_i^E \cdot P_i + C_i^R \cdot R_i \right)$$

subject to demand-supply balance $\sum_i P_i = D$, reserve requirement $\sum_i R_i \geq R_{\text{req}}$, and generator limits (including the coupling $P_i + R_i \leq P_i^{\max}$), among other technical constraints. Here C_i^E and C_i^R represent the offer cost of energy and reserve for generator i, respectively.

In practice, more detailed Security-Constrained Unit Commitment (SCUC) models are used for day-ahead co-optimization (incorporating generator startup costs, minimum output, etc.), resulting in a Mixed-Integer Linear Programming (MILP) formulation, while real-time dispatch uses a linear program with unit commitment fixed [12]. MILP formulations are widely employed in co-optimized energy-reserve market models to handle binary commitment decisions and complex technical constraints [12]. These formulations ensure that common constraints (like generator capacity, ramp rates, and transmission limits) are respected jointly for energy and reserves.

As an illustration, PJM's real-time market solves a Security Constrained Economic Dispatch that minimizes total system production cost = (energy costs + reserve costs + regulation costs, etc.), subject to power balance, reserve requirements, generator limits and network constraints [13]. This integrated approach yields shadow prices that simultaneously produce locational energy prices and reserve clearing prices as dual values from the same optimization run [13].

Crucially, co-optimization is not a multi-objective trade-off but a single objective optimization that integrates multiple products. By optimizing energy and ancillary services together, the algorithm fully captures the opportunity cost of providing reserves. Generators effectively bid their true costs for each product, and the co-optimization algorithm decides the optimal assignment. This contrasts with treating the objectives separately – co-optimization finds the global least-cost solution for meeting load and reserve needs together. As a result, markets for energy and operating reserves are "intricately intertwined" in the clearing process, reflecting the physical reality that providing reserve generally reduces a unit's available energy output and vice versa [11]. Because of this interdependence, co-optimized clearing has become a standard requirement in many modern electricity markets – it ensures that scarce generation capacity is allocated to energy vs. reserve in the most efficient way within one algorithm [11].

The mathematical structures used in co-optimization vary in complexity. Mixed-Integer Linear Programming (MILP) is commonly used for day-ahead market co-optimization, as it can incorporate unit commitment decisions (on/off status of generators) and other non-convex costs (like startup costs) [12]. In real-time or shorter intervals, a convex Linear Programming (LP) formulation is typically sufficient since commitment is already decided; the LP co-optimizes dispatch levels and reserve allocations for committed units. These co-optimization formulations are generally convex or linear (after appropriate linearization of unit constraints), which allows efficient solution even for large systems. Various enhancements like decomposition and relaxation techniques have been proposed in research to handle the computational complexity of co-optimization, but fundamentally the problem remains a single optimization with joint decision variables [12]. Overall, the formulation principles center on joint optimization under common constraints; ensuring, for example, that no generator is scheduled beyond its limit across energy and reserves, and that reserve requirements are met at minimum cost with the available capacity.

2.2.2 Economic and Operational Benefits

Co-optimizing energy and reserves yields significant economic benefits and operational efficiencies for the power system. By clearing both products together, the market minimizes total system production cost, which directly translates to cost savings and improved social welfare relative to sequential procurement. In a co-optimized dispatch, the system can utilize the lowest-cost resources to supply either energy or reserves as needed, rather than committing separate (potentially more expensive) units solely for reserve coverage. This joint clearing inherently accounts for generators' opportunity costs of providing reserves (foregoing energy sales), so the solution finds the optimal trade-off and avoids unnecessary expenditures. In practice, studies have shown that co-optimization leads to a more efficient overall dispatch. For instance, simulations by an Alberta system operator demonstrated that co-optimizing the energy and ancillary service markets produces a more efficient outcome overall compared to a sequential mechanism, with total system cost savings on the order of 1–2% of annual market value in their test cases [15]. Although the percentage savings can appear modest in normal conditions (e.g. 1-2% in years with lower prices), they become substantial in absolute terms over a large system and grow under tighter conditions [15]. The efficiency gains tend to be higher in periods of scarcity or high price volatility, since co-optimization can better reallocate resources in those moments.

More dramatic benefits have been quantified for larger systems. A recent European analysis estimated that implementing co-optimization in the day-ahead market across EU member states could save around €1.3 billion per year in operational costs system-wide, compared to the current sequential clearing of energy and reserves [14]. These savings represent the increase in total social welfare (producer plus consumer surplus) from jointly optimizing the procurement of balancing capacity with energy, rather than procuring reserves in a separate process. The same study found that if certain forecast uncertainties are not mitigated by intraday adjustments, the efficiency gains from co-optimization would nearly double, up to roughly €2.3 billion annually in the EU context, indicating co-optimization's value grows when the system faces more real-time uncertainty [14]. The economic intuition is that co-optimization properly accounts for fixed costs and opportunity costs in the scheduling process. Under sequential designs, generators might withhold or mis-price capacity due to uncertain future reserve needs or fixed start-up costs not reflected in energy market clearing. Co-optimization, by optimizing both fixed and variable costs together, commits the right mix of units and yields a lower total production cost for meeting both energy demand and reliability requirements [14]. In other words, the algorithm can choose an efficient commitment (perhaps committing an extra unit whose cost is justified because it can serve both energy and reserve needs), whereas a sequential process might either fail to commit that unit (causing a shortage of reserves or use of a costlier unit) or commit it too early without using it efficiently.

Beyond pure cost minimization, co-optimization brings operational benefits in terms of system flexibility and reliability. It provides system operators with enhanced flexibility because the market solution explicitly reserves headroom on generators for contingency and regulation needs in an optimal way. This reduces the likelihood of reserve shortfalls and reduces reliance on out-of-market actions. By procuring reserves jointly with energy, the system avoids over-procurement of reserves that can occur when energy and reserves are procured separately with conservative margins. In a sequential approach, operators might procure more reserves than economically necessary (or commit extra units) to ensure reliability, since the energy market did not account for those needs. Co-optimization avoids this by allocating just the necessary reserves from the most cost-effective sources, thereby trimming excess and associated costs. For example, if a generator that was providing only spinning reserve in a sequential market could actually have served some energy at low cost, co-optimization will utilize that generator for energy up to the point it is optimal and only the remainder of its capacity (or another unit's capacity) for reserves, achieving a more balanced utilization. This reduces reserve surpluses and directs capacity to where it has the highest value.

Another key benefit is the improved ability to integrate renewable energy and other uncertain resources. Co-optimized markets can more efficiently handle variability by adjusting the combined energy/reserve dispatch as conditions change, whereas sequential markets might commit reserve units day-ahead based on forecasts and then find those commitments suboptimal when real-time conditions differ. The co-optimization framework inherently provides built-in incentives for flexibility, units that can ramp quickly or respond are valued either through energy or reserve deployment as needed, all through the same optimization. Studies have noted that co-optimization helps avoid the pitfall of inflexible unit commitments blocking the deployment of cheaper resources. By selecting a mix of unit commitments not constrained by rigid minimum output levels, the system can rely as much as possible on low marginal-cost generation (such as wind, solar, or efficient gas units) to serve energy, while still maintaining reserves by committing additional flexible capacity if needed [14]. This ability to continuously re-dispatch resources for the most economic solution (within reliability constraints) means the system can respond to wind/solar forecast errors or demand fluctuations more economically. Indeed, case studies indicate that failing to co-optimize in high-renewable systems leads to higher production costs and potentially inefficient use of renewable output – co-optimization mitigates these issues by efficiently redistributing reserve assignments and energy output among resources when renewables deviate from forecast [19]. Overall, the joint approach minimizes the total required online capacity to meet both energy and reserve needs, which translates to lower fuel usage and lower costs to consumers, while still ensuring reliability criteria are met.

In summary, co-optimization improves system welfare by cost-minimization, yields lower electricity prices on average (since cheaper resources are better utilized), and enhances operational flexibility by optimally managing the trade-offs between energy production and standby reserve provision. It prevents scenarios where generators are kept idle for reserves despite higher-cost units running for energy, thereby eliminating those inefficiencies. Empirical analyses and simulations consistently show that a co-optimized dispatch achieves equal or lower total system cost compared to sequential dispatch in the same conditions [15][14]. The benefits become particularly pronounced during tight system conditions or high impact events, where co-optimization's ability to shuffle resources to where they are most needed (energy vs reserve) in real time can avoid costly emergency actions. Co-optimized markets also send better price signals: when reserves are scarce, the joint optimization will reflect that scarcity in both energy and reserve prices, improving investment incentives for flexible capacity. This holistic pricing is a direct result of co-optimization and is necessary for efficient long-run market signals for reliability. In contrast, sequential designs often rely on administratively determined adders or opportunity cost payments to handle scarcity pricing, which may not fully capture the true system marginal cost when resources are limited. Co-optimization inherently produces transparent scarcity pricing by co-clearing energy and reserves under constraints, thereby improving the economic signals for new capacity and flexibility.

2.2.3 Comparison to Sequential Clearing

Under a sequential market design, the energy market is cleared first (e.g. day-ahead energy auction), and then ancillary services or reserves are procured in subsequent auctions (e.g. a separate reserve market). This was historically the paradigm in many regions (and remains so in parts of Europe). There are important conceptual and operational differences between this sequential clearing and a co-optimized (simultaneous) clearing. In sequential designs, the reserve auction must take the results of the energy market as given – generators already committed for energy can only offer any leftover capacity for reserves, and generators not selected for energy might offer into reserves if they are still available. Because the markets are not solved together, generators have to internalize their opportunity costs for one product when participating in the other. For instance, a generator bidding into a standalone reserve market will include the opportunity cost of not selling energy with that capacity. This often makes reserve procurement more expensive or inefficient, since the energy market's outcome might not have been the cost-minimal way to also meet reserve needs. Sequential clearing thus inherently relies on complex opportunity cost pricing to approximate the coordination that co-optimization would naturally achieve [17]. In practice, this can lead to inconsistent or suboptimal dispatch: a generator that is cheapest to provide a reserve may not be selected if its opportunity cost (due to earning revenue in energy market) is high, causing the system to turn to a costlier unit for reserves. Co-optimization eliminates that inconsistency by evaluating the trade-off within one optimization – the unit will be assigned to whichever role yields the least system cost overall.

One key inefficiency in sequential dispatch is the misrepresentation of costs and inflexibilities. The energy market clearing in isolation may not commit some units that have high start-up costs or minimum output levels, because those costs might outweigh their value for energy alone. However, those units might have been very valuable for providing reserves. In sequential designs, the absence of co-optimization means such units could be left offline in the energy stage, only to find later that the system is short of reserves and must commit a unit on an emergency or out-of-market basis. This is a less efficient outcome. Alternatively, the system operator might procure extra reserves in the second stage to compensate for not having jointly optimized – effectively carrying a higher reserve margin "just in case," which increases costs. Studies have highlighted that sequential clearing tends to result in an inefficient commitment of resources due to the inability to properly account for fixed costs across markets. Fixed start-up and no-load costs get "spread" incorrectly: the energy market might not commit a unit because it cannot recover its cost on energy alone, but the reserve market would then have to either induce that unit online via a high reserve price or suffer a shortage. Co-optimization addresses this by considering both energy and reserve revenue for each unit simultaneously, so units with higher fixed costs can still be committed if they provide combined value in energy + reserve that justifies it. The result is a more efficient mix of online capacity. As a 2024 ACER report noted, in sequential designs the fixed costs are prone to misrepresentation (or not fully reflected), leading to suboptimal commitment, whereas co-optimization "improves overall efficiency by accurately optimizing both fixed and variable costs, resulting in better resource allocation" [14]. In essence, co-optimization picks up options that a sequential market would miss because it looks at the big picture.

The dispatch outcomes can also differ in how reserves are utilized. In a sequential market, once the reserve capacity is procured, it's often held idle unless an emergency occurs. The energy dispatch won't normally encroach on that reserved capacity. This means there could be simultaneous situations where some generators are backed down (or even offline) holding reserve, while other more expensive generators are running at full output to meet load – a clear inefficiency. Sequential dispatch might then require manual intervention to rebalance if, for example, a transmission constraint could be relieved by using some reserve capacity for energy, but the market design doesn't allow it. Co-optimization automatically handles such situations: since it co-clears, it will dispatch those reserves for energy if it is economic and if reliability constraints (like minimum reserve levels) are still satisfied. This leads to a more efficient dispatch, especially under stressed conditions. In fact, co-optimization can be seen as always operating on the efficient frontier of the trade-off between energy and reserves, whereas sequential solutions may operate interior to that frontier (not fully utilizing resources). Simulations comparing the two approaches frequently illustrate scenarios where sequential dispatch either fails to utilize available flexible capacity or pays more to reconfigure the dispatch after the fact. One analysis found that while not every hour sees large differences, on the whole a co-optimized dispatch had lower total costs and avoided out-of-merit commitments that were occasionally needed under sequential dispatch [15]. On average, about 40% of hours showed lower total system production cost under co-optimization in that study, with the biggest divergences during high-price periods or contingencies [15].

Another inefficiency of sequential markets is related to price signals and market power. In a sequential reserve market, suppliers may have an incentive to strategically bid high prices for reserves if they anticipate that energy commitments will limit competition (since many units might already be tied up serving energy). This can inflate reserve prices. Co-optimization mitigates that by considering all supply simultaneously – if a unit tries to withhold reserve or bid too high, the algorithm could choose an alternate energy/reserve configuration to avoid that cost. Thus, co-optimization tends to produce more competitive outcomes. Additionally, sequential markets may have to enforce ad-hoc corrections to reflect the value of reserves. For example, several systems introduced Operating Reserve Demand Curves (ORDC) or administrative adders to energy prices to approximate the "missing money" for reserves in an energy-only dispatch. These mechanisms are essentially attempts to incorporate some co-optimization principles back into a sequential framework by increasing energy prices when reserves are scarce (to signal committing more capacity). While ORDC has benefits, it's conceptually simpler in a co-optimized market where scarcity pricing arises naturally from the joint optimization (the reserve requirement constraint's shadow price will feed into energy prices when reserves are tight) [18]. In sequential designs without co-optimization, it's harder to get these prices right. Thus, co-optimization not only improves dispatch efficiency but also yields consistent pricing for energy and reserves that reflects their true scarcity values in each interval.

From an operational standpoint, sequential dispatch can also complicate system control. Because energy and reserve are decided separately, operators sometimes must perform iterative adjustments: e.g., clear energy, then see if reserve requirement is met; if not, commit another unit for reserve, which then also provides energy (potentially causing excess energy or need to back down others). This iterative process is less transparent and can result in non-optimal or delayed decisions. Co-optimization provides a single-step solution that meets all requirements at once, avoiding such iterations. It has been noted that in systems with significant uncertainty (like high renewables), a decentralized or sequential design struggles to "discover" the efficient outcome, since it's essentially solving a myopic sub-problem first [17]. By contrast, the integrated optimization can find a secure and economical dispatch considering uncertainty margins all at once (especially if stochastic or robust extensions are included). In sequential setups, reserve capacity may also lack a real-time reallocation mechanism – for example, Europe traditionally had no real-time market for reserve capacity; once reserves were procured day-ahead, they were fixed, which meant the system could not adjust reserve procurement if the energy outcome in real time was different [17]. Co-optimization in real-time (as done in many US markets) constantly readjusts the allocation between energy and reserves every dispatch interval, which greatly improves system response to changing conditions.

To illustrate an inefficiency: imagine a simple system with two generators, A and B. A has low energy cost but limited capacity, B has higher cost but larger capacity. Suppose the system needs X MW of energy and Y MW of reserve. A sequential market might clear generator A for energy up to X (because it's cheapest) and then procure Y of reserve from generator B (assuming A is at capacity so B is next available for reserves). But it's possible that a more efficient solution would be to back off A a little (produce slightly less energy from A, and let B produce some energy) so that A retains some headroom to provide part of the reserve. That way, both units share energy and reserve provision in a cost-minimizing way. A sequential market can miss this configuration because once A is maxed out in energy, it wasn't considered for reserves. A co-optimization would find the optimal mix – perhaps A provides some reserve (reducing its energy), and B increases energy output – if that lowers total cost given their offer prices. This kind of subtle trade-off is automatically handled in co-optimization, but would require guesswork or ex-post adjustments in a sequential context. In summary, sequential dispatch is suboptimal except in trivial cases, and numerous studies and trials have confirmed that joint clearing dominates it in efficiency [18][15]. Co-optimization resolves the illustrative inefficiencies of sequential dispatch by ensuring no cheap reserve capacity is left idle while expensive energy is produced elsewhere, and by avoiding procurement of reserves from high-cost units when lower-cost units could have provided it if scheduled differently.

2.2.4 Global Implementations and Practices

Co-optimized energy and reserve markets have been implemented in many regions, particularly in the United States, while other regions like Europe are now evaluating or moving toward this design. In U.S. wholesale markets operated by ISOs/RTOs, co-optimization of energy and ancillary services is a well-established practice. For example, PJM, MISO, NYISO, CAISO, and ISO-NE all clear their day-ahead and real-time markets with co-optimization. PJM introduced coordinated ancillary service markets in the early 2000s – by 2001 PJM was co-optimizing energy, regulation, and contingency reserves in an integrated market clearing process [16]. Similarly, NYISO has, since its start, co-optimized energy and reserves in real time, finding the least-cost way to meet load and multiple reserve requirements every five minutes [16]. In ISO New England, the market software co-optimizes energy and reserves such that the day-ahead commitment and real-time dispatch minimize total cost while respecting reserve needs (TMSR, TMNSR, TMOR products) [16]. MISO launched its ancillary services market in 2009 explicitly as a co-optimized addition to its energy market – both day-ahead and real-time markets in MISO simultaneously clear energy alongside spinning and supplemental reserves (and regulation) [16][18]. The co-optimization in these markets is achieved through the SCUC/SCED algorithms described earlier, yielding locational marginal prices for energy and corresponding reserve clearing prices for different reserve products at each location or zone. California ISO (CAISO) also implemented co-optimization when it restructured its market in 2009; CAISO procures its spinning reserve, non-spinning reserve, and regulation up/down together with energy in the integrated day-ahead market and again in real-time dispatch. The prevalence of co-optimization in U.S. markets is such that it is considered a standard design – any ISO with centrally dispatched energy markets also includes ancillary services in that dispatch to ensure efficiency.

These implementations have demonstrated the feasibility and benefits of co-optimization at scale. Market monitors report that co-optimization has reduced production costs and improved price formation by reflecting reserve shortages in energy prices. A co-optimized market will produce scarcity pricing when reserves are tight – for instance, if a certain reserve category becomes the binding constraint, the shadow price of that constraint is added to energy prices (in addition to creating a reserve price). This was evident in events such as tight winter or summer conditions where energy prices in ISO-NE, NYISO, etc., spiked in part due to reserve scarcity being co-optimized. Such outcomes incentivize generators to be available and flexible. In contrast, regions without co-optimization historically saw situations with flat energy prices even as operators struggled to maintain reserves (needing out-of-market actions). The U.S. experience also shows the operational benefits: system operators use a single platform to deploy energy and reserves, which simplifies dispatch and improves reliability. For example, if a transmission constraint or sudden generator outage occurs, the co-optimized real-time dispatch can automatically redispatch units to provide needed reserves or energy where required, instead of relying on a pre-contracted reserve that might not be in the right location. This leads to fewer manual interventions.

As for illustrative examples, consider PJM's reserve market: PJM co-optimizes several reserve products (regulation, synchronized reserve, non-synchronized reserve, etc.) with energy every five minutes. In practice, this means a generator in PJM can set the price for both energy and reserve if it is the marginal resource for both simultaneously (with appropriate adders). If reserves become scarce, the co-optimization algorithm will allow energy prices to rise (through reserve penalty factors) to reflect that scarcity, thereby either attracting more supply or curbing demand. This mechanism was not present before co-optimization – it had to be introduced via administrative pricing rules. Co-optimization in PJM has also reduced the need for separate "uplift" payments for reserves, because the integrated market more efficiently compensates resources through market clearing prices [13]. MISO's implementation in 2009 similarly led to more consistent pricing and reduced its reliance on emergency actions.

In contrast, Europe's markets have traditionally used sequential clearing for balancing reserves. Typically, European TSOs procure reserve capacity (for frequency restoration or replacement reserves) in separate auctions (day-ahead or even weeks ahead), and the day-ahead energy market (managed by the power exchange using the Euphemia algorithm) clears without considering those reserves. The result is the separation of energy trades from reserve procurement. This approach has been identified as a source of inefficiency, especially as renewable penetration increases and the value of flexibility rises. Europe is now actively exploring co-optimization as part of market design reforms. The EU Electricity Balancing Guideline (EBGL) introduced the concept of a "market-based allocation" of cross-zonal capacity for reserves, which is an intermediate step: e.g. in the Nordic countries, up to 10% of transmission capacity can be reserved for exchange of reserves before the energy market, based on a separate optimization. While this improves efficiency somewhat, it still is a two-step process. Full co-optimization would instead allocate cross-zonal capacity between energy and reserve entirely within one simultaneous auction. Recent studies under EU regulators (ACER) have strongly endorsed moving to a co-optimization approach for the day-ahead market coupling algorithm, citing the large welfare gains (the €1.3b/year savings mentioned earlier) [14]. As of 2024, ACER and the European Commission are consulting on amendments to enable co-optimised clearing of balancing capacity with energy in day-ahead. The barriers to adoption in Europe have been partly technical and partly institutional. One challenge is that Europe's day-ahead market currently uses "portfolio" bidding (generators submit aggregate supply curves per company, not unit-specific offers with detailed constraints). Co-optimization typically requires unit-specific offers to account for each plant's reserve capability and constraints. Integrating unit-based co-optimization into the existing market framework (and algorithm Euphemia) is a non-trivial task [17]. There are concerns about computational complexity when adding reserve capacity variables and constraints into the pan-European market coupling, which already involves thousands of bids and network constraints. However, research and pilot studies suggest it is feasible with modern solvers and computational power, especially if done in a simplified way or with proper decomposition. Another barrier has been the coordination between countries – reserve procurement has historically been a national TSO responsibility, and co-optimizing at an international level means TSOs entrust part of their reserve sizing to a central market mechanism. This requires regulatory alignment and agreement on cost-sharing for cross-border reserve activation. Despite these hurdles, several European initiatives are underway. The Nordic Balancing Model is moving toward closer integration of energy and reserves (though not full co-optimization yet), and ENTSO-E conducted an Implementation Impact Assessment detailing pathways for one-step vs two-step co-optimization in Europe [17]. The general trend is that Europe recognizes the inefficiency of strict sequential markets in a future with high renewables, and is gradually introducing co-optimization concepts.

To give a concrete example from Europe: currently in Spain and Portugal (MIBEL), energy is cleared day-ahead, and then secondary reserve (aFRR capacity) is procured afterward in a separate process at the national level. This is the "common" European sequential structure [18]. If co-optimization were introduced, Spain and Portugal would, in the day-ahead market, simultaneously procure some amount of reserve capacity while clearing energy, potentially using cross-border capacity more efficiently. The benefit would be that a plant in Portugal could be assigned to provide reserve for Spain if it's overall cheaper, as part of the market coupling result – something that today cannot happen because reserves are arranged separately. The ACER study's case simulations indeed modeled such scenarios and found large savings by allowing this cross-border, co-optimized allocation of resources [14]. The status as of now is that no European power exchange has full co-optimization of energy and reserve in production, but steps are being taken. The Nordic region's trial of market-based reserve capacity allocation and the EU-wide consultations indicate that within a few years, a form of co-optimized day-ahead market might be implemented. The barriers being tackled include updating algorithms (Euphemia) to handle co-optimization, changing bidding formats to include reserve offers or linkages, and ensuring fair and transparent governance for how reserve costs are recovered and priced. Stakeholders in Europe also discuss the complexity: some worry that co-optimization adds more complexity to markets that are already adjusting to flow-based transmission allocation and other changes. However, lessons from U.S. ISOs provide a blueprint showing that these challenges can be managed and that the efficiency gains outweigh the complexities in the long run.

In other regions, co-optimization adoption varies. Australia's NEM, for instance, until recently did not co-optimize FCAS (frequency control ancillary services) with energy in dispatch, but it has a rapid 5-minute dispatch with separate but coordinated procurement of reserves. There are ongoing discussions in Australia about moving closer to a co-optimized system as the needs for fast reserves grow. Some markets with less centralized dispatch (like certain Latin American countries) still use sequential methods or heuristic dispatch for reserves. But the global trend is clearly moving toward co-optimization as a best practice for modern electricity markets. Even ERCOT in Texas, which historically operated an energy-only market without co-optimization (relying on an administrative ORDC for scarcity pricing), decided to implement real-time co-optimization by 2020–2021 to improve efficiency and unit commitment in its market. In ERCOT's case, previously, ancillary services were procured day-ahead and not optimally re-dispatched in real time, meaning sometimes units carrying reserve were not used for energy even when it was economic to do so. The introduction of real-time co-optimization in ERCOT aimed to "dispatch the most economical resources to provide energy in real time, while assigning reserve responsibilities to other available resources," thereby finding the most efficient solution every 5 minutes [20]. This was a significant design change intended to reduce production costs for consumers and improve reliability by allowing the market to adjust ancillary service deployments on the fly [20]. It also highlights that even energy-only markets see value in co-optimization; by 2021, ERCOT received regulatory approval to implement it, overcoming initial stakeholder concerns about implementation cost and complexity [20].

In conclusion, co-optimization of energy and reserves is increasingly recognized and implemented as an essential feature of efficient electricity market design worldwide. The U.S. ISO markets serve as successful examples, having integrated co-optimization for over a decade or more with demonstrated benefits in cost savings and reliable operations. European markets are on the cusp of adopting similar mechanisms, driven by the need to handle large-scale renewable integration and to eliminate inefficiencies of their current sequential approach. Technical and regulatory challenges remain, such as modifying the market coupling algorithm and aligning stakeholder interests, but ongoing studies and pilot projects are paving the way for co-optimization in Europe in the near future. The overarching lesson from global implementations is that co-optimization improves both economic efficiency, by minimizing total costs and producing correct market signals – and operational robustness, by utilizing resources in the most flexible manner. As power systems worldwide continue to evolve (with higher renewables, storage, and demand response participation), the ability to co-optimize multiple services will be even more critical to ensure reliability is maintained cost-effectively. Therefore, we can expect the concept of energy-reserve co-optimization to become a standard component of market design in more regions as they reform their electricity markets for the future.

2.3 Battery Energy Storage Systems (BESS) in Market Operations

2.3.1 Technical Capabilities of BESS

Battery energy storage systems have distinct technical capabilities that make them highly flexible resources in power markets. Ramp rate refers to how quickly a BESS can change its output, and modern lithium-ion batteries can ramp from zero to full power in seconds or less – much faster than conventional generators [21]. For example, a large BESS has been shown to increase output by over 100 MW in under five seconds, far outpacing the response of typical thermal power plants [22]. Likewise, BESS exhibit very short response times, meaning they can go from idle to full discharge almost instantaneously (often sub-second) [23]. This rapid responsiveness enables batteries to provide immediate support to the grid for balancing and frequency control.

Another key attribute is efficiency. BESS have high round-trip efficiency, usually in the range of 85–95%, meaning most of the energy put into storage can be recovered on discharge [24]. High efficiency makes batteries effective at energy shifting with minimal losses. Storage duration (the maximum time a battery can sustain discharge at rated power) varies by system design; many grid-scale Li-ion BESS are designed for 1–4 hours of output, while other technologies like flow batteries can achieve even longer durations albeit at lower power density [21][24]. Cycle life is also an important capability; batteries can perform a finite number of charge/discharge cycles before degradation significantly reduces capacity. Advanced batteries now offer thousands of cycles over their lifetimes, which translates to years of operation under typical use [25].

In operating a BESS, tracking the state of charge (SoC) and managing degradation are critical.

The battery management system continuously monitors SoC and state of health to ensure the cells operate within safe limits [21]. The SoC (expressed as a percentage of full charge) dictates how much energy is available or if the battery needs recharging, which in turn constrains market dispatch. Degradation modeling is incorporated into many BESS control strategies because each charge–discharge cycle contributes to battery wear and capacity fade [26]. Researchers emphasize that ignoring degradation in operational scheduling can lead to suboptimal long-term outcomes, since a battery has a limited useful life measured in cycles [26]. Instead, operators must balance short-term market profits with long-term battery health. This is often done by assigning a cost to battery use or limiting deep cycles in optimization models [25][26]. In practice, advanced optimization and forecasting tools are used to maximize revenue from energy markets while minimizing unnecessary cycling, thereby extending battery life [27]. In summary, BESS combine fast and efficient power response with the need for careful SoC management and degradation-aware operation.

2.3.2 Participation in Energy and Reserve Markets

Battery storage resources are now actively participating in energy and ancillary service markets, but certain eligibility criteria and technical requirements apply. Many market operators have defined minimum size and performance standards for storage. For instance, in U.S. wholesale markets a BESS typically must be at least 100 kW to qualify, ensuring it can be effectively dispatched by the market operator [28]. Some reserve products also require a resource to sustain output for a specified duration (e.g. 30 or 60 minutes), which batteries must be sized to meet. Market rules have evolved in recent years (e.g. FERC Order 841 in the U.S.) to accommodate storage by recognizing its unique charge/discharge characteristics and removing barriers to entry [28]. Under these rules, an electric storage resource is broadly defined as any resource capable of receiving energy from the grid and injecting it back later, regardless of technology or location [28]. This allows BESS on the transmission system, distribution system, or even behind-the-meter to participate so long as they meet the technical requirements. Grid operators also implement state-of-charge management constraints in their dispatch algorithms to ensure batteries providing reserves have sufficient energy when called upon [24].

BESS act as flexible bidirectional assets in markets. Unlike conventional generators, a battery can function both as a supply resource (discharging power to the grid) and as a load (charging from the grid) depending on system needs. This flexibility means a single BESS can bid into both energy supply and energy demand segments of the market, or provide upward and downward reserve capacity as needed. Market participation models have been adapted to reflect this dual nature, for example, allowing batteries to set the market price when discharging, or to pay for energy when charging, within the same framework. Treating storage as both generation and load improves market efficiency by letting the battery respond to price signals in either direction [28]. In practice, a battery might be instructed to charge (act as demand) during times of excess supply or low prices, then later discharge (act as supply) when power is needed. System operators value this agility; a BESS can rapidly switch from charging to discharging mode, providing fast regulation up or down for frequency balancing [23]. In ancillary service markets, batteries have proven especially adept at frequency regulation and contingency reserves. They can satisfy strict performance requirements such as ramping nearly instantaneously and accurately following dispatch signals. Overall, BESS are recognized as a new category of market participant offering high flexibility, and regulatory changes continue to refine their participation rules (including allowing aggregated smaller batteries to enter markets in some regions).

2.3.3 Economic Role and Limitations

In market operations, BESS play several economic roles, but they also face limitations. A primary application is energy arbitrage; buying electricity when prices are low (charging) and selling it when prices are high (discharging). By shifting energy in time, battery operators can earn the price difference minus losses. This can help flatten demand peaks and reduce curtailment of renewables. For instance, a battery might charge using surplus solar generation at midday and discharge during the evening peak, profiting from the price spread and providing relief to the grid [24]. However, the pure arbitrage profits for a given battery are limited by the spread between off-peak and peak prices and the battery's efficiency and capacity. Studies show that arbitrage alone can be a thin margin business, and operators often seek multiple revenue streams.

BESS are highly valued for providing ancillary services such as frequency regulation, spinning reserve, and fast frequency response. Their fast response times give them an advantage in frequency control services. A BESS can inject or absorb power within milliseconds to correct frequency deviations, helping to stabilize the grid almost instantaneously [21]. In fact, batteries have successfully delivered sub-second frequency regulation and improved overall grid stability, outperforming slower resources in this role [21]. Many grid operators compensate fast-responding storage through performance-based regulation markets, making frequency regulation one of the more lucrative services for batteries. Batteries can also provide spinning reserve (standing ready to supply power if a generator trips) and even black start capability for restarting a grid, provided they are configured to do so. By supplying these reserves, a battery earns payments for availability and actual energy delivery during contingencies.

To maximize economic return, battery projects often pursue value stacking, i.e. providing multiple services and revenue streams. A single BESS can simultaneously or sequentially participate in energy arbitrage, frequency regulation, voltage support, capacity markets, and other services as allowed by the market rules. By stacking value streams, the asset's utilization is higher, potentially increasing total revenue and improving project economics [24]. For example, a utility-scale battery might do energy arbitrage daily and also offer regulation service in between, or defer an infrastructure upgrade (earning a reliability service value) while also earning market revenues. Successful demonstration projects have shown that stacking ancillary service revenues with energy trading can significantly shorten the payback period of a battery investment. The issue of degradation, however, becomes more pronounced with aggressive use. Each additional service or cycle contributes to battery wear, so there is a trade-off between capturing more revenue and consuming the battery's life. Operating a BESS for maximum short-term profit without regard to degradation can lead to early battery replacement and erode the long-term economic viability [26][27]. To address this, operators incorporate degradation costs into their dispatch decisions – effectively a marginal cost for using up battery life [27]. Strategies like limiting depth of discharge, resting the battery when revenues are low, or reserving some capacity for high-value periods are employed to manage degradation while stacking services [25][27].

Despite their many benefits, BESS still face policy and regulatory barriers that can limit their economic deployment. One key barrier historically has been the unclear asset classification of storage, neither pure generation nor load, which led to rules and tariff structures not designed for batteries. In some jurisdictions, this resulted in "double charging" of grid fees, where a battery pays network charges both when charging (as a consumer) and again when discharging (as a generator supplying energy) [29]. This double charging places storage at a competitive disadvantage relative to traditional power plants and has made some battery projects uneconomical until regulators intervened to remove such fees [29]. Other limitations have included minimum duration requirements or performance rules that were originally tailored to conventional generators, effectively excluding shorter-duration or fast-cycling batteries from certain markets. Progress is being made: for instance, regulatory reforms in the EU and US now mandate more storage-friendly market rules, such as allowing batteries to provide multiple services without violating exclusivity provisions and ensuring they are not penalized when switching between charge and discharge roles [28][29]. Finally, uncertainty in policy (e.g. how storage can participate in capacity markets, or who can own and operate storage under utility regulations) can impede investment. Clear policy frameworks that recognize the unique operating characteristics of BESS are crucial to unlock their full economic value. As these barriers are addressed, BESS are expected to play an increasingly prominent role in energy and reserve markets, providing flexibility and supporting the transition to a more dynamic, renewable-rich grid.

2.4 Modeling Battery Storage in Market Clearing

2.4.1 Battery Integration in Co-Optimized Clearing

In a co-optimized market clearing, the dispatch of energy and reserve capacity is determined simultaneously within one optimization framework [31]. This approach allows the market to optimally trade off the same megawatt of battery capacity between providing energy or reserves, recognizing that a unit of capacity cannot serve both at the same time [31]. By jointly clearing energy and ancillary services, the market accounts for the opportunity cost of using a battery for reserve (foregoing energy production) or vice versa. This leads to more efficient outcomes: for example, an analysis by the Alberta system operator comparing sequential vs. co-optimized clearing found that co-optimization was more cost-effective overall [32]. In fact, most organized power markets now implement co-optimization in their day-ahead and/or real-time markets to capture these efficiency and reliability benefits [31]. The European Union's 2017 Electricity Balancing Guideline also mandates that reserve capacity procurement be co-optimized and coupled with the energy market, reflecting the importance of this integration in future market design [33].

BESS Participation in Up/Down Reserve Products: Co-optimization is especially advantageous for battery energy storage systems (BESS) because it unlocks their full flexibility in both energy and reserve markets. In a co-optimized dispatch, a battery can be scheduled to provide energy and simultaneously offer upward and downward reserves within the same interval (subject to its capacity limits and state-of-charge). Upward reserve (contingency or regulation up) requires the battery to have headroom to increase output (i.e. discharge more if needed), while downward reserve requires room to decrease output or increase charging (i.e. the ability to absorb excess energy). Co-optimization naturally enforces these requirements by ensuring the battery's dispatch level and reserve awards are feasible together. For instance, if a battery is dispatched at mid-range, it could simultaneously offer reserve-up by reserving some charged energy to inject, and reserve-down by reserving charging capacity to soak up surplus power. System operators often impose constraints to guarantee deliverability of reserves from BESS: the battery must maintain sufficient state-of-charge (SoC) to deploy upward reserves and sufficient empty capacity to deploy downward reserves when called. In Germany's primary reserve market, for example, regulations require a battery providing frequency reserve to sustain an adequate SoC range for the entire service period, effectively mandating that a certain energy volume be held in reserve [37]. Co-optimized market clearing algorithms include these SoC-coupled constraints to ensure any reserve awarded to a BESS can be honored. Consequently, large-scale batteries have rapidly become major providers of ancillary services – for instance, in 2023 batteries provided the majority of the California ISO's regulation up and down capacity requirements [36]. Many early battery projects derived most of their revenue from frequency control reserves, and by 2018 a significant portion of installed battery capacity (especially in Europe) was participating in fast frequency response markets. This ability to switch roles quickly between charging, discharging, and standby reserve makes batteries ideal candidates for co-optimized dispatch.

Simultaneous Energy and Reserve Dispatch – Benefits of Flexibility: The flexibility of BESS in co-optimization yields several benefits for both system and asset owners. From the system perspective, co-optimized dispatch minimizes total production cost by allocating battery output to whatever service is most valuable each interval [31]. If the energy price is high, the market may discharge the battery for energy; if reserve scarcity is acute, the battery may instead hold back capacity for reserves, all decided in one optimization run. This dynamic allocation leads to lower overall costs and improved reliability, as evidenced by studies in both industry and academia. The AESO study noted above concluded that co-optimization saved costs relative to a sequential market design [32]. Likewise, computational experiments by Pavić et al. (2019) confirmed that a single MILP optimization can efficiently dispatch energy and reserves for all resources, capturing lost opportunity costs and reducing the need for out-of-market uplifts [34]. Co-optimization also produces transparent pricing for reserves that reflect their true opportunity cost (the foregone energy profit), thereby properly compensating storage providers for reserve provision [31]. From the battery owner's perspective, the co-optimized framework opens multiple revenue streams. A BESS can earn energy margin and reserve payments in the same time frame, or whichever is more profitable at that moment. This often increases the asset's total earnings compared to an energy-only operation. For example, a recent study demonstrated that when batteries optimize state-of-charge and bid into co-optimized energy/reserve markets with SoC-dependent offers, their profits can increase by 30–150% relative to simpler strategies [35]. Empirical market data also show batteries shifting towards energy arbitrage during peak price hours while still capitalizing on regulation services when profitable. In summary, co-optimization fully leverages battery flexibility: it improves social welfare (since the battery is used when and where it provides the greatest value) and it rewards the battery with revenue from all compatible services in each interval. Sioshansi (2014) noted that when generators behave competitively, introducing storage generally increases overall welfare by smoothing supply and demand imbalances [43]. Co-optimization is the market mechanism that ensures these welfare gains from storage are realized in practice by optimally allocating the resource's capacity.

2.4.2 Battery Integration in Sequential Clearing

Not all power markets currently co-optimize reserves with energy, some organize these products in sequential stages. In a sequential market clearing design, the energy market and reserve market are run separately (one after the other), rather than in a single joint optimization. Historically, many European electricity markets followed a sequential paradigm, with the day-ahead energy auction clearing first, and ancillary or balancing reserves procured in subsequent processes [38]. Under this approach, the allocation of battery capacity between energy and reserves is not decided simultaneously, which can lead to suboptimal or biased outcomes. Importantly, if a BESS is participating in sequential markets, it might end up being utilized in only one domain at a time (depending on the clearing sequence and rules), either the energy market or the reserve market, but not fully in both as in co-optimization.

"Energy-Only" vs. Reserve Participation in Sequence: In some sequential setups, batteries have been used primarily in the energy market step while largely excluded from reserve commitments. For example, if the day-ahead energy market clears without considering reserves, a battery will simply schedule charge/discharge for arbitrage and may not hold any capacity for reserve services. Early studies on storage often focused on such energy-only arbitrage participation. Sioshansi et al. (2009) examined the arbitrage value of a 1 MW storage in the PJM market (without reserve market participation) and showed that even just price arbitrage could yield modest profits and some load leveling benefits [42]. However, ignoring reserves in this way misses additional value streams and system services. More recent European market simulations confirm that treating battery storage as energy-only leads to lower revenues and potentially higher system costs compared to allowing multi-market participation [38][33]. In practice, sequential designs can inadvertently force a BESS to choose one market. For instance, if a battery is fully scheduled to charge or discharge in the energy market, it has no residual capacity for reserves cleared afterwards. Conversely, if a battery is procured entirely for reserve capacity in a prior stage, it may then sit idle in the energy market even if energy prices later spike – an inefficient outcome from a social viewpoint.

Reserve-First vs. Energy-First Assignment: The sequence in which markets clear matters for battery utilization. Two extreme approaches are conceivable in a sequential framework: reserve-first, where reserve procurement occurs before energy dispatch, and energy-first, where the energy market clears first. Each approach has drawbacks for batteries. In a reserve-first sequence, a BESS might be locked into providing standby reserve, charging or discharging minimally to preserve SoC, even if that battery could have been used to supply energy more cheaply than a generator during the energy market that follows. This can lead to higher energy costs, as found in a comparison by AESO where holding capacity for reserves before energy dispatch tended to be less cost-efficient than an integrated approach [32]. On the other hand, an energy-first sequence (common in traditional setups) commits the battery's output in the energy market without regard to reserve needs. The battery may chase energy arbitrage profits and end up fully charged or discharged, leaving no flexibility to respond if a reserve deployment is required later. The lost opportunity to provide reserves in this case is not accounted for during energy scheduling, so the system may end up calling on more expensive or slower resources for reserves. Researchers have noted that under sequential clearing, the market can experience production cost increases and revenue inadequacies that co-optimization would avoid, due to this misallocation of flexible capacity [34][44]. In summary, whether reserves are cleared first or second, any strictly sequential process fails to consider the coupling between a battery's energy and reserve roles at a given time. This decoupling leads to either over-commitment in one market or under-utilization in the other.

Hybrid and Balanced Allocation Strategies: To mitigate the inefficiencies of strict sequential clearing, various hybrid approaches for battery allocation have been proposed. One strategy is for the battery owner to proactively split its capability between markets; for example, withholding some capacity from the energy market to later offer as reserves (or vice versa). However, doing this optimally is complex and requires forecasting prices in both markets. Recent research has thus focused on coordinated optimization techniques that span multiple market stages. Finhold et al. (2023) develop a rolling horizon optimization for a "virtual battery," which computes the optimal distribution of a battery's flexibility between the day-ahead energy market and the balancing reserve market [38]. Their framework effectively simulates a quasi-co-optimization by iterating between markets and using updated forecasts, allowing the battery to achieve a balanced participation that maximizes its total profit across both markets. Similarly, Pandžić et al. (2020) proposed a bi-level optimization model for a battery participating in sequential European markets, where the upper level represents the battery's strategic offering (as a price-maker in reserves and price-taker in energy) and the lower level simulates market clearing [33]. Such models aim to "fill the gap" between fully sequential and fully co-optimized designs by guiding batteries to an optimal mix of energy and reserve deployment. For instance, the battery might charge cheaply in day-ahead energy, then reserve that energy for lucrative balancing deployment, or provide capacity in the reserve market but adjust its energy bids accordingly. Case studies in the German market have shown that these coordinated bidding strategies can significantly increase battery profits and improve system outcomes compared to naive sequential participation [33][38]. Another line of work considers ex-post adjustments: for example, after an initial energy market run, the system operator could allow a second-stage re-dispatch where batteries reposition to provide reserves (a "reserve coupling" step). Such hybrid market designs are still evolving, but they indicate that even without true co-optimization, it is beneficial to allow batteries to rebalance between energy and reserve commitments in a coordinated way. Indeed, numerical experiments by Chen et al. (2010) demonstrated that significant "room" can be available in real-time operations for shifting energy to reserves or vice versa, and that utilizing this room via improved market design can yield cost savings [44]. In practical terms, as battery fleets grow, market operators like ISO New England and ERCOT are moving away from sequential scheduling towards co-optimization (planned by 2025) to fully harness battery flexibility [31]. Until then, advanced optimization tools at the participant level (or multi-stage market processes) serve as interim solutions to achieve a more balanced battery allocation under sequential clearing.

2.4.3 Mathematical Approaches to Modeling BESS

The integration of BESS into market clearing formulations introduces unique modeling challenges. Battery operation is an inherently inter-temporal decision process: charging or discharging in one period affects the energy available in later periods. Moreover, batteries have non-trivial constraints like state-of-charge limits and mutually exclusive charge/discharge states. Researchers have employed a range of mathematical approaches to accurately model these features in market-clearing algorithms, from detailed mixed-integer formulations to simplified convex approximations.

Mixed-Integer Linear Programming (MILP) Formulations: The most common approach to model batteries in market clearing (e.g. unit commitment or economic dispatch problems) is to use MILP. In a MILP model, binary decision variables are introduced to capture the non-linear aspects of battery operation, primarily the fact that a battery cannot charge and discharge at the same time. This is often represented by a binary indicator y_t for each time period that takes value 1 if the battery is in charging mode and 0 if in discharging mode (or vice versa). The charging P_t^{ch} and discharging P_t^{dis} power variables can then be constrained with big-M linear inequalities:

$$P_t^{ch} \le P_{\max} \, y_t, \quad P_t^{dis} \le P_{\max} \, (1 - y_t), \quad y_t \in \{0, 1\},$$

where $P_{\max}$ is the battery's maximum charge or discharge rate. These constraints ensure that in any interval t, only one of P_t^{ch} or P_t^{dis} can be positive (the other is forced to zero by the binary y_t) – thus no simultaneous charge and discharge occurs. This binary enforcement is crucial because the naive alternative (allowing a single continuous net power variable that could be positive or negative) would make the problem nonlinear or could allow unphysical simultaneous operations if linearized. Indeed, Chen & Baldick (2021) note that "binary variables are in general required due to mutual exclusiveness of charging and discharging modes" in storage formulations [40].

MILP formulations also handle other on/off logical constraints, such as limiting the number of charge/discharge cycles or enforcing minimum online times if a battery unit has discrete modes. Another key set of MILP constraints are those tracking the state-of-charge (SoC) over time. The SoC is essentially the energy balance of the battery, and it links consecutive time periods. A typical SoC update equation used in many market models is:

$$SoC_t = SoC_{t-1} + \eta_c \, P_t^{ch} \, \Delta t - \frac{1}{\eta_d} \, P_t^{dis} \, \Delta t, \quad \forall t,$$

where η_c and η_d are the charge and discharge efficiency (fractions), and Δt is the interval duration (e.g. 1 hour). This linear difference equation accumulates the charged energy and subtracts the discharged energy (accounting for losses) to give the new SoC. Along with it, bounds are enforced: $SoC_{\min} \leq SoC_t \leq SoC_{\max}$ for all t, where $SoC_{\max}$ is the battery's usable energy capacity. Inter-temporal constraints like these turn what would otherwise be a set of independent single-period optimizations into a linked multi-period problem.

In power system markets, this is handled either by including the battery constraints in the centralized optimization (as some ISOs do for pumped hydro and are extending to batteries per FERC Order 841 [39]) or by requiring participants to manage SoC externally. The MILP approach explicitly incorporates SoC constraints into the market clearing. For example, Midcontinent ISO has experimented with adding binary battery models to its day-ahead unit commitment, finding that it can capture the economic trade-offs but with some computational cost penalty [50]. Tightening constraints (e.g. using valid inequalities) can help mitigate the MILP complexity. Overall, MILP provides a rigorous way to model the binary and coupling decisions for BESS, at the expense of higher computational complexity. It ensures that if a battery is scheduled to provide reserve, the SoC and power capacity are there to back it up, and if the battery is scheduled to charge or discharge, those decisions respect its physical limitations and inefficiencies.

Convex and Linearized Approaches: Given the computational burden of MILP (especially with large numbers of time periods or battery units), researchers have explored convex approximations of the battery modeling problem. One common relaxation is to omit or relax the charge/discharge exclusivity constraint. By allowing P_t^{ch} and P_t^{dis} to be nonzero simultaneously in the mathematical model (effectively treating the battery as capable of "fractional" charging and discharging at the same time), the problem becomes linear and convex, since the binary y_t can be dropped. The resulting linear program (LP) can be solved faster, but it may yield an physically infeasible dispatch (with overlapping charge/discharge) if taken literally. To cope with that, system operators sometimes use the net dispatch from the LP and count on the fact that in practice a battery cannot do both at once. For example, an LP might dispatch a battery to charge 50 MW and discharge 50 MW in the same interval (which net to 0, appearing to satisfy balance). In reality, the battery would simply sit idle (0 MW net), which is feasible but the SoC trajectory would differ. As a consequence, the optimized SoC from a relaxed model is typically a lower bound on the true SoC (since any simultaneous charge-discharge in the math model would cancel out net energy but actually could have been used to raise SoC). This can lead to suboptimal or unexpected results if not corrected. Recent work has proposed smarter convex formulations that preserve feasibility. For instance, one method is to split a battery into multiple fictitious sub-batteries that can be independently charged or discharged. By aggregating many small charge/discharge decisions (each of which can be modeled as always either charging or discharging at the continuum limit), the composite model can approximate a convex hull of the battery's operating region [32]. This approach, developed by Tindemans et al. (2024), yields a linear program whose solution can be mapped back to a physically achievable dispatch for the real battery, eliminating the simultaneous charge/discharge issue. Other convexification techniques include adding penalty terms for simultaneous charging and discharging or using piecewise linear loss models to avoid binary variables [31]. The goal of all these methods is to strike a balance between accuracy and tractability: a fully detailed MILP may be too slow for real-time market clearing with hundreds of intervals, whereas a relaxed LP might be fast but require out-of-model corrections. Convex approximations try to get the best of both: fast solving and near-physical accuracy. It's worth noting that many ISOs initially implemented very simple battery models (treating them as either negative loads or simple generators with no SoC constraints) in their markets, and only in recent years have moved to more rigorous formulations. For example, prior to 2023, several U.S. ISOs did not actively optimize battery SoC in dispatch, they relied on participants to manage it, meaning the market solution could inadvertently drive a battery to empty or full if left unchecked [49][40]. By late

2023, ISOs like CAISO introduced state-of-charge constraints directly into their market software to prevent such outcomes and to allow look-ahead dispatch to manage energy limits [39]. This evolution underscores the importance of proper BESS modeling: without inter-temporal constraints, a market might naively overuse a battery early and have nothing left later, or schedule infeasible patterns.

Inter-Temporal Optimization: Rolling Horizon vs. Snapshot Methods: Because batteries link across time, optimizing their use requires a multi-period outlook. In other words, the dispatch at hour t should consider needs at hour $t+1, t+2$, etc., to avoid myopic decisions (like a battery discharging completely in the morning only to find there is no capacity left for the evening peak). There are two broad approaches to incorporate this foresight in market clearing. The first is a rolling horizon optimization, where the market (or the battery's internal scheduler) solves a multi-period optimization over a future horizon and updates it frequently. This is analogous to model predictive control. For instance, the California ISO's real-time dispatch employs a multi-interval lookahead: every 15-minute market run actually optimizes over the next 65 minutes of intervals, and the day-ahead market optimizes over the full 24-hour horizon, specifically to account for energy-limited resources like storage [36]. This means the market software may deliberately charge or hold back a battery in the current interval if it anticipates higher value for that energy in a later interval. A notable result of this is that a battery can be dispatched to charge even when prices are relatively high if the algorithm foresees an extreme price spike later, essentially the market performs arbitrage on behalf of the battery to position it for future reliability needs. Such behavior was observed in CAISO, where at times batteries are instructed to charge at a loss (negative profit for that interval) because the advisory prices for upcoming hours justify it with an overall gain [36]. Rolling horizon optimization thus ensures inter-temporal constraints (SoC limits, cycle limits) are respected over time and avoids end-period effects by constantly re-solving as time moves forward.

In contrast, a snapshot optimization (or myopic method) would clear each time period independently or only consider a very short window, without linking SoC from one period to the next beyond maybe a trivial carry-over. A pure snapshot method is not used in any serious market for battery scheduling, since it would clearly fail to prevent infeasible outcomes; the battery could be scheduled to fully discharge every hour if each hour is optimized in isolation, which is inconsistent. However, some simplified market implementations have effectively treated storage myopically by requiring the resource to manage its own SoC. For example, an ISO might clear the battery as a generator or load in each interval based on bids, and it is the battery operator's responsibility to ensure it doesn't over-discharge; the market itself doesn't enforce multi-interval feasibility. This is essentially a manual "snapshot" approach and was common prior to storage-specific market rules. It often led to conservative operation (battery owners self-imposed SoC limits to avoid being caught empty when needed). With FERC Order 841 in the U.S., markets are now moving away from that: the Order required ISOs to implement bidding parameters for storage (like minimum SoC or maximum run time) and to account for state of charge if needed [39]. The modern trend is therefore towards rolling-horizon optimization in centralized markets, as it yields superior results for storage deployment. Studies have quantified the value of lookahead: for instance, an ISO simulation showed that explicitly optimizing storage with a 24-hour horizon increased system welfare and avoided the need for out-of-market adjustments, whereas a myopic approach either left money on the table or required manual SoC management [40][36]. Rolling horizon schemes do introduce computational complexity, so sometimes a compromise is used: a limited lookahead (e.g. 3–4 hours) or a two-step approach (optimize a long horizon coarsely, then refine the near-term schedule). In summary, rigorous modeling of BESS in market clearing calls for MILP or convex formulations to handle the charge/discharge decisions and SoC constraints, and a multi-interval optimization timeframe to properly schedule the battery's energy over time. Both academic studies and real-world implementations have shown that these mathematical considerations – non-convex formulations vs. relaxations, and rolling horizons – critically impact the efficiency of battery utilization in electricity markets [35][40][36]. As batte3y participation grows, continuing to improve these modeling approaches (e.g. faster algorithms for MILPs or improved convex relaxations) is an active area of research and a practical necessity for market operators to maintain reliability and economic efficiency with storage-rich grids.

2.5 Empirical Studies and Welfare Analysis

2.5.1 Co-Optimization vs. Sequential Clearing

Electricity market designs that co-optimize energy and ancillary services (reserves) have been shown to achieve higher overall welfare compared to sequential clearing (clearing reserves in a separate stage after energy). Multiple studies have compared these paradigms' outcomes on system-wide costs and reliability. Co-optimization inherently accounts for the opportunity costs between energy and reserve provision in one step, whereas sequential markets may lead to suboptimal commitments. For instance, a recent European analysis found that simultaneous day-ahead clearing of energy and reserve could save about €1.3 billion per year EU-wide relative to the current sequential approach [46]. In contrast, an intermediate "market-based" sequential design (allocating some cross-zonal capacity to reserves first, as practiced in the Nordic countries) yields only around €160–239 million in annual savings, underscoring the efficiency gap [46]. Key differences observed include:

- **System Costs**: Co-optimization yields lower total production cost and higher social welfare than sequential clearing. Simulations for Central Europe show 3–4% efficiency gains with co-optimization (translating to over €1.2 billion/year cost savings), whereas the sequential design leaves more expensive units online to meet reserve needs [46][47]. These savings come from better allocation of generation to simultaneously meet energy and reserve requirements at least cost.

- **Reserve Procurement Efficiency**: Under sequential clearing, reserve auctions conducted prior to or after energy markets can misrepresent generators' fixed costs and lead to inefficient unit commitment [46]. Generators might be scheduled in the energy market without considering reserve needs (or vice versa), requiring last-minute adjustments. Co-optimization avoids this by optimally committing resources for both energy and reserves in one pass, resulting in more efficient reserve procurement and lower reserve prices. Studies report that separate clearing creates uncertainty and even counter-intuitive dispatch outcomes under high reserve demands, whereas joint clearing modestly improves welfare and reliability when reserve requirements are high [47]. In other words, co-optimization becomes especially valuable as reserve needs increase (e.g. with more renewables or variability) [47].

- **Curtailment and Renewable Integration**: Co-optimization can reduce renewable energy curtailment relative to sequential markets. The joint clearing ensures that cheap renewable generation is not unnecessarily withheld due to reserve obligations. By optimizing energy and reserves together, the system can utilize renewable output more fully while still procuring reserves efficiently. In scenarios with high wind penetration, lack of co-optimization has been shown to cause inefficient use of wind (e.g. curtailment or spillage) and higher costs, whereas a co-optimized approach better harnesses available wind generation [47]. This leads to greater overall welfare (supply meets demand at lower cost) and aligns market dispatch with reliability needs without unduly constraining renewables.

Empirical evidence from existing market implementations corroborates these findings. In U.S. RTO markets (like ISO-New England and MISO), real-time co-optimization of energy and reserves is standard and is credited with minimizing operating costs while meeting reserve margins [46]. The European context, until recently, relied on sequential reserve procurement after day-ahead energy market clearing, which studies indicate has left significant welfare gains on the table. The push for co-optimized day-ahead markets in Europe (pursuant to EU regulations) is driven by these quantified benefits in cost reduction and efficiency. Overall, the literature strongly indicates that co-optimization dominates sequential clearing in terms of total welfare outcomes: it lowers system operating costs, leads to more optimal reserve procurement, and avoids scenarios where inflexible scheduling in sequential designs causes price distortions or unnecessary curtailment of low-cost resources [46][47]. Sequential designs tend to require more out-of-market corrections and incur higher reserve procurement costs, as seen in past European market outcomes. Notably, when intraday adjustments are limited, the efficiency gains from co-optimization become even more dramatic; one study noted potential savings could double (to €2.3 billion/year in Europe) if the system cannot fully readjust post-day-ahead, highlighting how valuable co-optimization is under inflexible conditions [46]. Thus, across a range of empirical simulations, co-optimized clearing consistently improves social welfare compared to the traditional sequential paradigm.

2.5.2 Role of BESS in System-Wide Welfare

Battery Energy Storage Systems (BESS) have emerged as pivotal assets for improving overall system welfare by providing flexibility. A BESS can charge during low-demand or low-price periods and discharge during peaks, a practice known as peak shaving, which reduces the need for expensive peaking generation. Numerous studies demonstrate that introducing BESS into power systems yields production cost savings and reliability improvements. For example, an early economic assessment on small isolated power systems showed that using storage for peak shaving and primary reserve significantly lowered operational costs [48]. In those case studies (Spanish islands), batteries supplying reserve and peak power led to measurable fuel and cost savings, underlining the welfare gains from even modest storage deployment [48]. Recent research has further quantified the system-wide benefits and sensitivities of BESS integration:

- **Sensitivity to Size and Efficiency**: The welfare impact of storage is highly sensitive to its size (energy/power capacity) and round-trip efficiency. An optimally sized BESS can maximize net benefits by providing just enough reserve and energy-shifting capacity without excessive idle investment. If the battery is too small, the system forgoes potential savings; too large, and diminishing returns set in. Adeyemo et al. (2025) found an optimal storage capacity that minimized total operating costs for a given system by allowing the displacement of costly generators kept online for reserves [49]. By providing spinning reserve from a BESS, the system could turn off or avoid running additional thermal units solely for reserve requirements, thereby cutting fuel consumption and emissions [49]. On the other hand, round-trip efficiency (the percentage of energy retained from charge to discharge) determines how effectively storage can arbitrage energy. A high-efficiency BESS (e.g. 90%+) delivers most of the charged energy back to the grid, maximizing its economic value, whereas a lower-efficiency device loses more energy as heat and provides a smaller net benefit. Studies indicate that improving battery efficiency directly translates to greater system cost savings and emissions reductions – for instance, a report notes that higher round-trip efficiency leads to more fuel displacement and pollution avoided per MWh cycled [50]. Thus, the assumptions about battery efficiency play a large role in welfare analysis: an 80–90% efficient storage yields significantly more arbitrage and peaking value than one at 60%. In practice, modern lithium-ion BESS often exceed 85% efficiency, enabling substantial welfare contributions through loss reductions [50].

- **Degradation and Lifetime Costs**: Battery degradation is another critical factor in welfare analysis. Each charge-discharge cycle incurs some wear and tear on the battery, effectively consuming a fraction of its finite lifetime. If degradation costs are not considered, models may overestimate the frequency with which a BESS should be cycled for small arbitrage gains. Recent studies embed battery degradation costs into operation planning to ensure dispatch decisions remain economically optimal over the battery's life. Yang et al. (2023) show that incorporating degradation in the optimization avoids overly aggressive cycling that would shorten battery life and lead to higher effective costs, thereby moderating the dispatch to balance short-term gains with long-term asset value [51]. Similarly, Schade et al. (2024) report that better representation of battery degradation in dispatch models leads to more prudent use of the battery (e.g. reserving cycles for higher-value periods), ultimately increasing the net welfare by extending battery life and reducing replacement costs [52]. In summary, accounting for degradation moderates the theoretical welfare contribution of BESS; the net benefit is still positive, but somewhat lower once battery wear costs are internalized. This sensitivity highlights that policy and market signals (like paying for throughput or cycling costs) may be needed to fully capture welfare-optimal behavior for storage owners.

- **Impact on Peak Shaving, Reserves, and Ramping**: BESS can have a transformative impact on peak shaving and ancillary service provision. By discharging during peak demand hours, storage lowers the peak net load, reducing the need to commit expensive peaker plants. This peak shaving not only cuts generation costs but can also defer investments in generation capacity and grid infrastructure. Analyses by NREL have noted that batteries effectively ensure adequate peaking capacity by replacing some gas-fired peakers, especially when paired with renewables to shift their output to peak hours [50]. In providing operating reserves, BESS can respond faster and more precisely than thermal generators. An appropriately sized BESS can supply spinning or fast-frequency reserves, meaning fewer thermal units must be kept running at part-load for contingency purposes. This improves overall efficiency since generators no longer need to be committed solely for reserve capacity [49]. The flexibility of batteries also contributes to ramping support: grids with high renewables face steep ramp-up or ramp-down periods (for example, solar output drops in the evening). BESS can smoothly handle these ramps by discharging or charging rapidly, which maintains system balance without requiring quick-start gas plants. Case studies have shown that even a single large battery can significantly reduce the net ramping requirement from conventional generators, improving system stability and lowering wear on thermal plants. In summary, the presence of BESS enhances system-wide welfare by shaving peak demand, providing reserve capacity more efficiently, and offering rapid ramping support, all of which lead to lower operating costs, improved reliability, and reduced emissions [48][49][50]. These benefits are sensitive to the technical parameters discussed (size, efficiency, degradation), but across many studies the qualitative finding is consistent: integrating storage yields a positive net welfare effect, especially as renewable penetration and flexibility needs grow.

2.5.3 Real-World Applications and Case Studies

The theoretical advantages of co-optimization and storage have been explored in simulations, and increasingly evidence is emerging from real-world market implementations. European market applications provide valuable case studies. In the Nordic countries, a sequential market-based reserve allocation mechanism has been in place, whereby a day-ahead balancing capacity auction allocates cross-zonal transmission capacity for reserves before the energy market clears. This approach, used in Norway, Sweden, Finland, and Denmark, has enabled some cross-border reserve sharing and improved efficiency over purely national, sequential procurement. However, studies suggest that while this Nordic model yields modest benefits, it does not capture the full potential welfare gains of a simultaneous co-optimization. The ACER consultancy report noted that the market-based allocation (Nordic-style sequential clearing) achieved only a small fraction (1̃5%) of the welfare gains that true co-optimization would deliver in Europe [46]. This finding has informed ongoing policy discussions in the EU, and as of 2024 the EU is moving towards implementing co-optimized day-ahead markets for energy and reserves. The Nordic experience thus serves as a real-world stepping stone: it proves that integrating reserves across zones brings benefits, but also that a more integrated clearing (co-optimization) could save roughly an additional billion euros annually [46].

Germany and the UK offer contrasting cases in national market design and the role of storage. Germany traditionally procures reserves after the day-ahead energy market (sequentially) and experienced a notable experiment in 2018–2019 with the so-called "mixed price" system. Under that scheme, Germany tried to combine energy and reserve capacity bids in the balancing reserve market to account for energy opportunity costs. In practice, this partial integration was short-lived: it led to a persistent upward trend in reserve capacity prices and required frequent operator interventions to maintain system balance, prompting its cancellation by mid-2019 [48]. Analyses of the mixed price episode indicated that the design inadvertently penalized flexible providers and created gaming opportunities, resulting in inefficiencies. The lesson from Germany's case was that poorly designed sequential markets (or half-measures toward co-optimization) can yield worse outcomes: during those nine months, reserve costs spiked and significant out-of-market actions were needed to keep the system in check [48]. Germany has since reverted to conventional separate auctions, but the experience has fueled interest in more robust co-optimization methods to avoid such issues in the future. Additionally, Germany has been a leader in deploying BESS for primary frequency control; batteries have been participating in the German primary reserve (FCR) market for several years, successfully providing fast frequency response. This real-world deployment demonstrates how storage can improve reliability and reduce dependence on thermal plants for frequency regulation. While data on system-wide welfare impact in Germany are still emerging, the trend of battery participation has been positive – frequency control costs have fallen, in part due to high-performance battery response displacing conventional units.

The United Kingdom has become a frontrunner in large-scale battery adoption and offers insights from both simulation studies and actual market data. The UK currently has the highest installed grid-scale BESS capacity in Europe (over 1.7 GW by some estimates) and one of the most active ancillary service markets for storage [54]. This is driven by the UK's aggressive renewable targets (e.g. a net-zero power system by 2035) and the need for flexibility on an island grid with limited interconnections. Market data from recent years show that UK batteries earn revenue through diverse streams: fast frequency response services (like Dynamic Containment), the Balancing Mechanism (energy balancing actions), and wholesale energy arbitrage. A Rabobank analysis noted that the UK's strong policy support and multiple revenue opportunities (capacity markets, ancillary services, arbitrage) make it particularly attractive for BESS investment [54].

The real-world performance has validated many theoretical benefits of storage. For example, during peak evening hours or rapid wind ramps, National Grid has increasingly turned to battery assets for balancing. This has improved response times and reduced reliance on standby gas plants. It was observed that as more batteries entered the frequency response markets, the prices for those services declined (by 2023, UK frequency response prices fell to less than half the European average), indicating that BESS are providing these services at lower cost [54]. However, this also introduces a new dynamic: as battery capacity grows, revenue from a single service can erode (a sign of market saturation). Operators and investors in the UK are responding by "stacking" multiple value streams (participating in energy arbitrage, reserve, and capacity markets concurrently) to maintain profitability. Overall, the UK's case confirms that storage can enhance system welfare: it contributes to peak shaving (batteries routinely reduce demand peaks, which in turn defers some network reinforcement), reserve sufficiency (the system comfortably meets reserve requirements with less spinning thermal capacity), and accommodates steep renewable output changes (mitigating wind variability). At the same time, it highlights the importance of market design: the UK is exploring adjustments like local flexibility markets and revised reserve products to ensure that the full value of BESS is captured and that revenue signals remain adequate as the fleet grows [54].

Other European regions and studies provide additional context. Several Nordic and UK simulation studies (e.g., using historical demand and weather data) reinforce these empirical trends. For instance, in Scandinavia, models show that allowing batteries and flexible demand to participate in reserve markets greatly improves adequacy during winter peaks and high wind periods. In Southern Europe, case studies have examined high solar systems, they find that storage smooths out the solar variability and prevents midday over-generation from being wasted, thereby increasing the utilization of renewable energy and raising overall welfare (by reducing curtailment and lowering reserve procurement of gas plants). Real-world trial programs, such as pilot battery projects in Italy and Spain providing fast reserves, have reported improved frequency control performance and cost savings for the TSO. In summary, the growing body of real-world evidence from Europe confirms the literature's main points: co-optimization of energy and reserves leads to substantial cost savings and more efficient resource use, and BESS deployment contributes significantly to system flexibility, reliability, and reduced operating costs. These case studies also offer practical insights – for example, they underscore the need for appropriate market rules (to avoid unintended consequences like Germany's 2019 episode) and illustrate that the value of storage can evolve as more is added to the system (as seen in the UK, where initial high revenues for fast response services have moderated over time with increased competition). Policymakers and market operators are leveraging these insights to refine market designs for maximizing social welfare in a renewable-heavy grid.

2.5.4 Temporal Effects and Value Variability

Another crucial aspect of welfare analysis is the temporal variability of value from storage and co-optimization. The economic benefits of these resources are not uniform across all times; instead, they fluctuate with seasonal patterns, daily demand cycles, and extreme events. Studies have highlighted that the value of energy arbitrage and reserve provision depends strongly on timing. For example, an analysis across European electricity markets found that arbitrage opportunities (and thus the profitability of storage) differ widely by region and time: markets that are less integrated or have larger price volatility offer greater arbitrage value, whereas highly integrated markets with smoother price profiles yield lower arbitrage gains [55]. This implies that the welfare contribution of a storage or co-optimization approach can be more pronounced in systems with sharp temporal price swings. Within any given market, seasonal trends play a significant role. During winter months in northern Europe, demand peaks in the evening are higher (due to heating and lighting), often causing higher prices – storage has more valuable opportunities to charge off-peak (night) and discharge at the evening peak, increasing its earnings and welfare impact. In summer or low-demand periods, the peak-trough spread may be less pronounced, slightly reducing arbitrage value. Empirical price data confirm these trends: one illustrative analysis of storage operating in the UK found markedly different optimal operations between winter and summer scenarios, corresponding to the differing demand and price patterns [56]. The storage would cycle more and earn higher revenues in winter when price spikes were frequent, whereas in summer it cycled less due to flatter demand. Seasonal renewable patterns also matter. For instance, in spring with abundant solar production, midday power prices can collapse (even go negative), which gives storage cheap charging opportunities and then profitable discharge later. Thus, the value per MWh of storage use can be significantly higher in certain seasons (or days) that have greater imbalance between supply and demand.

Daily and weekly demand patterns further drive variability in storage value. Weekdays tend to have higher peaks (industrial and commercial activity) and more pronounced morning/evening ramp events, whereas weekends generally exhibit lower, flatter load profiles. This leads to a consistent weekday-weekend effect observed in arbitrage revenues [56]. On weekdays, batteries often see two cycles (morning and evening peaks) with substantial price differences, making arbitrage highly lucrative on those days. In contrast, during weekends the peak demand is lower and mid-day troughs (especially with solar) can be higher, so price spreads shrink; storage may only do a single shallow cycle or even sit idle if spreads don't cover efficiency losses. Poonyth (2020) analyzed UK price data and noted clear patterns: arbitrage revenues fluctuated on a daily basis, with weekday peaks yielding significantly higher returns than weekends, and these patterns repeated weekly [56]. Over the course of a year, these daily/weekly fluctuations contribute to seasonal averages – e.g. more high-value days in winter, fewer in summer. The implication for system-wide welfare is that the marginal value of storage (in MWh saved or shifted) is not constant: it is high during periods of stress or high demand (when storage averts expensive generation or blackouts) and lower when the system is mostly in surplus.

Moreover, extreme events can greatly skew the temporal distribution of storage value. An analysis of the 2014 "Polar Vortex" winter in the US PJM system found that just a handful of extreme cold days contributed a disproportionate share of the annual arbitrage profits for a storage device [57]. During those days, electricity prices spiked to many times their normal level due to fuel shortages and high demand, and a storage unit that was available could earn as much in one event as it might in weeks of normal operations. Salles et al. (2017) quantified this, showing that accounting for such rare but extreme events significantly increases the long-run average value of storage in PJM – essentially, resource adequacy and resilience events create very high shadow prices that storage can capitalize on [57]. From a welfare perspective, this means that storage provides not only routine day-to-day cost savings but also a form of insurance value during crises (by preventing involuntary load shedding or reducing reliance on extremely expensive peaking generators). However, it also makes the revenue stream of storage quite variable year-to-year, as it depends on the occurrence of such events.

In summary, temporal effects are crucial in evaluating system-wide welfare from co-optimization and storage. Seasonality affects demand peaks and renewable output patterns, thereby influencing how often and how profitably storage is used across the year. Weekday vs. weekend and diurnal cycles create regular intra-week variability in value, with weekdays typically offering greater benefits for storage and flexible resources than weekends [56]. And finally, rare events and outlier days can contribute outsized value, highlighting the importance of considering not just average conditions but also volatility and extreme scenarios in welfare analyses [57]. Grid operators and planners incorporate these temporal factors by, for example, examining multiple year types (peak year vs normal year) when assessing storage investments or by designing time-differentiated price signals (such as higher reserve requirements or scarcity pricing in peak seasons) to ensure that the value of flexibility is reflected. Overall, acknowledging the variability of storage value over time leads to more robust and realistic welfare analysis, ensuring that co-optimization strategies and BESS deployments are evaluated under the full spectrum of operating conditions, from typical days to system stress events.

2.6 Identified Gaps and Research Direction

2.6.1 Literature Gaps

Insufficient modeling of hybrid strategies in sequential models

A clear gap in prior work is the lack of models that capture hybrid operational strategies across sequential electricity market stages (e.g. joint participation in day-ahead, intraday, and balancing markets). Traditional market designs and many studies treat these stages separately (sequential clearing), which can lead to suboptimal outcomes and missed synergies [58][59]. In fact, the conventional sequential approach has been shown to introduce efficiency losses compared to integrated optimization, as it cannot fully coordinate energy and ancillary services or co-located resources in one framework [58][59]. For example, co-optimizing energy and reserves together generally yields more cost-efficient dispatch than procuring them sequentially, yet most models in the literature do not allow such co-optimization. Recent research confirms this shortcoming: Zhu et al. (2023) note that no existing method simultaneously optimizes a battery hybrid system's bids in the day-ahead market, balancing market, and real-time operation under one strategy. Their work fills that gap with a new multi-market EMS model, underscoring that previous studies did not consider fully coordinated strategies across sequential markets (e.g. a battery providing both arbitrage and balancing services in tandem) [60]. In summary, the literature has focused on sequential market models in isolation, without adequately modeling hybrid or coordinated strategies that span multiple market layers, a gap this thesis will address.

Lack of Belgian-context empirical simulation studies

There is a noticeable underrepresentation of studies applying these models and strategies to the Belgian electricity market context. Most academic case studies on storage and market design have been conducted for large systems (e.g. U.S. RTOs or multi-national EU markets) or use generalized data, with very few focused specifically on Belgium's market conditions. This gap is partly due to the nascent status of battery storage in Belgium – as of 2021, Belgium had very limited battery capacity installed, and even lacked consolidated data on storage operations [61]. The International Energy Agency reported that battery storage was "not yet part of mandatory energy statistics" in Belgium, highlighting the historically low deployment and analysis of storage in the country [61]. Consequently, tailored simulation research for Belgium has been scarce. Only recently have a handful of studies begun to incorporate Belgian market data. For instance, Mercier et al. (2023) included Belgium in a pan-European arbitrage study and showed that unique local factors (like Belgium's storage grid fees) can significantly impact storage profits. Their inclusion of Belgian-specific tariffs, which reduced arbitrage value by 20–50%, underlines the importance of context, yet such detailed local analyses are the exception [62]. Similarly, Paredes and Aguado (2024) demonstrate a battery revenue-stacking strategy using Belgian day-ahead and aFRR market data, achieving a 17% profit increase by optimally combining energy and reserve trading [63]. In another example, Gonzalez-Saenz and Becerra (2024) optimize a battery operating on Belgium's day-ahead market to study arbitrage and degradation trade-offs [64]. These few studies show growing interest in Belgium, but they each cover limited aspects (one focuses only on spot vs. reserve stacking, another only on day-ahead arbitrage). There remains a gap in comprehensive, Belgium-specific simulations that consider multiple services, longer time spans, and welfare implications under realistic Belgian market constraints. In summary, the empirical literature has yet to extensively examine how proposed market models perform under Belgium's unique market design and upcoming energy transition (e.g. nuclear phase-out), a gap the present thesis aims to fill.

Underrepresentation of seasonality and intra-week value variation

A third gap is that many models do not capture seasonal and intra-week variations in storage operation and value. Numerous storage studies simplify the temporal domain – for example, optimizing over a single representative day or week, which risks overlooking longer-term patterns. Sioshansi et al. (2021) identify the choice of modeling horizon as a critical challenge, noting that too short a horizon leads to myopic decisions for storage dispatch [65]. Indeed, a systematic review by Weitzel and Glock (2018) found that most operational strategies for stationary batteries focus on short-term (daily/hourly) management, with little attention to multi-week or seasonal dynamics [67]. In practice, storage profitability and optimal use can vary widely between weekdays and weekends or between winter and summer, especially in systems with renewable fluctuations. However, these effects are often under-modeled. Many studies rely on time-aggregation techniques (e.g. a few typical days) that are suitable for short-duration storage but insufficient for capturing multi-day energy shifting [66]. Recent research confirms this limitation: Mantegna et al. (2024) show that using isolated representative days can substantially misestimate the value of long-duration storage, failing to account for carry-over of energy across days. They emphasize that properly modeling multi-day storage requires simulations spanning entire seasons or year-round with chronological detail [66]. In short, the literature has largely underrepresented seasonal cycles and intra-week variability, an important gap since storage operational strategy (and its economic welfare impact) can change when viewed over continuous weeks and months. Addressing this gap calls for using multi-season, multi-day scenario analyses to capture how storage operation in one day influences the next, and how value stacks up across diverse conditions. This thesis responds by considering a year-round scope with seasonal and weekly granularity, ensuring that conclusions account for temporal value variations that prior sequential models often neglect.

2.6.2 Contribution of This Thesis

Development of co-optimized and sequential models with battery storage

To address the first gap, this thesis develops two complementary market modeling approaches for battery storage participation: a co-optimized model and a sequential model. In the co-optimized framework, energy and reserve markets (and other services) are cleared together in an integrated optimization, allowing battery storage to optimally allocate its capacity between multiple uses in a single optimization run. In the sequential framework, the markets are cleared in their natural sequence (e.g. day-ahead followed by balancing), reflecting current practice, but the battery's strategy is modeled across these stages, enabling evaluation of "hybrid" strategies within the sequential process. By formulating both models, we can explicitly capture the strategic and outcome differences when a battery (or hybrid system) operates under joint optimization versus sequential market clearing. This is a novel contribution because prior studies typically analyze either a co-optimization approach or a sequential approach in isolation, whereas here they are developed side by side under consistent assumptions. The models incorporate battery operational constraints (state-of-charge dynamics, capacity limits, efficiency, degradation, etc.) and allow the battery to provide multiple services. Through this development, the thesis provides a more comprehensive toolset to evaluate how hybrid strategies (simultaneous energy arbitrage, reserve provision, etc.) perform under each market design. In doing so, it fills the literature gap by offering a rigorous comparison: how does a battery's optimal behavior and the resulting market outcomes differ between a co-optimized market versus the conventional sequential market structure? These new models will enable insights into the efficiency gains of co-optimization and identify any shortcomings of sequential designs in accommodating storage resources.

Empirical evaluation using multi-season, multi-day scenarios

To overcome the underrepresentation of long-term variability, the thesis conducts extensive simulations across multiple seasons and days. Rather than evaluating the models on a single typical week, we use multi-season, multi-day scenarios that cover a wide range of temporal conditions (e.g. winter peak vs. summer low demand, weekdays vs. weekends, renewable output patterns, etc.). The developed models are applied over consecutive days spanning different seasons to ensure that inter-day coupling and seasonal supply/demand variations are accounted for. This approach explicitly captures intra-week effects (such as a battery reserving energy over several days of high prices) and seasonal differences (such as lower solar generation in winter or higher demand peaks in summer). By testing the market models on these rich scenarios, the thesis can evaluate storage operation and economic outcomes in a manner that reflects real-world temporal complexities. This is a significant contribution beyond most existing studies, which often use limited time horizons or representative periods. Our multi-season evaluation will illustrate, for instance, how the value of battery storage and its optimal scheduling might be higher in one season (e.g. winter, with volatile prices) than another, or how a multi-day cold spell vs. a windy week impact the sequential vs. co-optimized dispatch differently. Ultimately, this comprehensive temporal analysis provides more robust evidence on the performance of each market model, ensuring that the conclusions drawn are valid under varied and realistic time-varying conditions, thereby directly addressing the literature gap on seasonality and long-horizon modeling.

Comparative welfare analysis with realistic Belgian market assumptions

Finally, this thesis contributes a detailed welfare analysis of the proposed market designs under realistic Belgian market conditions, helping to fill the noted context gap. All simulations are grounded in Belgian data and policy settings. For example, using actual Belgian demand profiles, generation mix, price statistics, and market rules (including those specific to Belgium such as capacity remuneration mechanisms or imbalance price structure). By calibrating the models to Belgium's context, we ensure that results reflect the operational constraints and costs relevant to Belgium's power system (e.g. the limited nuclear capacity post-2025, or the import/export capabilities of the Belgian grid). The thesis evaluates not just private profits for the battery, but also the broader economic welfare impacts of co-optimized vs. sequential market operation. This means comparing outcomes like total system cost, consumer surplus, producer revenues, and possibly reliability metrics between the two market designs. Such a welfare comparison under Belgian assumptions is rarely seen in prior literature; it effectively asks: if Belgium were to implement a co-optimized market for energy and reserves (with substantial storage participation) instead of the current sequential structure, what would be the net benefit to society? The analysis will quantify differences in efficiency (e.g. production cost savings or price reductions) and distributional effects (how surplus is allocated between consumers, producers, and storage owners) in each model. By doing so, the thesis provides empirically-backed insights for Belgian market stakeholders and policymakers. In summary, the research not only pioneers a Belgium-focused application of advanced market models for storage, but also offers a comparative welfare perspective. This addresses the gap in empirical simulations for Belgium and delivers practical implications: whether integrating battery storage via co-optimization yields appreciable welfare gains over the status quo, under the realistic market dynamics and constraints of Belgium. Together, these contributions, both methodological and context-specific, push the state of the art in line with the identified gaps, offering both new theoretical frameworks and regionally pertinent findings.

Κεφάλαιο 3

Methodology

3.1 Study Objective

This work quantifies the daily *social-welfare uplift* (in €/day) obtained by clearing Belgian day-ahead **energy and reserve markets jointly** rather than sequentially, while explicitly modelling *Battery Energy Storage Systems* (BESS).

As electricity systems evolve with increasing shares of renewables and decentralised flexibility, the coordination between energy and reserve markets becomes increasingly critical. Traditional sequential clearing frameworks—where reserves are procured prior to energy—may yield suboptimal system dispatch, fail to exploit synergies across services, and limit the value extracted from flexible assets such as batteries.

In this context, co-optimisation is proposed as a promising design alternative that can internalise system constraints and opportunity costs across services. This thesis models and compares both clearing paradigms under realistic operational constraints using a detailed MILP unit commitment formulation tailored to the Belgian power system.

The evaluation centres on welfare gains from BESS participation and improved scheduling efficiency, accounting for battery degradation costs, system ramping limits, and reserve delivery requirements. Four representative weekdays—Winter, Spring, Summer and Autumn—are analysed, each resolved at 96 fifteen-minute intervals (Section 3.2), ensuring adequate temporal granularity for capturing reserve activation and SoC evolution.

3.2 Temporal Granularity and Representative Days

The modelling horizon spans a full operational day, discretised into 24 hours $\times 4 = 96$ time intervals of 15 minutes each. This fine-grained temporal resolution is essential for accurately capturing operational constraints such as generator ramping limits, the activation timing and sustain duration of upward and downward reserves (both aFRR and mFRR), and the dynamic behaviour of Battery Energy Storage Systems (BESS), including state-of-charge (SoC) transitions and non-simultaneous charge/discharge operations.

Unlike rolling or multi-day optimisation horizons, this fixed 96-step setup simplifies the implementation while preserving sufficient granularity to evaluate short-term flexibility, particularly for fast-responding assets such as batteries and gas turbines. It also aligns with the activation periods used in real-time balancing markets operated by the Belgian TSO, Elia.

To capture seasonal diversity and reduce computational burden, a scenario reduction technique is applied to historical data from 2019 to 2022. Specifically, net-load time series—defined as total system demand minus renewable generation (wind, PV, run-of-river)—are aggregated at daily resolution and clustered using the `k-means` algorithm. Four clusters are selected, each representing a prototypical weekday in one of the four meteorological seasons (Winter, Spring, Summer, Autumn).

This seasonal classification ensures that the chosen test days are statistically representative of typical Belgian grid conditions across the year, balancing variations in demand, renewable availability, and flexibility needs. The methodology closely follows the clustering approach outlined in [68], which has been widely adopted in power system operations research.

All models are solved independently for each representative day, and results are aggregated to draw conclusions about annualised welfare benefits, flexibility gaps, and technology contributions.

3.3 Resource Portfolio

The simulated Belgian power system comprises a diverse portfolio of generation and storage technologies, each represented with a level of detail appropriate to their operational characteristics and role in flexibility provision. The model distinguishes between the following asset classes:

- **Thermal Units**: Includes Combined Cycle Gas Turbines (CCGT), Open Cycle Gas Turbines (OCGT), coal, biomass, and other fossil-fuelled or dispatchable units. Each generator is characterised by a piecewise-linear heat-rate curve, ramping limits, minimum up/down times, start-up costs, and no-load costs. These units form the primary source of dispatchable generation and participate actively in both energy and reserve provision.

- **Nuclear Units**: Treated as baseload generators with fixed availability and zero marginal cost. For realism, these units are excluded from reserve provision due to physical and regulatory limitations on fast-response capabilities. Their generation profile is assumed to be flat, representing inflexible operation over the optimisation horizon.

- **Hydropower (Pumped Storage)**: Pumped-storage units (PS) are included only in the co-optimised models. They are modelled with generation and pumping capabilities, cycle efficiency, reservoir capacity, and inter-temporal state-of-charge constraints. In sequential models, PS generation and pumping are treated as fixed, based on historical operation data, to isolate the marginal benefit of optimising battery storage.

- **Run-of-River, Wind, and Solar (RES)**: These are modelled as exogenous time series and treated as non-dispatchable resources with zero marginal cost. Their output is deducted from the demand to form the net-load curve that must be met by dispatchable and flexible units.

- **Battery Energy Storage Systems (BESS)**: Two lithium-ion battery units are modelled in detail. Each is defined by its maximum power (MW), energy capacity (MWh), round-trip efficiency, charge/discharge efficiency, and a cycle degradation cost (€/MWh cycled). BESS units participate in both energy arbitrage and reserve provision depending on the scenario. Their operation is governed by state-of-charge dynamics and a binary `mode` variable to enforce non-simultaneous charging and discharging.

This granular modelling of the resource portfolio ensures that each technology's physical constraints and economic characteristics are accurately captured. This enables a fair comparison of flexibility contributions across resources and supports a robust quantification of welfare benefits from co-optimising energy and reserve markets.

3.4 Reserve Products

In Belgium, the Transmission System Operator (TSO), Elia, is responsible for procuring balancing services to maintain real-time system frequency and security of supply. These services are divided into two main categories of frequency restoration reserves:

- *Automatic Frequency Restoration Reserve* (aFRR): also known as secondary control, aFRR is activated automatically via a centralised control signal from Elia's control room. It is deployed within a few seconds and sustained over a 15-minute period, ensuring rapid and continuous response to frequency deviations. Assets participating in aFRR must comply with stringent requirements in terms of response time, telemetry, and controllability.

- *Manual Frequency Restoration Reserve* (mFRR): also referred to as tertiary control, mFRR is activated manually by Elia and typically used to relieve aFRR or restore reserves after a major system event. It is commonly delivered through contracted capacity from large generators or aggregators and must begin ramping within 15 minutes of activation.

Both upward and downward directions are procured for each reserve product, ensuring that flexibility is available to both increase and decrease generation or consumption when needed. These reserves are cleared via dedicated procurement mechanisms, often through daily or weekly auctions.

Table 3.1 summarises the key operational parameters of each reserve product in terms of delivery time, sustain duration, and directional coverage:

Πίνακας 3.1: Reserve product definition

Product	**Direction**	**Delivery time**	**Sustain**
aFRR	Up / Down	15 s	15 min
mFRR	Up / Down	15 min	15 min

The modelling framework in this thesis reflects these definitions by enforcing reserve-specific constraints on delivery duration, minimum activation time, and sustained provision. The flexibility resources—such as conventional generators and BESS—are required to meet these performance criteria when scheduled for reserve provision in either the co-optimised or sequential clearing configurations. This fidelity ensures a realistic comparison between different market design scenarios.

3.5 Mathematical Formulations

3.5.1 Joint Energy–Reserve MILP (CO-OPT)

Decision variables include generation $p_{g,t}$, commitment $w_{g,h}$, start-up $z_{g,h}$, reserve provision $s_{g,t,r}$, pumped-storage variables, and BESS charge/discharge with binary *mode* when commitment binaries are active. The objective (Eq. ??) minimises fuel, start-up, no-load and cycle costs subject to energy balance, reserve requirements, ramping, min-up/down, and SoC constraints.

3.5.2 Nomenclature

Sets:

G Set of generation units, indexed by g

B Set of battery storage systems, indexed by b

P Set of pumped storage units, indexed by p

R Set of reserve products, indexed by r

T Set of time periods, indexed by t

Parameters:

- MC_g Marginal cost of generator g [/MWh]
- K_g, S_g No-load and start-up cost for generator g [/h,]
- $P_g^{\min}, P_g^{\max}$ Minimum and maximum generation of g [MW]
- $R_g^{r,\max}$ Reserve provision capacity of generator g for product r [MW]
- $\eta_b^{\text{ch}}, \eta_b^{\text{dis}}$ Charge/discharge efficiency of battery b [--]
- $P_b^{\max}, E_b^{\max}$ Max power and energy capacity of battery b [MW], [MWh]
- CycleCost_b Battery cycling cost [/MWh]
- Δt Time step duration [h]
- D_t Demand at time t [MW]
- RR_t^r Reserve requirement at time t for product r [MW]

Variables:

$p_{g,t}$ Power output of generator g at time t (MW)

$s_{g,t}^r$ Reserve provision of generator g for product r at time t (MW)

$p_{b,t}^{\text{ch}}, p_{b,t}^{\text{dis}}$ Charging/discharging of battery b (MW)

$soc_{b,t}$ State-of-charge of battery b (MWh)

$s_{b,t}^r$ Reserve provision of battery b for product r (MW)

l_t, l_t^{neg} Positive and negative load shedding (MW)

3.5.3 Problem Formulation

The day-ahead co-optimization problem is formulated as:

$$\min \sum_{t \in T} \left[\sum_{g \in G} (MCg, t \cdot p_{g,t} + K_g \cdot w_{g,t} + S_g \cdot z_{g,t}) + 3000 \cdot l_t + 3000 \cdot l_t^{\text{neg}} + \sum_{b \in B} \text{CycleCost}_b \cdot (p_{b,t}^{\text{ch}} + p_{b,t}^{\text{dis}}) \right] \tag{1}$$

subject to:

$$\sum_{g\in G} p_{g,t} + \sum_{b\in B} p^{\text{dis}}_{b,t} - \sum_{b\in B} p^{\text{ch}}_{b,t} + l_t - l^{\text{neg}}_t = D_t \qquad \forall t \in T \tag{2}$$

$$p_{g,t} + \sum_{r\in R} s^r_{g,t} \leq P^{\max}_g \cdot w_{g,t} \qquad \forall g \in G, t \in T \tag{3}$$

$$p_{g,t} \geq P^{\min}_g \cdot w_{g,t} \qquad \forall g \in G, t \in T \tag{4}$$

$$s^r_{g,t} \leq R^{r,\max}_g \qquad \forall g \in G, r \in R, t \in T \tag{5}$$

$$\sum_{g\in G} s^r_{g,t} + \sum_{b\in B} s^r_{b,t} \geq RR^r_t \qquad \forall r \in R, t \in T \tag{6}$$

$$soc_{b,t} = soc_{b,t-1} + \eta^{\text{ch}}_b \cdot p^{\text{ch}}_{b,t-1} \cdot \Delta t - \frac{1}{\eta^{\text{dis}}_b} \cdot p^{\text{dis}}_{b,t} \cdot \Delta t \qquad \forall b \in B, t > 0 \tag{7}$$

$$0 \leq soc_{b,t} \leq E^{\max}_b \qquad \forall b \in B, t \in T \tag{8}$$

$$p^{\text{dis}}_{b,t} + \sum_{r\in R^{\uparrow}} s^r_{b,t} \leq P^{\max}_b \qquad \forall b, t \in T \tag{9}$$

$$p^{\text{ch}}_{b,t} + \sum_{r\in R^{\downarrow}} s^r_{b,t} \leq P^{\max}_b \qquad \forall b, t \in T \tag{10}$$

$$\frac{1}{\eta^{\text{dis}}_b} \cdot \left(p^{\text{dis}}_{b,t} + \sum_{r\in R^{\uparrow}} s^r_{b,t} \right) \cdot \Delta t \leq soc_{b,t-1} \qquad \forall b, t \in T \tag{11}$$

$$\eta^{\text{ch}}_b \cdot \left(p^{\text{ch}}_{b,t} + \sum_{r\in R^{\downarrow}} s^r_{b,t} \right) \cdot \Delta t \leq E^{\max}_b - soc_{b,t-1} \qquad \forall b, t \in T \tag{12}$$

Constraints (2) enforce energy balance. Constraints (3)-(4) ensure that generator power and reserves do not exceed limits. Constraints (5)-(6) enforce unit and system reserve requirements. Constraints (7)-(12) model battery dynamics, including SoC updates, converter capacity, and energy availability for reserve activation.

3.5.4 Sequential Clearing

Step 1: Reserve Sub-problem Opportunity-cost formulation after Avila2018:

3.5.5 Nomenclature

Sets:

G Set of generation units, indexed by g

B Set of battery storage systems, indexed by b

R Set of reserve products, indexed by r

T Set of 15-minute time periods, indexed by t

H Set of hourly time intervals, indexed by h

Parameters:

- $MC_{g,t}$ Marginal cost of generator g at time t [/MWh]
- K_g, S_g No-load and start-up cost of generator g [/h,]

- $P_g^{\min}, P_g^{\max}$ Minimum and maximum generation of g [MW]
- $R_g^{r,\max}$ Maximum reserve capability of g for product r [MW]
- $\eta_b^{\mathrm{ch}}, \eta_b^{\mathrm{dis}}$ Charge/discharge efficiency of battery b [--]
- $E_b^{\max}, P_b^{\max}$ Energy and power capacity of battery b [MWh], [MW]
- $\mathrm{InitialSoC}_b$ Initial state-of-charge of battery b [MWh]
- RR_t^r System-level reserve requirement for product r at time t [MW]
- λ_t Market clearing price for energy at time t $[/\mathrm{MWh}]$

Variables:

- $p_{g,t}$ Scheduled power output of generator g at time t [MW]
- $s_{g,t}^r$ Reserve provision by generator g for product r at time t [MW]
- $w_{g,h}$ Binary commitment status of generator g at hour h
- $z_{g,h}$ Binary start-up indicator for generator g at hour h
- $c_{g,t}$ Generation cost proxy variable for generator g at time t []
- $s_{b,t}^r$ Reserve provision by battery b for product r at time t [MW]
- $soc_{b,t}$ State-of-charge of battery b at time t [MWh]

3.5.6 Problem Formulation

The reserve-only model without pumped storage is formulated as:

$$\min \sum_{t\in T}\sum_{g\in G} \mathrm{OCF}_{g,t}(s_g t^{+mFRR} + s_g t^{+aFRR}) + \sum_{t\in T}\sum_{g\in G} \mathrm{C}(P_g^{-} + s_g t^{-mFRR} + s_g t^{-aFRR}) + \sum_{h\in H}\sum_{g\in G} K_g \cdot w_{g,h} + S_g \cdot z_{g,h} \tag{1}$$

subject to:

$$
\begin{aligned}
&p_{g,t} \leq P_g^{\max} \cdot w_{g,h} && \forall g \in G, t \in T,\ h = \lfloor t/4 \rfloor && (2)\\
&\sum_{g \in G} s^r_{g,t} + \sum_{b \in B} s^r_{b,t} \geq RR^r_t && \forall r \in R, t \in T && (3)\\
&\sum_{r \in R} s^r_{g,t} \leq R_g^{r,\max} && \forall g \in G, t \in T && (4)\\
&\sum_{r \in R} s^r_{b,t} \leq P_b^{\max} && \forall b \in B, t \in T && (5)\\
&soc_{b,t} = soc_{b,t-1} && \forall b \in B, t > 0 && (6)\\
&\frac{1}{\eta_b^{\text{dis}}} \cdot \sum_{r \in R^{\uparrow}} s^r_{b,t} \cdot \Delta t \leq soc_{b,t-1} && \forall b \in B, t \in T && (7)\\
&\eta_b^{\text{ch}} \cdot \sum_{r \in R^{\downarrow}} s^r_{b,t} \cdot \Delta t \leq E_b^{\max} - soc_{b,t-1} && \forall b \in B, t \in T && (8)\\
&z_{g,h} \geq w_{g,h} - w_{g,h-1} && \forall g \in G, h \in H && (9)\\
&\sum_{q=h-UT_g+1}^{h} z_{g,q} \leq w_{g,h} && \forall g \in G, h \geq UT_g - 1 && (10)\\
&\sum_{q=h+1}^{h+DT_g} z_{g,q} \leq 1 - w_{g,h} && \forall g \in G, h \leq 23 - DT_g && (11)
\end{aligned}
$$

Constraints (2) enforce that generation does not exceed maximum capacity. Constraints (3) ensure that system-wide upward and downward reserve requirements are met. Constraints (4) and (5) limit the reserve capacity of generators and batteries. Constraints (6)–(8) model battery state-of-charge dynamics and energy feasibility. Constraints (9)–(11) enforce generator startup logic and minimum up/down time constraints. The opportunity cost function $\text{OCF}_{g,t}$ in (1) is defined based on the difference between marginal costs and energy prices, with a piecewise logic depending on the sign of $MC_{g,t} - \lambda_t$.

3.6 Opportunity Cost Function

$$
OCF_{g,t}(s^r_{gt}, w_{gt}; \lambda_t) = \begin{cases} 0, & \text{if } w_{gt} = 0 \\ \left(\frac{MC_g}{4} - \lambda_t\right) \cdot \left(P_g^- + s_{gt}^{\text{mFRR}} + s_{gt}^{\text{aFRR}}\right), & \text{if } w_{gt} = 1,\ \left(\frac{MC_g}{4} - \lambda_t\right) \geq 0 \\ \left(\frac{MC_g}{4} - \lambda_t\right) \cdot \left(-s_{gt}^{\text{mFRR}} - s_{gt}^{\text{aFRR}}\right), & \text{if } w_{gt} = 1,\ \left(\frac{MC_g}{4} - \lambda_t\right) \leq 0 \end{cases} \quad \text{(OCF)}
$$

Step 2: Energy Sub-problem Commitment may be *fixed* to reserve decisions. Pumped-storage is also fixed to historical Gen/Pump since there is no way to decompose it into reserve and energy without adding additional inefficiencies to the model which ultimately tries to isolate BESS value.

3.6.1 Nomenclature

Sets:

G Set of generation units, indexed by g

B Set of battery storage systems, indexed by b

T Set of time periods (15-minute intervals), indexed by t

H Set of hourly intervals, indexed by h ($H = 24$, $h = \lfloor t/4 \rfloor$)

Parameters:

- MC_g Marginal cost of generator g [/MWh]
- K_g, S_g No-load and start-up cost for generator g [/h,]
- $P_g^{\min}, P_g^{\max}$ Minimum and maximum generation of g [MW]
- $R_g^{\max}$ Ramp up/down limit of generator g [MW/15min]
- $\eta_b^{\text{ch}}, \eta_b^{\text{dis}}$ Charge/discharge efficiency of battery b [--]
- $P_b^{\max}, E_b^{\max}$ Power and energy capacity of battery b [MW], [MWh]
- CycleCost_b Battery cycling cost   [/MWh]
- λ_t Energy price forecast at time t (if arbitrage enabled)   [/MWh]
- Δt Time step duration   [h]
- D_t System demand at time t [MW]
- p_t^{ps} Net generation from pumped storage (fixed)   [MW]
- p_t^{ren} Renewable generation at time t [MW]
- $w_{g,h}^{\text{fixed}}$ Fixed commitment status of generator g at hour h (0 or 1)

Variables:

$p_{g,t}$ Power output of generator g at time t (MW)

$w_{g,h}, z_{g,h}$ Commitment and startup status of generator g at hour h

$p_{b,t}^{\text{ch}}, p_{b,t}^{\text{dis}}$ Charging/discharging power of battery b at time t (MW)

$soc_{b,t}$ State-of-charge of battery b at time t (MWh)

l_t, l_t^{neg} Positive and negative load shedding at time t (MW)

3.6.2 Problem Formulation

The energy-only market clearing problem minimizes generation and load-shedding costs, while satisfying demand and respecting operational constraints:

$$1/4 * \min \sum_{t \in T} \sum_{g \in G} c_{g,t} + \sum_{tinT} \text{VOLL} \cdot (l_t + l_t^{\text{neg}}) + \sum_{t\ inT} \sum_{b \in B} \text{CycleCost}_b \cdot (p_{b,t}^{\text{ch}} + p_{b,t}^{\text{dis}}) + \sum_{g\ inG} \sum_{tin} \cdot K_g * w_g t + S_g * z_{gt}$$

(3.1)

subject to:

$$
\begin{aligned}
&\sum_{g\in G} p_{g,t} + \sum_{b\in B}(p^{\text{dis}}_{b,t} - p^{\text{ch}}_{b,t}) + p^{\text{ren}}_t + p^{\text{ps}}_t + l_t - l^{\text{neg}}_t = D_t && \forall t \in T && (2)\\
&p_{g,t} \le P^{\max}_g \cdot w_{g,h(t)} && \forall g \in G, t \in T && (3)\\
&p_{g,t} \ge P^{\min}_g \cdot w_{g,h(t)} && \forall g \in G, t \in T && (4)\\
&p_{g,t} - p_{g,t-1} \le 15 \cdot R^{\max}_g && \forall g \in G, t > 0 && (5)\\
&p_{g,t-1} - p_{g,t} \le 15 \cdot |R^{\min}_g| && \forall g \in G, t > 0 && (6)\\
&z_{g,h} \ge w_{g,h} - w_{g,h-1} && \forall g \in G, h > 0 && (7)\\
&\sum_{q=t-UT_g+1}^{t} z_{g,h(q)} \le w_{g,h(t)} && \forall g \in G, t \ge UT_g - 1 && (8)\\
&\sum_{q=t+1}^{t+DT_g} z_{g,h(q)} \le 1 - w_{g,h(t)} && \forall g \in G, t \le 95 - DT_g && (9)\\
&soc_{b,t} = soc_{b,t-1} + \eta^{\text{ch}}_b \cdot p^{\text{ch}}_{b,t} \cdot \Delta t - \frac{1}{\eta^{\text{dis}}_b} \cdot p^{\text{dis}}_{b,t} \cdot \Delta t && \forall b \in B, t > 0 && (10)\\
&0 \le soc_{b,t} \le E^{\max}_b && \forall b \in B, t \in T && (11)\\
&\frac{1}{\eta^{\text{dis}}_b} \cdot p^{\text{dis}}_{b,t} \cdot \Delta t \le soc_{b,t-1} && \forall b \in B, t > 0 && (12)\\
&\eta^{\text{ch}}_b \cdot p^{\text{ch}}_{b,t} \cdot \Delta t \le E^{\max}_b - soc_{b,t-1} && \forall b \in B, t > 0 && (13)\\
&p^{\text{dis}}_{b,t} \le P^{\max}_b \cdot \text{mode}_{b,t} && \forall b \in B, t \in T && (14)\\
&p^{\text{ch}}_{b,t} \le P^{\max}_b \cdot (1 - \text{mode}_{b,t}) && \forall b \in B, t \in T && (15)
\end{aligned}
$$

Constraints (2) ensure energy balance, including renewables and pumped storage. Constraints (3)-(4) apply generator capacity limits. Constraints (5)-(6) enforce ramping limits. Constraints (7)-(9) model startup logic and minimum up/down times. Constraints (10)-(13) handle battery energy dynamics and availability. Constraints (14)-(15) prevent simultaneous battery charging and discharging via a binary mode variable.

3.6.3 Battery Model

$$\text{SoC}_t = \text{SoC}_{t-1} + \eta_{\text{ch}}\, p^{\text{ch}}_{t-1}\Delta t - \frac{1}{\eta_{\text{dis}}}\, p^{\text{dis}}_t \Delta t$$

Non-simultaneous charge/discharge is enforced via $\text{mode}_t \in \{0, 1\}$.

3.6.4 Dual–Price Extraction Methods

1. **LP-Relax** — drop binaries, solve LP once (lower bound, fast).
2. **Fixed-Binary LP (FB-LP)** — fix binaries at MILP optimum, re-solve LP (tighther).

3.7 Scenario Matrix

To assess the welfare impacts of alternative market-clearing approaches and storage participation levels, five distinct scenarios are constructed and evaluated independently across each representative day. These scenarios differ in the degree of co-optimisation, the inclusion of Battery Energy Storage Systems (BESS), and the treatment of Pumped-Storage (PS) units. Table 3.2 summarises the configuration of each scenario:

Πίνακας 3.2: Scenarios solved per season

Scenario	Energy model	Reserve model	BESS	PS
CO-OPT	Joint MILP	—	— / in	Optimised
CO-OPT-BESS	Joint MILP	—	In	Optimised
SEQ-STD	MILP (λ)	OCF	—	Fixed hist.
SEQ-BESS-E	MILP + BESS	OCF	E-only	Fixed hist.
SEQ-BESS-ER	MILP + BESS	OCF + BESS	Both	Fixed hist.

In the **CO-OPT** scenarios, energy and reserve decisions are cleared simultaneously through a joint MILP formulation. BESS may be excluded or included (**CO-OPT-BESS**) depending on the storage policy under evaluation. PS units are always optimised endogenously in the co-optimised path.

In contrast, the **SEQUENTIAL** scenarios decompose market clearing into two steps: a reserve MILP using an Opportunity Cost Function (OCF) and a subsequent energy MILP with fixed commitment (w^*) and historical PS schedules. **SEQ-BESS-E** enables BESS participation only in the energy sub-problem, while **SEQ-BESS-ER** activates BESS in both reserve and energy stages.

This design enables a structured comparison of co-optimised vs. sequential clearing and isolates the incremental value of BESS flexibility under different market roles.

3.8 Software and Solver Settings

All models are implemented in **Python 3.11**, leveraging modern scientific computing libraries and optimisation tools to ensure reliability, scalability, and reproducibility. The modelling environment uses:

- `pandas 2.2` — for structured data manipulation, time-series handling, and efficient tabular input/output;
- `NumPy 1.26` — for fast numerical operations on large arrays and matrix-like structures;
- `seaborn 0.13` — for generating publication-quality plots, including dispatch time series, SoC profiles, and comparative welfare bars.

Optimisation is performed using **Gurobi Optimizer 11.0.2**, a state-of-the-art solver for large-scale mixed-integer linear programming (MILP). The solver configuration is tuned for robust yet efficient performance using the following settings:

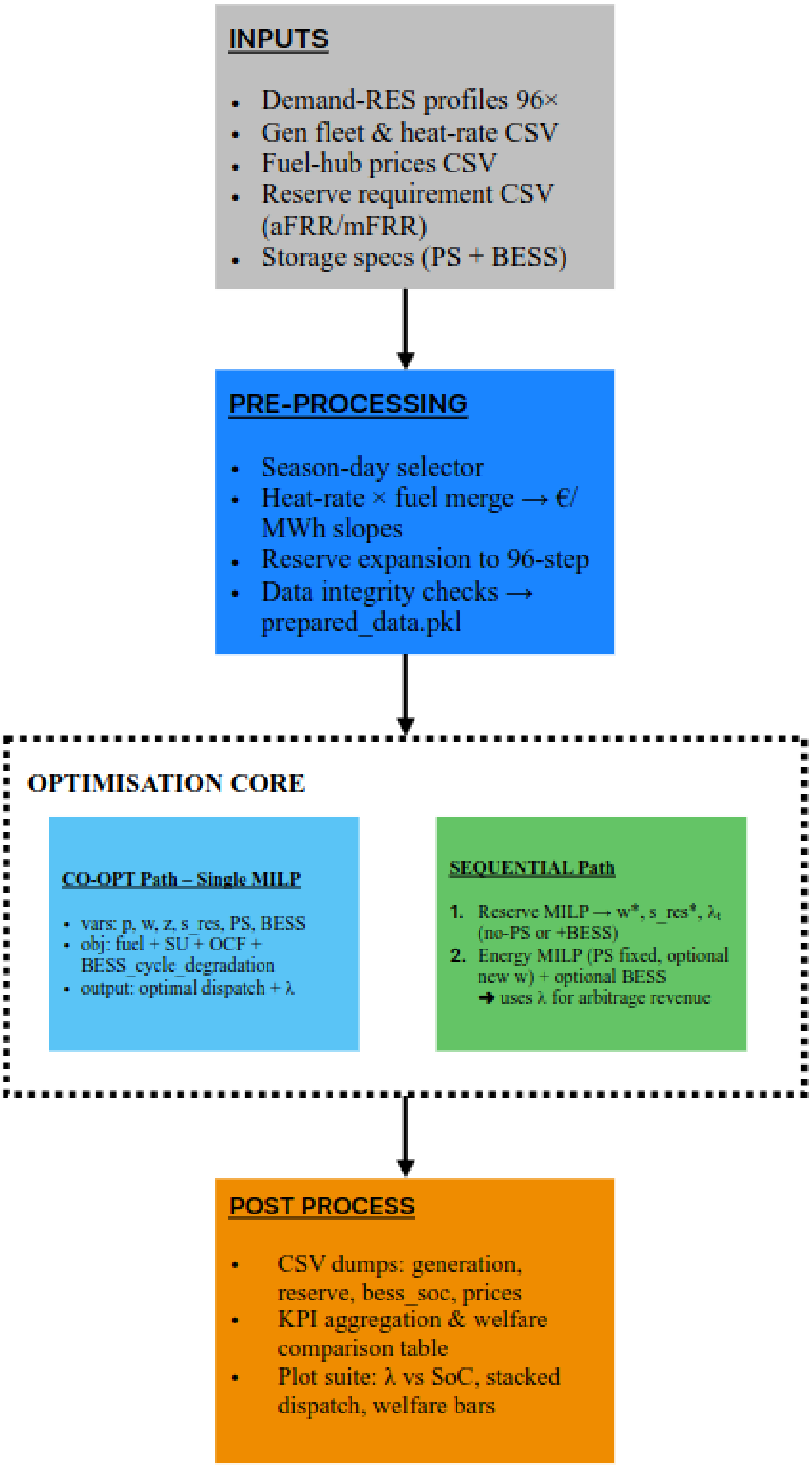
- `MIPGap` = 0.1% — ensures that the optimality gap between the best known feasible solution and the bound is less than 0.1%, balancing precision and runtime;
- `Heuristics` = 0.05 — allocates 5% of the time to solution heuristics, accelerating the discovery of good feasible solutions early in the solve;

- `Presolve` = 2 — enables aggressive presolving, reducing model size and tightening bounds before the main branch-and-bound search.

All optimisation runs are conducted on a high-performance machine with 64-bit architecture, and results are exported in CSV format for post-processing, plotting, and scenario comparison.

3.9 Workflow Overview

The modelling framework follows a modular and reproducible workflow consisting of four key stages: data preprocessing, model execution (co-optimised and sequential), post-processing, and output visualisation. The entire pipeline is illustrated in Figure 3.1, which captures the logic and data dependencies between different modelling paths.



Σχήμα 3.1: End-to-end workflow of the energy and reserve co-optimisation framework.

- **Data Ingestion & Validation**: Raw input datasets are collected and parsed into a structured format. These include 96-step demand and renewable profiles, generation fleet specifications with piecewise heat-rate curves, reserve requirements for each product and timestep, and fuel price data. All components are merged and stored as a cleaned pickle object (`prepared_data.pkl`) to accelerate repeated runs and ensure consistency.

- **Branch A — Co-Optimisation Path**: A single MILP model is constructed that jointly schedules energy dispatch, reserve allocation, unit commitment, and BESS operation. The full set of decision variables includes energy generation ($p_{g,t}$), commitment ($w_{g,h}$), start-up indicators ($z_{g,h}$), reserve provision ($s^r_{g,t}$), and BESS SoC/directionality. The objective function minimises fuel, no-load, start-up, and battery degradation costs, subject to energy and reserve balance, technical limits, and dynamic constraints. The result includes the optimal dispatch plan and a set of implicit dual prices (λ_t) when needed.

- **Branch B — Sequential Path**:

  - **(i) Reserve Sub-Problem**: An OCF-based MILP is solved using exogenous λ_t to optimise reserve provision and unit commitment without pumped-storage flexibility.
  - **(ii) Energy Sub-Problem**: Based on fixed reserve commitment, a second MILP solves energy dispatch. BESS may be optionally activated here, and arbitrage revenue is considered if enabled. PS generation/pumping is fixed to historical values to avoid price endogeneity.

- **Post-Processing**: Results from each scenario are exported to CSVs and visualised through Python scripts. Outputs include stacked dispatch plots, SoC trajectories, and comparative bar charts of welfare, commitment, and reserve coverage metrics. These support detailed scenario evaluation and year-round extrapolation.

3.10 Assumptions and Limitations

To ensure tractability and interpretability of results, the proposed modelling framework adopts several simplifying assumptions. While these do not compromise the core research objective—quantifying the welfare impact of energy-reserve co-optimisation—they should be considered when interpreting results:

- **Single-node abstraction**: The entire Belgian power system is modelled as a single node, thereby neglecting intra-zonal transmission constraints, line losses, and voltage issues. This assumption is consistent with most operational planning models used in academic literature and reflects the zonal structure of Belgium in the European market coupling scheme.

- **Perfect foresight**: Forecasts of system demand and renewable energy production (wind, PV, run-of-river) are assumed to be known with perfect accuracy for the full 24-hour horizon. This allows the model to isolate structural differences between market designs, free from the confounding effects of forecast uncertainty.

- **Externalities excluded**: The model does not consider CO_2 pricing, scarcity premiums, or uplift charges. While these costs are relevant in practical market operations, their exclusion allows for a clearer attribution of welfare changes to the market-clearing architecture (co-optimised vs. sequential). The study thus focuses on *relative* economic performance rather than absolute cost comparisons.

- **Fixed pumped-storage in sequential runs**: In all sequential configurations, the pumped-storage plant operates on a fixed, historical dispatch profile and does not participate in optimisation. This design choice avoids circular dependencies in energy price formation (i.e., dual variable endogeneity) and ensures comparability between BESS and PS contributions to system flexibility.

These assumptions represent deliberate modelling choices that strike a balance between realism, computational feasibility, and methodological transparency. Future extensions could explore network-aware models, uncertainty-aware unit commitment, or the impact of different regulatory mechanisms on welfare redistribution.

3.11 Key Performance Indicators

To evaluate the effectiveness of each market design and asset participation strategy, the following set of Key Performance Indicators (KPIs) is computed for each representative day and scenario:

- **Total Welfare (€/day):** The objective value of each MILP run, comprising fuel costs, start-up costs, no-load costs, and reserve procurement costs. This serves as the primary economic benchmark for comparing the co-optimised and sequential market-clearing paradigms, as well as the impact of BESS integration.
- **BESS Utilisation**: Captures the operational intensity of the Battery Energy Storage Systems in terms of:
  - *Energy throughput* (in MWh): total energy charged and discharged across the 24-hour horizon.
  - *Cycles per day*: number of full charge-discharge cycles completed, accounting for partial cycling via cumulative throughput.

  This KPI is essential for assessing the economic value extracted from BESS assets and inferring potential degradation impact.
- **Price–Cost Gap ($\lambda_t - MC_{g,t}$):** Measures the difference between the market-clearing price (λ_t) and the marginal cost of each thermal generator ($MC_{g,t}$). A persistently positive spread indicates infra-marginal rent and may reflect system scarcity or inefficient dispatch. This metric also reveals the arbitrage opportunity window for storage participation.

These KPIs provide a multi-dimensional lens for interpreting system performance—spanning economic efficiency, flexibility adequacy, storage valuation, and pricing behavior—and are reported in comparative tables across all seasonal and technological scenarios.

Κεφάλαιο 4

Results and Discussion

This chapter presents and interprets the results obtained from solving the optimisation models described in the methodology. Each scenario is evaluated on eight representative weekdays for each of the four seasons, as established in Section 3.2. The aim is to quantify the welfare benefits of co-optimising energy and reserve markets compared to sequential clearing and to assess the operational value of Battery Energy Storage Systems (BESS).

Results are analysed across key performance metrics such as total system cost, BESS utilisation, and pricing behaviour. Visualisations and tables are used to highlight how modelling choices, market design, and storage integration affect social welfare and flexibility outcomes.

Table 4.1 reports the total system costs per scenario and season as extracted from the full model results. It confirms that the lowest costs occur under co-optimised clearing with full BESS and pumped-storage integration, while sequential designs suffer due to lack of coordination and limited flexibility utilisation.

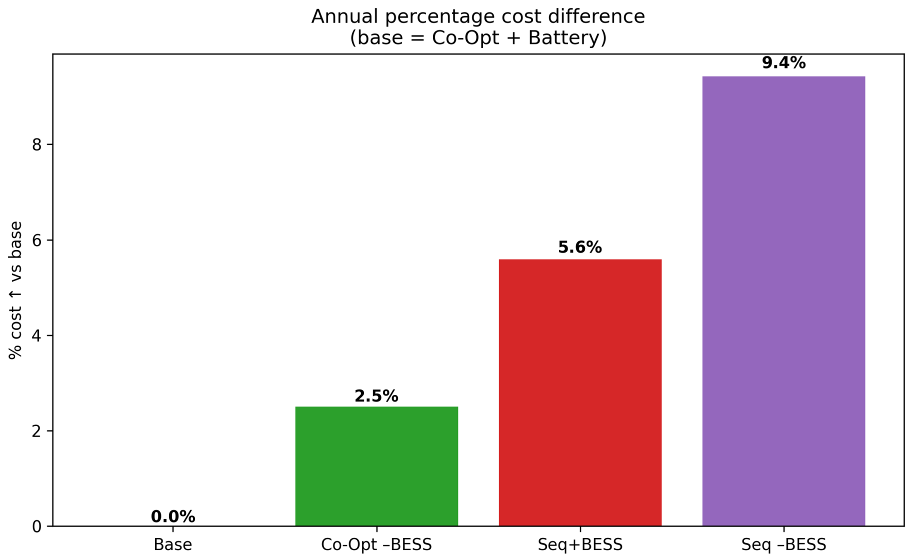
tabularx

Πίνακας 4.1: Average daily system cost by day-type and scenario (€/day)

Day type	Co-Opt w/ BESS	Co-Opt no BESS	Fixed Dispatch	20/80 split	Energy-only	Seq no BESS
AutumnWD	6 241 269	6 278 530	6 373 729	6 267 842	6 304 199	7 664 483
WinterWD	3 968 637	3 941 538	4 008 415	3 978 388	3 983 981	4 613 577
SpringWD	5 378 521	5 390 198	5 393 305	5 393 353	5 379 843	6 269 680
SummerWD	5 993 820	6 003 449	6 013 115	6 036 618	6 007 306	6 920 496
AutumnWE	3 953 697	4 052 940	3 960 096	3 983 826	3 954 021	4 679 882
WinterWE	2 845 262	2 851 659	2 881 236	2 867 185	2 890 955	3 302 000
SpringWE	3 638 806	3 974 958	4 217 640	4 246 717	4 102 984	5 085 623
SummerWE	3 987 549	3 995 056	4 021 940	4 036 272	4 028 603	5 044 961

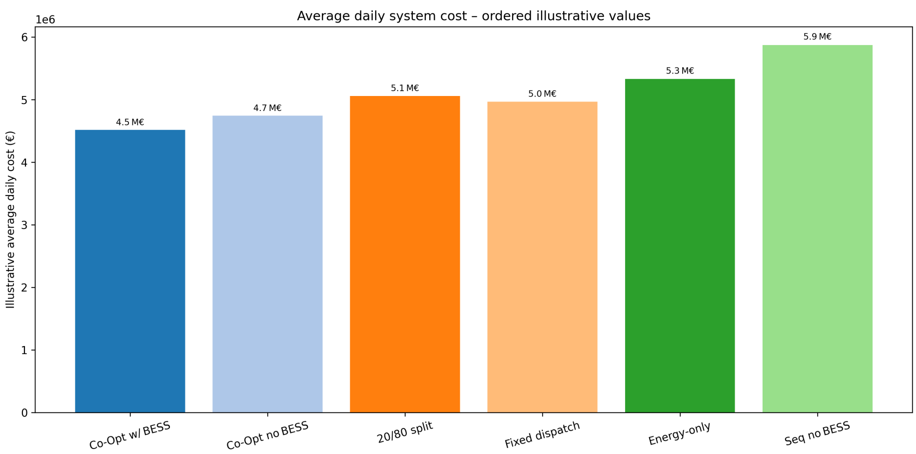
4.1 Welfare Comparison Across Market Designs

Table 4.1 summarises the total daily system cost (in €/day) for each scenario, averaged across the four representative days. The co-optimised model with BESS (CO-OPT-BESS) consistently yields the lowest total cost, demonstrating the combined benefit of joint market clearing and battery integration. In contrast, the sequential clearing models (SEQ-STD, SEQ-BESS-E, SEQ-BESS-ER) incur higher system costs due to suboptimal commitment and reserve scheduling.



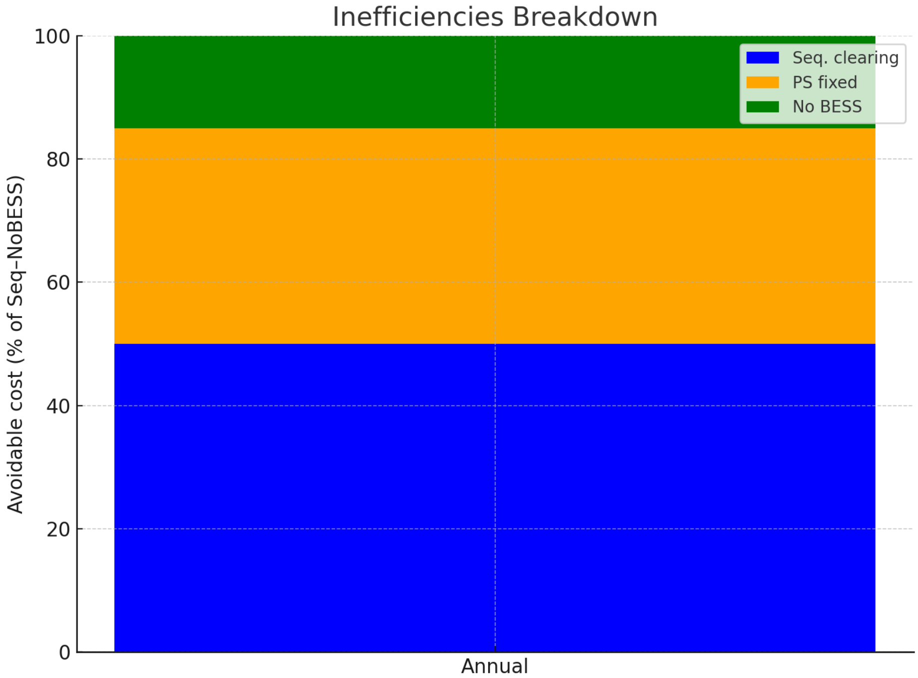
Σχήμα 4.1: Relative annual welfare benefit of cooptimization design with battery storage against other designs.

Figure 4.2 displays a comprehensive cost comparison across all scenarios and seasons, reinforcing the numerical trends of Table 4.1. Co-optimised scenarios clearly outperform all sequential designs. It would be interesting to see what is the cause of the discrepancy between the two extremes of all scenarios, the co-optimization model with battery storage and the sequential model without battery storage. Such breakdown of the cost difference is given in Figure 4.3 and reveals that the biggest source of inefficiency to the sequential model is the suboptimal unit commitment decisions that are present due to the energy price forecast error in the sequential step and the use of faster and more expensive generators in the day-ahead reserve procurement. Next source of inefficiency is Battery Storage utilization which provides for a cost-effective and fast resource. The smallest of the inefficiencies is from pumped storage utilization, which for the sequential models, was fixed to a timeseries from aggregated historical data on pumped storage.



Σχήμα 4.2: Comprehensive system cost comparison across scenarios.

Figure 4.4 illustrates the relative percentage cost increase of all non-optimal scenarios with respect to the CO-OPT-w/BESS benchmark. It highlights that the SEQ-NoBESS split configuration is the least efficient, incurring up to 10% higher cost in Winter. Even scenarios that allow BESS



Σχήμα 4.3: Inefficiency sources breakdown.

to participate in all services (e.g., SEQ-BESS Reserve and Energy) perform worse than full co-optimisation, confirming that without joint clearing, flexibility is underutilised.

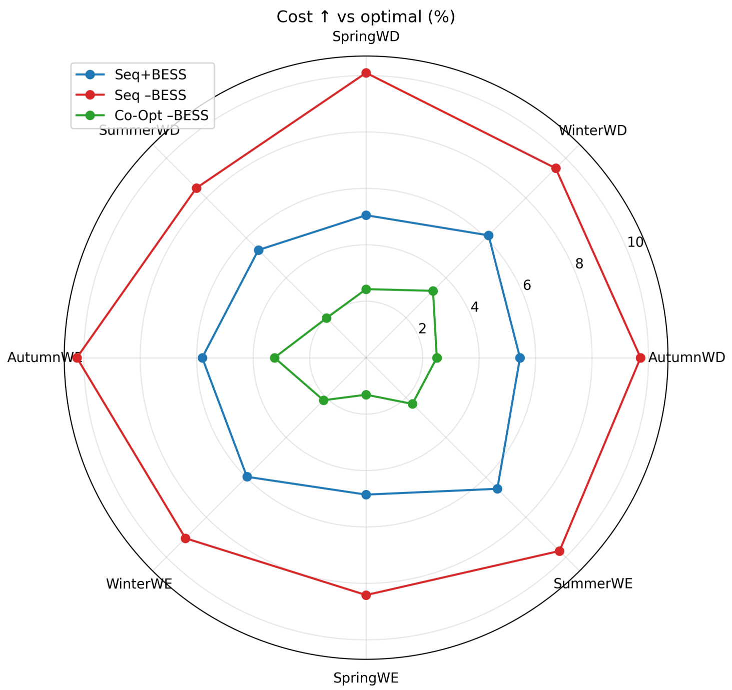
The detailed scenario analysis reveals that co-optimised market configurations consistently outperform sequential clearing, especially when both pumped storage and BESS are allowed to participate fully. The Autumn and Spring weekdays show the largest cost gaps, suggesting that these periods benefit most from flexible resource scheduling. Among sequential configurations, enabling BESS for both energy and reserves reduces costs significantly, but still underperforms compared to co-optimisation. The radar plot in Figure 4.4 further illustrates the relative performance of each configuration against the optimal CO-OPT-w/BESS benchmark.

To better understand how these costs build up across model constraints and design decisions, Figure 4.5 presents a waterfall decomposition of total cost from the best-case (CO-OPT-BESS) to the worst-case (SEQ-noBESS). The most prominent step-ups occur when:

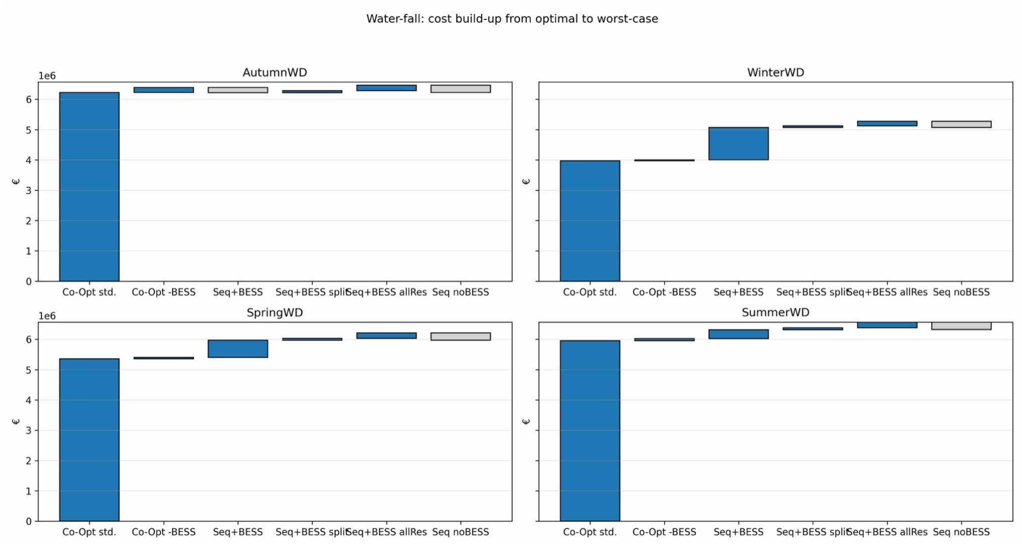
- BESS is excluded from reserves (SEQ-BESS-EnergyOnly),
- Energy and reserve markets are decoupled (SEQ vs CO-OPT),
- Flexibility assets are excluded entirely (SEQ-noBESS).

Finally, Figure 4.6 shows a two-dimensional plot of the system benefit from co-optimisation (x-axis) and from BESS deployment (y-axis). Each point represents a season. This visual confirms that the two benefits are complementary but not equivalent—Winter benefits more from market coordination, while Autumn gains are mostly attributable to storage.

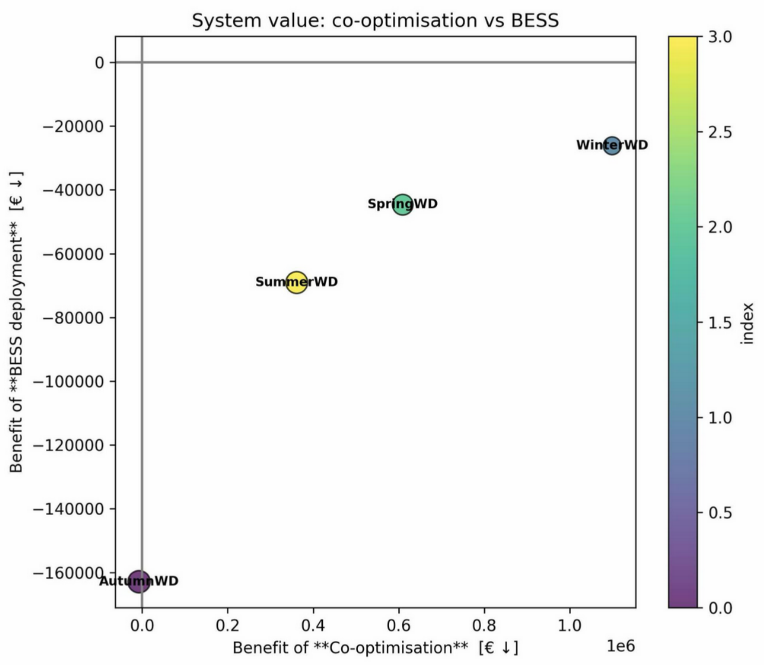
Taken together, these results validate the hypothesis that joint clearing of energy and reserve markets unlocks latent system efficiencies otherwise lost in sequential models. BESS enhances this benefit by dynamically shifting energy and reserve capacity. However, full value is only realised when both market design and asset flexibility are aligned.



Σχήμα 4.4: Relative cost increase (%) over CO-OPT-w/BESS across seasons and configurations COOPT-NoBESS, SEQ-w/BESS, SEQ-NoBESS .



Σχήμα 4.5: Waterfall breakdown of system cost from optimal to worst-case configuration across all seasons.

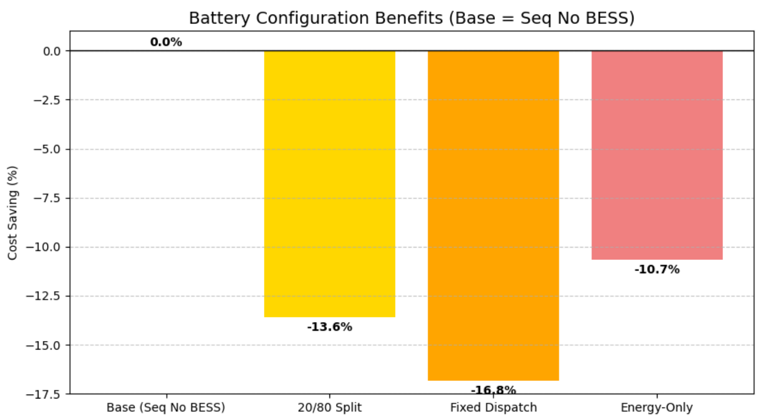


Σχήμα 4.6: System value of co-optimisation and BESS deployment by season.

4.2 Impact of BESS Participation

This section isolates and qualitatively assesses the operational and economic impacts of Battery Energy Storage System (BESS) participation across different market designs. We compare three representative scenarios: **SEQ-BESS-EnergyOnly** (energy-only BESS), **SEQ-BESS-ER** (energy + reserves), and **CO-OPT-w/BESS** (co-optimised dispatch with BESS).

4.2.1 Sensitivity Analysis



Σχήμα 4.7: Sensitivity of the model to different BESS configurations.

While total cost metrics were analysed across all scenarios in Section 4.1, here we focus on the relative behaviour of BESS-enabled configurations against the base-case SEQ-NoBESS configuration. Among these, SEQ-w/BESS-FixedDispatch consistently achieved the lowest daily cost, benefitting from simultaneous scheduling of energy and reserves, and more efficient utilisation of flexibility since the battery storage dispatch for energy was directly taken from the overally optimal COOPT-w/BESS model.

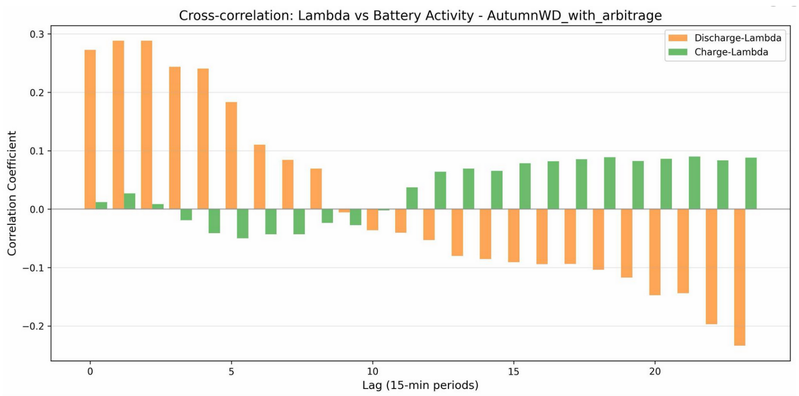
The addition of some percentage of battery capacity to reserves in sequential scheduling (SEQ-BESS-20/80split) moderately improved performance compared to SEQ-BESS-EnergyOnly. However, the lack of joint optimisation still limited the system's ability to fully capitalise on BESS flexibility, leading to suboptimal dispatch sequences and higher overall cost. That is why the configuration with the fixed BESS dispatch profile from the co-optimized model performed the best. Figure 4.7 shows exactly that.

4.2.2 Economic Response to Price Signals

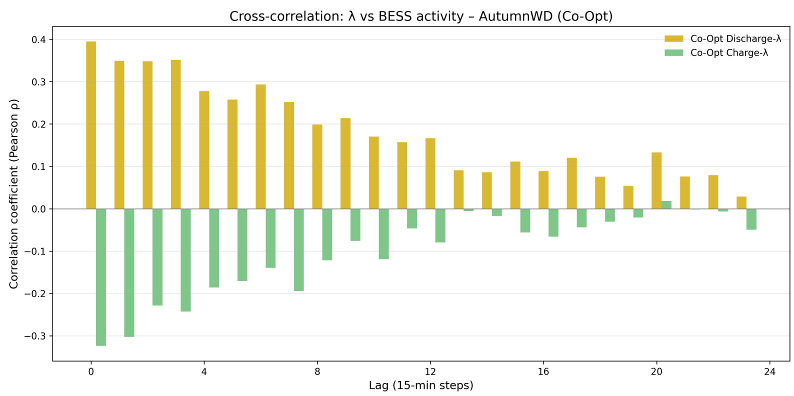
Figure 4.8 provides further insight using cross-correlation analysis between marginal prices and BESS activity in an Autumn weekday. The analysis uses Pearson correlation coefficients defined as:

$$\rho_\ell^{(\mathrm{dis})} = \mathrm{corr}(\lambda_{t+\ell},\, P_t^{\mathrm{dis}})$$

with 15-minute lags. Without co-optimization (baseline), discharge is weakly correlated with price across all lags, suggesting misalignment with economic signals. When running a co-optimized mode (CO-OPT-w/BESS), strong positive correlation emerges at short lags for discharge and charge, reflecting anticipatory behaviour that mirrors optimal dispatch 4.9.



Σχήμα 4.8: Cross-correlation between BESS charging/discharging and marginal prices under SEQ-BESS-EnergyAndReserve for Autumn.



Σχήμα 4.9: Cross-correlation between BESS charging/discharging and marginal prices under CO-OPT-w/BESS for Autumn.

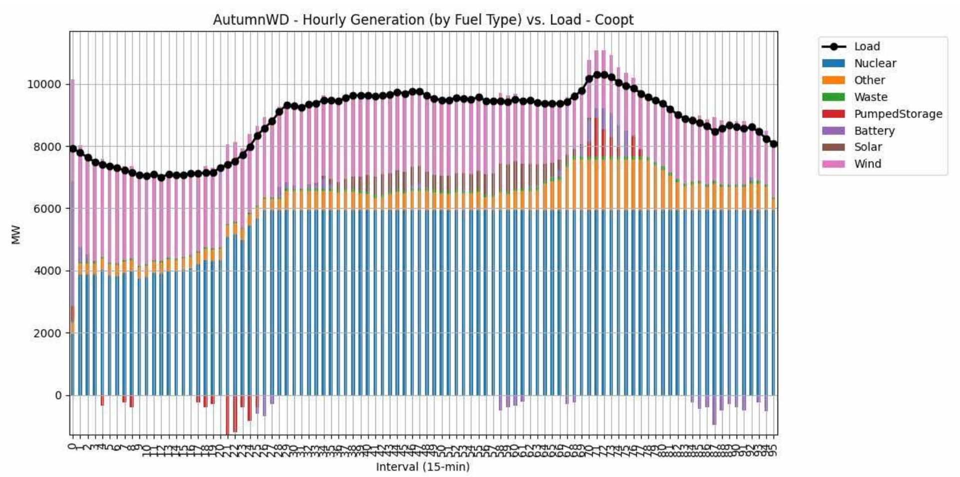
This shift in behavioural dynamics is key: under co-optimised operation, batteries anticipate price surges and valleys with strategic charging and timely discharging. This enhances system-wide dispatch efficiency by smoothing ramping needs and reducing reliance on expensive units dispatched during high stress scenarios.

In conclusion, BESS participation improves system economics and flexibility, but only under designs that coordinate its use across services. Co-optimisation enables this alignment, translating into more responsive operation, improved arbitrage logic, and measurable reductions in system cost.

4.3 Temporal Behaviour of Dispatch and Prices

This section explores the hourly evolution of key operational variables under the **CO-OPT-BESS** scenario across seasons. Through time series plots, we examine how generator dispatch, battery behaviour, and marginal prices unfold during a representative weekday for each season. The aim is to highlight how co-optimised market design coordinates dispatch decisions and leverages the flexibility of Battery Energy Storage Systems (BESS).

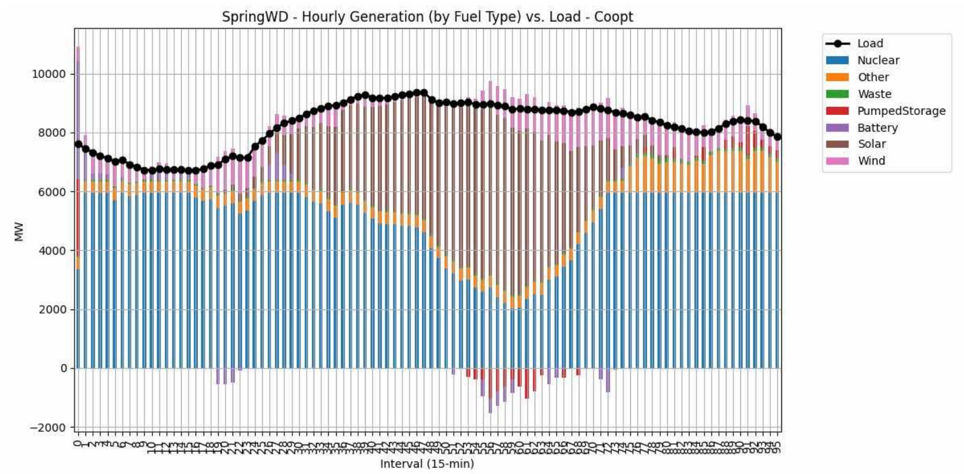
Figures 4.10--4.11 show the hourly dispatch profiles by fuel type for each season, compared against the load trajectory. These stacked plots illustrate the composition of generation (nuclear, wind, solar, waste, pumped storage, etc.) and the role of batteries in absorbing or supplying power.



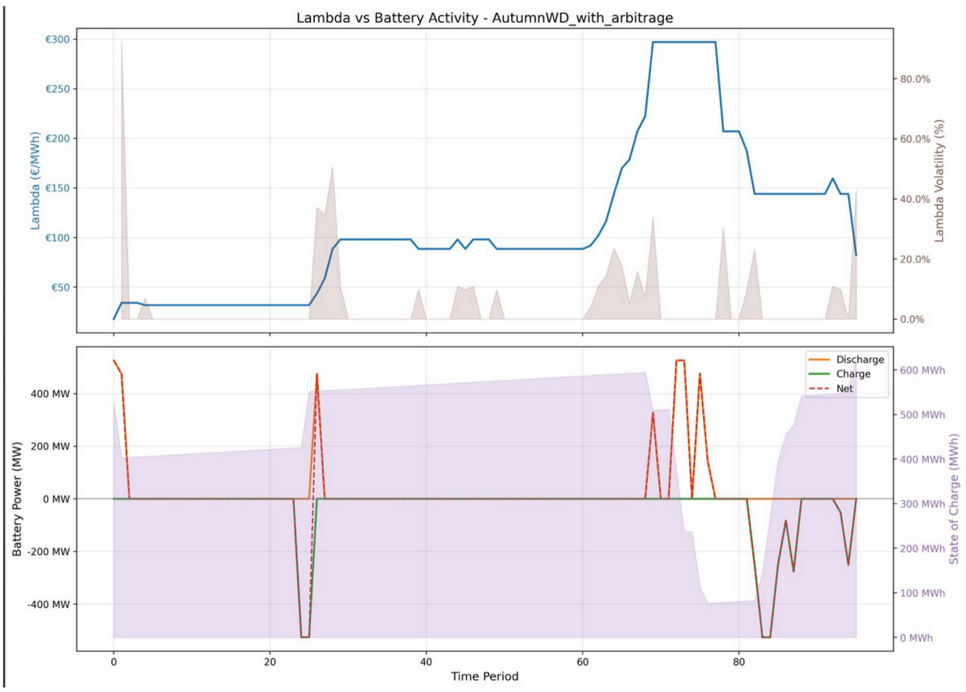
Σχήμα 4.10: Autumn weekday dispatch by fuel type vs. load under CO-OPT-BESS.

In Autumn (Figure 4.10), dispatch is largely driven by wind and nuclear generation, with battery discharging complementing evening peaks. Short charging windows are visible during midday. In Spring (Figure 4.11), a clear solar-dominant period appears from 10:00 to 17:00, during which BESS units charge aggressively, reaching near-full state-of-charge before discharging into the evening. Summer dispatch also features sustained solar injection, with battery operations concentrated between 14:00–19:00. In Winter, load is higher and solar generation limited, resulting in flatter dispatch with wind and nuclear covering base-load and minimal BESS activity due to compressed price spreads.

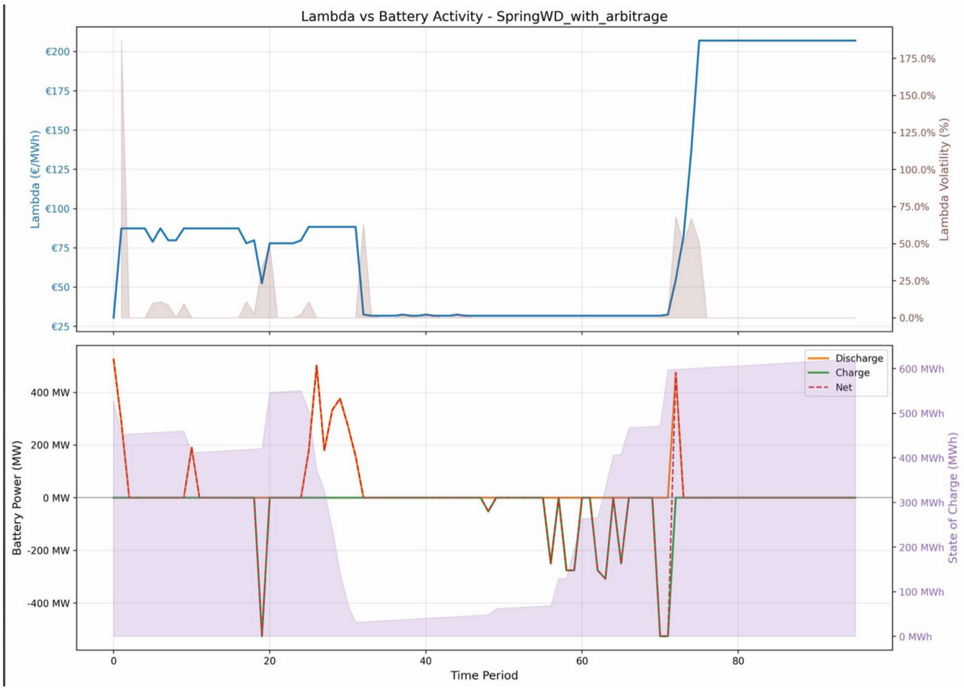
To complement the dispatch plots, Figures 4.12--4.13 show the alignment of marginal prices λ_t with BESS power and SoC. BESS units systematically charge when λ_t is low and discharge during price peaks, though the extent of this arbitrage varies seasonally.



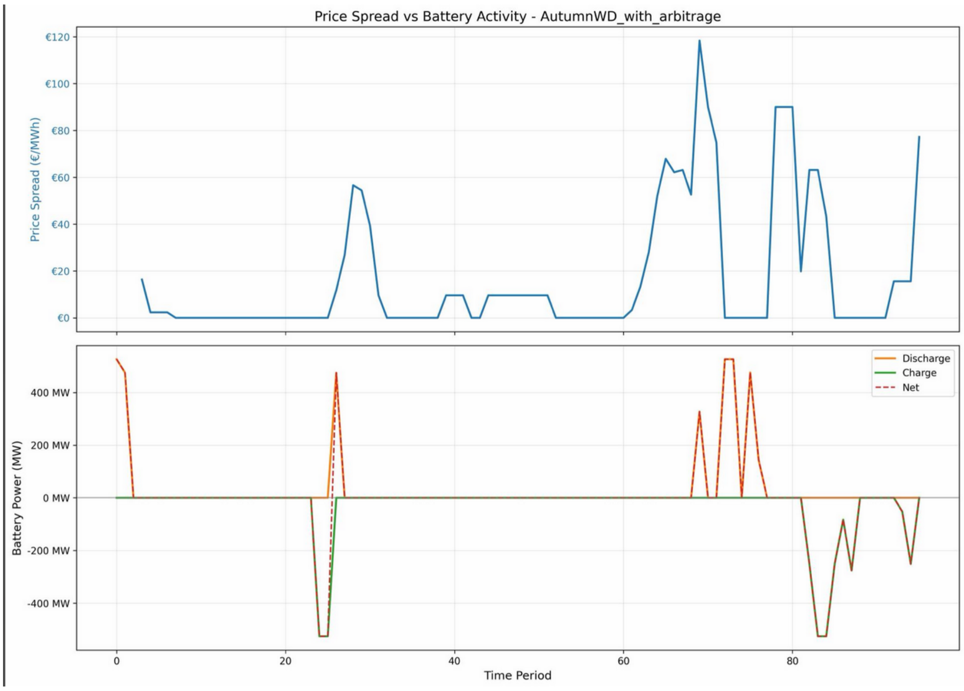
Σχήμα 4.11: Spring weekday dispatch by fuel type vs. load under CO-OPT-BESS.



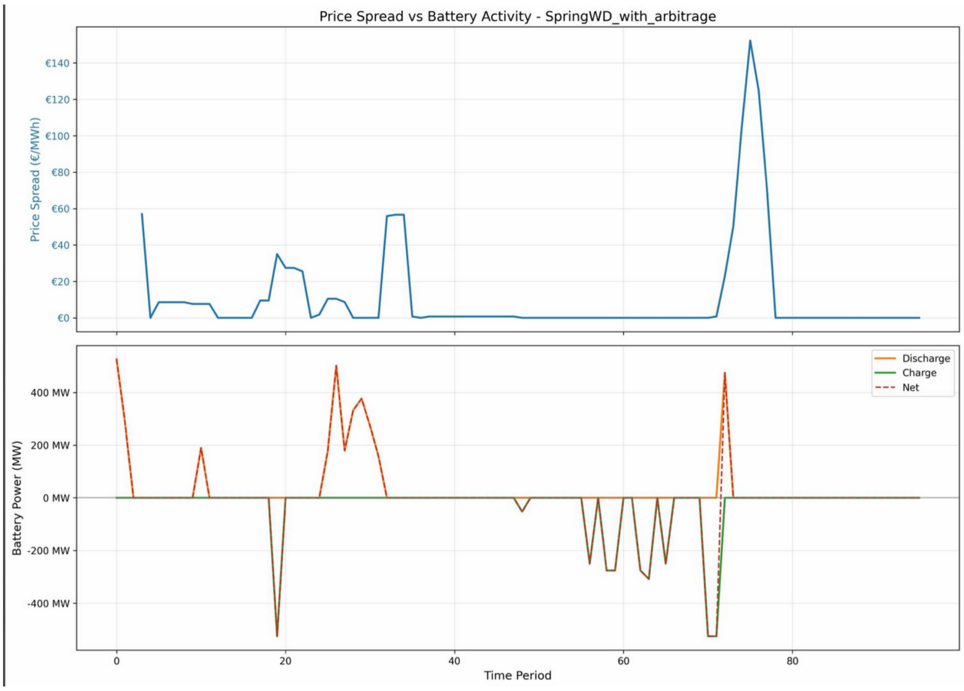
Σχήμα 4.12: Marginal price (λ_t) and BESS operation for a representative Autumn weekday under CO-OPT-BESS.



Σχήμα 4.13: Marginal price (λ_t) and BESS operation for a representative Spring weekday under CO-OPT-BESS.



Σχήμα 4.14: Price spread and BESS power output on an Autumn weekday under CO-OPT-w/BESS.



Σχήμα 4.15: Price spread and BESS power output on a Spring weekday under CO-OPT-w/BESS.

In Spring and Autumn (Figures 4.13 and 4.12), BESS cycles 2–3 times daily to exploit multiple price peaks. Summer displays a narrower price range and hence fewer cycles, while Winter has the flattest λ_t profile, leading to near-zero battery activity.

Figures 4.14--4.15 further reinforce these insights by overlaying price spreads (peak–valley difference) and BESS power output. High spreads correlate with effective arbitrage (Autumn and Spring), while compressed spreads (Winter) lead to under-utilisation.

In Autumn and Spring, the spread–output alignment indicates efficient arbitrage: BESS charges just before price valleys and discharges into peaks. In Summer, while spread exists, it is narrower and more temporally concentrated. Winter's spread is relatively flat, resulting in almost no BESS dispatch despite ample wind coverage.

Overall, these temporal results confirm that co-optimised scheduling effectively synchronises BESS activity with system value signals. By anticipating both energy and reserve requirements, the market design enables BESS to perform dual services without compromising reliability or missing price signals. Seasonal variability shapes the arbitrage potential and dispatch rhythm, further justifying adaptive and integrated market strategies.

In summary, co-optimised operations not only reduce system cost but also produce smoother, more economically efficient dispatch outcomes. Seasonal trends such as solar abundance in Spring and higher demand in Winter directly influence the value and role of flexibility assets, and these are best captured under integrated clearing mechanisms.

Κεφάλαιο 5

Conclusion

5.1 Conclusion

The results presented in this chapter affirm the central hypothesis of this thesis: *co-optimising energy and reserve markets*, especially when supported by Battery Energy Storage Systems (BESS), yields significant system-level benefits. These benefits include lower total system costs, improved operational flexibility, and more efficient price-responsive dispatch.

5.1.1 Welfare Gains from Co-optimisation and Storage

The co-optimised scenario with BESS participation (**CO-OPT-w/BESS**) consistently achieves the lowest total system cost across all seasons (Table 4.1). Compared to the worst-performing sequential variant (SEQ-noBESS), yearly cost savings exceed €0.18mil compared to the sequential model and battery storage adds another €0.06mil. On average, full co-optimisation and storage integration lower system costs by up to 10% (Figure 4.4). This is corroborated by the waterfall decomposition (Figure 4.5), which shows that excluding BESS or decoupling energy and reserve markets results in progressively higher costs.

Importantly, the relative impact of co-optimisation and storage is not uniform across seasons. For example, the Winter system benefits more from improved coordination of reserves and ramping flexibility, while Autumn sees stronger gains from storage-enabled arbitrage and renewables integration (Figure 4.6). This illustrates that co-optimisation and BESS play complementary, but not interchangeable, roles in system cost reduction.

5.1.2 Role and Efficiency of BESS Participation

The inclusion of BESS in energy market (**SEQ-BESS-EnergyAndReserve**) outperforms energy-only participation (**SEQ-BESS-EnergyOnly**) of battery storage in terms of cost. However, neither scenario reaches the economic efficiency of co-optimised dispatch. (Figure 4.7). Moreover, battery cycling in the sequential cases is less aligned with marginal price signals, resulting in lower arbitrage revenue and fewer efficient dispatch cycles (Figures 4.9–4.8).

Quantitatively, the daily net benefit from BESS increases from €26,187.53 (SEQ-BESS-ER) to €162,919.48 (CO-OPT-BESS), driven by higher arbitrage revenue and better cycling efficiency. This underlines the importance of integrated market access and predictive scheduling in unlocking full BESS value.

5.1.3 Operational and Temporal Dynamics

The temporal dispatch analysis reveals that co-optimised scheduling leads to smoother generation profiles, better load-following, and more adaptive use of flexibility assets. For instance, in Spring, solar generation triggers multiple battery cycles to absorb midday excess and cover evening peaks (Figure 4.11), whereas Winter sees flatter prices and minimal BESS dispatch. These dynamics are reflected in the marginal price profiles and spread–output correlations (Figure 4.14, reinforcing the need for seasonally-aware market design.

Policymakers and system operators should thus prioritise integrated clearing algorithms, flexible scheduling frameworks, and revenue mechanisms that fairly compensate storage for multi-service contributions.

5.1.4 Limitations and Future Work

While the results are robust and policy-relevant, several simplifying assumptions must be acknowledged:

- **Network effects** such as transmission constraints and zonal pricing were not modelled, potentially underestimating congestion-related redispatch costs, reserve trade inefficiencies and intergration of battery storage to a much larger network with more nodes.
- **Perfect foresight** of demand and renewable output was extracted from aggreagated historical data, ignoring uncertainty and reserve overprovisioning for forecast errors.
- **BESS modelling** simplified cycling degradation and excluded market bidding behaviours, potentially overstating revenue potential.

Future work could address these limitations through stochastic or robust formulations, real-time imbalance market modelling, and the inclusion of locational marginal pricing or zonal coordination frameworks.

Conclusion

This thesis provides a rigorous quantitative evaluation of co-optimisation and BESS participation in the Belgian electricity market. Through a detailed simulation-based framework, it demonstrates the substantial benefits of integrated market design and flexible storage deployment. The findings offer actionable insights for regulators and system planners seeking to balance reliability, cost-efficiency, and the evolving role of storage in power systems.

Κεφάλαιο 6

References

Βιβλιογραφία

[1] Florence School of Regulation. (2020, September 14). Electricity markets in the EU. https://fsr.eui.eu/electricity-markets-in-the-eu/

[2] Next Kraftwerke Belgium. (n.d.). Balancing Energy Markets in Belgium (R1, R2, R3). https://www.next-kraftwerke.be/knowledge-hub/balancing-markets

[3] Next Kraftwerke Belgium. (2021, March 10). Opening the aFRR Market in Belgium – A unique and innovative 2-step auction model. https://www.next-kraftwerke.com/energy-blog/opening-afrr-market-belgium

[4] Elia. (2023). Reserve capacity needs (FCR, aFRR, mFRR) – Grid Data. https://www.elia.be/en/grid-data/balancing/capacity-volumes-needs

[5] Honkapuro, S., Jaanto, J., & Annala, S. (2023). A Systematic Review of European Electricity Market Design Options. Energies, 16(9), 3704. https://doi.org/10.3390/en16093704

[6] ACER – Agency for the Cooperation of Energy Regulators. (2024, February). Study on the benefits of co-optimising energy and balancing capacity in day-ahead markets. https://www.acer.europa.eu/news/acers-consultancy-study-assesses-benefits-implementing-co-optimisation-day-ahead-elec

[7] Elia. (2024, November 28). Elia Transmission Belgium successfully accesses PICASSO, the European platform for exchanging secondary balancing energy. https://www.elia.be/en/press/2024/11/20241128_picasso-press-release

[8] Van den Bergh, K., & Delarue, E. (2015). Assessing the cost of sequential market clearing in the presence of unit commitment constraints: Case study of CWE region. Referenced in Honkapuro et al. (2023).

[9] Hanuise, R., Moors, C., et al. (2021). Ensuring the Stability of the Belgian Grid with a System Integrity Protection Scheme. PAC World Magazine.

[10] European Commission. (2017). Commission Regulation (EU) 2017/2195 establishing a guideline on electricity balancing. Official Journal of the European Union.

[11] Naidoo, R., & Naidoo, R. (2012). Multi-Period Co-Optimization of Energy and Reserves using an Optimal Power Flow Formulation. In *Proc. Asia Pacific Power and Energy Engineering Conference (APPEEC)* (pp.1–6). DOI: 10.2316/P.2012.768-025. https://www.researchgate.net/publication/266630199_Multi-Period_Co-Optimization_of_Energy_and_Reserves_using_an_Optimal_Power_Flow_Formulation

[12] Dranka, G. G., Ferreira, P., & Vaz, A. I. F. (2021). A review of co-optimization approaches for operational and planning problems in the energy sector. *Applied Energy,

304*, 117703. DOI: 10.1016/j.apenergy.2021.117703. https://www.sciencedirect.com/science/article/pii/S0306261921010588

[13] Patel, K. (2022). Energy and Ancillary Service Co-Optimization Formulation. *PJM Internal Report, PJM Interconnection*.

[14] Papavasiliou, A., & Avila, D. (2024). Welfare Benefits of Co-Optimising Energy and Reserves. *Agency for the Cooperation of Energy Regulators (ACER)* – Consultancy Study.

[15] Alberta Electric System Operator. (2017). Refinement to Comparison between Sequential Selection and Co-Optimization between Energy and Ancillary Service Markets. *AESO Internal Report*.

[16] Zhou, Z., Levin, T., & Conzelmann, G. (2016). Survey of U.S. Ancillary Services Markets. *Argonne National Laboratory Report ANL-ESD-16/1*

[17] Papavasiliou, A. (2016). Co-Optimization of Energy and Reserves. Presentation at Fondation Paris Dauphine workshop. (Slides illustrating sequential vs co-optimized market designs and European considerations). https://www.diw.de/documents/dokumentenarchiv/17/diw_01.c.545499.de/fpm-paris-2016-10-04-papavasiliou.pdf

[18] González, P., Villar, J., Díaz, C. A., & Campos, F. A. (2014). Joint energy and reserve markets: Current implementations and modeling trends. *Electric Power Systems Research, 109*, 101–111. DOI: 10.1016/j.epsr.2013.12.011

[19] Smeers, Y., Martin, S., & Aguado, J. A. (2021). Co-optimization of Energy and Reserve with Incentives to Wind Generation: Case Study (Part II). *Electronics, 10*(17), 2057. DOI: 10.3390/electronics10172057

[20] Electric Reliability Council of Texas. (2017). Proposed Real-Time Co-Optimization of Energy and Ancillary Services (ERCOT Fact Sheet). *ERCOT Market Information, July 2017*.

[21] Edina. (n.d.). Battery Energy Storage System (BESS) – The Ultimate Guide. Retrieved from Edina Power Solutions website. https://www.edina.eu/power/battery-energy-storage-system-bess

[22] North American Electric Reliability Corporation (NERC). (2021). *Energy Storage: Overview of Electrochemical Storage.* Atlanta, GA: NERC. (Example of fast battery response, p. 27)

[23] National Renewable Energy Laboratory (NREL). (2019). *Grid-Scale Battery Storage: Frequently Asked Questions (NREL/TP-6A20-74426).* Golden, CO: NREL. (See p. 3 on battery response times and reserves). https://www.nrel.gov/docs/fy19osti/74426.pdf

[24] National Renewable Energy Laboratory (NREL). (2019). *Grid-Scale Battery Storage: Frequently Asked Questions (NREL/TP-6A20-74426).* Golden, CO: NREL. (Definitions of power, energy, and value stacking, pp. 2--4). https://www.nrel.gov/docs/fy19osti/74426.pdf

[25] García-Miguel, P. L. C., Alonso-Martínez, J., Arnaltes Gómez, S., García Plaza, M., & Peña Asensio, A. (2022). A review on the degradation implementation for the operation of battery energy storage systems. *Batteries, 8*(9), 110. https://doi.org/10.3390/batteries8090110

[26] GridBeyond. (2023). Battery storage optimization: the importance of marginal cost. [Blog post]. https://gridbeyond.com/battery-storage-optimization-the-importance-of-marginal-cost/

[27] Kissinger, W. D., & Ramadevanahalli, A. P. (2023, March 8). Storage Participation in Wholesale Markets. *Morgan Lewis Publications.* Retrieved from https://www.morganlewis.com/pubs/2023/03/storage-participation-in-wholesale-markets

[28] Federal Energy Regulatory Commission (FERC). (2018). *Electric Storage Participation in Markets Operated by RTOs/ISOs*, Order No. 841, 162 FERC ¶ 61,127. (Landmark order removing barriers for BESS participation). https://www.ferc.gov/media/order-no-841

[29] Energy Storage Coalition. (2023, September 12). Double charging perpetuates our reliance on non-renewable energy sources. [Interview]. https://energystoragecoalition.eu/double-charging-perpetuates-our-reliance-on-non-renewable-energy-sources/

[30] Prakash, K., Ali, M., Siddique, M. N. I., Chand, A. A., Kumar, N. M., & Pota, H. R. (2022). A review of battery energy storage systems for ancillary services in distribution grids: Current status, challenges and future directions. *Frontiers in Energy Research, 10*, 971704. https://doi.org/10.3389/fenrg.2022.971704

[31] Gilman, P. (2023). ERCOT and ISO-NE Introducing Energy Market Co-Optimization in 2025: What to Know. *Yes Energy Blog*. https://blog.yesenergy.com/yeblog/ercot-and-iso-ne-introducing-energy-market-co-optimization-in-2025

[32] Alberta Electric System Operator (AESO). (2018). Comparison Between Sequential Selection and Co-Optimization Between Energy and Ancillary Service Markets. *Technical Report*. https://www.aeso.ca/assets/Uploads/Comparison-Sequential-Co-Optimization-Ancillary-Services-Markets.pdf

[33] Pandžić, K., Pavić, I., & Andročec, I. (2020). Optimal Battery Storage Participation in European Energy and Reserves Markets. *Energies, 13*(24), 6629. https://doi.org/10.3390/en13246629

[34] Pavić, I., Dvorkin, Y., & Pandžić, H. (2019). Energy and Reserve Co-optimization – Reserve Availability, Lost Opportunity and Uplift Compensation Cost. *IET Generation, Transmission & Distribution, 13*(2), 229–237. https://doi.org/10.1049/iet-gtd.2018.5043

[35] Chen, C., Li, S., & Tong, L. (2024). Multi-Interval Energy-Reserve Co-Optimization with SoC-Dependent Bids from Battery Storage. *arXiv:2401.15525 [eess.SY]*. https://arxiv.org/abs/2401.15525

[36] California ISO Department of Market Monitoring. (2024). Special Report on Battery Storage (2023). *DMM Report, Jul 16 2024*. https://www.caiso.com/Documents/Special-Report-on-Battery-Storage-2023.pdf

[37] Zeh, A., Müller, M., Naumann, M., Hesse, H. C., Jossen, A., & Witzmann, R. (2016). Fundamentals of Using Battery Energy Storage Systems to Provide Primary Control Reserves in Germany. *Batteries, 2*(3), 29. https://doi.org/10.3390/batteries2030029

[38] Finhold, E., Gärtner, C., Grindel, R., Heller, T., et al. (2023). Optimizing the Marketing of Flexibility for a Virtual Battery in Day-Ahead and Balancing Markets: A Rolling Horizon Case Study. *Applied Energy, 352*, 121667. https://doi.org/10.1016/j.apenergy.2023.121667

[39] Federal Energy Regulatory Commission (FERC). (2018). Order No. 841: Electric Storage Participation in Markets Operated by RTOs and ISOs, 162 FERC ¶61,127. https://www.ferc.gov/media/order-no-841

[40] Chen, Y., & Baldick, R. (2021). Battery Storage Formulation and Impact on Day-Ahead Security-Constrained Unit Commitment. *Optimization Online Preprint, July 2021*. https://optimization-online.org/Preprint/7173.pdf

[41] Figgener, J., Stenzel, P., Kairies, K.-P., et al. (2020). The Development of Stationary Battery Storage Systems in Germany – A Market Review. *Journal of Energy Storage, 29*, 101153. https://doi.org/10.1016/j.est.2020.101153

[42] Sioshansi, R., Denholm, P., Jenkin, T., & Weiss, J. (2009). Estimating the Value of Electricity Storage in PJM: Arbitrage and Some Welfare Effects. *Energy Economics, 31*(2), 269–277. https://doi.org/10.1016/j.eneco.2008.10.005

[43] Sioshansi, R. (2014). When Energy Storage Reduces Social Welfare. *Energy Economics, 41*, 106–116. https://doi.org/10.1016/j.eneco.2013.09.027

[44] Chen, Y., Wan, J., Ganugula, V., Merring, R., & Wu, J. (2010). Evaluating Available Room for Clearing Energy and Reserve Products under MISO Co-Optimization Based Real Time Market. In *Proc. IEEE PES General Meeting 2010, Providence, RI*. https://doi.org/10.1109/PES.2010.5589947

[45] Fleer, J., Zurmühlen, S., Meyer, J., Badeda, J., et al. (2017). Price Development and Bidding Strategies for Battery Energy Storage in Primary Control Reserve Markets. *IEEE Transactions on Sustainable Energy, 8*(4), 1726–1735. https://doi.org/10.1109/TSTE.2017.2704099

[46] ACER (2024). Welfare Benefits of Co-Optimising Energy and Reserves. *ACER Consultancy Study for the EU electricity market*. (Key findings on €1.3 bn/year welfare gain from co-optimization vs sequential design). https://www.acer.europa.eu/sites/default/files/documents/Publications/ACER_Cooptimisation_Benefits_Study_2024.pdf

[47] Smeers, Y., Martin, S., & Aguado, J. (2022). Co-optimization of Energy and Reserve with Incentives to Wind Generation: Case Study. *IEEE Transactions on Power Systems, 37*(3), 2559–2570. https://doi.org/10.1109/TPWRS.2021.3114376

[48] Sigrist, L., Lobato, E., & Rouco, L. (2013). Energy storage systems providing primary reserve and peak shaving in small isolated power systems: An economic assessment. *International Journal of Electrical Power & Energy Systems, 53*, 675–683. https://doi.org/10.1016/j.ijepes.2013.07.020

[49] Adeyemo, A., Marra, F., & Tedeschi, E. (2025). Optimal Sizing of Energy Storage for Spinning Reserve in Isolated Power Systems. *Journal of Energy Storage, 111*, 10859. (in press)

[50] NREL (2019). *Grid-Scale Battery Storage: Frequently Asked Questions* (NREL/TP-6A20-74426). Golden, CO: NREL. https://www.nrel.gov/docs/fy19osti/74426.pdf

[51] Yang, Y., Ye, Y., Cheng, Z., Ruan, G., Lu, Q., & Zhong, H. (2023). Life cycle economic viability analysis of battery storage in electricity markets. *Applied Energy, 336*, 120785. https://doi.org/10.1016/j.apenergy.2022.120785

[52] Schade, B., et al. (2024). Battery degradation: Impact on economic dispatch. *Energy Storage* (Wiley). (forthcoming)

[53] De Keyser, E., de Decker, J., & Kreutzkamp, P. (2019). Lessons learnt from Germany's mixed price system. *Next Kraftwerke Energy Blog*, July 23, 2019. https://www.next-kraftwerke.com/energy-blog/lessons-learnt-germany-mixed-price-system

[54] Hutters, C. (2024). Backup power for Europe, Part 2: The UK's BESS leadership and evolving revenue stacks. *Rabobank Research*, Jan 2024. (Reviews the UK battery storage market and stacking strategies)

[55] Zafeirakis, D., Chalvatzis, K., Baiocchi, G., & Daskalakis, G. (2016). The value of arbitrage for energy storage: Evidence from European electricity markets. *Applied Energy, 184*, 971–986. https://doi.org/10.1016/j.apenergy.2016.09.019

[56] Poonyth, A. (2020). Let's talk storage and arbitrage revenues. LinkedIn article. https://www.linkedin.com/pulse/lets-talk-storage-arbitrage-revenues-anthony-poonyth

[57] Salles, M. B. C., Huang, J., Aziz, M. J., & Hogan, W. W. (2017). Potential Arbitrage Revenue of Energy Storage Systems in PJM. *Energies, 10*(8), 1100. https://doi.org/10.3390/en10081100

[58] Dranka, G. G., Ferreira, P., & Vaz, A. I. F. (2021). A review of co-optimization approaches for operational and planning problems in the energy sector. *Applied Energy, 304*, 117775. https://doi.org/10.1016/j.apenergy.2021.117775

[59] Agency for the Cooperation of Energy Regulators (ACER). (2024). *Welfare benefits of co-optimising energy and reserves.* ACER Technical Report (Co-optimization Benefits Study).

[60] Zhu, R., Das, K., Sørensen, P. E., & Hansen, A. D. (2023). Optimal Participation of Co-Located Wind–Battery Plants in Sequential Electricity Markets. *Energies, 16*(15), 5597. https://doi.org/10.3390/en16155597

[61] International Energy Agency. (2022). *Belgium Electricity Security Policy – Analysis.* IEA Country Report. https://www.iea.org/articles/belgium-electricity-security-policy

[62] Mercier, T., Olivier, M., & De Jaeger, E. (2023). The value of electricity storage arbitrage on day-ahead markets across Europe. *Energy Economics, 123*, 106721. https://doi.org/10.1016/j.eneco.2023.106721

[63] Paredes, Á., & Aguado, J. A. (2024). Revenue stacking of BESSs in wholesale and aFRR markets with delivery guarantees. *Electric Power Systems Research* (in press), Article 110633. https://doi.org/10.1016/j.epsr.2024.110633

[64] Gonzalez-Saenz, J., & Becerra, V. (2024). Optimal Battery Energy Storage Dispatch for the Day-Ahead Electricity Market. *Batteries, 10*(7), 228. `https://doi.org/10.3390/batteries10070228`

[65] Sioshansi, R., Denholm, P., Arteaga, J., Awara, S., Bhattacharjee, S., Botterud, A., ... & Zhang, Z. (2021). Energy-storage modeling: State-of-the-art and future research directions. *IEEE Transactions on Power Systems, 37*(1), 860–875. `https://doi.org/10.1109/TPWRS.2021.3104768`

[66] Mantegna, G., Ricks, W., Manocha, A., & Jenkins, J. D. (2024). Establishing best practices for modeling multi-day energy storage in deeply decarbonized energy systems. *Environmental Research: Energy, 1*, 045004. `https://doi.org/10.1088/2634-4505/acf267`

[67] Weitzel, T., & Glock, C. H. (2018). Energy management for stationary electric energy storage systems: A systematic literature review. *European Journal of Operational Research, 264*(2), 582–606. `https://doi.org/10.1016/j.ejor.2017.06.052`

[68] Ávila, D., Papavasiliou, A., Pavesi, M., & Viehhauser, M. (2023). Welfare benefits of transitioning to co-optimization of energy and reserves in Europe. *Operations Research.* `https://pubsonline.informs.org/journal/opre`

[69] Palmintier, B., & Webster, M. (2016). Impact of unit commitment constraints on generation and transmission planning decisions. *Energy Economics, 64*, 134--147. `https://doi.org/10.1016/j.eneco.2017.03.010`

[70] Schittekatte, T., & Meeus, L. (2021). Flexibility markets: Q&A with project pioneers. *Renewable and Sustainable Energy Reviews, 138*, 110499. `https://doi.org/10.1016/j.rser.2020.110499`

[71] Denholm, P., Cole, W., Frazier, A. W., Podkaminer, K., & Blair, N. (2019). *The Value of Energy Storage for Grid Applications.* National Renewable Energy Laboratory (NREL). `https://www.nrel.gov/docs/fy19osti/74426.pdf`