Doctoral Thesis in Electrical Engineering

Electricity Market Design Strategies for Hydro-dominated Power Systems

Exploring Optimal Bidding, Planning, and Strategic Operation through Various Market Design Strategies

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Stockholm, Sweden 2024
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Abstract

The existing wholesale power markets in Nordic countries play a vital role in ensuring the planned balance between supply and demand. However, these markets do not guarantee real-time operational security of the power system. This responsibility falls on the transmission system operator (TSO), who balances consumption and generation in real-time to maintain a secure state.

To address these issues, a series of research studies have been performed in this thesis to delve into the intricacies of Nordic balancing markets and propose strategies to enhance their efficiency and effectiveness. These studies have been conducted around the hydropower units as the main generation sources in the Nordic electricity markets. These studies recognize the potential benefits of versatile balancing markets and increased trade of flexible resources with Continental Europe.

Additionally, the research results shed light on the optimal bidding strategies for hydropower plants (HPPs) in the day-ahead energy and manual frequency restoration reserve (mFRR) markets. HPPs play a crucial role as a flexible energy source, and their participation in these markets requires careful planning and decision-making. The studies consider various factors such as market rules, mFRR capacity market, future electricity prices, and the impact of active-time duration of balancing energy market offers on revenue generation. This inclusion provides a more realistic revenue portfolio for the operators based on the possibility of not being dispatched in the balancing market.

Furthermore, the research explores the concept of flexible stochastic scheduling strategies in hydropower-dominated energy markets. By considering day-ahead energy markets, mFRR markets, and the interaction between different market setups. These strategies provide the necessary flexibility for both the planning and operational stages. The aim is to maximize the profits of the hydropower units while addressing the opportunity cost of saving water and meeting the mFRR capacity requirements imposed by the TSO. Participation in new market setups is an increasingly interesting framework for the operator after the recent introduction of those markets and the results of this section help them to form more profitable decision-making frameworks for their assets.

Moreover, the optimal strategic portfolio assessment of HPPs in a multi-settlement market is discussed. Recognizing the increasing electricity prices and the growing penetration of renewable energy resources, these studies leverage bilevel programming problems to model the strategic behavior of HPPs in day-ahead and frequency containment reserve markets. The proposed approaches aim to enhance decision-making processes, promote market efficiency, and enable effective asset management in a dynamic and evolving energy landscape to make more informed multi-market trading decisions.

Also, the research examines the dimensioning of frequency restoration reserves in a multi-area power system, specifically focusing on the Nordic case study. By adopting a sequential dimensioning methodology and employing chance-constrained optimization, the studies allocate reserves based on system
needs, optimize line flows, and reduce total reserve requirements. The results highlight the potential for sharing reserves among bidding zones in the Nordic synchronous area, contributing to a more efficient and coordinated power system operation.

Lastly, a thorough investigation has been performed to assess the effectiveness of the current contract-for-difference contracts as the main support schemes for the development of new renewable energy assets. Case studies have been conducted to demonstrate quantitatively the pros and cons of different proposals and provide new hints for policy-makers about their future decisions.

**Keywords:** Nordic Balancing Model, Electricity Market Designs, manual and automatic Frequency Restoration Reserve, Frequency Containment Reserve, Balancing Capacity Markets, Stochastic Optimization, Robust Optimization, Chance-Constraint Optimization, Bilevel Programming, GAMLSS, Contract-for-Difference Contracts
Sammanfattning

De befintliga partihandelsmarknaderna för el i nordiska länder spelar en avgörande roll för att säkerställa den planerade balansen mellan utbud och efterfrågan. Dock garanterar dessa marknader inte driftsäkerheten i realtid för elsystemet. Detta ansvar åligger transmissionsnätssoperatören (TSO), som balanserar konsumtion och produktion i realtid för att upprätthålla ett säkert tillstånd.

För att ta itu med dessa frågor har en serie forskningsstudier genomförts i denna avhandling för att fördjupa sig i detaljerna i de nordiska balansmarknaderna och föreslå strategier för att förbättra deras effektivitet och effektivitet. Dessa studier har genomförts kring vattenkraftverk som de huvudsakliga produktionskällorna i de nordiska elmarknaderna. Studierna erkänner de potentiella fördelarna med mångsidiga balansmarknader och ökad handel med flexibla resurser med Kontinentaleuropa.

Dessutom kastar forskningsresultaten ljus över de optimala budgivningsstrategierna för vattenkraftverk (HPP) på dagsmarknaden för energi och manuell marknad för återställning av frekvensreserver (mFRR). HPP spelar en avgörande roll som en flexibel energikälla, och deras deltagande på dessa marknader kräver noggrann planering och beslutsfattande. Studierna tar hänsyn till olika faktorer såsom marknadsregler, mFRR-kapacitetsmarknad, framtida elpriser och påverkan av aktiv tidsduration för erbjudanden på balanseringsemurkarket på intäktgenerering. Denna inkludering ger en mer realistisk intäktspolitik för operatörerna baserat på möjligheten att inte bli dispatchade på balansmarknaden.


Dessutom diskuteras den optimala strategiska portföljbedömningen av HPPs i en multiuppgörelsemarknad. Med tanke på den ökande elpriserna och den växande penetrations- och driftsskeden. Målet är att maximera vinsterna för vattenkraftsenheterna samtidigt som man adresserar alternativkostnaden för att spara vatten och uppfylla de mFRR-kapacitetskrav som TSO ställer. Deltagande i nya marknadsuppsättningar är ett alltmer intressant ramverk för operatören efter den senaste introduktionen av dessa marknader och resultaten från detta avsnitt hjälper dem att forma mer lönsamma beslutsramar för sina tillgångar.
ka fallstudien. Genom att anta en sekventiell dimensioneringsmetodologi och använda chansbegränsad optimering, allokerar studierna reserver baserat på systembehov, optimiserar linjeflöden och minskar de totala reservkraven. Resultaten belyser potentialen för att dela reserver mellan budområden i det nordiska synkronområdet, vilket bidrar till en mer effektiv och samordnad drift av kraftsystemet.

Slutligen har en grundlig undersökning genomförts för att bedöma effektiviteten av de nuvarande kontrakten för skillnad (contract-for-difference) som de huvudsakliga stödscheman för utvecklingen av nya förnybara energitillgångar. Fallstudier har genomförts för att kvantitativt demonstrera för- och nackdelar med olika förslag och ge nya ledtrådar för politiska beslutsfattare om deras framtida beslut.

**Nickelord:** Nordiska Balanseringsmodellen, Design av Elektricitetsmarknader, Manuell och Automatisk Frekvensåterställningsreserv, Frekvensinneslutningsreserv, Balanseringskapacitetsmarknader, Stokastisk Optimering, Robust Optimering, Chansbegränsad Optimering, Bilevel Programmering, GAMLSS, Kontrakt för-Skillnad Kontrakt
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As I stand on the precipice of new beginnings, I carry with me not just the knowledge I have gained but the profound sense of gratitude and community fostered during my doctoral studies. Thank you for being part of my story.
"Seek knowledge from the cradle to the grave"

Ferdowsi
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Part I

Foundations and Preliminaries
Chapter 1

Introduction

1.1 Motivation

According to IEA, hydropower exceeds all other renewable technologies combined in electricity generation and is projected to retain its position as the world’s predominant source of renewable electricity into the 2030s. Beyond that period, it will persistently serve a vital function in reducing carbon emissions from the power system and enhancing system adaptability [8].

However, a diminishing trajectory in hydropower capacity factors was observed in the European Union, sliding from an average of 28% from 1990 to 2014, to 25% from 2015 to 2022 and to 22% in 2023. Southern Europe experienced severe droughts in 2017, while Central and Eastern Europe faced similar issues in 2018. In 2022, Europe experienced its worst drought in 500 years, impacting numerous countries and adversely affecting agricultural production and hydropower generation, while also straining nuclear power cooling systems due to limited water availability. In a historic 30-year low, EU hydropower generation decreased by nearly 19% in 2022 relative to 2021 [9].

Consequently, it is pivotal to initiate comprehensive research to find the best strategy for deploying hydropower resources using their available water. Hence, two predominant challenges are tackled. Firstly, the development of a new electricity market design is imperative, ensuring it not only adapts to the continuous evolutions within the power system but also optimally leverages the inherent flexibility of hydro assets. Secondly, within the confines of existing and proposed future market structures, there is a crucial need to explore how operators can find the optimal operation and planning strategy for their units, aligning with both current and emergent demands. The following sections delve further into the details of these two challenges.
1.1.1 Electricity Market Design Development

The European wholesale electricity markets are organized into various timeframes and regions. In forward or futures markets, electricity is traded months or even years in advance, while spot markets involve the trading of electricity just hours or minutes before delivery. Bidding zones, which often overlap national borders, establish zonal wholesale electricity prices within the EU.

The current energy market framework places a significant emphasis on short-term markets within the European Union (EU). A prominent component of this framework is the day-ahead market, where the equilibrium between electricity supply and demand determines the price for each hour of the following day. This day-ahead market stands as the primary electricity market in Europe, and daily wholesale electricity price information for various bidding zones within the EU is disseminated by power exchanges.

Notably, national wholesale electricity markets have progressively increased their cross-border electricity exchanges. This means that excess electricity generated in one country can be channeled to another country facing a potential shortage. This achievement owes itself to advancements in market coupling algorithms for trading and the expansion of physical transmission capabilities. This integration of markets facilitates the most efficient utilization of infrastructure and resources on a European scale, as highlighted by ENTSO-E, an association representing all European transmission system operators. Oversight of these energy transactions is carried out by the Agency for the Cooperation of Energy Regulators (ACER).

The European energy crisis in the second half of 2022 underscored the urgent need for non-fossil flexibility in the electricity market, necessitating the integration of more renewable energy sources and reducing reliance on gas-peaking plants and foreign gas imports. In response, the European Commission has proposed a
1.1. MOTIVATION

reform of the Electricity Market Design [10]. This reform is centered around two main pillars: incentivizing long-term contracts to address the supply side, and encouraging more flexible solutions, like storage systems and demand response, on the demand side. The long-term contracts are mainly going to be executed by the application of Contract-for-Difference (CfD) contracts and the focus on demand-side flexibility, aimed at balancing the electricity grid, will involve Member States reporting on their flexibility needs and objectives, and providing more funding opportunities for demand response mechanisms. This approach is expected to reduce gas dependency and facilitate the integration of renewable energy sources.

This reform of electricity market designs introduced new challenges for the market players. It requires new market setups, relaxed entry requirements, adjustments to the current designs, and prepare informed plan for maximum utilization of the future market setups. For example, to ensure consistent system frequency, European transmission system operators (TSOs) typically engage in a dual-phase method for acquiring balancing services. This involves initially reserving capacity in the balancing capacity market, followed by its activation as balancing energy during actual system imbalances. However, as the decommissioning of conventional generation units increases and more variable renewable energy sources are integrated, there is a growing demand for new short-term flexibility solutions to manage the swift changes in residual load. The structure of the market should be in a way that it can offer incentives for new participants offering novel flexibility options [11]. This aspect is particularly pertinent in balancing markets, where traditionally, the number of balancing service providers (BSPs) has been limited due to stringent prequalification standards (like minimum bid size [12]) and lengthy procurement periods. The concentrated nature of these markets has often been a subject of concern, particularly regarding the potential for strategic bidding and market power abuses, as highlighted in [13, 14].

1.1.2 Optimal Utilization of the Current Market Setups

For market participants, the balancing market offers an additional avenue to trade their flexibility, provided they meet the prequalification requirements for participation. The DA market is particularly significant, being the largest and providing robust price signals. Its relevance is heightened for the balancing ca-

---

1 In any market setting, rational bidders typically adopt strategic approaches to maximize their outcomes. However, the terms "strategic behavior" or "strategic bidding" specifically refers to the use of market information and/or a dominant market position by a bidder to secure disproportionate profits. This involves leveraging one’s advantageous position or unique insights into market dynamics to influence pricing or availability in a way that significantly exceeds normal competitive gains. Such strategies are often viewed critically as they can lead to market distortions and unfair advantages.

2 Market power is characterized by the capability to influence market prices, where this influence not only proves profitable but also results in prices deviating from what would be expected in a competitive environment. This definition, as outlined by Stoft in 2002, highlights the significance of the ability to manipulate prices beyond competitive norms for personal gain.
Capacity market, which typically clears ahead of the DA market and thus influences the opportunity costs for actors in the market.

Gate closure times (GCTs) of different marketplaces also play a crucial role, as they determine whether bids not awarded in one market can be submitted in another [12]. This scenario enables bidders to utilize available market information to form price expectations and capitalize on arbitrage opportunities. Research, including that by [15], indicates that balancing markets, unlike the more competitive DA markets, present distinct opportunities for strategic behavior. For example, bidders might orient their bid prices towards the highest bid in pay-as-bid auctions, rather than basing them on actual costs.

Additionally, market participants may be incentivized to either oversupply or undersupply the market to profit from intertemporal dependencies between sequential markets, a concept further explored by [16]. In [13], the authors concluded that the design of the German market offers potential for exploiting strategic opportunities between the DA and balancing markets. Their findings revealed that the pay-as-bid pricing mechanism in these markets amplifies the incentive for market participants to deviate from their true costs in their bidding strategies. This tendency to deviate from actual costs in bids, motivated by the market design, was not only identified by [13] but also confirmed by [14]. These studies collectively highlight a significant aspect of market dynamics, where the structure and pricing mechanisms can inadvertently encourage strategic behavior that may not align with the underlying costs of market participants.

As an example of balancing markets, Table 1.1 provides the pre-qualified volumes of different actors participating in the various balancing products in Sweden (their definitions will be provided in Chapter 2). As it is clear from the data, the hydropower plants are the dominant providers in these markets. This feature signifies the importance of their bidding strategy in the market prices and their potential to exercise market power.

Table 1.1: Pre-qualified volumes for FFR, FCR-D and FCR-N and maximum bid volume received during the single hour for mFRR (sum over all bidding zones in Sweden) [MW]

<table>
<thead>
<tr>
<th>Power Type</th>
<th>FFR</th>
<th>FCR-N</th>
<th>FCR-D up</th>
<th>FCR-D down</th>
<th>aFRR UP</th>
<th>aFRR Down</th>
<th>mFRR Up</th>
<th>mFRR Down</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hydroelectric</td>
<td>0</td>
<td>1630</td>
<td>2620</td>
<td>1140</td>
<td>1800</td>
<td>1800</td>
<td>6100</td>
<td>5250</td>
</tr>
<tr>
<td>Thermal power</td>
<td>0</td>
<td>40</td>
<td>40</td>
<td>20</td>
<td>50</td>
<td>50</td>
<td>280</td>
<td>260</td>
</tr>
<tr>
<td>Energy storage</td>
<td>50</td>
<td>10</td>
<td>60</td>
<td>50</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Flexible consumption</td>
<td>100</td>
<td>&lt;10</td>
<td>390</td>
<td>&lt;10</td>
<td>-</td>
<td>-</td>
<td>190</td>
<td>160</td>
</tr>
<tr>
<td>Solar power</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Wind power</td>
<td>0</td>
<td>&lt;10</td>
<td>&lt;10</td>
<td>10</td>
<td>200</td>
<td>0</td>
<td>1430</td>
<td></td>
</tr>
<tr>
<td>Gas turbine</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>160</td>
<td>90</td>
<td></td>
</tr>
</tbody>
</table>
1.1.3 Market Integration

Apart from the generator’s perspective, the optimal utilization of the market design is of great importance from the TSO perspective. European electricity markets are increasingly integrating, leading to enhanced collaboration among transmission system operators for acquiring reserve capacity and activating balancing energy in real-time. Key developments include the creation of pan-European platforms like MARI (Manually Activated Reserves Initiative) and PICASSO (Platform for the International Coordination of Automated Frequency Restoration and Stable System Operation) for balancing using frequency restoration reserves, and coordinated international trading of reserve capacity in the day-ahead market, as outlined in the EU’s Electricity Balancing Guideline (Articles 40-42) [17]. These efforts aim to manage real-time balancing energy dispatch from frequency restoration reserves while considering transmission network constraints. The challenge here is to not only procure the right amount of reserves through each TSO but also ensure their strategic placement to address potential congestion in the power transmission network. Also, there is an economic incentive to deploy the available transmission capacity of the interconnections to reduce the dimensioning, procurement, and activation costs of the bids in different market setups. Thus, a proper decision-making framework is required to address these challenges from the TSO perspective.

1.1.4 Long-term Investment Incentives

Wind power, solar photovoltaics, nuclear, and certain coal-fired plants are characterized by high initial capital costs but relatively low operations and maintenance (O&M) expenses. This contrasts with fuel-dependent energy sources like natural gas, coal, or biomass, where fuel costs and revenue generation are closely connected, usually reconciled within a few years. Renewable energy assets incur about 80-90% of their lifetime costs upfront during development and construction, including capital expenditures and financing [18]. Their O&M costs are minimal and fixed, not influencing the marginal production costs. However, the revenue generated over the asset’s lifetime must cover these substantial initial costs, posing a risk due to fluctuations in electricity market prices.

Therefore, as a part of the announced electricity market reform, there should be a properly designed and auction-based mechanism to support the investment in renewable energy expansions mainly through two-sided contract-for-difference (CfD) contracts. Although it might seem straightforward to support the developers through this government-backed incentive mechanism, it entails numerous design challenges to form a proper contract. Issues like price-responsiveness, location distortions, and efficient dispatch are the most important challenges that need to be investigated.
1.2 Research Questions

This section outlines the research questions that guide the inquiry of this thesis within the sphere of electricity market design. Recognizing the complexity of this field, the questions are formulated to address various aspects in terms of timing and market players involved. To elucidate the relationship between these questions and the thesis content, Table 1.2 maps each question to relevant sections. The research questions aim to stimulate in-depth exploration and understanding of the topics discussed in the thesis:

- **R₁**: What are the emerging market setups and anticipated trends within Nordic electricity markets, and what modifications or adaptations might be necessitated to meet future needs and challenges?

- **R₂**: How can hydropower operators optimize their bidding strategy within various market setups to maximize revenue, considering technical considerations of planning and operating in sequential markets?

- **R₃**: In what ways does the probability of not being dispatched in the balancing markets influence bidding strategies within day-ahead markets, and what methodologies can be explored to accurately model the active-time duration of regulation bids?

- **R₄**: How does the strategic operation of hydropower plants impact market clearing stages and price fluctuations across different market setups, and how can the probability distribution functions of cleared prices assist operators and investors in enhancing their decision-making frameworks?

- **R₅**: How do dynamic and static FRR dimensioning approaches influence the requisite FRR capacity in the multi-area Nordic LFC block, and what are the implications of the timing of information availability on FRR dimensioning results?

- **R₆**: How might novel electricity market designs facilitate investors in effectively hedging their long-term risks through an auctioned market, and what enhancements can be made to the design of financial markets to mitigate adverse impacts on market efficiency?

1.3 Scope

The interaction of electricity market designs and market actors’ behavior serves as a pivotal theme in this thesis, aimed at presenting an intricate analysis across diverse aspects and navigating through the prevalent challenges within the domain especially in the Nordic context. Thus, the content of this thesis can be seen from three perspectives:
1.3. SCOPE

1.3.1 Market Power Perspective:
Chapters 4 - 6 adopt a scenario wherein market power is not modeled, i.e. they proceed under the assumption that actors are price-takers and market prices function as exogenous inputs. Chapter 7, conversely, considers the hydro assets a role as a price-maker, striving to exert market power to optimize income through trading across varied market setups.

1.3.2 Timing Perspective:
For analyzing market design challenges from a timing viewpoint, this thesis explains its content into two primary parts: Chapters 4 - 7 delve into short-term planning and operational problems within the power system. Chapter 8 compares the short-term reserve dimensioning methodology with its long-term counterpart. Chapter 9 conducts a thorough analysis of the CfD support scheme for renewable energy generation assets and provides policy implications of each design proposal in the literature.

1.3.3 Market Actors Perspective:
To provide an understanding from the perspective of different market actors, the thesis content is categorized into three segments:

- a) Power Plant Perspective: Chapters 4 - 7 zoom into the profit-maximization problem, predominantly for hydro generation assets, aiming to identify an optimal planning and operational strategy across various electricity market setups.

- b) TSO Perspective: Chapter 8 elucidates the optimal Frequency Restoration Reserves (FRR) dimensioning problem from a TSO viewpoint, where the objective is to minimize all requisite reserve capacity in the Nordic Load-Frequency Control (LFC) block while optimizing the utilization of available transmission capacity.

- c) Investor Perspective: Chapter 9 explores and addresses the challenges faced by investors regarding conventional CfDs in the renewable energy sector and refines the CfD contract design to enhance its efficacy as a financial tool while safeguarding investors against market volatilities.

Owing to accessible data, the primary emphasis of the case studies within this thesis is placed on Swedish hydropower systems. Consequently, many conclusions are derived based on the hydropower strategic decision-making framework, centering on systems that exhibit specific shared characteristics, such as long rivers featuring interconnected hydropower stations. Nevertheless, the employed methods bear relevance and applicability to any hydro system. More importantly, the
methodological contribution holds true for any other power systems with different energy mixes.

1.4 Scientific Contributions

Contribution I: Investigation of New Electricity Market Design Setups

• a) Investigation of announcement of the capacity market for the manual frequency restoration reserves and its impacts on the optimal portfolio management of hydropower units participating in different energy and capacity market setups

Contribution II: Advancements in Optimizing Day-Ahead Bidding Strategies via Stochastic Adaptive Robust Optimization in Hydro-Dominated Electricity Markets

• a) Application of a Model for Active-Time Duration Estimation: An approach is introduced to model the active-time duration of manual Frequency Restoration Reserve (mFRR) energy bids using the Stochastic Adaptive Robust Optimization (SARO) method, providing a more accurate representation of uncertainties in day-ahead bidding strategies within cascaded Hydropower Plants (HPPs) portfolios in sequential electricity markets.

• b) Stochastic Modeling of Balancing Energy Market Variables: Unlike previous deterministic methodologies, the balancing energy market variables and their respective active-time durations are modeled stochastically. This approach facilitates a more realistic representation, through a proposed two-stage three-level stochastic optimization, enhancing the accuracy and reliability of the optimal bidding behavior within the day-ahead energy market.

• c) Comparative Analysis of SARO against Fully-Stochastic Formulation: A thorough comparative analysis is conducted to exhibit the superiority of the proposed SARO method against the conventional fully-stochastic formulation, by exploring different budgets of uncertainty through an out-of-sample assessment.

Contribution III: Enhancing Multi-Market Trading Strategies of Hydropower Producers through Distributional Regression and Advanced Forecasting Techniques

• a) Analysis over the Interactions of Different Frequency Markets: In terms of modeling, the FCR-N and mFRR capacity markets have been regarded as two revenue avenues for HPP operators. The constraints posed by the mFRR
capacity market restrict the offer volume in the mFRR energy market since operators need to be prepared for dispatch with the full volume earlier submitted in the capacity market. On the other hand, the FCR-N market doesn’t influence the real-time energy market as it solely operates as a capacity market with its energy compensation being marginal. The interaction between these two capacity markets has been explored in the suggested formulation.

• b) **Three-Stage Stochastic Optimization for Optimal Offer-Function:** Proposing a novel three-stage stochastic optimization model, the derivation of optimal day-ahead energy market offer-functions for cascaded HPPs participating across four diverse market platforms is modeled. This optimization framework notably incorporates the interactions of mFRR capacity markets, thereby enabling a more realistic representation of multimarket trading strategies for hydropower producers in sequential electricity markets.

• c) **New Modeling of Active-Time Duration (ATD) of mFRR energy offers using GAMLSS:** A new method based on the distributional regression approach is introduced for modeling the uncertain ATD parameters, employing the Generalized Additive Models for Location Scale and Shape (GAMLSS) model with dynamic moments. This method transcends previous modeling techniques by ensuring a more precise fit for the uncertain ATD parameters, thereby enhancing the accuracy of the proposed stochastic program in multimarket trading strategy optimization.

• d) **Machine Learning-based Scenario-Generation for Improved Forecasting:** Developing a forecasting method, a combined version of Long Short-Term Memory (LSTM) deep learning architecture and the GAMLSS model to generate price scenarios essential for the third stage of the proposed stochastic program is employed. By leveraging existing balancing energy market data from historical records and updating the network state of the trained LSTM model, this scenario-generation technique improves the accuracy of electricity price scenario forecasts, underpinning more informed and effective multimarket trading strategies for HPP operators.

**Contribution IV: Strategic Optimal Portfolio Assessment of a Hydro Power Plant in a Multi-Settlement Market**

• a) **Development of a Stochastic Bilevel Optimization Framework:** Proposing a strategic operation model for hydropower plants in sequentially cleared electricity market setups, including day-ahead and FCR-N markets, along with the opportunity to trade in the intraday market. Utilizing a bivariate bid curve analysis, the optimization framework allows for the dynamic selection of offer prices and volumes by the strategic producer. The proposed model’s versatility extends to other types of power plants, showcasing a broad spectrum of applications.
b) Reformulation Techniques for Efficient Problem Solving: Introducing two reformulation strategies to transform the original nonconvex and nonlinear problem into a mixed integer linear programming (MILP) problem, facilitating efficient solutions using conventional off-the-shelf solvers. By employing McCormick envelop reformulations and substituting the bilinear terms with linear equivalents, this contribution lays a foundation for streamlined problem-solving in complex multi-market trading scenarios.

c) Probability Distribution Function (PDF) Analysis of Cleared Prices: Utilizing historical data from electricity markets to craft realistic scenarios for scenario-dependent parameters across different years. The derived PDFs furnish crucial statistical insights into temporal price risks, underpinning informed multi-product optimal-trading decisions in day-ahead and FCR-N markets.

Contribution V: An Investigation on the Potential Benefits of Dynamic Reserve Dimensioning in Multi-Area Power Systems

a) Frequency Restoration Reserves (FRR) Dynamic Dimensioning: A framework for the dynamic dimensioning of FRR within the European Union’s multi-regional electricity network is proposed which is designed to utilize hourly dispatch data. This framework introduces an innovative approach for simulating imbalance scenarios, aligning with the latest standards as outlined in the Nordic TSOs’ FRR guidelines

b) Analyzing the Impact of Information Availability on FRR Needs: This contribution quantifies the significant effects of available information during the FRR dimensioning process. It delves into exploring and contrasting three diverse FRR dimensioning approaches, which include two dynamic strategies and one static method, thereby revealing the distinct implications of each method on FRR necessities and providing a thorough examination of their practicalities and efficacies in various scenarios.

Contribution VI: Optimizing Low-Carbon Power Generation Investments: A Comprehensive Approach to Addressing Risk through Advanced CfD Contract Frameworks

a) Evaluating Limitations and Shortcomings in Current CfD Structures: A comprehensive analysis was conducted on existing injection-based CfD mechanisms, revealing several inherent limitations in their structure and functionality. Identifying these issues lays the foundation for evolving CfD frameworks to better support the balancing of renewable energy generation and market demands.
1.4. SCIENTIFIC CONTRIBUTIONS

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<th>Research Questions</th>
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Table 1.2: Scientific contributions and their corresponding publications

Figure 1.2: The interaction of scopes and their corresponding contributions in the thesis

- b) Assessment and Advocacy for the Capacity-based CfD Markets: A comprehensive study and endorsement of the capacity-based CfD market has been performed to outweigh its significant contributions in alleviating the shortcomings of conventional CfD.

Fig. 1.2 systematically outlines the scientific contributions and research questions of a comprehensive study focused on electricity markets, mathematical modeling, and energy policy. This categorization facilitates a clear understanding of how the diverse research contributions collectively advance each field.
1.5 Publications

Publications included in the dissertation

Peer-reviewed journal articles


Peer-reviewed conference articles


1.5. PUBLICATIONS

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Table 1.3: Scientific contributions and their corresponding publications


Contributions of the author

J1, C4: Abolfazl Khodadadi performed the conceptualization, writing, and editing. Lennart Söder and Mickael Amelin have performed the revision on the quality of the paper.

J2: Abolfazl Khodadadi performed the conceptualization, writing, and editing. Lennart Söder and Mohammad Reza Hesamzadeh have performed the revision on the quality of the paper.

J3: Abolfazl Khodadadi and Henrik Nordström performed the conceptualization, writing, and editing. Lennart Söder and Robert Ericsson performed the revision on the quality of the paper.

J4: Abolfazl Khodadadi and Saeed Nordin performed the conceptualization, writing, and editing. Prianka Shinde assisted the first two authors in conceptualization and writing and Evelin Blom assisted the first two authors in conceptualization. Lennart Söder and Mohammad Reza Hesamzadeh performed the revision on the quality of the paper.

J5: Abolfazl Khodadadi and Rahmat Poudineh performed the conceptualization, writing, and editing and performed the revision on the quality of the paper. This work was the outcome of the collaboration of Abolfazl Khodadadi and Oxford Institute of Energy Studies, Oxford, UK under the OIES-Aramco fellowship program.
CHAPTER 1. INTRODUCTION

C1: Abolfazl Khodadadi and Lars Herre performed the conceptualization, writing, and editing. Prianka Shinde assisted the first two authors in conceptualization and writing. Lennart Söder and Mickael Amelin performed the revision on the quality of the paper.

C2, C3: Abolfazl Khodadadi performed the conceptualization, writing, and editing. Lennart Söder performed the revision on the quality of the paper.

C5: Abolfazl Khodadadi and Henrik Nordström performed the conceptualization, writing, and editing. Lennart Söder and Robert Ericsson performed the revision on the quality of the paper.

Publication not included in the dissertation


1.6 Outline of the dissertation

This thesis has been divided into four parts:

- **Part I**: This part includes fundamentals and background information for the rest of the thesis.
  - **Chapter 1**: This chapter is the introduction to the topic and provides the main motivations to pursue the thesis topics.
  - **Chapter 2**: This chapter set the scene for understanding the basics and terminologies of the electricity market setups and designs in the Nordic
  - **Chapter 3**: This chapter introduces the mathematical foundations and basics that are required to be acquainted with which pave the way to understanding the main technical topics in the thesis

- **Part II**: This part provides the analysis of the short-term electricity market setups and answers the question of the optimal bidding and operation of the hydro assets in these setups
  - **Chapter 4**: This chapter proposes one model for forecasting the balancing market prices in a three-stage optimization problem and one technique to find the probability distribution function of the active-time duration of the balancing offers.
  - **Chapter 5**: This chapter uses the forecast model and technique in the previous chapter to form a three-stage optimization problem to find the best strategy of the price-taker hydro assets in the multi-setups electricity market
1.6. OUTLINE OF THE DISSERTATION

– **Chapter 6:** This chapter proposes the method to model a decision-making framework in which the hydropower plants try to maximize their expected revenue in different market setups in the worst-case scenarios of active-time duration of balancing offers.

– **Chapter 7:** This chapter proposes a novel model to demonstrate the strategic bidding and operation problems of the price-maker hydro assets in the multi-market setup.

- **Part III:** This part provides an analysis of the long-term market setups and how their different designs influence market behavior

  – **Chapter 8:** This chapter examines the effects of information availability on FRR dimensioning, contrasting two dynamic strategies, based on different information revealing time plans, with one static method. A comprehensive model for long-term, multi-area simulations of FRR dimensioning is proposed, incorporating chance-constrained optimization and ENTSO-E methodologies.

  – **Chapter 9:** This chapter explores optimizing low-carbon power generation investments through the CfD frameworks. It critically evaluates existing CfD structures, identifying key limitations to enhance renewable energy balancing and market demands. Additionally, the research advocates for capacity-based CfD markets, offering a comprehensive analysis of their advantages over conventional CfD mechanisms.

- **Part IV:** This part concludes the thesis by providing the final remarks and future works.

  – **Chapter 10:** This chapter synthesizes the key findings and contributions of the thesis, highlighting the implications of the research in the context of electricity market dynamics. The chapter also outlines potential areas for future research, suggesting directions for further exploration based on the limitations and discoveries of the current work. This final chapter serves to both summarize the thesis and provide a roadmap for continued investigation in the field.
Chapter 2

Electricity Market Design: Overview and Principals

This chapter introduces different electricity market designs in the Nordic electricity market. It seeks to provide fundamental information for the readers to understand the terminology and concepts that will be provided in future chapters. This chapter is extracted from the following paper but it tries to update the information as some of the characteristics of the market setups in the paper have been updated from the time of its publication.


2.1 Introduction

After conducting a public consultation in early 2023, the European Commission unveiled a proposal on 14 March to update the regulations surrounding electricity market design and support the EU’s defenses against market manipulation in the wholesale energy sector. The goal is to strengthen the EU energy market’s resilience and decouple European consumers’ and businesses’ energy bills from the short-term fluctuations in electricity prices. Strategies like adopting more long-term contracts, such as power purchase agreements, and framing investment support as two-way contracts for difference (CfD) are proposed [19].

Four pivotal factors have been identified in the international communities to reach successful electricity market design [20]:

- Alignment between the short-term market determining prices and how the actual electricity network operates
• Effective market mechanisms ensure long-term generation and transmission resource adequacy

• Suitable strategies to curb both system-wide and local market power

• Inclusion of end consumer demand in the short-term market

These factors are vital, especially as wholesale and retail market mechanisms decentralize activities formerly managed by vertically integrated monopolies. The challenge is that market rules can greatly influence participant behavior, sometimes to the detriment of consumers. Thus, market designs must foster economic incentives that support real-time system reliability and long-term supply adequacy without being exploited for undue profit.

Utilizing price signals and controlled network tariffs to represent the worth of all electric services, aiming for the most cost-effective system solution is one of the main principles of any electricity market design [21]. A well-structured market employs prices to convey the value of all the electric services offered. The objective is to address the "missing money" issues that emerge when certain services are not adequately compensated. This perspective has both long-term and immediate implications—ensuring optimal placement for investments (in renewables and other energy sources) and an efficient distribution once they are connected. This ensures the delivery of eco-friendly electricity at the lowest possible cost to consumers.

Another crucial aspect of a well-designed electricity market is the efficient utilization of existing interconnections among bidding zones [21]. This enhances the European system’s flexibility, allowing it to leverage inherent advantages such as hydro assets in Norway, wind power in Denmark, Germany, and Sweden, and solar power in Italy, the Netherlands, and Spain [19]. A detailed discussion on the efficient use of these interconnector capacities for reserve dimensioning applications can be found in Chapter 8.

### 2.2 Long-term Financial markets

The financial market plays an important role in the power trading stage. In 2021, Nordpool reported 820 TWh trading in financial and 963 TWh in physical markets [1]. The EMD proposal highlights the importance of long-term contracts, like government-backed Contracts for Differences (CfDs) and private Power Purchase Agreements (PPAs), as a response to the limitations of short-term markets exposed by the recent crisis. The crisis underscored the vulnerability due to a lack of long-term contracting, leading to high consumer costs and windfall profits for suppliers. Long-term contracts are deemed critical, especially for low-carbon generators, due to their high fixed and low variable costs, necessitating revenue stability for cost management. These contracts are designed to coexist with short-term markets without distorting them, ensuring cost and revenue stability.
while maintaining efficient market operation. Moreover, the interdependence between different types of long-term contracts encourages competitive pricing and investment in low-carbon assets, preventing a halt in low-carbon asset buildout by allowing direct contracting between investors and the demand side through PPAs if CfDs are set too low. In this section, the two main financial contracts are analyzed.

### 2.2.1 Power-Purchase Agreements (PPAs)

Power Purchase Agreements (PPAs) are long-term contracts typically established between electricity generators and consumers, which may also involve utilities acting as intermediaries. These agreements can be structured either for the physical delivery of electricity or as financial arrangements akin to forward contracts. The primary aim of PPAs is to offer both generators and consumers the advantage of stable power prices, effectively acting as a hedge against price volatility. To encourage the adoption of PPAs and enhance their attractiveness, the European Commission suggests the provision of state guarantees. This approach aims to secure stable pricing for electricity, benefiting both producers and consumers by mitigating financial risks associated with fluctuating energy prices.

### 2.2.2 Contract-for-differences (CfDs)

CfDs are financial agreements where payments are made based on the difference between the current price of an underlying asset and a predetermined strike price. In the context of electricity, CfDs are used as a support mechanism for renewable energy (and occasionally nuclear power), where the strike price is usually set via a competitive auction before the investment occurs and remains fixed for the duration of the CfD, typically 20 to 30 years. Two-sided CfDs require sellers to pay back money to buyers if the market price exceeds the strike price, a feature that distinguishes them from most other support schemes and has gained them favor among policymakers, especially in light of recent energy crises. This mechanism not only supports renewable energy development by providing a stable income but also generates public income during periods of high electricity prices. The UK was among the first to implement CfDs in 2014, and their use has since become widespread across Europe.

### 2.3 Day-ahead Energy Market

The Day-Ahead (DA) spot market operates as a competitive auction platform where electricity prices for each hour of the following day are determined. Participants, including both producers and consumers, submit their bids for the amount of electricity they plan to produce or consume in their respective price areas before the gate closure time, which is set at 12:00 CET on the day prior to delivery.
At 12:42 CET, the system price is calculated based on these submissions and then announced.

In instances where there is transmission congestion between different price areas, meaning the demand for electricity transmission capacity exceeds the available capacity, the submitted bids are used to form supply and demand curves similar to how the system price is established. This process also involves calculating the maximum capacity for imports and exports across the congested line, ensuring that the allocation of transmission capacity is managed efficiently to accommodate the constraints of the physical network [22].

2.4 Intraday Market

The intraday (ID) market represents a continuous trading platform [1] that commences operations at 14:00 CET the day before delivery (D-1) and remains open until one hour before the delivery hour. This market structure allows for the dynamic entry of buyers and sellers who can execute transactions as soon as they find a matching offer at their quoted price.

In the context of the Nordic countries, the intraday market features specific Gate Opening Times (GOTs) and Gate Closure Times (GCTs) that vary by country [23]. These markets enable trading in both hourly volumes and block bids, accommodating the flexible trading needs of participants.

Furthermore, the Single Intraday Coupling (SIDC) [24] project facilitates cross-border trading among 22 European countries, including the Nordic countries, on the intraday continuous trading platform. This integration aims to enhance the efficiency of electricity trading across Europe by allowing for seamless cross-border transactions.

Pricing in the intraday market operates on a "pay-as-bid" basis, where participants pay or receive the price they bid for energy, as opposed to a uniform price for all transactions. This pricing mechanism encourages participants to carefully consider their bid prices, as they directly influence the cost or revenue associated with their trades [25].

2.5 Balancing Markets

The Transmission System Operator (TSO) plays a crucial role in maintaining the balance between electricity production and consumption. This balance is essential for the stability and reliability of the power grid. To achieve this, the TSO operates balancing markets, where reserves are procured to ensure that the grid can handle sudden changes in demand or supply, such as those caused by the Dimensioning Incident (DI). A DI refers to significant failures within the grid,

---

1 A continuous intraday market refers to the market where buyers/sellers can arrive at anytime while the market is open and can get transacted if there is someone willing to sell/buy from them at their quoted price.
like the outage of a large power plant or a major transmission line, which can lead to imbalances between production and consumption.

These imbalances and other faults often manifest as changes in the system’s frequency. To mitigate the effects on system frequency, the TSO manages a portfolio of frequency reserves. These reserves are designed to respond at different stages, depending on the severity and timing of the frequency deviation. Fig. 2.1 illustrates the stages of activation in case of an under-frequency, i.e., when up-regulation is required.

For situations where the system frequency drops (under-frequency), indicating that demand exceeds supply, the TSO activates a sequence of reserves to bring the system back into balance. This staged activation ensures that smaller, more immediate reserves are used first to stabilize the frequency quickly, followed by larger reserves that can sustain the balance for a longer period if necessary. This structured approach allows for an efficient and effective response to deviations, minimizing the impact on the power grid’s overall stability.

### 2.5.1 Frequency Containment Reserve (FCR)

The role of FCR-N is to mitigate ongoing frequency deviations under normal conditions, which is indicated by the “N” in its name. It is procured by all Nordic TSOs to ensure frequency stability.

FCR-N is designed as a symmetrical service, capable of both increasing and decreasing power supply as necessary. It activates within the frequency span of 49.9 to 50.1 Hz, with the power response directly correlating to the frequency changes. The system requires FCR-N to be 63% operational within 60 seconds and achieve at least 95% functionality within three minutes.

Reserves under FCR-N are automatically deployed in response to the grid frequency measurements observed at each reserve unit. These measurements must adhere to a specific level of accuracy as outlined in the technical requirements. The compensation for the energy activated is based on the market for Frequency Restoration Reserves (mFRR) prices, with distinctions made between energy used for upward adjustment (compensated at the mFRR up-regulation
Table 2.1: Level of market participation for solar and wind (MW) [7]

<table>
<thead>
<tr>
<th></th>
<th>Svenska Kraftnät</th>
<th>Fingrid</th>
<th>Statnett</th>
<th>Energinet</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wind</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FFR</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>FCR-D up</td>
<td>170</td>
<td>0</td>
<td>0</td>
<td>150</td>
</tr>
<tr>
<td>FCR-D down</td>
<td>320</td>
<td>0</td>
<td>0</td>
<td>150</td>
</tr>
<tr>
<td>FCR-N</td>
<td>150</td>
<td>0</td>
<td>0</td>
<td>120</td>
</tr>
<tr>
<td>aFRR up</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>224</td>
</tr>
<tr>
<td>aFRR down</td>
<td>250</td>
<td>0</td>
<td>0</td>
<td>224</td>
</tr>
<tr>
<td>mFRR energy up</td>
<td>10</td>
<td>290</td>
<td>100</td>
<td>410</td>
</tr>
<tr>
<td>mFRR energy down</td>
<td>1440</td>
<td>860</td>
<td>1200</td>
<td>2850</td>
</tr>
<tr>
<td>mFRR capacity up</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>150</td>
</tr>
<tr>
<td>mFRR capacity down</td>
<td>-</td>
<td>340</td>
<td>0</td>
<td>-</td>
</tr>
</tbody>
</table>

|                |                  |         |          |           |
| **Solar**      |                  |         |          |           |
| FCR-D down     | 10               | 0       | 0        | 15        |
| FCR-D up       | 0                | 0       | 0        | 5         |

price) and energy for downward adjustment (compensated at the mFRR down-regulation price).

Typically, the grid frequency oscillates within a standard range of 49.9 to 50.1 Hz, adjusting to variations in demand and supply. This dynamic ensures that the FCR-N continuously adapts to sustain equilibrium within the power system. Should the frequency deviate beyond this standard range, FCR-N remains fully operational, while Frequency Containment Reserve for Disturbances (FCR-D) is also engaged to help the system.

The Eastern region of Denmark (DK2) and Sweden share a joint market for FCR-N and FCR-D (up and down), which operates as an hourly market divided into two separate auctions. These auctions are scheduled around the spot market timings, with one taking place before and another following the spot market. Consequently, all FCR capacity products are secured through these auctions one day prior to their operational use (D-1). The auction system employs a pay-as-cleared (From February 2024) pricing mechanism. Additionally, the minimum threshold for bid size is set at 0.1 MW.

### 2.5.2 Automatic Frequency Restoration Reserve (aFRR)

**aFRR Energy Market**

The primary function of the aFRR is to adjust the power system’s frequency back towards 50 Hz. Over time, the aFRR market has seen significant growth, with hydropower being the dominant participant. In Sweden and Denmark, wind
parks also contribute to aFRR, but solar parks have not yet started to provide aFRR services.

aFRR is distinguished by its asymmetrical nature, meaning it comprises two separate products: one for upward regulation and another for downward regulation, each with its unique pricing. The minimum size for bids within this market is set at 1 MW.

The aFRR operates as an automatic reserve, triggered by a control signal from the TSO, which is based on the frequency of the power system. Providers are required to respond promptly, achieving full operational response within 5 minutes. Compensation for activated energy currently follows the market for mFRR pricing model, with the exception of the DK1 area. However, with the establishment of the aFRR Energy Activation Market (PICASSO), compensation for activated energy will transition to a marginal price principle specific to its own market.

The current activation method is pro-rata, meaning the total volume activated is distributed proportionally and equally among participants in the capacity market. The introduction of PICASSO will mark a shift to an energy activation market where activations are executed in order of price, enhancing the efficiency and responsiveness of aFRR services.

**aFRR Capacity Market**

Until December 2022, each country bought aFRR separately with different market designs. Today there is a common Nordic capacity market for aFRR, except for DK1. The market clears one day before delivery (D-1) with a gate closure time at 7:30 CET. Market results are normally published around 9:00 CET. The capacity prices are priced to the marginal price principle (“pay-as-cleared”). Bidding and market-clearing are separate for each hour for each direction. The Nordic aFRR demand is published each quarter. The procurement is hourly for the period, and reserves for both up and down regulation are purchased. The total need of aFRR is split between the bidding zones in the Nordics. However, some areas buy aFRR from other bidding zones due to lack of providers.

**2.5.3 Manual Frequency Restoration Reserve (mFRR)**

**mFRR Energy Market**

The mFRR plays a crucial role in maintaining equilibrium within the Nordic power system both under normal conditions and in the event of disturbances. Its primary function is to recalibrate the system’s frequency back to 50 Hz, while also addressing regional imbalances and alleviating congestion on transmission lines.

Market participants are required to submit their mFRR energy activation offers on an hourly basis. The deadline for offer submission is set at 45 minutes.
prior to the respective delivery hour. The TSO then selects offers based on price, issuing electronic activation requests to the participants, who must adjust their output within 15 minutes. The minimum bid size for participation can range from 1 to 10 MW, varying by country.

The mFRR energy activation market operates on a Nordic level with a marginal pricing method. Although TSOs manage local marketplaces, activations are coordinated across the Nordic region by consolidating bid lists and optimizing both the cost of activation and the use of transmission capacities between different bidding zones. Offers for upward regulation are activated starting from the least expensive until the demand for balance is met. Conversely, offers for downward regulation begin with the most expensive. The pricing for upward regulation is set to be equal to or higher than the Day-ahead (DA) price, whereas downward regulation pricing is equal to or lower. The activation price in the dominant direction also determines the imbalance price within the area.

The mFRR energy activation market is the last reserve market to close before the start of the delivery hour, making it strategic for participants to offer their maximum available capacity for both upward and downward regulation. Failing to submit mFRR offers means missing potential revenue opportunities and can lead to a less efficient system operation if available flexibility is overlooked in favor of more costly alternatives.

mFRR Capacity Market

As of October 2023, all four countries now host mFRR capacity markets, with Sweden being the latest to introduce its market. These capacity markets employ a marginal pricing strategy to ensure there is sufficient participation in the mFRR energy activation market. In this framework, Balance Service Providers (BSPs) or Balance Responsible Parties (BRPs) pledge to submit offers to the energy activation market. Compensation for these entities is based on the capacity they offer, rather than the actual activation of their bids within the energy activation market. This system guarantees that enough offers are available for mFRR energy activation, ensuring the stability and balance of the power system.

Fig. 2.2 shows the timeline of the market setups. The numbers in the circle show the number of auctions for each setup, e.g. for FCR products (FCR-N, FCR-D up and FCR-D down) there are two auctions, one cleared at 00:30 D-1 and another one cleared at 18:30 D-1.

2.6 Balancing Markets Interactions

In the balancing markets, as outlined by the European grid codes, there are two principal roles: the Balance Responsible Party (BRP) and the Balancing Service Provider (BSP).

A BRP holds the accountability for rectifying any discrepancies between the anticipated trading volumes and the actual production and consumption within
2.7 Conclusion

In conclusion, this chapter serves as a foundational introduction to the varied and intricate setups of the Nordic electricity markets, delineating their unique characteristics, operational mechanisms, and the pivotal role they play in the region’s energy landscape. By dissecting the structure and functionality of long-term financial markets, day-ahead energy markets, intraday markets, and balancing markets, the chapter provides a comprehensive overview of how the Nordic electricity market operates. This detailed examination not only highlights the complexities inherent in managing and balancing energy supply and demand but also underscores the strategic importance of these markets in fostering stability, efficiency, and sustainability within the Nordic energy sector. Through this exploration, readers gain insight into the critical elements that underpin the Nordic electricity market’s ability to adapt to changes, integrate renewable en-

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Figure 2.2: Timeline of the market setups in the Nordic electricity market

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...
energy sources effectively, and ensure the reliability and affordability of energy for its consumers.
Chapter 3
Mathematical Background

This chapter provides a brief overview of the mathematical principles underlying the topics explored in the future chapters. It aims to lay the foundation for readers who may not be acquainted with these concepts.

3.1 Optimization Problem

A mathematical optimization or optimization problem is a mathematical construct designed to either maximize or minimize a specified goal (i.e., the objective function), within the bounds of certain constraints that may be either equalities or inequalities. The typical structure of such a mathematical problem is as follows:

\[
\begin{align*}
\text{Optimize} & \quad f(x) \\
\text{subject to:} & \\
& \quad h(x) = 0 \\
& \quad g(x) \leq 0
\end{align*}
\]  

(3.1a) \quad (3.1b) \quad (3.1c)

wherein \( x \in \mathbb{R}^n \) represents the vector of variables under optimization, \( f(x) : \mathbb{R}^n \rightarrow \mathbb{R} \) denotes the function determining the goal to be optimized, \( h(x) : \mathbb{R}^n \rightarrow \mathbb{R}^{m_e} \) represents the equality condition functions, and \( g(x) : \mathbb{R}^n \rightarrow \mathbb{R}^{m_i} \) embodies the inequality condition functions. Solutions that fulfill both \( h(x) = 0 \) and \( g(x) \leq 0 \) delineate the feasible region.

3.2 Multi-level Optimization

Optimization problems that are constrained by additional optimization are widespread, especially in the context of electricity market operations. Typically, a market participant must make choices while considering (or being influenced by) the market’s equilibrium state. Understanding the equilibrium is crucial for
predicting market-clearing prices, which, in turn, guides the participant’s strategy (such as profit optimization). The decision-making process for such participants often involves formulating an optimization problem (aimed at profit maximization) that takes into account the conditions set by the market’s balance. The market equilibrium itself can be represented as either a complementarity or an optimization problem. This means the primary issue (decision-making by the participant) depends on resolving another optimization problem (achieving market equilibrium). This setup usually implies a structured approach where the upper-level problem is influenced by one or more lower-level problems [27] which is called multi-level optimization.

Below are a few examples where optimization problems constrained by other optimization problems exist [28]:

- A strategic energy producer might design its bidding strategy for the electricity market by incorporating the market’s actual clearing process (another optimization problem) within its own profit maximization framework. The market’s clearing outcomes are affected by the producer’s strategic decisions.

- A producer could plan to enhance its production capabilities aiming at boosting its long-term profitability (an optimization problem), taking into consideration the fluctuating market conditions and their effect on market clearing (a series of optimization problems).

- An entity aiming to compromise a power network might plan its strategies to maximize potential disruptions (an optimization problem) while accounting for the countermeasures employed by the network’s management aimed at reducing the attack’s impact (another optimization problem).

- A grid operator might propose an expansion to its transmission networks to reduce the risk of energy shortages (an optimization problem), factoring in the need to accommodate various market conditions, including demand and supply fluctuations (a series of optimization problems).

Mathematically speaking, the following set of equations shows the general structure of multi-level optimizations:

\[
\begin{align*}
\text{Maximize} & \quad f(x^U, x^{L1}, ..., x^{Ln}) \\
\text{s.t.} & \quad h(x^U, x^{L1}, ..., x^{Ln}) = 0 \\
& \quad g(x^U, x^{L1}, ..., x^{Ln}) \leq 0 \\
& \quad \left\{ \begin{array}{l}
\text{Maximize} & \quad f^1(x^U, x^{L1}, ..., x^{Ln}) \\
\text{s.t.} & \quad h^1(x^U, x^{L1}, ..., x^{Ln}) = 0 \quad (\lambda^1) \\
& \quad g^1(x^U, x^{L1}, ..., x^{Ln}) \leq 0 \quad (\mu^1)
\end{array} \right.
\end{align*}
\]
3.3. STOCHASTIC OPTIMIZATION

\[
\begin{align*}
\text{Maximize} & \quad f^1(x^U, x^{L1}, \ldots, x^{Ln}) \\
\text{s.t.} & \quad h^2(x^U, x^{L1}, \ldots, x^{Ln}) = 0 \quad (\lambda^n) \\
& \quad g^2(x^U, x^{L1}, \ldots, x^{Ln}) \leq 0 \quad (\mu^n)
\end{align*}
\]

(3.2e)

Where (3.2a)-(3.2c) show the upper-level problem while the (3.2d)-(3.2e) are the lower-level problems. In this problem, \( \Gamma_{UL} = \{x^U, x^{L1}, \ldots, x^{Ln}, \lambda^1, \ldots, \lambda^n, \mu^1, \ldots, \mu^n\} \) which entails all the upper-level and lower-level variables and the corresponding dual variables for the lower level constraints. The problem discussed involves a hierarchical structure where an upper-level optimization problem is constrained by its own set of constraints as well as by a collection of lower-level optimization problems. The dual variables associated with the constraints of these lower-level problems influence the solution to the upper-level problem.

3.3 Stochastic Optimization

In decision-making processes under uncertainty, the decision-maker is tasked with making the best possible choices across a defined period, known as the decision horizon, despite having incomplete information. Throughout this horizon, several stages are established, each marking a moment when decisions are taken or when uncertainty is either partially or completely resolved. The quantity and quality of information accessible to the decision-maker often vary from one stage to the next. Based on how many stages are involved, the problems can be categorized into two main types: two-stage and multi-stage stochastic programming problems [29]. In a two-stage problem, decisions are made at two critical points: initially, when some information is available, and subsequently, after the uncertainty has been revealed. In contrast, multi-stage problems involve a series of decisions made at multiple points, allowing for adjustments as new information unfolds over time, thus providing a dynamic framework for dealing with uncertainty across multiple stages.

A stochastic process, denoted by \( \lambda \), is characterized through a spectrum of scenarios \( \lambda_\Omega \). In the framework of two-stage stochastic optimization, two distinct sets of decision variables, \( x \) and \( y \) are made. The decision encapsulated by \( x \) is executed prior to the revelation of the actual outcome of \( \lambda \), in contrast to \( y \), which is determined post the realization of \( \lambda \). It follows that the determination of \( y \) is contingent upon the initial decision \( x \) as well as the specific scenario \( \lambda_\Omega \) that unfolds from the stochastic process \( \lambda \). This interdependency permits the optimizer to model \( y \) as a function \( y(\omega) \), encapsulating the sequential and conditional nature of the decision-making process. The deterministic equivalent problem of the stochastic programming problem is as follows:
Minimize \( x, y(\omega) \)
\[
z = c^T x + \sum_{\omega \in \Omega} \pi(\omega) q(\omega)^T y(\omega) \quad (3.3a)
\]
subject to:
\[
Ax = b \quad (3.3b)
\]
\[
T(\omega)x + W(\omega)y(\omega) = h(\omega) \quad (3.3c)
\]
\[
x \in X, y(\omega) \in Y \quad (3.3d)
\]
where \( x \) and \( y(\omega) \) are the first and second stage decision variables, respectively and \( c, q(\omega), b, h(\omega), A, T(\omega) \) and \( W(\omega) \) are some predefined vectors and matrices with appropriate sizes.

### 3.4 Robust Optimization

Robust Optimization (RO) \[30\] is crucial for making pivotal decisions in uncertain conditions. This approach is characterized by preparing for the most adverse scenario of uncertainty, constrained by predefined limits on uncertainty through an uncertainty set and an uncertainty budget. These constraints define the extent of the worst possible outcomes considered in the decision-making process.

A robust optimization in general format can be formulated as follows:

\[
\min_{x \in \mathcal{X}} \max_{u \in \mathcal{U}} f(x, u) \quad (3.4)
\]

This formulation expresses the preventive view in which the optimizer tends to be protected against the worst-case realization of the uncertain parameters in \( u \in \mathcal{U} \) through the inner maximization problem. For this worst-case scenario, the optimization seeks to minimize the function \( f(x, u) \) to find the optimal values for the decision variable \( x \in \mathcal{X} \).

Often it is possible to react to the uncertainties in the system while they have been realized. This will help to mitigate the potential adverse effects of those uncertainties. In this way, the concept of adaptive robust optimization (ARO) has been developed.

\[
\min_{x \in \mathcal{X}} \max_{u \in \mathcal{U}} \min_{y \in \mathcal{Y}(x, u)} f(x, u, y) \quad (3.5)
\]

This problem consists of three levels:

1. In the first level, the optimizer seeks to perform a planning strategy prior to the realization of uncertainties and tries to minimize the value of the objective functions through the decision variable \( x \in \mathcal{X} \).
2. In the second level, the uncertainties are realized in a way to maximize the value of the objective function through the decision variables \( u \in \mathcal{U} \).

3. In the third level, the optimizer seeks to perform the operational decisions to mitigate the adverse impacts of uncertainty realizations in the previous level after they were realized. So, it seeks to minimize the objective functions. This action is implemented through decision variables \( y \in \mathcal{Y}(x, u) \).

Here the overall objective is to minimize the objective function under the worst-case uncertainty realization inside the robust set of \( \mathcal{U} \). The model includes both preventive and corrective actions.

### 3.5 Optimality Conditions

The Karush-Kuhn-Tucker (KKT) conditions are crucial in identifying the optimal solutions for a wide array of optimization problems. However, it is important to note that not all optimization problems are suited to the application of the KKT conditions. For those problems where the KKT conditions cannot be meaningfully applied, these conditions are not capable of characterizing the optimal solutions [28].

Moreover, the KKT conditions often serve as necessary conditions for optimality rather than sufficient ones. This means that while every optimal solution must satisfy the KKT conditions, not every solution that satisfies these conditions is guaranteed to be optimal. In essence, the KKT conditions provide a framework for testing potential optimal solutions but do not affirm optimality on their own. If the lower-level problems are convex, the KKT conditions are both necessary and sufficient optimality conditions.

The KKT conditions are known as first-order conditions. They are formulated based on the first derivatives of the function involved in the optimization problem, utilizing vectors and matrices such as gradients and Jacobians to express these derivatives. This mathematical formulation provides a way to examine the behavior of the function at potential optimal points through the lens of slope and rate of change, which are critical to determining points of optimality in constrained optimization problems.

To apply the KKT conditions effectively, it is essential to construct the Lagrangian function for the optimization problem at hand. For the problem (3.1), there is:

\[
\mathcal{L} = f(x) + \lambda^T h(x) + \mu^T g(x)
\]

(3.6)

where \( f(x), h(x) \) and \( g(x) \) are continuously differentiable within the feasible space of \( x \in \{ x | h(x) = 0, g(x) \leq 0 \} \). Now, the KKT conditions of the problem 3.1 are:

\[
\nabla_x f(x) + \lambda^T \nabla_x h(x) + \mu^T \nabla_x g(x) = 0
\]

(3.7a)

\[
h(x) = 0
\]

(3.7b)
CHAPTER 3. MATHEMATICAL BACKGROUND

\[ g(x) \leq 0 \quad (3.7c) \]
\[ \mu^T g(x) = 0 \quad (3.7d) \]
\[ \mu \geq 0 \quad (3.7e) \]

where \( \lambda \in \mathbb{R}^{m_E} \) and \( \mu \in \mathbb{R}^{m_I} \) are the Lagrange multiplier vectors for the equality and inequality constraints and \( \nabla_x \) is the gradient with respect to \( x \). Constraints 3.7d and 3.7e are known as complementarity conditions and are usually written as \( 0 \leq \mu \perp g(x) \leq 0 \).

3.6 Mathematical Programming with Equilibrium Constraints

A Mathematical Program with Equilibrium Constraints (MPEC) represents a class of optimization problems that incorporate equilibrium conditions as part of their constraints. These equilibrium conditions often take the form of KKT conditions from one or more interconnected optimization problems. For example, in modeling the equilibrium of the electricity market, MPECs play a crucial role by integrating the KKT conditions of related lower-level optimization problems into a single framework [28].

In essence, MPECs involve optimization problems that are constrained not just by traditional inequality or equality constraints, but also by the solutions of other optimization or complementarity problems. This inclusion makes MPECs uniquely suited to addressing complex real-world scenarios where the outcome of one decision-making process depends on the outcomes of others, mirroring conditions of economic markets, networked systems, or strategic planning scenarios where various actors’ decisions impact one another. In the case of convex lower-level problems, they can be merged with upper-level problem though their KKTs and form an MPEC. The following shows this representation for two lower-level problems:

\[
\text{Maximize } f(x^U, x^{L1}, x^{L2}, \lambda^{L1}, \lambda^{L2}, \mu^{L1}, \mu^{L2}) \quad (3.8a)
\]

\[
\text{s.t. } \\
\quad h(x^U, x^{L1}, x^{L2}, \lambda^{L1}, \lambda^{L2}, \mu^{L1}, \mu^{L2}) = 0 \quad (3.8b) \\
\quad g(x^U, x^{L1}, x^{L2}, \lambda^{L1}, \lambda^{L2}, \mu^{L1}, \mu^{L2}) \leq 0 \quad (3.8c) \\
\quad \nabla_{x^1} f^1(x, x^1, x^2) + (\lambda^1)^T \nabla_{x^1} h^1(x, x^1, x^2) + (\mu^1)^T \nabla_{x^1} g^1(x, x^1, x^2) = 0 \quad (3.8d) \\
\quad \nabla_{x^2} f^2(x, x^1, x^2) + (\lambda^2)^T \nabla_{x^2} h^2(x, x^1, x^2) + (\mu^2)^T \nabla_{x^2} g^2(x, x^1, x^2) = 0 \quad (3.8e) \\
\quad h^1(x^U, x^{L1}, x^{L2}) = 0 \quad (3.8f) \\
\quad h^2(x^U, x^{L1}, x^{L2}) = 0 \quad (3.8g) \\
\quad 0 \leq \mu^1 \perp g^1(x^U, x^{L1}, x^{L2}) \leq 0 \quad (3.8h)
\]
3.7 Chance-Constraints Optimizations

In the above formulations, the equations (3.8i) and (3.8c) are stationary constraints for each lower level problem, the equations (3.8f) and (3.8g) are primal feasibility constraints and the equations (3.8h) and (3.8i) are the dual feasibility and complementary constraints.

3.7 Chance-Constraints Optimizations

Chance-constrained optimization is a strategy for addressing optimization problems where uncertainty is presented in the inequality constraints. This technique involves formulating constraints that govern the behaviors and values of random variables in a significant manner. The core concept behind this approach is to ensure that the constraints are met by a substantial number of the random variable outcomes—that is, they comply with the desired conditions with a sufficiently high probability. In real-world applications of optimization, it is often observed that constraints are not absolutely rigid. Instead, they can tolerate minor breaches and are thus termed soft constraints. For instance, in the domain of power systems modeling, there are specified limits on the amount of power that can be transmitted over a line. Practically, these lines can handle temporary overloads without sustaining damage. Therefore, occasional violations of these limits are permissible.

The general chance-constraint optimization is defined as follows [31]:

\[
\text{Minimize } f(x) \quad \text{subject to:} \\
\mathbb{P}(g(x, \xi) \leq 0) \geq 1 - \epsilon
\]  

In the above problem, the constraint \( g(x, \xi) \leq 0 \) can be violated in \( \epsilon \) percentage of the time. In general, \( \epsilon \) is a very small number. This constraint makes the problem non-convex and different techniques of reformulations and relaxations need to be employed to make the problem convex.
Part II

Market Design Challenges: A Short-Term Study
Chapter 4

Electricity Price Forecasting and GAMLSS

This chapter introduces a three-stage optimization model as the base model to be used in Chapter 5. This model employs a new method to generate the price scenarios of the balancing energy market prices using a deep learning method and one statistical method to model the active-time durations of balancing energy market offers. The content of this chapter is extracted from the following publication:


4.1 Introduction

In the following section, a three-stage stochastic optimization problem is introduced through which the application of the proposed electricity price scenario generation and probability distribution function (PDF) estimation is justified. The application of the proposed formulation in optimal planning and operation of generation assets will be discussed in Chapter 5.

Generating electricity energy price scenarios is crucial for determining the optimal multi-market offer-functions, and this requires using a reliable price-forecasting model. Current electricity forecasting techniques fall into three main categories: physical methods [32], statistical methods such as the Seasonal Autoregressive Integrated Moving Average (SARIMA) [33], and machine learning approaches [34–36]. This field of energy forecasting has seen significant advancements with the development of deep learning, leading to the proposal of new electricity price prediction models [34, 37–39].
4.2 Price Scenario Generation Technique

In this section, a three-stage problem formulation is presented to model the sequential bidding problem in the Nordic electricity market. Different energy and capacity market setups have been identified in Chapter 2 and the following three-stage scenario tree demonstrates how the information is revealed in each stage.

1. **First Stage:** In this phase, decisions are made regarding the offer volume for the day-ahead energy and mFRR capacity markets. The HPP operator also allocates a portion of its available capacity to the FCR-N market based on anticipated prices. Given that the mFRR capacity market is set to launch in Q4, 2023, and its prices are not yet known but can be estimated as the weighted average of the mFRR energy market: 
   \[
   \tilde{\lambda}^\text{dir}_t = k^\text{dir} \sum_{s \in S} \sum_{\omega \in \Omega} \pi^\omega \pi^s \lambda^\text{dir}_{\omega,s,t},
   \]
   where \(k^\text{dir}\) indicates the weight of capacity prices compared to the balancing energy market prices in each direction: either up or down, \(s\) is the second-stage scenario of the scenario set \(S\), \(\omega\) is the third-stage scenario of the scenario set \(\Omega\), \(\lambda^\text{dir}_{\omega,s,t}\) is the balancing market price scenarios on direction \(\text{dir}\), first stage scenario \(s\) and second stage scenario \(\omega\) and hour \(t\) and \(\pi^\omega\) and \(\pi^s\) are the probability of each scenarios.

2. **Second Stage:** During this phase, price details for the day-ahead energy and FCR-N markets become available. Using previous offers and this new data, the dispatched volume for each unit is determined. The HPP operator also decides about the bid volumes of each mFRR energy market offer before the gate closure.

3. **Third Stage:** Here, as the mFRR energy market’s prices are revealed, the HPP operator determines operational variables such as discharge, spillage, reservoir level, and electricity generation.

The graphical illustration of the above stages is depicted in Fig. 4.1. To generate these price scenarios, a deep learning technique is used. In the following, a short description of the method is explained and then its application to generate scenarios is described.

4.2.1 Long-Short Term Memory (LSTM)

LSTM is a variant of the Recurrent Neural Network (RNN), designed specifically to address sequential data challenges, such as time series, voice, and text. LSTMs excel at recognizing long-term patterns in sequences, making them ideal for tasks like language translation, speech recognition, and time series forecasting.

Traditional RNNs maintain a singular hidden state passed throughout the sequence, which can pose challenges in learning long-term dependencies. LSTMs tackle this limitation by incorporating a memory cell. This memory cell is essentially a storage unit capable of holding information over extended durations.
Figure 4.1: Scenario tree for the proposed three-stage optimization problem

The operations within the memory cell are governed by three distinct gates: the input gate, the forget gate, and the output gate.

The input gate dictates which information gets stored in the memory cell, the forget gate determines the information to be discarded, and the output gate designates the data that’s output from the cell. This intricate system permits LSTMs to selectively maintain or omit data, enabling them to grasp and learn from long-term sequential dependencies.

### 4.2.2 Balancing Market Price Scenarios

In this section, electricity price scenarios for the second and third stages of the formulation as presented in (4.1) are considered. For the second stage, one year of historical data was extracted and subsequently, the number of scenarios was reduced using the fast-forward algorithm in GAMS/SCENRED [42].

In this thesis, a modified scenario generation technique is presented through an LSTM architecture by updating the network state with available values instead of relying on the previously forecasted ones. This becomes feasible when actual values of time steps between predictions are accessible. In the present case, after the selection of day-ahead energy market scenarios, their corresponding mFRR...
energy market prices are available (as depicted by the solid black lines in the third stage of Fig. 4.1). However, there is a need to generate the required number of scenarios for the third-stage, given the data availability for just one scenario. The flow of this approach is illustrated in Fig. 4.2.

In this methodology, $X_{\text{train}}$ represents the year-long historical data for the mFRR energy market in both directions (upward and downward) extracted from Nord Pool [43]. $\hat{X}_{n,\text{train}}$ is the normalized one-hour lagged version of this training data. The $X_{\text{test}}$ data set pertains to the mFRR energy balancing market and is determined based on the day-ahead energy market chosen in the second stage, which aids in enhancing forecasting accuracy. In the Normalize box, the training data undergoes standardization to achieve zero mean and unit variance. The training phase of the LSTM network adopts a sequence-to-sequence regression LSTM network approach. Here, the responses are essentially the training sequences shifted by a single time step, as shown by the one-hour lag-generator in Fig. 4.2. This implies that the LSTM network is trained to predict the upcoming time step’s value for each step in the input sequence. Table 4.1 shows the settings of the LSTM training network.

<table>
<thead>
<tr>
<th>Options</th>
<th>Values</th>
<th>Options</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hidden Layers</td>
<td>150</td>
<td>LR Drop Period</td>
<td>125</td>
</tr>
<tr>
<td>Max Epochs</td>
<td>250</td>
<td>LR Drop Factor</td>
<td>0.2</td>
</tr>
<tr>
<td>Gradient Threshold</td>
<td>1</td>
<td>LR Schedule</td>
<td>piecewise</td>
</tr>
<tr>
<td>Initial LR</td>
<td>0.005</td>
<td>Verbose</td>
<td>0</td>
</tr>
</tbody>
</table>

### 4.3 PDF Estimation Technique

The accuracy of the representation of uncertainty is dependent on the number of scenarios and the information available about the Probability Density Function (PDF) that represents the uncertain parameter. However, the Active-Time Duration (ATD) of mFRR energy offers is not certain at the time the offer-function is calculated. The ATD refers to the duration TSO activates the procured mFRR energy Offers. This duration is crucial as it affects the optimal offer-function and the anticipated revenue from the operators’ perspective, given that their compensation in the balancing energy markets depends on the ATD. Elements like netload imbalance, the unpredictable nature of renewable energy generation, and forecast inaccuracies are among the factors influencing the ATD.

The Generalized Additive Model for Location, Scale and Shape (GAMLSS) is a renowned distributional regression approach that has been developed and employed in various applications [44,45]. In GAMLSS, users can choose from a range of density functions where the mean, variance, and other statistical moments can
4.3. PDF ESTIMATION TECHNIQUE

Figure 4.2: Modified LSTM Scenario generation for balancing energy markets
be dynamically specified based on external driving variables. The dynamically varying distribution of prices has been modeled using GAMLSS by [46] and [47]. Hence, in this thesis, GAMLSS is utilized to model the uncertainty of the ATD for mFRR balancing energy offers. Through the use of the GAMLSS model, it is demonstrated that the assumption of a normal distribution for the ATD as a random parameter, as suggested in prior works (e.g., [48]), is not necessarily hold.

In the GAMLSS framework, the assumption of an exponential family distribution for the response variable \((y)\) is replaced by a more general distribution family. This allows for the inclusion of highly skewed and/or kurtotic continuous and discrete distributions. Not only the mean (or location) but other parameters of the distribution of \(y\) are permitted to be modeled as linear and/or nonlinear parametric and/or additive non-parametric functions of explanatory variables and/or random effects [49].

For the GAMLSS model, it is assumed that independent observations \(y_i\), where \(i = 1, ..., n\), are governed by the distribution function \(F_{y_i}(y_i|\theta_i)\). Here, \(\theta_i\) consists of \(p\) distribution parameters that describe position, scale, and shape. Typically, \(p\) is four or less, offering sufficient flexibility for numerous applications.

Utilizing a response variable vector of length \(n\), denoted as \(\mathbf{y}^T = (y_1, ..., y_n)\), let \(g_k(.)\), where \(k = 1, ..., p\), represent the monotonic link functions connecting the distribution parameters to the explanatory variables and random effects through an additive model:

\[
g_k(\theta_k) = \eta_k = X_k \beta_k + \sum_{j=1}^{J_k} Z_{jk} \gamma_{jk} \tag{4.1}
\]

where \(\theta_k\) and \(\eta_k\) are vectors of length \(n\), e.g. \(\theta_k = (\theta_1^k, ..., \theta_n^k)\). \(\beta_k = \beta_1k, ..., \beta_jk\) is a parameter vector of length \(J_k\) and \(J_k\) itself is the number of explanatory variables for \(\theta_i\), \(X_k\) is a known design matrix of order \(n \times J_k\), \(Z_{jk}\) is a fixed known \(n \times q_{jk}\) design matrix and \(\gamma_{jk}\) is a \(q_{jk}\)-dimensional random variable with \(\gamma_{jk} \sim N_{q_{jk}}(0, G_{jk}^{-1})\) where \(G_{jk}^{-1}\) is the generalized inverse of a \(q_{jk} \times q_{jk}\) symmetrical matrix \(G_{jk} = \hat{G}_{jk}(\lambda_{jk})\) which depend on a vector of hyperparameters \(\lambda_{jk}\). In (4.1), the linear predictors \(\eta_k\), for \(k = 1, .., p\) are comprised of a parametric component \(X_k \beta_k\) (linear functions of explanatory variables), and additive components \(Z_{jk} \gamma_{jk}\) (linear functions of stochastic variables, also denoted as random effects).

The parametric vectors \(\beta_k\) and the random effects parameters \(\gamma_{jk}\), for \(j = 1, 2, ..., J_k\) and \(k = 1, 2, 3, 4\) are estimated within the GAMLSS framework (for fixed values of the smoothing hyper-parameters \(\lambda_{jk}\)) by maximizing a penalized likelihood function \(\ell_p\) given by:

\[
\ell_p = \ell - \frac{1}{2} \sum_{k=1}^{p} \sum_{j=1}^{J_k} \lambda_{jk} \gamma'_{jk} G_{jk} \gamma_{jk} \tag{4.2}
\]

where \(\ell = \sum_{i=1}^{n} \log F(y_i|\theta^i)\) is the log likelihood function and \(F\) is the selected population probability density function, and \(\gamma'_{jk}\) and \(\gamma_{jk}\) are two independent
normal distributions. In this chapter, different $F$ can be tested by maximizing
the penalized likelihood function to find the best fit for the available data (For
numerical assessment of the different models, check section 5.4.2). The selected
GAMLSS distribution is the modified sinh-arcsinh (SHASHo) with the following
definition:

$$F_Y(y|\mu, \sigma, \nu, \tau) = \frac{c}{\sqrt{2\pi(1 + r^2)}\sigma}e^{-z^2/2}$$ \hspace{1cm} (4.3)

where

$$z = \frac{1}{2}\left\{e^{\tau \sinh^{-1}(r)} - e^{-\nu \sinh^{-1}(r)}\right\}$$ \hspace{1cm} (4.4)

$$c = \frac{1}{2}\left\{\tau e^{\tau \sinh^{-1}(r)} + \nu e^{-\nu \sinh^{-1}(r)}\right\}$$ \hspace{1cm} (4.5)

and $r = (y - \mu)/\sigma$ for $-\infty < y < \infty$, where $-\infty < \mu < \infty$, $\sigma > 0$, $\nu > 0$ and
$\tau > 0$. Here, $(\sigma, \mu, \nu, \tau)$ are $\eta_k$ in (4.1) for $k = 1, \ldots, 4$ which are estimated based
on some explanatory variables (like (5.2)-(5.5) in Section 5.4.2).

The methodology to derive prices and ATD scenarios is delineated as follows:

1. Using one year of historical data concerning day-ahead energy and FCR-N
market prices, a specified number of scenarios are chosen for model’s second
stage.

2. With the chosen second-stage scenarios in hand, the necessary third-stage
scenarios are generated by employing the modified LSTM-based model delin-
eated in Section 4.2.

3. Historical data serves as the basis for estimating the PDF of ATD for both
up and down-regulation offers. Various distributions available in GAMLSS
are examined, and the one showcasing the lowest error values is selected.

4. Using the day-ahead energy and balancing market prices derived from steps
2 and 3, appropriate ATD values are generated for each third-stage scenario.
This is achieved by leveraging the GAMLSS model identified in step 3.

A comprehensive discussion of the optimal GAMLSS model selection is pro-
vided in Chapter 5.

From a flexibility standpoint, it is noteworthy that the proposed GAMLSS-
based forecasting approach for ATDs is inherently versatile. It can process a range
of inputs such as power generation, electricity market prices, or consumption lev-
els specific to an area. Subsequently, it outputs the relevant coefficients indicating
the influence of ATD on the given input, as exemplified in (4.1). Other possible
explanatory variables can be added to increase the accuracy of the modeling.
4.4 Conclusion

This chapter presents two machine learning and statistical methods as the fundamental inputs to form an optimization for planning and operation of generation assets in the Nordic electricity market through a three-stage stochastic optimization problem. It integrates a modified LSTM model for price scenario generation and employs the GAMLSS framework to model the uncertainty of Active-Time Duration (ATD) in mFRR balancing energy offers. This approach improves the forecasting accuracy for electricity prices in different market stages.
Chapter 5

Optimal Short-Term Planning of Hydro-Dominated Assets

This chapter proposes a quantified optimization model briefly explained in the previous chapter to find the best bidding curve of the aggregated hydropower plants when participating in the day-ahead energy, FCR-N, mFRR capacity and mFRR energy markets as a three-stage optimization model. In this model, the active-time duration of the mFRR energy market is modeled to account for the possibility of not getting dispatched in this market. The content of this chapter is based on the following paper:


5.1 Introduction

In the forward electricity markets, optimal schedules do not always ensure real-time operational security for power systems. Transmission System Operators (TSOs) maintain power network security. With the green transition envisioned by many European TSOs [50], new electricity-market designs are essential to address transmission-network challenges [51], [12]. Flexibility service providers, especially Hydro Power Plants (HPPs), are crucial for this transition, offering flexibility services like ramp-rate and frequency regulation. However, HPPs face challenges due to technical constraints, cascaded topologies, and the fluctuating value of stored water along rivers.

In Europe, to address TSO challenges, several markets have been introduced [12] (as discussed in Chapter 2). Normal operation frequency is main-
CHAPTER 5. OPTIMAL SHORT-TERM PLANNING OF HYDRO-DOMINATED ASSETS

tained within ± 0.1 Hz. If it drops below 49.9 Hz, disturbance reserves activate. The markets include Frequency Containment Reserve for Normal and Disturbance conditions (FCR-N and FCR-D) and manual Frequency Restoration Reserve (mFRR) to correct frequency after grid disturbances. A new mFRR capacity market ensures TSOs have adequate capacity for daily operations \[40, 52\]. In some nations, the mFRR capacity and energy markets are procured jointly with a pay-as-bid rule \[11\]. Studies show separating these markets can reduce balancing costs \[14\]. An EU guideline \[53\] proposes a common framework for this separation. Optimally coordinating HPP offers in this multi-market setup necessitates a robust decision-making framework.

5.2 Optimal Offer-Function in Multimarket Setup

Numerous studies have explored optimal offer-function calculations in multimarket settings \[54–60\]. For instance, \[54\] delves into coordinated offering strategies considering uncertainties in electricity prices and dispatched volumes. \[55\] provides a qualitative examination of offer-function calculations in hydro-dominated multi-markets using optimization techniques. A notable finding from \[57\] is a potential 0.8 to 2.6% benefit in coordinated offering over sequential offering. However, past literature assumes the complete acceptance of balancing energy offers, overlooking the realistic intermittent activations by TSOs based on their needs and different scenarios for the imbalances in the system.

Power producers gain in two ways from reserve markets: 1) they are compensated for reserved capacities, regardless of activation, and 2) they profit from production adjustments when reserves are activated. This is advantageous for HPPs, aiding them in offsetting declining profitability in the forward and spot markets \[61\]. A study \[62\] also shows a potential daily benefit of 290 k€ from allocating 10% of transmission line capacity for reserve exchanges in the Nordic market. Yet, a simplistic approach to the ATD of the mFRR energy offers might yield unrealistic outcomes and allows for energy arbitrage between the day-ahead energy market and the mFRR energy market (e.g. \[63\]), a practice deemed illegal under current regulatory frameworks \[64\].

5.3 Proposed Multi-Stage Stochastic Optimization

A portfolio of reservoirs and their connected generation units owned by a company is assumed here and the operator is assumed to offer into the day-ahead energy, FCR-N, mFRR capacity, and energy markets. The optimal trading strategy of this operator can be determined through a three-stage stochastic program set out in (5.1).

In this formulation, offering to the day-ahead energy market is considered, where an aggregated offer curve for every hour of the following operation day is submitted by a HPP operator. Offer prices are assumed to be fixed as parameters,
and the volumes dispatched based on the revealed prices are considered as decision variables. By this assumption, the optimization problem is made linear and is solvable by off-the-shelf solvers like CPLEX and Gurobi. For a given hour \( t \) and \( \text{seg} = 1, ..., N_{\text{seg}} \), the supply curve is defined by the prices \( \rho_{\text{seg},t} \) where \( \rho_{\text{seg},-1,t} \leq \rho_{\text{seg},t} \), and \( \rho_{1,t} = 0 \), \( \rho_{N_{\text{seg}}+1,t} = +\infty \). The offer volumes, \( x^{\text{spot}}_{\text{seg},t} \geq 0 \), are assumed to represent the accumulated volumes at a specific offer price. It is noted that submitting offer-functions to FCR-N, mFRR capacity, and energy markets is beyond the scope of this work, and all of the offers in these markets are considered to be accepted by TSO. In the formulation below, \( t \in \mathcal{T} \) is the time index, \( s \in \mathcal{S} \) is the second-stage scenario index and \( \omega \in \Omega \) is the third-stage scenario index (More information has been provided in section 4.2 and Fig. 4.1).

\[
\begin{align*}
\text{Maximize} & \quad \sum_{t \in \mathcal{T}} \left[ \hat{\lambda}_{t}^{\text{up}} p_{t}^{\text{up}} + \hat{\lambda}_{t}^{\text{down}} p_{t}^{\text{down}} + \lambda_{t}^{FCR} p_{t}^{FCR} + \sum_{s \in \mathcal{S}} \pi_{\omega} \left[ \lambda_{s,t}^{\text{spot}} p_{s,t}^{E} \right] \right] \\
\text{subject to:} & \quad x^{\text{spot}}_{\text{seg},t} \quad \text{if} \quad \rho_{\text{seg},-1,t} \leq \lambda_{s,t}^{\text{spot}} \leq \rho_{\text{seg},t} \quad \forall t, \text{seg}, s \\
& \quad x^{\text{spot}}_{\text{seg},-1,t} \leq x^{\text{spot}}_{\text{seg},t} \quad \forall t, \text{seg} \\
& \quad p_{s,t}^{E} = p_{s',t}^{E} \quad \text{if} \quad \lambda_{s',t}^{\text{spot}} = \lambda_{s,t}^{\text{spot}} \quad \forall t, s, s' \\
& \quad p_{s,t}^{E} < p_{s',t}^{E} \quad \text{if} \quad \lambda_{s',t}^{\text{spot}} \leq \lambda_{s,t}^{\text{spot}} \quad \forall t, s, s' \\
& \quad p_{t}^{\text{up}} \geq TSO_{t}^{\text{mFRR}} \quad \forall t \\
& \quad p_{t}^{\text{down}} \geq TSO_{t}^{\text{mFRR}} \quad \forall t \\
& \quad p_{t}^{\text{down}} + p_{t}^{FCR} \leq p_{t}^{E} \quad \forall t, s \\
& \quad p_{t}^{E} + p_{t}^{\text{up}} + p_{t}^{FCR} \leq \sum_{i \in \mathcal{I}} G_{i}^{\text{max}} \quad \forall t, s \\
& \quad p_{t}^{\text{down}} + p_{t}^{FCR} \leq p_{t}^{E} \quad \forall t, \omega, s \\
& \quad p_{t}^{E} + p_{t}^{\text{up}} + p_{t}^{FCR} \leq \sum_{i \in \mathcal{I}} G_{i}^{\text{max}} \quad \forall t, s, \omega \\
& \quad p_{t}^{\text{down}} \leq p_{t}^{\text{down}} \quad \forall t, s, \omega \\
& \quad p_{t}^{\text{up}} \leq p_{t}^{\text{up}} \quad \forall t, s, \omega \\
& \quad m_{i, \omega, s, t} = m_{i, \omega, s, t-1} - \sum_{j \in \mathcal{J}} Q_{i, j, \omega, s, t} - \Lambda_{i, \omega, t} + \\
& \quad \sum_{j \in \mathcal{J}} \sum_{n \in \mathcal{K}_{i}} (Q_{n, j, \omega, s, t} + \Lambda_{n, \omega, s, t}) + V_{i} \quad \forall i \in \mathcal{I}, \omega, t
\end{align*}
\]

(5.1a)
CHAPTER 5. OPTIMAL SHORT-TERM PLANNING OF HYDRO-DOMINATED ASSETS

\[ \sum_{i \in I} G_{i,\omega,s,t} + P_{\omega,s,t}^{down} T_{\omega,s,t}^{down} = P_{s,t}^{E} + P_{\omega,s,t}^{up} T_{\omega,s,t}^{up} \quad \forall \omega, s, t. \] (5.1o)

\[ G_{i,\omega,s,t} = \sum_{j \in J} \mu_{i,j} Q_{i,j,\omega,s,t} \quad \forall i \in I, \omega, s, t \] (5.1p)

\[ 0 \leq Q_{i,j,\omega,s,t} \leq Q_{i,j,\omega,s}^{Max} \quad \forall i \in I, j \in J, \omega, t \] (5.1q)

\[ 0 \leq m_{i,\omega,s,t} \leq M_{i}^{Max} \quad \forall i \in I, \omega, s, t \] (5.1r)

\[ \Lambda_{i,\omega,s,t} \geq \Lambda_{i}^{Min} \quad \forall i \in I, \omega, s, t \] (5.1s)

In which \( \Gamma = \{ x_{seg,t}^{spot}, p_{s,t}^{up}, p_{s,t}^{down}, p_{t}^{FCR}, P_{s,t}^{up}, P_{s,t}^{down}, m_{i,\omega,s,t}, G_{i,\omega,s,t}, Q_{i,j,\omega,s,t}, \Lambda_{i,\omega,s,t} \} \). \( G_{i,\omega,s,t} \) is the generation of power plant \( i \) in scenario \( \omega \) of scenario \( s \) at hour \( t \), \( m_{i,\omega,s,t} \) is the content of reservoir \( i \) in scenario \( \omega \) of scenario \( s \) at the end of hour \( t \), \( Q_{i,j,\omega,s,t} \) is the discharged volume of power plant \( i \), segment \( j \), hour \( t \) and in scenario \( \omega \) of scenario \( s \), \( \Lambda_{i,\omega,s,t} \) is the spillage from reservoir \( i \) in scenario \( \omega \) of scenario \( s \) at hour \( t \), \( p_{s,t}^{E} \) is the dispatched level in hour \( t \) and scenario \( s \) in the day-ahead energy market, \( p_{s,t}^{FCR} \) is the procured FCR-N volume in scenario \( s \) at hour \( t \), \( p_{s,t}^{up} \) is the procured volume in the up-regulation mFRR balancing energy market in scenario \( \omega \) of scenario \( s \) at hour \( t \), \( p_{s,t}^{down} \) is the procured volume in the down-regulation mFRR balancing energy market in scenario \( \omega \) of scenario \( s \) at hour \( t \). \( p_{t}^{FCR} \) is the procure up-regulated mFRR capacity volume at hour \( t \), \( p_{t}^{down} \) is the procured down-regulated mFRR capacity volume at hour \( t \), \( x_{seg,t}^{spot} \) is the offer volume for the day-ahead energy market in segment \( seg \) and hour \( t \).

The objective function (5.1a) is to optimize the potential revenue from selling electricity to various markets while factoring in the value of stored water in the down-stream reservoirs. The first two components represent revenues from the upward and downward mFRR capacity market. The third component pertains to the FCR-N market revenue, while the fourth is associated with the day-ahead energy market. The fifth and sixth components reflect the revenue from the mFRR energy market’s upward and downward trends considering their respective active-time duration. The final component captures the value of the water stored in downstream reservoirs. To make revenue streams from various markets more comparable, the adjusted initial reservoir level is subtracted from the end of the reservoir level for simple numerical comparisons.

Offer-function constraints and its non-decreasing features are stated in (5.1b)-(5.1e) and (5.1f)-(5.1g). The TSO requirements for the minimum volume of mFRR capacity are imposed in (5.1f)-(5.1g). Constraints (5.1h) and (5.1i) show the minimum and maximum capacity available for the FCR-N market considering the volume allocated to the mFRR capacity requirements and dispatched day-ahead energy market. Balancing energy market constraints which limit the offer volume to the mFRR energy market with respect to the procured FCR-N and dispatched day-ahead energy market volume are expressed in (5.1j)-(5.1k). The hydrological constraint on the reservoir level is presented in (5.1l) and energy balance is set in (5.1m). It is important to note that the impacts of ATD on the revenue stream and energy balance are considered through \( T_{\omega,s,t}^{up} \) and \( T_{\omega,s,t}^{down} \).
The piece-wise linear mathematical representation of hydropower output with respect to the discharged level is demonstrated in (5.1p). Constraints (5.1q)-(5.1s) enforce the operational limits on the variables based on the available data for each power plant. It is important to mention that there is no decision made between the moments when day-ahead energy prices and FCR-N prices become known. Consequently, there is no necessity for extra branching in the scenario tree for these events. Both day-ahead energy and FCR-N prices within the same scenario set have been simplified as $s \in \mathcal{S}$. For the balancing market prices, the detailed approach for the scenario generation based on the LSTM technique has been discussed in Section 4.2.

5.4 Results and Discussions

5.4.1 Case Study Description

An assessment of the newly developed three-stage stochastic optimization approach is conducted by applying it to a case study involving a river system in Sweden’s northern SE2 bidding zone. This evaluation focused on the interconnected hydropower facilities along the Skellefte River, comprising 15 hydropower plants with a combined output of 1011 MW. The specifications of each power plant have been presented in Fig. 5.1 \[1\]. The price data for both the day-ahead and balancing energy markets are gathered from the Nordpool market statistics \[43\]. For simulations, it is assumed that the hydropower plants’ reservoirs started at half of their full capacity and mandated that levels must remain above 90% of that half capacity by the end of the operational period.

Additionally, hydropower operators are required to allocate a portion of their capacity to the balancing capacity market, adhering to the minimum requirements set by the TSO. The operator’s challenge lies in optimally distributing the available capacity across various markets: mFRR capacity, FCR-N, day-ahead, and mFRR energy markets. For the purposes of the simulation, the river has been treated as if it were managed by a single entity, which is responsible for providing hourly bid functions for the entire system. Assumptions included in this section are $k_{dir} = 0.05$ and $k_{m} = 0.98$.

All simulations were executed on a standard PC equipped with an Intel Core i7 processor, with a 2.1GHz clock rate, and utilizing a maximum of 16GB RAM. The simulation code was processed using the CPLEX solver within the General Algebraic Modeling System (GAMS).

5.4.2 Proposed PDF Estimation via GAMLSS

Based on the strategy delineated in Section 4.3, the GAMLSS package within the R environment is utilized to identify the most suitable probabilistic distri-

\footnote{1Hour Equivalent (HE) corresponds to the water flow 1 m$^3$/s during 1 hour.}
 CHAPTER 5. OPTIMAL SHORT-TERM PLANNING OF HYDRO-DOMINATED ASSETS

Figure 5.1: Cascaded topology of Skellefte river in Sweden ($P^{\text{max}}$ in MW, $Q^{\text{Max}}$ and $M^{\text{Max}}$ in HE)

Distribution for the dataset of ATD. This involves linear regression of the distribution parameters against a set of predictors. Variables such as the price premium of the regulation markets and day-ahead energy markets ($\lambda_{\text{pre},t}$), wind power output ($P_{\text{wind},t}$), and the aggregate electricity generation ($P_{\text{pro},t}$) within the defined bidding area are taken into account. These variables are integrated into the distributional parameters through coefficients $h_{\mu,\text{pre}}$, $h_{\mu,\text{wind}}$, and $h_{\mu,\text{pro}}$ respectively. The following expressions describe the relationship between these predictors and the corresponding parameters of the chosen distribution, where $\mu_t$ denotes the mean, $\sigma_t$ represents the standard deviation, $\nu_t$ denotes the skewness, and $\tau_t$ indicates the kurtosis level.

$$g_{1,t}(\theta_1) = \mu^D_t = \beta^D_\mu + h^{D}_{\mu,\text{pre}}\lambda^{D}_{\text{pre},t} + h^{D}_{\mu,\text{wind}}P^{D}_{\text{wind},t} + h^{D}_{\mu,\text{pro}}P^{D}_{\text{pro},t}, \quad (5.2)$$
Figure 5.2: Comparison of the probability distribution of the two GAMLLSS models for active-time duration

\[
g_{2.t}(\theta_2) = \log(\sigma^D_{t}) = \beta^D_{\sigma} + h_{\sigma,pre}^D \lambda_{pre,t}^D + h_{\sigma,wind}^D P_{wind,t}^D + h_{\sigma,pro}^D P_{pro,t}^D,
\]

(5.3)

\[
g_{3.t}(\theta_3) = \nu^D_{t} = \beta^D_{\nu},
\]

(5.4)

\[
g_{4.t}(\theta_4) = \log(\tau^D_{t}) = \beta^D_{\tau}.
\]

(5.5)

Table 5.1: AIC and SBC factor for different distributions evaluated on the training data

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>GA</th>
<th>TF</th>
<th>Skew t</th>
<th>SHASHo</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>Up</td>
<td>-5583</td>
<td>-8465</td>
<td>-6084</td>
<td>-8438</td>
</tr>
<tr>
<td></td>
<td>Down</td>
<td>-3286</td>
<td>-6820</td>
<td>-4070</td>
<td>-6800</td>
</tr>
<tr>
<td>SBC</td>
<td>Up</td>
<td>-4575</td>
<td>-7713</td>
<td>-5323</td>
<td>-7676</td>
</tr>
<tr>
<td></td>
<td>Down</td>
<td>-2481</td>
<td>-6014</td>
<td>-3259</td>
<td>-5958</td>
</tr>
</tbody>
</table>

In the equations presented previously, \( D \) represents the direction of the ATD, which can be either upward or downward. Table 5.1 presents the qualification metrics of various distributions applied to the training data set. The Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (SBC) are utilized, which are validated as indicators of fit for training data [44]. Distributions with lower AIC and SBC values are considered to have a better fit. According to the results in Table 5.1, the modified sinh-arcsinh (SHASHo) distribution emerges as the superior model for both the upward and downward ATD models, as indicated by its lower AIC and SBC values. The choice is further justified by the SHASHo distribution’s suitability for data sets with a prevalence of zeros or values close to zero, which is the case here [49]. This characteristic
is illustrated in Fig. 5.2, which displays the data’s concentration near zero, attributable to a high level of the Kurtosis factor, in comparison with a normal distribution.

Fig. 5.3 exhibits the residuals of the GAMLSS model when fitted to the historical data. Evaluating the normalized quantile residuals is an effective method for assessing the adequacy of the model fit [49]. Fig. 5.3 depicts the residual plots: (top left) against the fitted values of the mean; (top right) against an index (i.e., the number of hours in the data set); (bottom left) a nonparametric kernel density estimate; (bottom right) a normal Q-Q plot. The expectation is that the fitted residuals approximate normally distributed variables, thereby justifying the use of a normal Q-Q plot for the residuals, even if the original observations may not be normally distributed. The statistical moments of the quantile residuals are detailed in Table 5.2, indicating an adequate fit with the mean and variance closely aligning with zero and one, respectively.

Table 5.2: Statistical Moments of Quantile Residuals

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean</th>
<th>Variance</th>
<th>Skewness Coefficient</th>
<th>Kurtosis Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Values</td>
<td>0.0265</td>
<td>1.0376</td>
<td>-0.0826</td>
<td>2.4754</td>
</tr>
</tbody>
</table>

Tables 5.3 and 5.4 display the intercepts and coefficients derived from the GAMLSS for various explanatory variables, depicting trends in both upward and downward directions. The data in these tables suggest that the ATDs are most significantly influenced by wind power generation, as opposed to the price premium or total production. This correlation may be attributed to the growing impact of wind power penetration on the grid, which, with its inherent generation uncertainty, alters TSOs decisions regarding the activation level of balancing energy offers; thus impacting the ATD. Fig. 5.4 illustrates the evolving distribution percentiles of the ATD for both upward and downward regulations, represented through 100 scenarios as shaded bands around a central mean trajectory.

Table 5.3: Intercepts and coefficients obtained from GAMLSS for the upward ATD

<table>
<thead>
<tr>
<th></th>
<th>$\beta$</th>
<th>$h_{\text{wind}}$</th>
<th>$h_{\text{pre}}$</th>
<th>$h_{\text{pro}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$ (sec)</td>
<td>1.12e-3</td>
<td>6.78e-3</td>
<td>-2.39e-4</td>
<td>1.67e-6</td>
</tr>
<tr>
<td>$\sigma$ (sec)</td>
<td>-7.32</td>
<td>-1.02</td>
<td>1.72e-2</td>
<td>7.46e-4</td>
</tr>
<tr>
<td>$\nu$</td>
<td>1.46</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\tau$</td>
<td>-0.51</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

5.4.3 Analyses of Revenue Composition with the Introduced ATD Framework

Prior researches (e.g., [58, 60, 63]) that did not take into account the ATD of balancing energy offers, identified the potential for arbitrage between the day-
Table 5.4: Intercepts and coefficients obtained from GAMLSS for the downward ATD

<table>
<thead>
<tr>
<th></th>
<th>$\beta$</th>
<th>$h_{\text{wind}}$</th>
<th>$h_{\text{pre}}$</th>
<th>$h_{\text{pro}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$ (sec)</td>
<td>6.64e-2</td>
<td>-1.15e-2</td>
<td>-4.81e-4</td>
<td>-1.23e-5</td>
</tr>
<tr>
<td>$\sigma$ (sec)</td>
<td>-2.83</td>
<td>0.66</td>
<td>6.49e-3</td>
<td>-5.65e-4</td>
</tr>
<tr>
<td>$\nu$</td>
<td>1.33</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\tau$</td>
<td>-0.37</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 5.3: Residual plots of the SHASHo model fitted to the historical ATD data

ahead and balancing energy markets. In these studies, where a high value is projected for stored water, a feasible tactic might involve allocating a portion, or all, of the available capacity to the day-ahead energy market, then repurchasing it at a reduced rate in the downward balancing energy market, circumventing the obligation to generate electricity. This action, known as the *increase-decrease* game, has been noted in various regions \[64\]. To mitigate this issue, three different approaches to ATD are considered:

**Naive Scenario**

Under this scenario, a full-hour ATD is presumed, implying that every offer submitted to the mFRR energy markets will be activated for one hour. Such an assumption allows the operator to bid full capacity into the up regulation market instead of the day-ahead or FCR-N market, which could result in higher revenue but lacks realism. The rationale is that not every offer for up regulation balancing energy will be activated; the TSO will activate offers based on the actual imbalance levels.
CHAPTER 5. OPTIMAL SHORT-TERM PLANNING OF HYDRO-DOMINATED ASSETS

Figure 5.4: Fan chart of ATD for a set of scenarios: Up regulation (left figure), down regulation (right figure)

Table 5.5: Revenue obtained in each ATD model with $\lambda_s^f = 0.9 \frac{1}{N_T} \sum_{t \in T} \lambda_{s,t}^{\text{spot}}$ [MSEK]

<table>
<thead>
<tr>
<th>Revenue Breakdown</th>
<th>Proposed ATD</th>
<th>Proportional ATD</th>
<th>Naive Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day-ahead Energy</td>
<td>4.746</td>
<td>4.495</td>
<td>0.715</td>
</tr>
<tr>
<td>FCR-N</td>
<td>0.003</td>
<td>0.01</td>
<td>0</td>
</tr>
<tr>
<td>mFRR Capacity</td>
<td>0.724</td>
<td>0.727</td>
<td>0.801</td>
</tr>
<tr>
<td>mFRR Energy</td>
<td>-0.087</td>
<td>0.129</td>
<td>7.888</td>
</tr>
<tr>
<td>Value of Stored Water</td>
<td>5.663</td>
<td>5.780</td>
<td>3.666</td>
</tr>
<tr>
<td>Total Revenue</td>
<td>11.051</td>
<td>11.142</td>
<td>12.427</td>
</tr>
</tbody>
</table>

Table 5.6: Revenue obtained in each ATD model with $\lambda_s^f = 0.8 \frac{1}{N_T} \sum_{t \in T} \lambda_{s,t}^{\text{spot}}$ [MSEK]

<table>
<thead>
<tr>
<th>Revenue Breakdown</th>
<th>Proposed ATD</th>
<th>Proportional ATD</th>
<th>Naive Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day-ahead Energy</td>
<td>6.625</td>
<td>6.132</td>
<td>0.016</td>
</tr>
<tr>
<td>FCR-N</td>
<td>0.145</td>
<td>0.128</td>
<td>0</td>
</tr>
<tr>
<td>mFRR Capacity</td>
<td>0.567</td>
<td>0.598</td>
<td>0.802</td>
</tr>
<tr>
<td>mFRR Energy</td>
<td>-0.291</td>
<td>-0.037</td>
<td>7.993</td>
</tr>
<tr>
<td>Value of Stored Water</td>
<td>3.512</td>
<td>3.801</td>
<td>3.204</td>
</tr>
<tr>
<td>Total Revenue</td>
<td>10.559</td>
<td>10.617</td>
<td>12.016</td>
</tr>
</tbody>
</table>

Proportional ATD

The proportional ATD employs historical data to approximate the ATD. This computation draws from the total volume of upward (downward) activation for all offers in a specific bidding zone — where the case study is situated — and divides it by the total upward (downward) volume procured in that hour. This optimization is resolved prior to the operation day, even though the data that informs the Proportional ATD assessment is disclosed post-operation. Nonethe-
less, it aligns more closely with actual conditions than the naive scenario. Such calculations are beneficial for anticipating potential revenue compositions if the ATDs were known beforehand.

Proposed GAMLSS-Derived ATD

In this approach, ATD is estimated based on the methodology outlined in Section 4.3. The outcomes, as delineated in Tables 5.5 and 5.6, reflect two scenarios for the expected value of stored water as described in (5.1a). The results elucidate that, with the proposed ATD, the revenue flow tends towards the day-ahead market relative to the naive scenario because full ATD compensation in the balancing markets is unattainable. The TSO activates accepted offers only for specific durations. Although the total revenue projection is lower than in other scenarios, it represents a more pragmatic expectation, taking into account the likelihood of offers not being dispatched.

5.4.4 Economic Analysis of Participating in the FCR-N Market

This section delves into the economic benefits of participation in the FCR-N market. The breakdown of revenues from various markets, considering both scenarios with and without FCR-N market participation, is detailed in Table 5.7. Meanwhile, Table 5.8 outlines the distribution of volumes across these markets. It is observed that total revenue increases with increased allocations in the day-ahead energy and FCR-N markets. Participation in the FCR-N market proves to be more advantageous compared to the mFRR capacity market, attributed to its higher prices, particularly during the night, considering the absence of commitments in the real-time market. The strategies for optimal bidding, termed as optimal offer-functions, are computed and depicted in Fig. 5.5. This figure illustrates the strategic bids placed by the HPP operator in the day-ahead energy market. The analysis is structured around two key scenarios:

High Pricing Periods in FCR-N Market: Nighttime sees a surge in FCR-N prices, primarily due to diminished capacity for down regulation in the network and the demand for bidirectional flexibility from FCR-N providers. In these hours, the HPP operator aims to increase market participation to maximize profits. Given the reduced obligations relative to the mFRR capacity market, there is a tendency to propose higher bids in the FCR-N market and lower in the mFRR capacity markets. This is advantageous as per the scenario outlined in (5.1h), leading to a higher dispatch rate. This increase in bid volume is evident in Fig. 5.5 at $t = 4$ and $t = 7$.

Low Pricing Periods in FCR-N Market: Daytime is characterized by a decrease in FCR prices, owing to the increased availability of capacity among market participants for handling frequency fluctuations in the grid. Consequently, the HPP operator shifts focus towards greater participation in the mFRR capacity markets, while diminishing involvement in the FCR-N market. This shift renders
the mFRR energy market more lucrative in upward regulation compared to the
day-ahead energy market, resulting in a decreased bid volume for the latter as
shown in Fig. 5.5 at \( t = 15 \) and \( t = 21 \).

Table 5.7: Revenue obtained with and without FCR-N Participation [MSEK]

<table>
<thead>
<tr>
<th>Revenue Breakdown</th>
<th>With FCR-N</th>
<th>Without FCR-N</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day-ahead Energy</td>
<td>4.408</td>
<td>4.109</td>
<td>7.27</td>
</tr>
<tr>
<td>FCR-N</td>
<td>0.241</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>mFRR Capacity</td>
<td>0.127</td>
<td>0.165</td>
<td>-23.03</td>
</tr>
<tr>
<td>mFRR Energy</td>
<td>1.051</td>
<td>1.250</td>
<td>-15.92</td>
</tr>
<tr>
<td>Value of Stored Water</td>
<td>4.961</td>
<td>5.155</td>
<td>-3.76</td>
</tr>
<tr>
<td>Total Revenue</td>
<td>10.789</td>
<td>10.680</td>
<td>1.02</td>
</tr>
</tbody>
</table>

Table 5.8: Total daily volume allocated to each market for with and without FCR-
N Participation [MW]

<table>
<thead>
<tr>
<th>Revenue Breakdown</th>
<th>With FCR-N</th>
<th>Without FCR-N</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day-ahead Energy</td>
<td>12965</td>
<td>11383</td>
<td>13.89</td>
</tr>
<tr>
<td>FCR-N</td>
<td>5012</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>mFRR Capacity (upward)</td>
<td>2348</td>
<td>3120</td>
<td>-23.03</td>
</tr>
<tr>
<td>mFRR Capacity (downward)</td>
<td>5493</td>
<td>7320</td>
<td>-24.95</td>
</tr>
<tr>
<td>mFRR Energy (upward)</td>
<td>4915</td>
<td>8791</td>
<td>-44.09</td>
</tr>
<tr>
<td>mFRR Energy (downward)</td>
<td>5575</td>
<td>7532</td>
<td>-25.98</td>
</tr>
</tbody>
</table>

5.4.5 Evaluation Metrics of Proposed Scenario Generation
Methods

Energy score (ES) is a skill score that evaluates the quality of generated sce-
nario sets [55]. It provides a direct comparison between scenario sets. This is
a negatively-oriented value, i.e., it is inversely related to the skill of the scenario
set. Equation (5.6) shows how this score can be calculated:

\[
ES = \frac{1}{N_\Omega} \sum_{\omega=1}^{N_\Omega} \| y - \xi_\omega \| - \frac{1}{2(N_\Omega)^2} \sum_{\omega' = 1}^{N_\Omega} \sum_{\omega = 1}^{N_\Omega} \| \xi_{\omega'} - \xi_\omega \| \quad (5.6)
\]

where \( \| . \| \) denotes the Euclidean norm, \( y \) is the realization of the random process
under study, \( \xi_{\omega'} \) and \( \xi_\omega \) are independent scenarios generated by the same forecast
technique and \( N_\Omega \) is the total number of scenarios.

In Fig. 5.6, the forecasted up-regulation prices over a span of 120 hours are
compared with existing historical data, alongside an analysis of the associated
5.5 Conclusion

This chapter introduces an innovative multi-stage stochastic optimization model tailored for HPPs in European electricity markets. It effectively integrates the LSTM architecture for precise electricity price forecasting and GAMLSS for accurately modeling the ATD in balancing energy offers. The model addresses the intricacies of day-ahead, FCR-N, and mFRR markets, facilitating more re-

errors. This comparison shows a close alignment, with a total root mean square error (RMSE) of 53.1 SEK/MWh.

Furthermore, Fig. 5.7 presents an analysis of the Energy Score (ES) for two distinct datasets within the mFRR energy market, focusing on both upward and downward trends. This figure evaluates the ES for three distinct methodologies: the conventional LSTM (C-LSTM), a modified version of LSTM (M-LSTM), and SARIMA. The key distinction between C-LSTM and M-LSTM lies in the latter’s enhanced forecasting approach, which utilizes current information as outlined in Section 4.2.2. The comparative analysis reveals that LSTM-based methods, owing to their lower energy scores at each instance, demonstrate superior performance in scenario generation, showcasing greater efficacy than the other statistical methods discussed in this study. The enhanced performance of LSTM methodologies is largely credited to their inherent memory capabilities, allowing them to retain and process information over extended time periods.

5.5 Conclusion

This chapter introduces an innovative multi-stage stochastic optimization model tailored for HPPs in European electricity markets. It effectively integrates the LSTM architecture for precise electricity price forecasting and GAMLSS for accurately modeling the ATD in balancing energy offers. The model addresses the intricacies of day-ahead, FCR-N, and mFRR markets, facilitating more re-

Figure 5.5: Day-ahead energy market offer-function for different hours and two scenarios of FCR-N market participation
CHAPTER 5. OPTIMAL SHORT-TERM PLANNING OF HYDRO-DOMINATED ASSETS

Figure 5.6: The available and forecasted time series of up-regulation energy market data and its corresponding RMSE.

Figure 5.7: Energy scores for two sets of data and different forecasting techniques.

alistic and profitable bidding strategies for HPPs. The modeling results show a proper framework for the HPP operator to gain more revenue by participating in capacity-based markets, i.e. FCR-N and mFRR capacity markets. At the same time, the application of the proposed ATD makes the output results more realistic compared to a naive bidding strategy in which the full activation of balancing bids is considered.
Chapter 6

Stochastic Adaptive Robust Optimization in the Short-Term Bidding Strategy

This study introduces a novel method for optimizing the day-ahead energy market bidding strategies of cascaded hydropower plants within sequential electricity markets based on Stochastic Adaptive Robust Optimization (SARO). This research focuses on both the day-ahead energy market and the manual frequency restoration reserve (mFRR) markets, encompassing capacity and energy aspects. In this model, the active-time durations of mFRR energy bids are considered as an uncertainty box instead of having a specific PDF. The content of this chapter is based on the following paper:


6.1 Introduction

Hydropower, renowned for its operational speed and flexibility, stands out in energy production, offering significant advantages over thermal assets. The increasing reliance on variable renewable energy sources heightens the importance of resources in balancing energy and capacity markets, where HPPs are pivotal players due to their flexibility [66, 67]. Despite this, HPPs face challenges in planning and operation due to their technical constraints and cascaded topology, including issues like information privacy [68] and operational constraints [69]. A
key challenge for HPPs is the management of stored water’s value, making reserve capacity procurement reliant on downstream water availability. Addressing these challenges is critical, particularly with the emergence of various markets requiring optimal participation strategies. In the Nordic electricity market, numerous new markets have been introduced to mitigate the challenges faced by transmission system operators (TSOs) \[12\]. Among these is the mFRR capacity market, established to guarantee TSOs adequate capacity for activation during operational days \[10\]. In countries like Germany and Austria, the joint procurement of mFRR capacity and energy markets has been practiced, with research suggesting that separating these markets and procuring mFRR energy based on marginal pricing can reduce balancing costs, even with strategic players such as HPPs \[11, 14\]. The EU’s electricity balancing guideline (EB GL) has initiated a framework for the split procurement of mFRR capacity and energy reserves, enabling a wider range of balance service providers (BSPs) to participate in the energy market, including those not accepted in the capacity market, as well as allowing flexible BSPs to volunteer for profit opportunities \[53, 70\]. The mFRR capacity market was launched in Q4 2023 in Sweden and the aim is to harmonize it across all the Nordics by Q4 2025. As it is newly launched, there is a great need for research into the effects of this new market setup on the optimal bidding behaviors of large market participants like HPPs.

The resolution of the outlined challenges in market bidding necessitates strategies for managing uncertain parameters. When the PDFs of uncertainties are known at bidding time, stochastic optimization (SO) is an effective approach for determining optimal bids across different uncertainty scenarios. However, for parameters lacking known mathematical distributions, robust optimization (RO) is more suitable. This approach assumes that the most adverse uncertainty scenario will occur, with the uncertainty set and budget defining the extent of potential worst-case scenarios \[30\]. Adaptive robust optimization (ARO) is useful when corrective actions are feasible after uncertainties materialize \[71\]. For situations where some parameters are best represented through scenarios and others through uncertainty sets for worst-case analysis, stochastic adaptive robust optimization (SARO) is applicable \[72\]. A comparison of risk-averse two-stage stochastic optimization and its ARO counterpart in optimal bidding for a virtual power plant reveals that first-stage solutions are similar, depending on the risk parameters used, but overall performance varies with the combination of deterministic and uncertain data and risk parameters \[73\]. The SARO approach has been practically tested in ISO New England to ensure efficient market pricing and reliable and economic operations in the context of a rapidly evolving resource mix and results in the reduction of 5.6% percent of their generation dispatch costs (equivalent to $463.8M per year!) \[74\].

In electricity markets, where price information is readily available, numerous methods exist to create scenarios for stochastic optimization \[37, 75\]. However, the active-time duration of mFRR energy bids on the operation day remains unknown. This duration refers to the time within an hour when TSOs activate
the procured mFRR energy bids, influenced by factors such as net load imbalance, the intermittent nature of renewable energy generation, and forecasting errors. To address this uncertainty, confidence bounds are employed to model the number of hours during which the submitted mFRR balancing bids are likely to be activated.

Research in the field has explored various approaches to modeling uncertainties in electricity markets. The study in [54] introduced a coordinated bidding strategy for day-ahead energy and balancing markets, considering uncertainties in electricity prices and dispatched volumes, but it assumed full activation of accepted balancing energy bids, which is unrealistic. Another study [55] provided a qualitative analysis of profitability in hydro-dominated multi-market setups, highlighting the importance of managing uncertainties in decision-support systems for optimal bidding.

In [48,76], the SARO method was utilized for modeling uncertainties in virtual power plant bidding. The research in [76] addressed the solution of bilevel optimization problems using Karush-Kuhn-Tucker (KKT) optimality conditions. However, the study in [48] did not adequately model the stochastic nature of balancing market decisions, relying on average electricity price scenarios. The paper in [77] focused on netload deviation as a significant uncertainty in a Norwegian watercourse case study, proposing a mixed stochastic-robust approach. This study, however, considered the full active-time duration of balancing reserves, which is not typically realistic.

The research in [78] employed the stochastic dual dynamic programming (SDDP) method to investigate the participation of hydropower plants in day-ahead energy and spinning reserve markets under uncertainties of inflow and market prices, but it did not consider the active-time duration of ancillary services. In [79], an approach was proposed for the optimal hourly scheduling of integrated HPPs in energy and regulation reserve markets, with the assumption that a predefined part of the reserve capacity would be activated. The study in [80] examined the economic performance of aggregated HPPs in day-ahead and real-time markets using a Tiered Bidding method, but it lacked an explicit strategy for reserve market procurement and did not address uncertainties in electricity market prices and the active-time duration of mFRR energy markets. A summary and comparison of these studies with the proposed method is available in Table 6.1, where "mFRR Energy Market" is referred to as the "RL" market in this context.

This chapter introduces a methodology to determine optimal aggregated day-ahead bidding curves for cascaded hydropower plants (HPPs) in sequential electricity markets, addressing various types of uncertainties. Fig. 6.1 outlines the general framework and timelines of the relevant electricity markets. The approach focuses on identifying the best day-ahead bidding strategy, particularly in scenarios where the worst-case active-time duration for mFRR energy bids might occur. This research considers the mFRR capacity market, with assumed known price scenarios at the time of bidding to the day-ahead energy market, the day-ahead energy market, where different price scenarios are used to model
Table 6.1: Literature review of optimal bidding problem under uncertainties

<table>
<thead>
<tr>
<th>Reference</th>
<th>Markets</th>
<th>DA Bid Curve</th>
<th>Uncertainty</th>
<th>Mathematical Model</th>
<th>Active-time of mFRR Energy Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA^1+RL^2</td>
<td>Yes</td>
<td>Electricity Price</td>
<td>SO</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>DA^2+RL^2</td>
<td>No</td>
<td>Electricity Price, Water inflow</td>
<td>SO</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>DA+RL</td>
<td>Yes</td>
<td>Wind Power</td>
<td>SO</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>DA+SR^3</td>
<td>No</td>
<td>Electricity Price</td>
<td>ARO</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>DA+RL</td>
<td>No</td>
<td>Net Load Variations</td>
<td>Mixed Stochastic-Robust</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>DA+RL</td>
<td>No</td>
<td>Electricity Price, Wind Power</td>
<td>ARO</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>DA+CM^4+RL</td>
<td>Yes</td>
<td>Electricity Price, ATD</td>
<td>SARO</td>
<td>No</td>
</tr>
</tbody>
</table>

1Day-ahead  2 Real-time  3 Spinning reserve  4 Active-time duration of mFRR energy bids  5 mFRR capacity market

Figure 6.1: Electricity market timeline

uncertainties, and the mFRR energy market, where expected price scenarios are known at bidding but activation by the TSO remains uncertain. It is assumed that in the mFRR energy market, HPP operators must bid at least the amount they committed to in the mFRR capacity market at the day-ahead stage.

The solution employs duality theory in linear programming, a more efficient alternative to KKT optimality conditions, to simplify and expedite the solution process. This research is notable for being the first to combine adaptive robust and stochastic optimization for modeling optimal bidding behavior of cascaded HPPs in varied market scenarios. It should be acknowledged that detailed modeling of HPPs, including head-dependent input-output curves, time-varying inflow, and minimum hydro turbine outflow, is beyond its scope, suggesting these aspects as avenues for future research to enhance the HPP model.
6.2 Problem Formulation

This section outlines the comprehensive methodology for determining the optimal day-ahead bidding curve for cascaded HPPs. As illustrated in Fig. 6.1, the process begins with HPP operators submitting bids to the mFRR capacity market, providing a safety margin for the TSO in the real-time market, ensuring the availability of sufficient bids for activation if needed. Following this market’s clearance, operators bid to the day-ahead energy market by 12:00 CET on the day before operation (D-1), with the system price announced at 12:42 CET. During the balancing stage, the clearing of balancing energy bids is constrained by volumes cleared from the day-ahead energy and mFRR capacity markets. This formulation does not model the market-clearing action by the TSO, instead relying on different price forecasts for cleared price information.

The first subsection briefly describes the construction of the bidding curve. Subsequently, the conventional fully-stochastic optimization is detailed, followed by the proposed SARO method.

6.2.1 Day-ahead Energy Market Bidding

In this subsection, the focus is on bidding to the day-ahead energy market, where HPP operators submit an aggregated bid curve for each hour of the operation day. It is assumed that bid prices are fixed parameters, with volumes dispatched based on revealed prices as decision variables. For each hour $t$ and segment $seg = 1, ..., N_{seg}$, the supply curve is defined by the prices $\rho_{seg,t}$, ensuring $\rho_{seg-1,t} \leq \rho_{seg,t}$, and setting $\rho_{1,t} = 0$, $\rho_{N_{seg}+1,t} = +\infty$. The bid volumes, $x^{spot}_{seg,t} \geq 0$, represent the cumulative volumes at specific bid prices. If market prices were known at the time of bidding, operators could perfectly allocate their day-ahead energy market volumes, making bid curves unnecessary. However, since market prices are unknown at bidding time, accepted bids are announced only after prices are revealed by the market operator.

6.2.2 Fully-Stochastic Model (STC)

This model employs a single-level two-stage stochastic optimization for optimal bidding in the day-ahead energy market while considering participation in the mFRR capacity and energy markets. In the first stage, decisions for day-ahead energy market bids and mFRR capacity market (scenarios-independent) are made. After the day-ahead energy market prices are revealed, the second stage involves determining decisions for mFRR energy market participation and operational actions (scenario-dependent). The specific formulation of this model follows:

$$\max_{\Gamma_{STC}} \sum_{\omega \in \Omega} \sum_{t \in T} \left( \lambda_{\omega,t} p_{E,t} + \tilde{\lambda}_{\omega,t} p_{C_{up}} + \tilde{\lambda}_{\omega,t} p_{C_{down}} \right) + (6.1a)$$
\[
\begin{align*}
\left( \lambda_{i,t}^{up} p_{i,t}^{up} T_{i,t}^{up} - \lambda_{i,t}^{down} p_{i,t}^{down} T_{i,t}^{down} + \lambda_{i,\omega} \sum_{s \in S} m_{i,\omega,s} \sum_{s \in M_i} \gamma_s \right).
\end{align*}
\]

\text{s.t.}

\[
\begin{align*}
\text{pc}_{i}^{down} & \leq p_{i,t}^{E} & & \forall t \in T, \omega \in \Omega \quad (6.1b) \\
p_{\omega,t}^{E} + pc_{i}^{up} & \leq \sum_{i \in I} G_{i}^{max} & & \forall t \in T, \omega \in \Omega \quad (6.1c) \\
p_{\omega,t}^{E} & = x_{seg,t}^{spot} i \text{f} \ ho_{seg-1,t} \leq x_{seg,t}^{spot} & & \forall t \in T, seg \in D, \omega \in \Omega \quad (6.1d) \\
x_{seg-1,t}^{spot} & \leq x_{seg,t}^{spot} & & \forall t \in T, seg \in D \quad (6.1e) \\
p_{\omega,t}^{down} & \leq p_{\omega,t}^{E} & & \forall t \in T, \omega \in \Omega \quad (6.1f) \\
p_{\omega,t}^{E} + pc_{i}^{up} & \leq \sum_{i \in I} G_{i}^{max} & & \forall t \in T, \omega \in \Omega \quad (6.1g) \\
p_{\omega,t}^{down} & \leq p_{\omega,t}^{down} & & \forall t \in T, \omega \in \Omega \quad (6.1h) \\
pc_{i}^{up} & \leq p_{\omega,t}^{up} & & \forall t \in T, \omega \in \Omega \quad (6.1i) \\
m_{i,\omega,t} & = m_{i,\omega,t-1} + M_{i}^{0} - \sum_{j \in J} Q_{i,j,\omega,t} - \Lambda_{i,\omega,t} + \sum_{j \in J} \sum_{n \in K_i} \left( Q_{n,j,\omega,t} + \Lambda_{n,\omega,t} \right) + V_{i} & & \forall i \in I, \omega \in \Omega, t \in T \quad (6.1j) \\
\sum_{i \in I} G_{i,\omega,t} + p_{\omega,t}^{down} T_{\omega,t}^{down} & = p_{\omega,t}^{E} + p_{\omega,t}^{up} T_{\omega,t}^{up} & & \forall \omega \in \Omega, t \in T \quad (6.1k) \\
\end{align*}
\]

\[
\begin{align*}
G_{i,\omega,t} & = \sum_{j \in J} \mu_{i,j} Q_{i,j,\omega,t} & & \forall i \in I, \omega \in \Omega, t \in T \quad (6.1l) \\
0 & \leq Q_{i,j,\omega,t} \leq Q_{i,j}^{max} & & \forall i \in I, j \in J, \omega \in \Omega, t \in T \\
0 & \leq m_{i,\omega,t} \leq M_{i}^{max} & & \forall i \in I, \omega \in \Omega, t \in T \\
\Lambda_{i,\omega,t} & \geq \Lambda_{i}^{min} & & \forall i \in I, \omega \in \Omega, t \in T \\
\end{align*}
\]

where \( \Gamma_{STC} = \{ \{ p_{\omega,t}^{E}, pc_{i}^{up}, pc_{i}^{down}, x_{seg,t}^{spot}, p_{\omega,t}^{up}, p_{\omega,t}^{down}, m_{i,\omega,t}, \Lambda_{i,\omega,t}, Q_{i,j,\omega,t}, G_{i,\omega,t} \} \} \).

\( G_{i,\omega,t} \) generation of power plant \( i \) in scenario \( \omega \) and hour \( t \), \( m_{i,\omega,t} \) content of reservoir \( i \) in scenario \( \omega \) and at the end of hour \( t \), \( m_{i,\omega,T} \) content of reservoir \( i \) in scenario \( \omega \) and at the end of planning period, \( Q_{i,j,\omega,t} \) discharged volume of power plant \( i \) segment \( j \), hour \( t \) and scenario \( \omega \), \( \Lambda_{i,\omega,t} \) spillage from reservoir \( i \) in scenario \( \omega \) and hour \( t \), \( p_{\omega,t}^{E} \) procured volume in scenario \( \omega \) and hour \( t \) in the day-ahead energy market, \( p_{\omega,t}^{up} \) procured volume in scenario \( \omega \) and hour \( t \) in the up-regulation mFRR balancing energy market, \( p_{\omega,t}^{down} \) procured volume in scenario \( \omega \) and hour \( t \) in the down-regulation mFRR balancing energy market, \( pc_{i}^{up} \) procured up-regulated mFRR capacity volume at hour \( t \) in the day-ahead energy market, \( pc_{i}^{down} \) procured down-regulated mFRR capacity volume at hour \( t \) in the day-ahead energy market, \( x_{seg,t}^{spot} \) bid volume for the day-ahead energy market in segment \( seg \) and hour \( t \). The parameters are: \( V_{i} \) hourly inflow in reservoir \( i \), \( G_{i}^{max} \) maximum power production of plant \( i \), \( M_{i}^{0} \) initial reservoir content of plant \( i \), \( \mu_{i,j} \) marginal production equivalent of power plant \( i \), segment
The objective function of the model comprises several key terms representing different revenue streams from market participation. The first term indicates the revenue from participating in the day-ahead energy market. The second and third terms highlight the revenue generated from the mFRR capacity market. The fourth and fifth terms pertain to revenues from the mFRR energy market. These latter revenues depend on the activation requests by the system operator, which are influenced by the direction of the system imbalance and the corrective actions taken during the activation process [82].

At this stage of the model, it is assumed that all mFRR capacity and energy bids are accepted \( \Box \). However, the actual remuneration for mFRR energy bids is contingent upon their respective active-time durations, denoted as \( T_{\omega,t}^{up}, T_{\omega,t}^{down} \). Essentially, these variables reflect the system operator’s need for balancing volumes in response to a range of uncertainty factors, such as wind power fluctuations, unplanned generation loss, or sudden shifts in demand. Although the requirement for balancing volumes in a specific hour is acknowledged, the duration of this need remains uncertain.

The equations (6.1b) and (6.1c) delineate the minimum and maximum capacities available for the day-ahead energy market, considering the volume allocated for mFRR capacity requirements. Equations (6.1d) and (6.1e) detail the bidding behavior as described in Section 6.2.2. The energy equivalents of these capacity constraints are presented in equations (6.1f)-(6.1g). According to these equations, bids in the mFRR energy market must not be less than the volumes committed in the capacity market. While not all energy bids may be activated by the system operator, HPP operators are required to be prepared for such eventualities, a condition reflected in equations (6.1h)-(6.1i).

The model assumes the participation of HPP operators in the mFRR capacity market. In cases where an HPP operator fails to provide at least the preprocured volume in the mFRR capacity market while participating in the mFRR energy market, they face penalties from the TSO as per predefined terms and conditions. As discussed in [11], balance service providers (BSPs) not cleared in the balancing capacity market may still participate in the energy market as voluntary bids. However, those whose capacity bids have been accepted in the mFRR capacity

\[ j, \gamma \] expected future production equivalent of power plant \( i \), \( Q_{i,j}^{max} \) maximum discharge of power plant \( i \), segment \( j \), \( \lambda_{e,\omega}^{pot} \) day-ahead energy market prices in scenario \( \omega \), \( \lambda_{\omega,t}^{up} \) mFRR energy price in up-regulation mode, \( \lambda_{\omega,t}^{down} \) mFRR energy price in down-regulation mode, \( \Lambda_{i}^{Min} \) minimum spillage of power plant \( i \), \( \pi_{\omega} \) probability of occurrence of each price scenarios, \( \lambda_{\omega,t}^{up} \) mFRR capacity price in up-regulation mode, \( \lambda_{\omega,t}^{down} \) mFRR capacity price in down-regulation mode, \( \rho_{seg,t} \) bid price for the segment \( seg \) and hour \( t \), \( \Upsilon^{R} \) uncertainty budget.

\( \Box \) Otherwise, the market clearing level is required to form a bilevel problem formulation in which the second level is cleared by the TSO. This is modeled in Chapter 4.
market are obliged to bid their pre-contracted volumes in the mFRR energy market, a practice also observed in the Dutch market [83].

The model incorporates hydrological constraints on reservoir levels, as outlined in equation (6.1j), and establishes an energy balance equation (6.1k) that accounts for day-ahead energy bids, activated mFRR energy bids, and actual generation. This equation also considers the active-time duration of each balancing offer, with these durations approximated based on the total active-time of each balancing energy market (upward and downward) in SE2, using data available from NordPool [43]. This approximation is derived by dividing the total activated volume (upward or downward) of all bids in SE2 by the total procured volume in that hour. The piece-wise linear relationship of hydropower output relative to discharge level is represented in equation (6.1l) [84], and equations (6.1m)-(6.1o) impose operational limits on variables based on available data for each power plant.

6.2.3 Uncertainty Set Definition

The uncertainty set definition acknowledges the challenge of making decisions without perfect information, promoting the use of methods to address uncertainties. Stochastic optimization is formulated to implicitly weigh each solution against each input data set. A crucial assumption here is the availability of information about the PDFs of uncertain parameters and their probabilities [29]. However, in cases where the PDF of an uncertain parameter is unknown, intervals for parameter deviation are defined, and robust optimization is employed to identify the optimal solution under worst-case scenarios (instances where expected profit is minimized or expected cost is maximized). Two approaches are used in this model to tackle uncertainties:

a) **Stochastic Optimization**: This approach uses public historical data on electricity prices and forecasting techniques from the literature to generate scenarios. The representation’s accuracy of uncertainty is contingent on the number of scenarios and the available information about their PDFs.

b) **Robust Optimization**: For uncertainties where accurately determining PDFs is challenging, such as wind power production [85] and the active-time duration of mFRR energy bids, robust optimization is applied. Handling these uncertainties can involve using a large scenario set, which may lead to computational difficulties, or employing cardinality-constrained uncertainty sets [86]. In this study, polyhedral uncertainty sets are utilized to determine worst-case uncertainty realizations, which correspond to the vertices of the uncertainty set [87].

In the proposed model, the active-time duration of mFRR energy bids is represented by parameters $T_{up,\omega,t}, T_{down,\omega,t}$, which range from 0 to 1. The uncertainty budget, denoted as $\Upsilon_R$, indicates the maximum number of hours the TSO is expected to activate the mFRR energy reserves. As previously noted, in general cases, $T_{up,\omega,t}, T_{down,\omega,t}$ will either be zero or one, representing the vertices of the corresponding uncertainty set in the worst-case scenario approach within the
polyhedral uncertainty sets. This section defines the resulting uncertainty set as follows:

\[ T^\omega(T_{\omega,t}^{up}, T_{\omega,t}^{down}, \Upsilon^R) := \left\{ \Gamma_{ML} : T_{\omega,t}^{up}, T_{\omega,t}^{down} \in \{0, 1\} \right\} \quad (6.2a) \]

\[ T_{\omega,t}^{down} + T_{\omega,t}^{up} \leq 1 \quad \forall \omega \in \Omega, \forall t \in \mathcal{T} \quad (6.2b) \]

\[ \sum_{t} T_{\omega,t}^{down} + T_{\omega,t}^{up} \leq \Upsilon^R \quad \forall \omega \in \Omega \quad (6.2c) \]

Here, \( T^\omega \) is defined as an uncertainty set that encapsulates all uncertainties and their constraints within the robust optimization framework. Equation (6.2b) specifies that up-regulation and down-regulation activities cannot occur simultaneously. Meanwhile, equation (6.2c) manages the conservativeness level of the model by utilizing the uncertainty budget over the operational period.

The value of \( \Upsilon^R \), the uncertainty budget, plays a crucial role in determining the extent of mFRR energy reserve activation by the TSO. If \( \Upsilon^R = 0 \), it implies that the TSO will never activate the mFRR energy reserves of the aggregated HPPs. Conversely, if \( \Upsilon^R = 24 \), it indicates that HPPs are expected to be available for providing balancing reserves in either upward or downward modes throughout the entire day. This parameter thus directly influences how the model anticipates and prepares for the activation of energy reserves by the TSO.

### 6.2.4 Two-stage Stochastic Adaptive Robust Formulation

This section introduces a trilevel optimization formulation designed to determine the optimal bidding curve for cascaded HPPs in the day-ahead energy market. This approach particularly accounts for the worst-case active-time duration of mFRR energy offers in real-time, as visualized in Fig. 6.2.

At the uppermost level, HPP operators aim to identify the optimal bid curve for the day-ahead energy market. This process involves considering participation in the mFRR capacity market and maximizing expected profits from real-time actions under worst-case scenarios. The middle level of the formulation focuses on pinpointing the worst-case active-time duration of mFRR energy offers. This step is crucial as it minimizes expected profit in real-time, assuming perfect information about the accepted day-ahead bids is available.

The final level, based on the decisions made in the upper and middle levels, involves taking corrective operational actions. These actions are designed to maximize expected profit from participation in the mFRR energy market, as well as to optimize the value of the stored water at the end of the operational horizon.

The specific details and components of this problem formulation are presented in the subsequent part of the section.
CHAPTER 6. STOCHASTIC ADAPTIVE ROBUST OPTIMIZATION IN THE SHORT-TERM BIDDING STRATEGY

Figure 6.2: Cascaded structure of the proposed method

\[ \begin{align*}
\text{Max} \sum_{\omega \in \Omega} \sum_{t \in T} \left[ p_{E,\omega,t}^{\text{spot}} \pi_{\omega} + \lambda_{\omega,t}^{\text{up}} p_{t}^{\text{up}} + \lambda_{\omega,t}^{\text{down}} p_{t}^{\text{down}} \right] + \\
\text{Min} \sum_{\omega \in \Omega} \left[ \sum_{t \in T} \left[ \lambda_{\omega,t}^{\text{up}} p_{t}^{\text{up}} t_{\omega,t}^{\text{up}} - \lambda_{\omega,t}^{\text{down}} p_{t}^{\text{down}} t_{\omega,t}^{\text{down}} \right] + \lambda_{\omega} \sum_{i \in I} m_{i,\omega,T} \sum_{s \in M_{i}} \gamma_{s} \right] \\
\text{s.t.} \\
\Gamma_{UL}: \{ p_{E,\omega,t}, p_{t}^{\text{up}}, p_{t}^{\text{down}}, x_{\text{spot},t} \} \\
p_{E,\omega,t}^{\text{down}} \leq p_{E,\omega,t}^{\text{up}} \quad \forall t \in T, \omega \in \Omega \\
p_{E,\omega,t}^{\text{up}} + p_{t}^{\text{up}} \leq \sum_{i \in I} G_{i}^{\max} \quad \forall t \in T, \omega \in \Omega \\
p_{E,\omega,t}^{\text{spot}} = x_{\text{spot},t} \quad \text{if } \rho_{\omega,t}^{\text{spot}} \leq \lambda_{\omega,t}^{\text{spot}} \leq \rho_{\omega,t}^{\text{seg}} \quad \forall t \in T, \omega \in \Omega \\
x_{\text{seg}-1,t}^{\text{spot}} \leq x_{\text{spot},t}^{\text{spot}} \quad \forall t \in T, \omega \in \Omega \\
\Gamma_{ML}: \{ p_{E,\omega,t}, p_{t}^{\text{down}}, m_{i,\omega,t}, \Lambda_{i,\omega,t}, Q_{i,j,\omega,t}, G_{i,\omega,t} \} \\
p_{E,\omega,t}^{\text{down}} \leq p_{E,\omega,t}^{\text{up}} : \epsilon_{\omega,t}^{\text{down}} \quad \forall t \in T, \omega \in \Omega \\
p_{E,\omega,t}^{\text{up}} + p_{t}^{\text{up}} \leq \sum_{i \in I} G_{i}^{\max} : \epsilon_{\omega,t}^{\text{up}} \quad \forall t \in T, \omega \in \Omega
\end{align*} \]
6.3 Solution Methodology

The proposed structure of SARO can be described in three parts:

1. The upper level is a maximization problem, which formulates a strategy in anticipation of unknown factors. This stage aims to optimize the objective function with respect to the planning variables, denoted as $\Gamma_{UL}$

2. The intermediate level is a middle min-problem that represents the most adverse outcomes of uncertainty realizations. The goal here is to minimize the objective function concerning the uncertainty variables, $\Gamma_{ML}$

3. The lower level is an operation level that represents the active time of mFRR energy bids.
3. The lower level is a maximization problem focused on operational decisions to address the impact of these worst-case scenarios. It aims to maximize the objective function based on the operational variables, \( \Gamma_{LL} \).

The SARO model integrates both preventative and responsive measures: It begins with planning, then addresses the emergence of uncertainties, and then focuses on mitigation strategies. This approach ensures proactive protection through planning and reactive adjustments through operational decisions.

To solve the proposed SARO problem in Section 6.2, a constraint-and-column generation technique, as outlined in [88], is employed. This method decomposes the problem into two parts: a subproblem and a master problem, illustrated in Fig. 6.3. These components are resolved iteratively to achieve an optimal solution.

### 6.3.1 Outer Level: Master Problem

The master problem is formulated as follows:

\[
\begin{align*}
\text{Max} & \quad \sum_{\gamma \in \Omega} \sum_{i \in I} \left( \lambda_{i,\omega,t}^{\text{spot}} p_{i,\omega,t}^E + \tilde{\lambda}_{i,\omega,t}^{\text{up}} p_{i,\omega,t}^{\text{up}} + \tilde{\lambda}_{i,\omega,t}^{\text{down}} p_{i,\omega,t}^{\text{down}} \right) + \Xi \\
\text{s.t.} & \quad \Xi \leq \lambda_{i,\omega,t}^{\text{up}} p_{i,\omega,t}^E T_{i,\omega,t}^{\text{up}} \quad \forall \omega \in \Omega, \kappa \leq \nu \\
& \quad \lambda_{i,\omega,t}^{\text{down}} m_{i,\omega,t}^{\text{down}} \sum_{s \in M_i} \gamma_s \quad \forall \kappa \leq \nu \\
& \quad p_{i,\omega,t}^E \leq p_{i,\omega,t}^E \quad \forall t \in T, \omega \in \Omega, \kappa \leq \nu \\
& \quad p_{i,\omega,t}^E + p_{i,\omega,t}^{\text{up}} \leq \sum_{i \in I} \gamma \quad \forall t \in T, \omega \in \Omega, \kappa \leq \nu \\
& \quad p_{i,\omega,t}^{\text{down}} \leq p_{i,\omega,t}^{\text{down}} \quad \forall t \in T, \omega \in \Omega, \kappa \leq \nu \\
& \quad p_{i,\omega,t}^{\text{up}} \leq p_{i,\omega,t}^{\text{up}} \quad \forall t \in T, \omega \in \Omega, \kappa \leq \nu \\
& \quad m_{i,\omega,t}^{\text{down}} = m_{i,\omega,t-1}^{\text{down}} + M_i^0 - \sum_{j \in J} Q_{i,j,\omega,t}^{(\gamma)} - \Lambda_{i,\omega,t}^{(\gamma)} + \sum_{n \in K_i} (Q_{n,j,\omega,t}^{(\gamma)} + \Lambda_{n,\omega,t}^{(\gamma)}) \\
& \quad + V_i \quad \forall i \in I, \omega \in \Omega, t \in T, \kappa \leq \nu \\
& \quad \sum_{i \in I} G_{i,\omega,t} + p_{i,\omega,t}^{\text{down}} T_{i,\omega,t}^{\text{down}} = p_{i,\omega,t}^E + p_{i,\omega,t}^{\text{up}} T_{i,\omega,t}^{\text{up}} \quad \forall \omega \in \Omega, t \in T, \kappa \leq \nu \\
& \quad G_{i,\omega,t}^{(\gamma)} = \sum_{j \in J} \mu_{i,j} Q_{i,j,\omega,t}^{(\gamma)} \quad \forall i \in I, \omega \in \Omega, t \in T, \kappa \leq \nu \\
& \quad 0 \leq Q_{i,j,\omega,t}^{(\gamma)} \leq Q_{i,j,\omega}^{\text{Max}} \quad \forall i \in I, j \in J, \omega \in \Omega, t \in T, \kappa \leq \nu \\
& \quad 0 \leq m_{i,\omega,t}^{(\gamma)} \leq M_i^{\text{Max}} \quad \forall i \in I, \omega \in \Omega, t \in T, \kappa \leq \nu
\end{align*}
\]
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\[ \Lambda^{(\kappa)}_{i,\omega, t} \geq \Lambda_{i}^{Min} \quad \forall \ i \in I, \omega \in \Omega, t \in \mathcal{T}, \kappa \leq \nu \quad (6.4m) \]

The master problem, as described in Section 6.2.4, is a relaxed variant of the original problem where constraints from the lower level are integrated, and the auxiliary variable, \( \Xi \), is employed to determine the worst-case outcome of the subproblem. As the iteration count, denoted by \( \nu \), increases, the complexity and size of the master problem also expand, complicating its resolution. \( \kappa \) shows iterations over the copy of all variables in the previous iterations. Nonetheless, as demonstrated in [88], this methodology, in comparison to the Bender-dual decomposition approach, exhibits fewer iteration counts and enhanced adaptability in managing various types of variables presented in the lower-level problem formulation.

6.3.2 Inner Level : Subproblem

In this level, the inner problem utilizes a bilevel formulation to determine the worst-case active-time durations of mFRR bids. The process involves two operators, detailed as follows:

- The \textit{min} operator’s objective is to identify the active-time duration that minimizes the subproblem’s objective function. The optimization variables in this context are represented by \( \Gamma_{ML} \), specifically including \( \{ T_{down}^\omega, T_{up}^\omega \} \).

- The \textit{max} operator is tasked with making ex-post correction decisions in response to the challenging scenarios introduced by the middle level’s \textit{min} operator. The optimization variables at this level are encompassed within the set \( \Gamma_{LL} \), as previously defined.

During each iteration, denoted as \( \nu \), of the master problem, the subproblem is resolved based on the formulation in (6.5) to determine the aforementioned variables. The structure of the subproblem in each iteration is as follows:

\[
\begin{align*}
\min_{\Gamma_{ML}} \max_{\Gamma_{LL}} & \quad \sum_{\omega \in \Omega} \pi_{\omega} \left[ \sum_{t \in \mathcal{T}} \left[ \lambda_{\omega, t}^\text{up} p_{\omega, t}^\text{up} T_{\omega, t}^\text{up} - \lambda_{\omega, t}^\text{down} p_{\omega, t}^\text{down} T_{\omega, t}^\text{down} \right] \\
& + \lambda_{\epsilon, \omega} \sum_{i \in I} m_{i, \omega, T} \sum_{s \in M_i} \gamma_s \right] \\
\text{s.t.} & \quad p_{\omega, t}^\text{down} \leq \underline{p}_{\omega, t}^E(\nu) \quad \forall t \in \mathcal{T}, \omega \in \Omega \\
& \quad \overline{p}_{\omega, t}^E(\nu) + p_{\omega, t}^\text{up} \leq \sum_{i \in I} G_{i, \omega, t}^\text{max} \quad \forall t \in \mathcal{T}, \omega \in \Omega \\
& \quad \overline{p}^E(\nu) \leq p_{\omega, t}^\text{down} \quad \forall t \in \mathcal{T}, \omega \in \Omega 
\end{align*}
\]
CHAPTER 6. STOCHASTIC ADAPTIVE ROBUST OPTIMIZATION IN THE SHORT-TERM BIDDING STRATEGY

\[
\bar{p}_{i}^{up}(\nu) \leq p_{i}^{up} : \eta_{i}^{up} \quad \forall t \in T, \omega \in \Omega \\
m_{i,\omega,t} = m_{i,\omega,t-1} + M_{i}^{0} - \sum_{j \in J} Q_{i,j,\omega,t} - \Lambda_{i,\omega,t} + \sum_{j \in J} \sum_{t \in T} (Q_{n,j,\omega,t} + \Lambda_{n,\omega,t})
\]

\[+V_{i} : \psi_{i,\omega,t} \quad \forall i \in \mathcal{I}, \omega \in \Omega, t \in T \quad (6.6e)\]

\[\sum_{i \in \mathcal{I}} G_{i,\omega,t} + p_{i}^{down} T_{i,\omega,t}^{down} = p_{i}^{u}(v) + p_{i}^{up} T_{i,\omega,t}^{up} : \alpha_{i,\omega,t} \quad \forall \omega \in \Omega, t \in T. \quad (6.6f)\]

\[G_{i,\omega,t} = \sum_{j \in J} \mu_{i,j} Q_{i,j,\omega,t} : \phi_{i,\omega,t} \quad \forall i \in \mathcal{I}, \omega \in \Omega, t \in T \quad (6.6h)\]

\[0 \leq Q_{i,j,\omega,t} \leq Q_{i,j,\omega,t}^{Max} : \sigma_{i,j,\omega,t}^{min}, \sigma_{i,j,\omega,t}^{max} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, \omega \in \Omega, t \in T \quad (6.6i)\]

\[0 \leq m_{i,\omega,t} \leq M_{i}^{Max} : \nu_{i,\omega,t}^{min}, \nu_{i,\omega,t}^{max} \quad \forall i \in \mathcal{I}, t \in \Omega, t \in T \quad (6.6j)\]

\[\Lambda_{i,\omega,t} \geq \Lambda_{i}^{Min} : \theta_{i,\omega,t} \quad \forall i \in \mathcal{I}, \omega \in \Omega, t \in T \quad (6.6k)\]

In the aforementioned formulation, parameters marked with \((\nu)\) are imported from the master problem and are considered constant within the subproblem. As previously discussed, this subproblem is a bilevel problem characterized by a linear objective function in relation to its decision variables. This linearity permits the application of strong duality theory, allowing for the reformulation of the lower-level problem. References such as \[89\], \[90\], and \[91\] provide insights into this reformulation process. Consequently, the lower-level problem can be integrated with the middle-level problem, effectively transforming it into a single-level optimization problem. This approach aligns with the methodology outlined in \[92\]. The resulting single-level optimization problem is formulated as follows:

\[
\begin{align*}
\text{Min} & \quad \sum_{\omega \in \Omega} \left[ \sum_{t \in T} \left( e_{i,\omega,t}^{up}(\nu) - \sum_{i \in \mathcal{I}} G_{i,\omega,t}^{Max} - (c_{\omega,t}^{down} + \alpha_{\omega,t}) p_{i}^{u}(v) + \eta_{\omega,t}^{up} p_{i}^{up}(\nu) + \eta_{\omega,t}^{down} p_{i}^{down}(\nu) + \sum_{i \in \mathcal{I}} \theta_{i,\omega,t} \Lambda_{i,\omega,t} - \nu_{i,\omega,t}^{max} M_{i}^{Max} - \sum_{j \in \mathcal{J}} \sum_{t \in T} \sigma_{i,j,\omega,t}^{max} Q_{i,j,\omega,t}^{max} \right) \right] \\
& \quad + \sum_{i,\omega,t \neq 1} \psi_{i,\omega,t} V_{i} \\
\text{s.t.} & \quad \alpha_{\omega,t} + \phi_{i,\omega,t} = 0 \quad \forall i \in \mathcal{I}, t \in T, \omega \in \Omega \quad (6.6c) \\
& \quad \psi_{i,\omega,t} = \sum_{t \in M_{i}} \psi_{n,\omega,t} - \mu_{i,j} \phi_{i,\omega,t} - \sigma_{i,j,\omega,t}^{min} + \sigma_{i,j,\omega,t}^{max} = 0 \quad \forall i, j, t, \omega \in \mathcal{I}, \mathcal{J}, T \quad (6.6d) \\
& \quad \psi_{i,\omega,t} = \sum_{t \in M_{i}} \psi_{n,\omega,t} - \theta_{i,\omega,t} = 0 \quad \forall i \in \mathcal{I}, \omega \in \Omega, t \in T \quad (6.6e) \\
& \quad -\pi_{\omega \lambda,\omega} \sum_{s \in M_{i}} \gamma_{s} + \psi_{i,\omega,t} + \nu_{\omega,t}^{max} - \nu_{\omega,t}^{min} = 0 \quad \forall i \in \mathcal{I}, \omega \in \Omega, t = T \quad (6.6f)
\end{align*}
\]
6.3. SOLUTION METHODOLOGY

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{flowchart.png}
\caption{CCG flowchart for the proposed optimization}
\end{figure}

\begin{align}
\psi_{i,\omega,t} - \psi_{i,\omega,t+1} + \nu_{\omega,t}^{max} - \nu_{\omega,t}^{min} &= 0 \quad \forall i \in \mathcal{I}, \omega \in \Omega, t \neq T \quad (6.6g) \\
-\pi_{\omega} \lambda_{\omega,t}^{up} T_{\omega,t}^{up} - \alpha_{\omega,t} T_{\omega,t}^{up} + \epsilon_{\omega,t}^{up} - \eta_{\omega,t}^{up} &= 0 \quad \forall \omega \in \Omega, t \in \mathcal{T} \quad (6.6h) \\
\pi_{\omega} \lambda_{\omega,t}^{down} T_{\omega,t}^{down} + \alpha_{\omega,t} T_{\omega,t}^{down} + \epsilon_{\omega,t}^{down} - \eta_{\omega,t}^{down} &= 0 \quad \forall \omega \in \Omega, t \in \mathcal{T} \quad (6.6i) \\
\epsilon_{t,\omega,t}^{up}, \epsilon_{t,\omega,t}^{down}, \theta_{t,\omega,t}, \eta_{t,\omega,t}, \psi_{i,\omega,t}^{max}, \nu_{t,\omega,t}^{max}, \sigma_{i,j,\omega,t}^{max}, \sigma_{i,j,\omega,t}^{min} &\geq 0 \quad (6.6j)
\end{align}

In which, $\Gamma_D = \{T_{\omega,t}^{down}, T_{\omega,t}^{up}, \epsilon_{t,\omega,t}^{up}, \epsilon_{t,\omega,t}^{down}, \theta_{t,\omega,t}, \eta_{t,\omega,t}, \psi_{i,\omega,t}^{max}, \nu_{t,\omega,t}^{max}, \sigma_{i,j,\omega,t}^{max}, \sigma_{i,j,\omega,t}^{min}, \phi_{i,\omega,t}, \psi_{i,\omega,t}\}$. Here, (6.6b) represents the middle-level constraint and (6.6c)-(6.6j) are the lower-level feasibility constraints. There are two non-linear terms ($\alpha_{\omega,t} T_{\omega,t}^{down}$ and $\alpha_{\omega,t} T_{\omega,t}^{up}$) in (6.6h) and (6.6i) which are the product of the middle-level primal and lower-level dual variables. This issue can be handled by replacing them with their equivalent mixed-integer linear expression using the techniques proposed in [93].
6.3.3 Algorithm

The column-and-constraint generation (CCG) approach, as previously discussed, actively identifies key scenarios of uncertainty, subsequently developing corresponding recourse decision variables and their associated constraints. This technique differs significantly from the Benders cutting plane method in that it does not require dual information to generate variables and constraints, which are directly relevant to the decision-maker [94]. In contrast, the CCG method operates by breaking down the principal problem into two parts: a master problem and a subproblem. The master problem, addressed in Section 6.3.1, is responsible for dynamically formulating inter-problem constraints that respond to the fluctuations of uncertain parameters, while also determining an upper-bound solution for the problem at hand. Conversely, the subproblem, discussed in Section 6.3.2, focuses on identifying the most adverse scenario of uncertainties, based on the decision variables set by the master problem, thereby establishing a lower-bound for the overall problem. The resolution is achieved through an iterative process between these two components until a convergence threshold is met. The procedural steps involved in this method are outlined in the following:

1) Set the lower and upper bounds to $-\infty$ and $+\infty$, respectively, and select a convergence criterion $\epsilon$.

2) Initialize the iteration counter $\nu = 0$.

3) Solve the master problem in Section 6.3.1. Note that in the first iteration, the constraints (6.4c)-(6.4m) should not be considered.

4) Find the optimal value of the auxiliary variable ($\Xi$) in the master problem’s objective value and set it as the updated UB ($\nu$).

5) Based on the obtained results in Step 3), set $\bar{p}_{\omega,t}^E(\nu) = p_{\omega,t}^E(\nu), \bar{p}_{t}^{up}(\nu) = \bar{p}_{t}^{up}(\nu)$ and $\bar{p}_{t}^{down}(\nu) = \bar{p}_{t}^{down}(\nu)$ in which the bar sign means the fixed values in (6.5) and the star sign shows their optimal values.

6) Solve the subproblem in Section 6.3.2 using the values set in Step 5).

7) Update the lower bound using the following equation:

$$LB^{(\nu)} = \max\{LB^{(\nu-1)}, z_{\text{sub}}^{(\star)}\} \quad (6.7)$$

which $z_{\text{sub}}^{(\star)}$ is the optimal value of the subproblem’s objective function in (6.6).

8) If the error tolerance is reached ($\frac{UB^{(\nu)} - LB^{(\nu)}}{UB^{(\nu)}} \leq \epsilon$), the algorithm stops and final solution would be $p_{\omega,t}^E, \bar{p}_{t}^{up}$ and $\bar{p}_{t}^{down}$; otherwise, continue the next step.
9) Update the iteration counter \( \nu = \nu + 1 \)

10) Update the middle-level variables and fix them to the values obtained in Step 6), i.e., \( T_{\omega,t}^{up(\kappa)} = T_{\omega,t}^{up(*)} \) and \( T_{\omega,t}^{down(\kappa)} = T_{\omega,t}^{down(*)} \)

11) Go back to the Step 3).

6.4 Simulation Results and Discussion

This section starts with a detailed presentation of the case study, followed by a comprehensive analysis of the effectiveness of the proposed approach and a discussion of its implications.

6.4.1 Description of case study

The following case study focuses on a river situated in the northern region of Sweden, within the SE2 bidding zone, to assess the efficacy of the proposed optimization model. This study revolves around the Skellefte river, featuring a series of 15 cascading HPPs with a combined generation capacity of 1011 MW. A detailed depiction of each power plant is provided in Fig. 5.1. Market data, including day-ahead and balancing energy prices, was sourced from the Nordpool market [43]. For the purpose of this study, reservoir levels were maintained at 50% of their maximum capacity, ensuring that they do not fall below 90% of this value by the operation date’s conclusion. It is important to note that operators are not mandated to participate in the balancing capacity market. Therefore, they must strategize the allocation of their available capacity between balancing capacity and the day-ahead market. In the hypothetical scenario, a single entity manages the entire river, submitting a separate bid curve for each hour for the entire river system. All simulations were performed on a standard PC equipped with an Intel Core i7 CPU, operating at a clock rate of 2.1GHz, and utilizing a maximum of 16GB of RAM. The computational analysis was conducted using the CPLEX solver within the GAMS programming environment.

6.4.2 Bid Curve Analysis

This section delves into the analysis of optimal bidding curves of HPPs for participation in the day-ahead energy market when employing the SARO method. The focus is on the variation in bidding strategies at different times of the day, particularly under conditions of maximum uncertainty.

Fig. 6.6 illustrates these bid curves, capturing the dynamic nature of bidding across various hours. This is especially evident when the uncertainty budget is at its peak. Additionally, the analysis incorporates forecasted day-ahead price data, using ARIMA (Autoregressive Integrated Moving Average) series to simulate market price scenarios. This data is visually represented in the fanchart of
Fig. 6.5, where the prices are segmented into 19 quantiles, ranging from 0.05 to 0.95.

A key observation from this data is the fluctuation in average electricity prices throughout the day, with higher prices typically observed around 9 AM and lower prices around 3 AM. In scenarios where the price falls below the average future electricity price, assumed here at 320 SEK/MWh, the most advantageous strategy involves minimal bidding. This approach is aimed at conserving water for times when prices are higher. Conversely, during periods of maximum price hours, a higher bid volume is advantageous. This is evident from the observed bidding pattern, where the bid volume peaks at 987 MW at 9 AM.

Through this analysis, the study showcases how optimal bidding strategies are shaped by fluctuating market prices and the need to balance resource conservation with revenue maximization.

In this analysis, it is examined to know how the optimal bidding strategies for cascading HPPs adjust with changes in the budget of uncertainty at two distinct hours. This is visualized in Fig. 6.7a and 6.7b, highlighting two contrasting
6.4. SIMULATION RESULTS AND DISCUSSION

Figure 6.7: Day-ahead bid curves for different uncertainty budget (a) at t=4 and (b) at t=11

scenarios based on electricity market prices and the level of conservativeness in the operators’ approach.

a) **High price scenario**: This scenario, occurring at hour 11 (t = 11), is characterized by high electricity prices. Here, the operator’s level of conservativeness plays a crucial role in determining the bidding strategy. For a lower level of conservativeness ($\Upsilon^R = 2$), it is assumed that the TSO is less likely to activate the mFRR energy bids frequently. In this case, the optimal strategy for HPP operators is to place higher bids in the day-ahead energy market, as illustrated in Fig. 6.7b. Conversely, with a higher level of conservativeness ($\Upsilon^R = 23$), the likelihood of mFRR energy bids activation increases, prompting operators to reserve more volume for the mFRR market and bid less in the day-ahead market.

b) **Low price scenario**: At hour 4 (t = 4), when the price is comparatively low, the general strategy for HPP operators is to bid lower in the day-ahead energy market. This approach is driven by the rationale to conserve water resources for future usage when prices might be higher. The key factor influencing the bidding strategy in this scenario is the likelihood of activating mFRR energy bids, which can lead to profitable trading opportunities in the mFRR market. Therefore, with a higher probability of activation (indicated by a higher $\Upsilon^R$), operators tend to bid more, while a lower probability of activation (lower $\Upsilon^R$) leads to more conservative bidding, as depicted in Fig. 6.7a.

Through these scenarios, the analysis underscores how the interplay between market prices, uncertainty levels, and operators’ risk tolerance significantly impacts their bidding strategies in the energy market.
6.4.3 Revenue Breakdown Assessment

This section provides a detailed analysis of how varying the uncertainty budget influences the revenue streams from different market mechanisms. It specifically examines the impact on expected revenues from the day-ahead stage, including both day-ahead energy and mFRR capacity markets, as well as the revenues from the mFRR energy market. Additionally, it considers the value of stored water and the total revenue. These findings are comprehensively detailed in Table 6.2.

As the uncertainty budget expands, HPP operators tend to increase their bids in the day-ahead energy market. This strategy is driven by the anticipation of potential down-regulation opportunities in the mFRR energy market, which could yield additional revenue. Consequently, revenues from the day-ahead energy market tend to rise. However, an increase in potential down-regulation hours leads to a decrease in mFRR energy market revenue, primarily because this revenue is negatively factored into the objective function.

A general observation is that a larger uncertainty budget prompts a more conservative strategy, resulting in reduced total revenue. This conservatism is rooted in the operators’ consideration of worst-case scenarios, such as extended active-time durations of mFRR energy bids executed by the TSO and the associated risk of penalties for failing to provide the promised mFRR capacity volume in real-time. Consequently, the expected total profit diminishes.

The value of stored water, given the substantial capacity of reservoirs in the case study, remains relatively stable across different uncertainty budget scenarios. Additionally, the algorithm’s performance in accommodating various uncertainty budgets, measured in terms of upper and lower bounds within the CCG algorithm, is illustrated in Fig. 6.8. The optimization process adheres to a convergence tolerance set at 0.2%, which is satisfactorily achieved in this study.

Moreover, Table 6.2 reveals that the total revenue under the SARO approach is higher compared to the STC method. As discussed in Section 6.2.2, the STC approach is based on certain assumptions regarding the active-time duration. Removing these assumptions and adopting a naïve approach, where all bids are fully active (i.e., for 1 hour), could potentially elevate the STC results above the current ones. However, this study opts for a more realistic approach than the simplified one-hour active-time duration commonly used in previous literature, thereby ensuring a more accurate representation of the market dynamics and revenue potential.

6.4.4 Out-of-Sample Assessment

To demonstrate the superiority of the SARO approach over STC method, an out-of-sample assessment was conducted, as detailed in [29]. This assessment involves several key steps:

- **Scenario Generation**: Utilizing the ARIMA model, a range of scenarios were generated to determine optimal day-ahead bid curves, along with par-
Table 6.2: Revenue Breakdown Analyses for Different Values of Uncertainty Budget (MSEK)

<table>
<thead>
<tr>
<th>$\Upsilon^R$</th>
<th>Day-ahead mFRR Capacity</th>
<th>mFRR Energy</th>
<th>Total Market-Based Revenue</th>
<th>Value of Stored Water</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.21</td>
<td>0.46</td>
<td>1.01</td>
<td>9.68</td>
<td>365</td>
</tr>
<tr>
<td>3</td>
<td>8.25</td>
<td>0.43</td>
<td>0.98</td>
<td>9.66</td>
<td>365</td>
</tr>
<tr>
<td>9</td>
<td>8.39</td>
<td>0.41</td>
<td>0.82</td>
<td>9.62</td>
<td>365</td>
</tr>
<tr>
<td>13</td>
<td>8.46</td>
<td>0.37</td>
<td>0.79</td>
<td>9.62</td>
<td>365</td>
</tr>
<tr>
<td>17</td>
<td>8.51</td>
<td>0.34</td>
<td>0.75</td>
<td>9.60</td>
<td>365</td>
</tr>
<tr>
<td>23</td>
<td>9.12</td>
<td>0.32</td>
<td>0.15</td>
<td>9.59</td>
<td>365</td>
</tr>
<tr>
<td>STC</td>
<td>6.70</td>
<td>0.41</td>
<td>0.39</td>
<td>7.50</td>
<td>366</td>
</tr>
</tbody>
</table>

Figure 6.8: Number of iterations, upper bound and lower bound

- Running the Optimization Problem: With the day-ahead strategy established, the next step involves running a separate optimization problem (6.8). In this phase, certain parameters like $x_{seg,t}^{\text{spot}}$, $pc_{t}^{up}$, and $pc_{t}^{down}$ are fixed. The focus here is on identifying the operational variables.

- Data Utilization: For this optimization, electricity price scenarios were extracted from historical data available at NordPool (Fig. 6.10a), covering a period of 90 days. Additionally, the active-time duration of these scenarios was calculated based on the methodology outlined in Section 6.2.2, as depicted in Fig. 6.10b and 6.10c.

- Meeting mFRR Energy Offers: As previously mentioned, the mFRR energy offers should at least match the commitments made in the capacity market during the day-ahead stage, as outlined in equations (6.3i) and (6.3j). However, there may be instances where HPP operators are unable to fulfill
their commitments in the mFRR capacity market in real-time, leading to imbalances. The penalty for these imbalances is set at 10 kSEK/MWh.

- **Modeling Imbalances**: Imbalances are represented through four variables: \( Imb_{\omega,t}^{up} \) and \( Imb_{\omega,t}^{down} \) for positive and negative imbalances in the upward mFRR energy market, respectively, and \( Imb_{\omega,t}^{down+} \) and \( Imb_{\omega,t}^{down-} \) for the downward mFRR market. Fig. 6.9 illustrates the process of this assessment.

The optimization problem, thus formulated, aims to assess the real-world applicability and effectiveness of the SARO approach in managing uncertainties and operational challenges in the energy market, especially in comparison to the STC method.

\[
\begin{align*}
\text{Max} & \sum_{\omega \in \Omega^{(s)}} \pi_{\omega} \sum_{t \in T} \left( \lambda_{\omega,t}^{spot(s)} E(s) + \lambda_{\omega,t}^{up} p_{\omega,t}^{up} + \lambda_{\omega,t}^{down(s)} p_{\omega,t}^{down} + \lambda_{e,\omega}^{(s)} \sum_{i \in I} m_{i,\omega,T}^{(s)} \sum_{s \in M_i} \gamma_s \right) \\
& - \sum_{\omega \in \Omega^{(s)}} \pi_{\omega} \sum_{t \in T} C_p \left( Imb_{\omega,t}^{up+} + Imb_{\omega,t}^{up-} + Imb_{\omega,t}^{down+} + Imb_{\omega,t}^{down-} \right). \\
\text{s.t.} & \quad \overline{p}_{t}^{down} \leq p_{\omega,t}^{E(s)} \quad \forall t \in T, \omega \in \Omega^{(s)} \\
& \quad p_{\omega,t}^{E(s)} + \overline{p}_{t}^{up} \leq \sum_{i \in I} G_{i}^{max} \quad \forall t \in T, \omega \in \Omega^{(s)}
\end{align*}
\]
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Figure 6.10: Input data for the out-of-sample simulation (a) Day-ahead energy market (b) Active-time duration of upward mFRR balancing energy bids (c) active-time duration of downward mFRR balancing energy bids

\[ p_{\omega,t}^{E(s)} = \frac{\text{spot}}{\pi_{\omega,t}} \text{ if } \rho_{\omega,t} \leq \rho_{\omega,t}^{\text{spot}} \forall t, s, \omega \in \mathcal{T}, D, \Omega_s \] (6.8d)

\[ p_{\omega,t}^{\text{down}(s)} \leq p_{\omega,t}^{E(s)} \forall t, \omega \in \Omega_s \] (6.8e)

\[ p_{\omega,t}^{E(s)} + p_{\omega,t}^{\text{up}(s)} \leq \sum_{i \in \mathcal{I}} G_{i,\omega,t}^{\text{max}} \forall t, \omega \in \Omega_s \] (6.8f)

\[ p_{\omega,t}^{\text{down}(s)} - p_{\omega,t}^{\text{up}(s)} \leq \text{Imb}_{\omega,t}^{\text{down}(s)} - \text{Imb}_{\omega,t}^{\text{up}(s)} \forall t, \omega \in \Omega_s \] (6.8g)

\[ m_{i,\omega,t}^{(s)} = m_{i,\omega,t-1} + M_i^{(s)} - \sum_{j \in \mathcal{J}} Q_{i,j,\omega,t}^{(s)} - \Lambda_{i,\omega,t}^{(s)} + \sum_{j \in \mathcal{J}} \sum_{n \in \mathcal{K}_i} (Q_{i,j,\omega,t}^{(s)} + \Lambda_{i,n,\omega,t}^{(s)}) 
+ V_i \forall i \in \mathcal{I}, \omega \in \Omega_s, t \in \mathcal{T} \] (6.8i)

\[ \sum_{i \in \mathcal{I}} G_{i,\omega,t}^{(s)} + p_{\omega,t}^{\text{down}(s)} T_{\omega,t}^{\text{down}(s)} = p_{\omega,t}^{E(s)} + p_{\omega,t}^{\text{up}(s)} T_{\omega,t}^{\text{up}(s)} \forall \omega \in \Omega_s, t \in \mathcal{T} \] (6.8j)

\[ G_{i,\omega,t}^{(s)} = \sum_{j \in \mathcal{J}} \mu_{i,j} Q_{i,j,\omega,t}^{(s)} \forall i \in \mathcal{I}, \omega \in \Omega_s, t \in \mathcal{T} \] (6.8k)

\[ 0 \leq Q_{i,j,\omega,t}^{(s)} \leq Q_{i,j}^{\text{Max}} \forall i \in \mathcal{I}, j \in \mathcal{J}, \omega \in \Omega_s, t \in \mathcal{T} \] (6.8l)

\[ 0 \leq m_{i,\omega,t}^{(s)} \leq M_i^{\text{Max}} \forall i \in \mathcal{I}, \omega \in \Omega_s, t \in \mathcal{T} \] (6.8m)

\[ \Lambda_{i,\omega,t}^{(s)} \geq \Lambda_i^{\text{Min}} \forall i \in \mathcal{I}, \omega \in \Omega_s, t \in \mathcal{T} \] (6.8n)

Where \( \Gamma_{\text{out}} = \{ p_{\omega,t}^{E(s)}, p_{\omega,t}^{\text{up}(s)}, p_{\omega,t}^{\text{down}(s)}, Q_{i,j,\omega,t}^{(s)}, \Lambda_{i,\omega,t}^{(s)}, m_{i,\omega,t}^{(s)}, G_{i,\omega,t}^{(s)}, \text{Imb}_{\omega,t}^{\text{up}(s)}, \text{Imb}_{\omega,t}^{\text{down}(s)}, \text{Imb}_{\omega,t}^{\text{up}(s)} \} \).

For comparing the performances of out-of-sample assessments, the following parameters are defined. The \( \bar{I}_{\text{avg}} \) is the average sampled imbalance caused by the equations (6.8g)-(6.8h) and \( R_{\text{avg}} \) is the revenue obtained from trading in day-ahead energy, mFRR capacity and energy markets plus the value of the stored water at the end of the planning horizon. They are defined as follows:
\[ R_{\text{avg}} = \sum_{\omega \in \Omega^{(s)}} \pi_\omega \sum_{t \in T} \left( \lambda_{\omega,t}^{\text{spot}} \frac{E(s)}{p_{\omega,t}} + \tilde{\lambda}_{\omega,t}^{\text{up}} \frac{p_{c,t}^{\text{up}}}{p_{c,t}^{\text{down}}} + \tilde{\lambda}_{\omega,t}^{\text{down}} \frac{p_{c,t}^{\text{down}}}{p_{c,t}^{\text{up}}} \right) + \text{(6.9a)} \]

\[ I_{\text{avg}} = \frac{1}{T} \sum_{\omega \in \Omega^{(s)}} \pi_\omega \sum_{t \in T} \left( \overline{\text{Imb}}_{\omega,t}^{\text{up}+} + \overline{\text{Imb}}_{\omega,t}^{\text{up}-(s)} + \overline{\text{Imb}}_{\omega,t}^{\text{down}-(s)} + \overline{\text{Imb}}_{\omega,t}^{\text{down}+(s)} \right) \text{(6.9b)} \]

The examination of the optimal values derived from the out-of-sample optimization problem (6.8) reveals how changes in the uncertainty budget affect overall performance. The bar sign above variables in this context indicates their optimal values from the problem.

The results, as listed in Table 6.3, show a clear trend: as the uncertainty budget increases, moving towards a more conservative strategy, there is a corresponding decrease in both the average sampled imbalances and profit. This happens because a higher uncertainty budget \( (\Upsilon^R) \) means HPP operators are better prepared for different activation orders from TSO, leading to reduced expected imbalances.

Comparing these results with those from a fully-stochastic approach, it is evident that the latter, with an average imbalance of 32.52 MW and an average revenue of 385 MSEK, performs less favorably than even the most conservative setting in the proposed approach. This highlights the effectiveness of the SARO method over the fully-stochastic approach.

Furthermore, Table 6.4 assesses the out-of-sample simulation for the solution provided with the fully-stochastic model across different numbers of scenarios. As the scenario count increases, there is a notable decrease in both average sampled imbalances and revenue. This decrease in imbalances results from including more comprehensive expected price information in the optimal bidding problem (6.1), thereby minimizing unnecessary imbalances. Notably, the economic benefits of even the most conservative strategy in the SARO approach exceed all outcomes of the full-stochastic model, underscoring the SARO method’s superior balancing of operational risks and economic returns in complex and uncertain market environments.

In the process of solving the optimization problem outlined in (6.3), the quantity of scenarios used for electricity price forecasts plays a crucial role in balancing the computational effort and the precision of the outcomes. The relationship between the number of scenarios, computational time, and the level of imbalance is depicted in Fig. 6.11.

The figure highlights a key trend: as the number of scenarios increases, there is a notable decrease in the level of imbalance. This improvement is attributed
Table 6.3: Total imbalance volume and revenue of the optimal bid curve for different numbers of uncertainty budgets

<table>
<thead>
<tr>
<th>$\gamma^R$</th>
<th>$I^{avg}$ [MW]</th>
<th>$R^{avg}$ [MSEK]</th>
<th>$\gamma^R$</th>
<th>$I^{avg}$ [MW]</th>
<th>$R^{avg}$ [MSEK]</th>
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</thead>
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<tr>
<td>11</td>
<td>19.08</td>
<td>387.18</td>
<td>23</td>
<td>10.33</td>
<td>385.53</td>
</tr>
</tbody>
</table>

Table 6.4: Total imbalance volume and revenue of the optimal bid curve for different number of scenarios for the fully stochastic model

<table>
<thead>
<tr>
<th>Number of Scenarios</th>
<th>$I^{avg}$ [MW]</th>
<th>$R^{avg}$ [MSEK]</th>
</tr>
</thead>
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<tr>
<td>20</td>
<td>22.5</td>
<td>385.35</td>
</tr>
<tr>
<td>50</td>
<td>15.25</td>
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<td>200</td>
<td>1.37</td>
<td>384.42</td>
</tr>
</tbody>
</table>

to a more accurate representation of the bidding curve, which becomes possible when a larger dataset is utilized for scenario generation. Essentially, with more scenarios, the model can better capture the variability and potential extremes of electricity prices, leading to more robust and realistic bidding strategies.

However, this increase in scenario count has a trade-off in terms of computational effort. The complexity of the trilevel optimization problem in (6.3) escalates with the addition of more scenarios, resulting in longer computational times. This rise in computational demand is a consequence of the model needing to process and integrate a greater volume of data to arrive at an optimal solution.

6.5 Conclusion

This chapter introduces an innovative approach to managing the inherent uncertainties in the optimal planning and operation of cascaded HPPs within sequential electricity markets. The proposed method, termed SARO, is designed to assist HPP operators in strategically allocating their available resources across day-ahead energy, mFRR capacity, and energy markets. This allocation takes into account the uncertainties associated with current and future electricity prices, as well as the active-time duration of accepted mFRR energy bids.
A key finding from the out-of-sample assessment of this approach is its superiority in revenue generation compared to traditional stochastic optimization methods. Even when employing the most conservative strategy under SARO, the revenue achieved consistently surpasses that of conventional methods.

Looking ahead, future extensions of this research could explore the influence of stochastic wind power generation, particularly as it becomes an increasingly significant component of the power generation mix. Additionally, addressing the variability in local inflow to each reservoir presents another layer of complexity. This variability, driven by the stochastic nature of weather conditions, necessitates sophisticated modeling techniques to accurately predict and manage the impacts on hydropower operations.

Overall, the insights provided by this chapter pave the way for more effective and efficient strategies in managing hydropower resources in the face of evolving market conditions and uncertainties, offering a robust framework for future developments in the field.
Chapter 7

Strategic Operation of Hydropower Plants in the Multi-Market Setups

This chapter presents a comprehensive study of optimal strategic trading behaviors of power plants in sequential day-ahead, intraday, and frequency-regulation markets, focusing on the growing importance of their integration into frequency-regulation markets. A bilevel multi-product optimization model is introduced, utilizing transformation techniques and reformulated into a mixed-integer linear programming problem with uncertain parameters. The study thoroughly investigates various aspects of this model, emphasizing the optimal trading strategies for hydropower plant assets, supported by multiple case studies. The content of this chapter is extracted from the following paper:


7.1 Introduction

As Europe moves towards a low-carbon power system, the energy landscape is undergoing significant structural transformations. These changes include a marked increase in wind power usage, the phased shutdown of thermal power plants, the introduction of new interconnectors to boost exchange capacities, and the creation of new electricity markets. Alongside these developments, there is an escalating need for fast-responding reserves to maintain the security and stability of the power system [95].
In this changing environment, hydropower producers hold a unique position compared to conventional power generators, primarily due to their intrinsic storage capabilities and their ability to quickly adjust production levels. The capacity to store water empowers them to maximize revenue across various market segments, posing both a challenge and an opportunity for these entities [22]. Additionally, the shift towards more renewable energy sources like wind and solar power has amplified the demand for short-term balancing services. Hydropower, especially when proximate to these intermittent energy resources, emerges as a sustainable solution for delivering such critical services. Consequently, hydropower producers are increasingly focusing not just on supplying energy in the day-ahead (DA) market but also on providing adjustment in intraday (ID) and balancing markets. This shift positions them as pivotal contributors in multiple market frameworks.

To navigate this evolving scenario successfully, hydropower producers need to strategically approach their market bidding as an integrated problem. Decisions in one market can significantly affect the flexibility and opportunities in other markets [55, 96]. Their dominant presence in balancing markets, notably in countries like Sweden and Norway, often casts them in the role of a price-maker, influencing market-clearing prices. This dynamic is typically modeled as a bilevel problem in energy economics literature, acknowledging the complex interplay between market strategies and their broader impact on the power system [95, 97].

Bilevel modeling has become a prominent tool in electricity market research, particularly for capturing the interactions between various entities, some of which may exhibit strategic behavior. In these models, the entities are categorized as either strategic or non-strategic, based on their positioning within the upper or lower level of the model. The electricity market literature, especially regarding long-term expansion planning, often employs bilevel structures to illustrate the dynamics between system operators and generation or consumption companies [98–101].

Predominantly, bilevel models in the literature have been concentrated on the DA electricity market. For instance, [102] optimizes energy storage arbitrage revenue at the upper level, while modeling the market-clearing process, incorporating energy storage and wind power, at the lower level. Another example is a model with revenue and network constraints in the DA market, which includes inter-temporal constraints related to generation scheduling, demand-side bidding, and marginal pricing [103].

Additionally, some studies using bilevel programming address interactions between different markets, such as DA and balancing markets. In [104], the participation of an electricity retailer in DA and real-time markets is modeled at the upper level, whereas distributed renewable energy producers are represented at the lower level. Bilevel models considering demand-side perspectives in electricity markets are also explored in literature [105, 107].

Hydropower planning problems have primarily been modeled as multistage stochastic programming problems, often solved using various decomposition tech-
niques [62, 108–110]. Yet, many of these models consider hydropower as price takers in the market. Limited studies address price-making hydropower producers, and often, these employ simplifying assumptions or omit certain aspects like hydrological balance and topological details [111,112].

Studies like [113] have examined market power in hydrothermal systems deterministically, focusing on the residual demand curve (RDC) without considering transmission constraints. Other works, such as [114] and [115], have similarly focused on single hydropower producers with certain limitations, like neglecting transmission constraints.

A strategic hydropower offering model based on RDC scenarios, considering the effects of the forbidden zone, is proposed in [116]. This paper extends the scope by considering multiple strategic and non-strategic hydropower producers and thermal generators participating in the day-ahead, intraday, and FCR-N markets, thereby offering a more comprehensive and nuanced understanding of market dynamics and strategic interactions in the energy sector.

Table 7.1: Literature review on various bilevel models in the electricity market literature on hydro power producers

<table>
<thead>
<tr>
<th>Papers</th>
<th>i</th>
<th>ii</th>
<th>iii</th>
<th>iv</th>
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7.2 Proposed Bilevel Formulation for Hydro-Dominated Power System

This section presents a bilevel formulation to derive an optimal solution for the coordinated operation of strategic hydropower producers across three key electricity markets: DA, FCR-N, and ID. In this context, these strategic hydropower units are considered price-makers in the DA and FCR-N markets, indicating their influence on market prices due to their substantial market share or strategic bidding behavior. However, in the ID market, these units are treated as price-takers, meaning they accept the market price as given, without having a significant impact on setting it. The structure of the proposed model is shown in Fig. 7.1. The diagram outlines the architecture of the optimization model, shedding light on
the roles and interplay among various power plants within the market framework. It begins with showcasing a strategic hydropower plant that not only impacts but also adapts to the DA and FCR-N markets, although it merely collects data from the ID market without exerting any influence. Subsequent sections depict a price-taking hydro plant and a thermal power plant, highlighting their passive market interaction—they gather market information but do not influence pricing. Below this, a timeline provides an overview of market scheduling, where “D” symbolizes the operation day and “D-1” the day preceding the operation. It is noted that both DA and FCR-N markets conclude their operations a day ahead, whereas the ID market remains active post-DA closure, ending roughly an hour before operations start.

Figure 7.1: Structure of the proposed model.

For the sake of clarity, the interaction of units and different markets with their respective constraints are depicted in Fig. 7.2 and elaborated in the following subsections.

7.2.1 Upper-level Problem Formulation

The upper-level problem formulation is written in 7.1a to 7.8b for set of variables $X^{UP} = \{g_{DA}^{ntw}, P_{DA}^{nstw}, P_{ID}^{nstw}, P_{ID}^{ntw}, g_{FC}^{ntw}, P_{FC}^{ntw}, P_{FC}^{ntw}, h_{FC}^{ntw}, h_{FC}^{ntw}, q_{DA}^{ntw}, q_{FC}^{ntw}, q_{kntw}\}$.
7.2. PROPOSED BILEVEL FORMULATION FOR HYDRO-DOMINATED POWER SYSTEM

Day-ahead Bidding: Maximize the strategic producer’s expected profit in DA market

Intraday: Maximize the strategic producer’s expected profit in ID market

FCR-N Bidding: Maximize the strategic producer’s expected profit in FCR-N market

Day-ahead clearing: Minimize cost plus value of stored water
Subject to:
- Load balance
- Hydrological balance
- Operational limits
- Transmission limits

FCR-N clearing: Minimize cost + value of stored water
Subject to:
- Load balance
- Participation limit
- Transmission limits
- Energy limits

Figure 7.2: Schematic of the proposed bilevel programming problem.

In which \( n \in \mathbb{N} = \{1, 2, \ldots, NH\} \) as the node index, \( t \in \mathbb{T} = \{1, 2, \ldots, NT\} \) as the time index, \( w \in \mathbb{W} = \{1, 2, \ldots, NW\} \) as the scenario index, \( k \in \mathbb{K} = \{1, 2, \ldots, NH\} \) as the hydro generation segment index, \( l \in \mathbb{L} = \{1, 2, \ldots, NL\} \) as the line index, \( s \in \mathbb{S} = \{1, 2, \ldots, NB\} \) as the price and volume segments. \( Y^\text{DA}_w \) and \( Y^\text{FC}_w \) are defined as the set of optimal solutions for the lower-level DA and FCR-N markets, respectively. The definition of the variables are as follows:

- \( g^\text{DA}_{ntw} \) signifies dispatched power by NST units in the DA market in MWh,
- \( p^\text{DA}_{nstw} \) indicates dispatched power by ST units in the DA market,
- \( p^\text{bDA}_{nst} \) and \( p^\text{bFC}_{nst} \) represent quantity offers of hydro units in the DA and FCR-N markets, respectively, both measured in MW,
- \( g^\text{FC}_{ntw} \) and \( p^\text{FC}_{nstw} \) reflect dispatched power by NST and ST units in the FCR-N market, respectively,
- \( p^\text{ID+}_{ntw} \) and \( p^\text{ID-}_{ntw} \) deal with dispatched power in the ID market in MWh,
- \( p^L_{ltw} \) pertains to the power of a line in the DA market,
- \( q^\text{DA}_{ntw} \) describes hydro reservoir content for the DA market in cubic meters,
- \( b^\text{DA}_{nst} \) and \( b^\text{FC}_{nst} \) relate to the price bids of hydro units in the DA and FCR-N markets, in Euros per MWh and MW, respectively and finally, \( q^\text{kntw} \) denotes the discharge volume in cubic meters.

In the Nordic electricity market, the dynamics between the DA market and the ID are particularly intriguing and vital for market participants. After the DA market is cleared, the clearing price and dispatched power from this market become reference points for participants in the ID market. Historical data analysis reveals a strong, mostly linear, correlation between the prices in the DA and ID markets. This relationship between the ID market prices (\( \lambda^\text{ID+}_{ntw} \) and \( \lambda^\text{ID-}_{ntw} \)) and the DA market price (\( \lambda^\text{DA}_{ntw} \)) is quantified through statistical analysis, the details of which are elaborated in the numerical results section of this chapter.
CHAPTER 7. STRATEGIC OPERATION OF HYDROPOWER PLANTS IN THE MULTI-MARKET SETUPS

The statistical properties of the DA and ID market prices, along with their linear relationship, provide a foundational understanding for modeling market behaviors and strategies. It is important to note that the power volumes traded in the ID market are generally smaller compared to the DA market, typically ranging between 1-7% of the DA market volumes. This difference in volume scale is an important aspect of market dynamics and impacts strategic decision-making for market participants.

Given this disparity in volumes, the volume limit in the ID market denoted as $P_{ID}$, is determined based on the dispatched powers from the DA market, represented by $g_{DA}^{ntw}$ and $p_{DA}^{ntw}$. This linkage ensures that the operational strategies and market bids take into account the realistic constraints and opportunities presented by the capacity of the units in both markets. By integrating these market dynamics into the modeling framework, the proposed bilevel formulation can offer more accurate and practical insights for strategic hydropower producers operating concurrently in the DA, FCR-N, and ID markets.

Maximize $X^{UP}$, $Y_{DA}^{w}$, $Y_{FC}^{w} P^{w} \pi^{w}$ ($P^{n} \in N_{ST}, s, t$) $+$ $\sum_{n \in N_{ST}, s, t} p_{FC}^{ntw} P^{FC} + \sum_{n \in N_{ST}, t} (\lambda^{ID+} + \lambda^{ID-} - \lambda^{ID-} P^{ntw}) + \lambda_{w}^{F} \sum_{n \in N_{ST}} m_{nTw} \sum_{j \in N} A^{D} n_{j}^{k^{F}}$; (7.1a)

where the first term constitutes the revenue from selling to the DA market, the second term is the revenue from the FCR-N market, the third and fourth terms are the revenue from selling and buying to/from the ID market and the last term is the value of the stored water in the unit’s reservoirs and all the downstream ones (if included in the ST subset). The above objective function is subjected to the following constraints. The balance between production and discharge is enforced by (7.2). The expression "∀t, w" is dropped from now on for the sake of brevity.

$\sum_{k} \mu_{kn} \gamma_{kntw} = \sum_{s} p_{DA}^{ntw} + p_{FC}^{ntw} - \gamma_{ntw}, \forall n \in N_{ST}$; (7.2)

Reservoir content at station $n$, spillage from station $n$, and discharge volume of station $n$ are limited by their minimum or maximum values in (7.3).

$M_{n} \leq m_{ntw} \leq M_{n}$; $s_{ntw} \leq S_{n}$; $Q_{kn} \leq q_{kntw} \leq Q_{kn}$, $\forall n \in N_{ST}$; (7.3)

Price offer of hydro unit $n$ in DA and FCR-N markets are limited by their minimum/maximum bid price in (7.4).

$B_{DA}^{n} \leq b_{n}^{DA} \leq B_{DA}^{n}$; $B_{FC}^{n} \leq b_{n}^{FC} \leq B_{FC}^{n}, \forall n \in N_{ST}$; (7.4)

The requirements on the FCR-N offers are specified in (7.5).

$\sum_{s} p_{FC}^{ntw} \geq (2P_{n} \Delta f_{t})/\gamma_{n}, \forall n \in N_{ST}$; (7.5)
7.2. PROPOSED BILEVEL FORMULATION FOR HYDRO-DOMINATED POWER SYSTEM

To make sure that the bidding curve is descending the constraints (7.6) are used.

\[ b_{n,s-1,t}^{DA} \leq b_{n,s,t}^{DA}; \quad b_{n,s-1,t}^{ST} \leq b_{n,s,t}^{ST}; \quad \forall n \in N^{ST}; \quad (7.6) \]

Total power generation at node \( n \) is limited by maximum/minimum generation capacity in (7.7a) and (7.7b).

\[ \sum_s (p_{n,s,t}^{DA} + p_{n,s,t}^{FC}) + \mu_{n,t}^D - \rho_{n,t}^D \leq P_n^D, \quad \forall n \in N^{ST}; \quad (7.7a) \]
\[ \sum_s (p_{n,s,t}^{DA} - p_{n,s,t}^{FC}) + \mu_{n,t}^D + \rho_{n,t}^D \geq 0, \quad \forall n \in N^{ST}; \quad (7.7b) \]

Buy and sell volumes in the ID market are limited in (7.8a) to the maximum possible capacities, respectively.

\[ \nu_{n,t}^{DA} \leq \nu_{n,t}^D; \quad \nu_{n,t}^D \leq \nu_{n,t}^{DA}, \quad \forall n \in N^{ST}; \quad (7.8a) \]
\[ b_{n,t}^{ID} \leq g_{n,t}^{ID}; \quad g_{n,t}^{ID} \leq b_{n,t}^{ID}, \quad \forall n \in N^{ST}; \quad (7.8b) \]

7.2.2 DA market clearing

The market clearing process is captured in a series of equations, ranging from (7.9) to (7.16). In the equation (7.9), the primary goal is to minimize the cost associated with meeting the demand required by the market operator in the DA market. The first and second terms are the costs of procurement from ST and TH units and the last term is the value of the stored water for the NST units. The decision variables for the DA market, represented as \( x^{DA}_w \), include \( p_{n,tw}^{DA} \), \( g_{n,tw}^{DA} \), \( p_{ltw}^{L} \), \( q_{ntw} \), \( s_{ntw} \), and \( m_{ntw} \). These variables, which must all be non-negative, are defined within the set \( x^{DA}_w = \{ p_{n,tw}^{DA}, g_{n,tw}^{DA}, p_{ltw}^{L}, q_{ntw}, s_{ntw}, m_{ntw} | \nu_{n,tw}^{DA} \geq 0, g_{n,tw}^{DA} \geq 0, q_{ntw} \geq 0, s_{ntw} \geq 0, m_{ntw} \geq 0 \} \), delineating the range of possible decisions and actions in the DA market.

\[ y^{DA}_w := \arg\min_{x^{DA}_w} \sum s, t, n \in N^{ST} \nu_{n,tw}^{DA} p_{n,tw}^{DA} + \sum_{t,n} P_{ntw}^{DA} g_{ntw}^{DA} + \sum_{n} m_{ntw} A_{ntw}^{FD} \]
\[ \text{Subject to: } (7.10), (7.11), (7.12), (7.13), (7.14), (7.15), \text{and} \ (7.16); \]

Power balance in DA market for all stations (strategic and non-strategic) is written in (7.10).

\[ \sum_s P_{ntw}^{DA} + g_{ntw}^{DA} + \sum_{t} A_{ntw}^{FD} = D_{ntw}^{DA} \cdot \lambda_{ntw}; \quad (7.10) \]

Hydrological balance constraint is formulated in (7.11).

\[ m_{ntw} = m_{n,t-1,w} + V_{ntw} - \sum_{k} q_{kntw} - s_{ntw} + \sum_{j} A_{nj}^{FD} (\sum_{k} q_{k,j-\tau,j,w} + s_{j,t-\tau,j,w}); \quad \eta_{ntw}^1, \quad \forall n \in N^{ST} \cup N^{\text{ST}}; \quad (7.11) \]
Discharge volume, reservoir content, and spillage from station \( n \) are limited in \((7.12)\):

\[
q_{kn} \leq q_{kntw} \leq \bar{q}_{kn} : \nu_{kntw}^2, \forall n \in N^{ST} \cup N^{-ST};
\]
\[
\bar{M}_{n} \leq m_{ntw} \leq \bar{M}_{n} : \nu_{ntw}^3, \forall n \in N^{ST} \cup N^{-ST};
\]
\[
\bar{S}_{n} \leq s_{ntw} \leq \bar{S}_{n} : \nu_{ntw}^4, \forall n \in N^{ST} \cup N^{-ST};
\]

Power of lines \( p_{ltw} \) are limited in \((7.13)\):

\[
-\bar{C}_{l} \leq p_{ltw} \leq \bar{C}_{l} : \nu_{ltw}^5, \forall n \in N^{ST} \cup N^{-ST};
\]

Dispatched power has to be less than the offered quantity as enforced by \((7.14)\). Hat symbol is used to show that the upper-level variable is used as a parameter in the lower-level problem.

\[
0 \leq p_{nstw}^{DA} \leq \hat{p}_{nstw}^{DA} : \nu_{nstw}^6, \forall n \in N^{ST};
\]

In order to ensure that the dispatched power by non-strategic unit is less than the maximum power generation capacity, the following has been imposed \((7.15)\).

\[
0 \leq g_{ntw}^{DA} \leq \bar{P}_{n} : \nu_{ntw}^7, \forall n \in N^{ST} \cup N^{TH};
\]

Using the production equivalent and discharge volume, the dispatched power for the non-strategic unit can be calculated according to \((7.16)\).

\[
g_{ntw}^{DA} - \sum_{k} q_{kntw} \mu_{kn} = 0 : \eta_{ntw}^2, \forall n \in N^{ST};
\]

### 7.2.3 KKT of DA market clearing

The KKT conditions of the DA market clearing is straightforward to obtained and they are not derived here. However, the followings will be used later in the Reformulation 1 and 2 which are stated here:

\[
\hat{b}_{nstw}^{DA} + \lambda_{nstw}^{DA} + \nu_{nstw}^6 - \nu_{nstw}^6 = 0 : p_{nstw}^{DA}, \forall n \in N^{ST};
\]
\[
\nu_{nstw}^6 (p_{nstw}^{DA} - p_{nstw}) = \nu_{nstw}^6 (p_{nstw}^{DA} - p_{nstw}) = 0, \forall n \in N^{ST};
\]

### 7.2.4 FCR-N market clearing

The formulation for clearing the FCR-N market is outlined from \((7.18)\) to \((7.21)\). In \((7.18)\), the objective function aims to minimize the total cost of securing the necessary FCR-N resources across all units.

A key aspect to consider is the treatment of certain terms in this objective function. Notably, the opportunity cost associated with stored water for non-strategic HPPs is not included in \((7.18)\), unlike in \((7.9)\). This exclusion is primarily because the FCR-N market is a capacity market without energy activation.  

\[\text{1}\]While there is energy activation in the FCR-N market, and reimbursements are based on real-time market prices, the impact of changing the reservoir level of hydropower plants is minor enough to be overlooked.
contrast, the DA market involves clearing the market for energy activation during the operation day, necessitating consideration of related operational constraints and variables.

For non-strategic HPPs, however, it is essential to account for the opportunity cost, which represents the expected profit foregone in the DA market due to allocation to the capacity market. Our proposed approach calculates the expected future electricity price for the DA energy market and uses this as the capacity cost for non-strategic HPPs. It is important to note that non-strategic HPPs do not exert market power and are passive observers of market dynamics, whereas strategic HPPs actively exercise market power to maximize their expected profit.

The decision variables for the FCR-N market are represented in the set \( X^\text{FC} = \{ p^\text{FC}_{n,tw}, g^\text{FC}_{ntw} | p^\text{FC}_{n,tw} \geq 0, g^\text{FC}_{ntw} \geq 0 \} \). This set encompasses the choices available to participants in the FCR-N market, ensuring that the market-clearing process accounts for the unique characteristics and constraints of this market segment.

\[
\forall_{ntw}^\text{FC} := \arg\min_{X^\text{FC}} \sum_{s,t, n \in N^\text{ST}} \hat{p}^\text{FC}_{nstw} p^\text{FC}_{n,tw} + \sum_{t, n \in N^\text{ST} \cup N^\text{TH}} c^\text{FC}_{ntw} g^\text{FC}_{ntw};
\]

Subject to: (7.19), (7.20), (7.21), and (7.22a);

(7.18)

Power balance in FCR-N market for all stations (strategic and non-strategic) is written in (7.19).

\[
\sum_{n \in N^\text{ST}} s^\text{FC}_{n,tw} + \sum_{n \in N^\text{TH} \cup N^\text{ST}} g^\text{FC}_{ntw} = D^\text{FC}_t : \lambda^\text{FC}_t; \quad (7.19)
\]

Constraint (7.20) is enforced to make sure that the dispatched power for the strategic hydro unit \( n \) in FCR-N market is less than the offered quantity by the hydro unit \( n \) in FCR-N market.

\[
p^\text{FC}_{n,tw} \leq \hat{p}^\text{FC}_n : \theta^1_{ntw}, \forall n \in N^\text{ST}; \quad (7.20)
\]

The FCR-N requirements for the non-strategic players are included in (7.21).

\[
g^\text{FC}_{ntw} \geq (2P_n \Delta f_t)/\delta_n : \theta^6_{ntw}, \forall n \in N^\text{ST} \cup N^\text{TH}; \quad (7.21)
\]

According to (7.22a), the maximum power generation capacity of the non-strategic unit is accounted for while dispatching it in the FCR-N market where the DA dispatch \( \hat{g}^\text{DA}_{ntw} \) is considered to be a parameter.

\[
g^\text{FC}_{ntw} + \hat{g}^\text{DA}_{ntw} \leq \hat{P}_n : \theta^7_{ntw}, \forall n \in N^\text{ST} \cup N^\text{TH}; \quad (7.22a)
\]

\[
p^\text{FC}_{n,tw} \leq \hat{g}^\text{DA}_{ntw}_n : \theta^9_{ntw}, \forall n \in N^\text{ST}; \quad (7.22b)
\]

\[
g^\text{FC}_{ntw} \leq \hat{g}^\text{DA}_{ntw} : \theta^{10}_{ntw}, \forall n \in N^\text{ST} \cup N^\text{TH}; \quad (7.22c)
\]

7.2.5 KKT conditions for FCR-N market clearing

Similarly, the KKT conditions of the FCR-N market clearing is straightforward to obtained and they are not derived here. However, the followings will be used
CHAPTER 7. STRATEGIC OPERATION OF HYDROPOWER PLANTS IN THE MULTI-MARKET SETUPS

later in the Reformulation 1 and 2 which are stated here:

\[ v_{n_{st}}^{FC} + \lambda_{t_{w}}^{FC} + \theta_{n_{stw}}^{1} + \theta_{n_{stw}}^{q} = 0 : P_{n_{stw}}^{FC}; \forall n \in \mathbb{N}_{TB} \]  
\[ \theta_{n_{stw}}^{1}(p_{n_{stw}}^{b_{FC}} - p_{n_{stw}}^{FC}) = 0, n \in \mathbb{N}_{TB}, \]  

7.2.6 The Linear Programming (LP) Equivalent

The nonlinear terms in the original objective function, specifically referred to as \( E_{n_{stw}}^{(1)} \) and \( E_{n_{stw}}^{(2)} \), are addressed and linearized. The process involves the application of stationary conditions, complementary slackness conditions, and two specific reformulations, Reformulation 1 and Reformulation 2.

By applying these conditions and reformulations, the original objective function, designated as (7.1a), which contains the bilinear terms \( E_{n_{stw}}^{(1)} \) and \( E_{n_{stw}}^{(2)} \), is transformed into a linear equivalent, referred to as (7.24a). This transformation is a critical step in linearizing the model, as it effectively removes the nonlinear characteristics associated with these terms.

However, it is important to note that this linearization does not completely eliminate all nonlinear elements from the model. After applying (7.24a), the term \( g_{n_{tw}}^{DA} \theta_{n_{tw}}^{7} \) remains as the only nonlinear component in the proposed model. This remaining term is planned to be addressed by replacing it with \( E_{n_{tw}}^{(3)} \) at a later stage.

\[ \text{Maximize} \quad \sum_{w} \pi_{w} (\sum_{t,n_{TB}} m_{n_{TB}} \lambda_{n_{TB}}^{DA} g_{n_{tw}}^{DA} + \sum_{n_{TB}} (\sum_{j} A_{n_{TB}}^{D} \lambda_{n_{TB}}^{j} + \sum_{t,n_{TB}} D_{n_{TB}}^{DA}) \lambda_{n_{TB}}^{DA} + \sum_{n_{TB}} V_{n_{TB}} n_{TB} + \sum_{t,n_{TB} \cup n_{TB}} \theta_{n_{TB}}^{1} \lambda_{n_{TB}}^{DA} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{5} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{4} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{3} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{2} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{1} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{0}) \]

\[ \text{Subject to} \quad \sum_{t,n_{TB}} \theta_{n_{TB}}^{6} (2P_{n_{TB}} - \Delta_{n_{TB}}) / \delta_{n_{TB}} + \sum_{t,n_{TB}} (P_{n_{TB}} \theta_{n_{TB}}^{1} - \sum_{t,n_{TB}} \theta_{n_{TB}}^{10}) + \sum_{t,n_{TB}} \theta_{n_{TB}}^{DA} \lambda_{n_{TB}}^{DA} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{DA} g_{n_{TB}}^{DA} + \sum_{t,n_{TB}} \theta_{n_{TB}}^{DA} E_{n_{TB}}^{(4)} + \sum_{t,n_{TB}} \lambda_{n_{TB}}^{(1)}(A_{n_{TB}}^{D} p_{n_{TB}}^{E} + \sum_{t,n_{TB}} m_{n_{TB}} \sum_{j} A_{n_{TB}}^{j} \lambda_{n_{TB}}^{j}) \]  

Reformulation 1: The nonlinear total revenue of strategic hydro units in DA market \( E_{n_{stw}}^{(1)} \) can be equivalently replaced by a linear sum of upper and lower limits multiplied by their corresponding Lagrangian dual variables.
7.2. PROPOSED BILEVEL FORMULATION FOR HYDRO-DOMINATED POWER SYSTEM

Proof: First the original bilinear formulation for $E_{nstw}^{(1)} = p_{nstw}^D \lambda_{nstw}^D$ is formulated. The aim is to find a linear equivalent for $E_{nstw}^{(1)}$. First, the strong duality condition for DA market clearing is written in (7.25). Let us state that:

$$\sum_{s,t,n \in N^{ST}} b_{nstw}^D p_{nstw}^D = \sum_{t,n \in N^{ST}} m_{ntw}^T \sum_j A^D_{nj} \mu^F_j =$$

$$\sum_{t,n \in N^{ST}} D_{ntw}^D \lambda_{ntw}^D + \sum_{t,n \in N^{ST}} (D_{ntw}^D \lambda_{ntw}^D + V_{ntw} \eta_{ntw}^D) +$$

$$\sum_k (Q_{kn}^F \lambda_{ntw}^F + M_n^3 \lambda_{ntw}^F) + \sum_{s,t,n \in N^{ST}} p_{nstw}^D \lambda_{nstw}^D$$

From (7.17a), the following can be concluded: $p_{nstw}^D \lambda_{nstw}^D = p_{nstw}^D \lambda_{nstw}^D$. It gives us $E_{nstw}^{(1)} = p_{nstw}^D \lambda_{nstw}^D = \lambda_{nstw}^D p_{nstw}^D$. Finally the strong duality condition (7.25) is rewritten as $\lambda_{nstw}^D p_{nstw}^D = \sum_{n \in N^{ST}, s} p_{nstw}^D \lambda_{nstw}^D = \sum_{n \in N^{ST}, s} p_{nstw}^D \lambda_{nstw}^D$.

Reformulation 2: The nonlinear total revenue of strategic hydro units in FCR-N market ($E_{nstw}^{(2)}$) can be equivalently replaced by a linear sum of upper and lower limits multiplied by their corresponding Lagrangian dual variables.

Proof: First, start with the original bilinear formulation for $E_{nstw}^{(2)} = p_{nstw}^F \lambda_{nstw}^F$. The aim is to find a linear equivalent for $E_{nstw}^{(2)}$. Let us state that:

$$\sum_{s,t,n \in N^{ST}} b_{nstw}^F p_{nstw}^F = \sum_{t,n \in N^{ST}} m_{ntw}^T \sum_j A^F_{nj} \mu^F_j =$$

$$\sum_{t,n \in N^{ST}} D_{ntw}^F \lambda_{ntw}^F$$

Similarly, from (7.23a), the following can be concluded $p_{nstw}^F b_{nstw}^F + p_{nstw}^F \lambda_{nstw}^F + p_{nstw}^F \theta_{nstw}^1 + p_{nstw}^F \theta_{nstw}^9 = 0$; and from (7.23b) the following can be concluded $\theta_{nstw}^1 b_{nstw}^F + \theta_{nstw}^1 \lambda_{nstw}^F$.

It gives us $E_{nstw}^{(2)} = p_{nstw}^F \lambda_{nstw}^F = -p_{nstw}^F b_{nstw}^F - \theta_{nstw}^1 b_{nstw}^F$.
Finally, the strong duality condition in (7.26a) is rewritten as
\[ \sum_{n \in N^{ST}, s, t} P_{ntw}^{FC} P_{nstw}^{M_1} F_{ntw} = \sum_{n \in N^{ST}, s, t} E_{ntw}^{(2)} = -\sum_{s, t, n \in N^{ST}} P_{ntw}^{FC} P_{nstw}^{M_1} F_{ntw} - \sum_{s, t, n \in N^{ST}} \theta_{nstw}^{DA} F_{nst}^{M_1} F_{ntw} - \sum_{t, n \in N^{ST}} \frac{\theta_{ntw}^{DA} (2P_n \Delta f_i) / \delta_n}{\theta_{ntw}^{M_1}} + \sum_{t, n \in N^{ST}} \theta_{ntw}^{DA} F_{ntw}^{M_1} F_{ntw} + \sum_{t, n \in N^{ST}} \theta_{ntw}^{M_1} (\theta_{ntw}^{DA})^{(2)} \frac{G_{ntw}}{\theta_{ntw}^{M_1}} \text{ which is a linear reformulation for } E_{ntw}^{(2)}. \]

The McCormic envelopes could be used to have a convex relaxation for \( E_{ntw}^{(3)} = g_{ntw}^{DA} \theta_{ntw}^{7} \) where \( 0 \leq g_{ntw}^{DA} \leq P_n \) and \( 0 \leq \theta_{ntw}^{7} \leq M^{17} \) which are written in (7.27).

By using \( E_{ntw}^{(3)} \) instead of \( g_{ntw}^{DA} \theta_{ntw}^{7} \) in (7.24a), the proposed model becomes an MILP problem which can be solved with the commercially available solvers.

\[ E_{ntw}^{(3)} \geq 0, n \in N^{ST} \cup N^{TH}; \]  
\[ E_{ntw}^{(3)} \geq P_n \theta_{ntw}^{7} + M^{17} g_{ntw}^{DA} P_n M^{17}, n \in N^{ST} \cup N^{TH}; \]  
\[ E_{ntw}^{(3)} \leq P_n \theta_{ntw}^{7}; E_{ntw}^{(3)} \leq M^{17} g_{ntw}^{DA} n \in N^{ST} \cup N^{TH}; \]

The McCormic envelopes could be used to have a convex relaxation for \( E_{ntw}^{(4)} = g_{ntw}^{DA} \theta_{ntw}^{10} \) where \( 0 \leq g_{ntw}^{DA} \leq P_n \) and \( 0 \leq \theta_{ntw}^{10} \leq M^{20} \) which are written in (7.28).

By using \( E_{ntw}^{(4)} \) instead of \( g_{ntw}^{DA} \theta_{ntw}^{10} \) in (7.24a), the proposed model becomes an MILP problem.

\[ E_{ntw}^{(4)} \geq 0, n \in N^{ST} \cup N^{TH}; \]  
\[ E_{ntw}^{(4)} \geq P_n \theta_{ntw}^{10} + M^{20} g_{ntw}^{DA} P_n M^{20}, n \in N^{ST} \cup N^{TH}; \]  
\[ E_{ntw}^{(4)} \leq P_n \theta_{ntw}^{10}; E_{ntw}^{(4)} \leq M^{20} g_{ntw}^{DA} n \in N^{ST} \cup N^{TH}; \]

### 7.2.7 Data and model parameters

The parameters that vary based on different scenarios and the origins of the historical data utilized include \( V_{ntw} \) (inflow), \( m_{n0w} \) (initial value of the reservoir), \( D_{ntw}^{DA} \) (DA demand), \( c_{ntw}^{FC} \) (Provision costs of the FCR-N for TH unit), \( D_{ntw}^{FC} \) (FCR-N demand), \( \lambda_{ntw}^{DP+} \) (Selling prices for ID), and \( \lambda_{ntw}^{DP-} \) (Buying prices for ID). These parameters are crucial for adapting to various situations and are derived from specific sources. For instance, the market data relevant to these parameters is obtained from Nord Pool, which plays a significant role in scenario generation. Additionally, the hydrological data, specifically \( V_{ntw} \) and \( m_{n0w} \), are sourced from historical records of the Ljungan river. The data for stations 1, 2, 3, 4, 5, and 6 is collected from stations Flåsjön-Grucken, Lännässjön, Rätan, Turinge, Bursnäs, and Havern-Mellansjön, respectively.

### 7.3 Numerical Results and Case Studies

The proposed model’s numerical outcomes are examined through six distinct case studies, as detailed in Table 7.2. From Case I to Case V, the model’s performance

| Case | Description | Performance
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Base case</td>
<td>Excellent</td>
</tr>
<tr>
<td>II</td>
<td>Scenario 1</td>
<td>Good</td>
</tr>
<tr>
<td>III</td>
<td>Scenario 2</td>
<td>Moderate</td>
</tr>
<tr>
<td>IV</td>
<td>Scenario 3</td>
<td>Poor</td>
</tr>
<tr>
<td>V</td>
<td>Scenario 4</td>
<td>Very Poor</td>
</tr>
</tbody>
</table>

The model’s performance is evaluated based on the deviation from the optimal solution and the computational time required for each case.
under varying conditions and problem sizes is evaluated. Fig. 7.3 shows an illustration for the case studies I and II.

Table 7.2: Overview of the model setup in the case studies

<table>
<thead>
<tr>
<th>CASE</th>
<th>NN</th>
<th>NST</th>
<th>ST</th>
<th>TH</th>
<th>NT</th>
<th>NW</th>
<th>NL</th>
<th>DEMONSTRATION GOAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>Illustrate Market Clearing</td>
</tr>
<tr>
<td>II</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>Illustrate Transmission Network</td>
</tr>
<tr>
<td>III</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>Market Interaction of HPP and Water Value</td>
</tr>
<tr>
<td>IV</td>
<td>118</td>
<td>14</td>
<td>1</td>
<td>4</td>
<td>24</td>
<td>1</td>
<td>2</td>
<td>Market Power Exercise</td>
</tr>
<tr>
<td>V</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>Sensitivity Analysis</td>
</tr>
</tbody>
</table>

NN: Number of buses (NN); NST: Number of non-strategic HPP (NN^{c(ST)}); ST: Number of strategic HPP (NN^{ST}); TH: Number of non-strategic thermal units (NN^{TH}); NT: Number of time steps (NT); NW: Number of time scenarios (NT); NL: Number of lines (NL);

Figure 7.3: Schematic of illustrative example. ST: strategic unit, NST: non-strategic units, TH: non-strategic thermal power plant, $D^{FC}$ is not for any specific bus/unit.

### 7.3.1 Case I: (Market Clearing Illustrate)

This section applies a simple version of the proposed model to demonstrate DA and FCR-N market clearing processes. Simplifications include omitting constraints related to the ID market and water flow from the detailed formulation in Section 7.2. As Table 7.2 indicates, for ease, it is presumed that all sets of indices, except $N$ and $L$, contain just one element, and there is a single scenario with a probability of one. The setup involves three interconnected units: Unit 1 (ST), Unit 2 (NST), and Unit 3 (TH), with capacities of them being 100 MW, 50 MW, and 100 MW, respectively.

Generation portfolios and market clearing prices for high, medium, and low DA demand scenarios are outlined in Table 7.3, with analysis divided into segments with and without FCR-N market considerations.

**DA Market Clearing Without FCR-N:**
- **Low Demand**: The NST unit, having zero marginal cost, is chosen by the market operator, leading to zero DA prices $\lambda_{\text{DA}}$.
- **Medium Demand**: The DA market demand surpasses the NST unit’s total capacity, prompting the ST unit to manage generation. It bids at the TH unit’s cost to ensure clearance, setting the price at 15 €/MWh.
- **High Demand**: Demand exceeds the combined capacity of ST and NST units, necessitating the operation of the TH unit. The ST unit, as the price-maker, bids up to the maximum allowed, 200€/MWh. This results in higher earnings for the ST unit despite lower power generation.

**DA Market Clearing with FCR-N**: In this scenario, DA demands mirror the previous case, but with an additional FCR-N demand of 20MW.
- **Low Demand**: The NST unit meets all DA market demands to reserve capacity for the FCR-N market (as per eq. (7.22a)).
- **Medium Demand**: After the NST unit reaches its capacity, the ST unit begins generation, bidding up to the TH unit’s variable cost while reserving some capacity for the FCR-N market. The TH unit sets DA market prices, whereas the ST unit, as the marginal producer in the FCR-N market, bids up to the price cap.
- **High Demand**: At this demand level, both NST and TH units operate at full capacity in the DA market, making the ST unit the price-setter for both DA and FCR-N markets.

**Table 7.3: Generation Portfolio and Market Clearing Prices in Case I**

<table>
<thead>
<tr>
<th>NETWORK FC</th>
<th>DEMAND</th>
<th>GENERATION</th>
<th>λ</th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>(50, 50, 70)</td>
<td>NA</td>
<td>(20, 50, 100)</td>
</tr>
<tr>
<td>M</td>
<td>(50, 50, 40)</td>
<td>NA</td>
<td>(90, 50, 0)</td>
</tr>
<tr>
<td>L</td>
<td>(4, 5, 25)</td>
<td>NA</td>
<td>(0, 34, 0)</td>
</tr>
<tr>
<td>w/o Net.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>w/ Net.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>w/o FC</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>w/ FC</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- i) (ST, NST, TH) different values for each unit; ii) (x)=(x,x,x) same for all units; iii) FCR-N market demand is not unit-specific; H: High; M: Medium; L: Low; NA: Not applicable; w/ Net.: with NTC limits; w/o: without NTC limits; Bold: marginal producer.

Fig. 7.4 displays the merit order listing for all units in Case I and can be interpreted using two following dynamics:

**DA Market Price Dynamics**: The DA market demand for ST, NST, and TH units is set to (50, 50, 70) MW respectively, while FCR-N market demand is zero.
- **Low Total DA Demand (< 50 MW):** The NST unit, with a marginal price of zero, sets the market price at 0 €/MWh, as observed in the low demand situation in Case I.

- **Moderate Total DA Demand (50 - 150 MW):** The ST unit becomes the marginal producer, resulting in a market price of 15 €/MWh. This price prevails as the ST unit does not bid above the TH unit’s marginal cost of $c^{DA}_{n} = 15$ €/MWh.

- **High Total DA Demand (> 150 MW):** NST and TH units reach their capacity limits and cannot be marginal producers. Consequently, the ST unit bids up to the maximum price cap of 200 €/MWh.

**FCR-N Market Price Dynamics:** For the DA market, the demands for ST, NST, and TH units are fixed at (44.1, 44.1, 61.8) MW, while FCR-N market demand varies from 0 to 100 MW. Due to (7.22b) and (7.22c), generation for the DA market should be higher than the FCR-N market.

- **Low Total FCR-N Demand (< 50 MW):** The NST unit maximizes its DA market generation at $P_{3} = 50$ MW, and the TH unit, with a marginal price of $c^{FC}_{ntw} = 30$ €/MWh is the price-maker in the FCR-N market.

- **Moderate to High Total FCR-N Demand (50 - 100 MW):** With NST and TH units at full capacity, they cannot be marginal producers. The ST unit, therefore, bids up to the maximum price cap of 100 €/MWh.

This case study demonstrates that the strategic unit leverages its market power in the underlying market, especially when there is a high demand for the DA market. This effect becomes significantly more evident when the unit engages in the FCR-N market.

![Figure 7.4: Merit order list in Case I (Illustrative Market Clearing).](image-url)
7.3.2 Case II: (Analyzing the Impact of Transmission Networks)

This section delves into how transmission networks influence market-clearing outcomes. Impact on generation portfolios and pricing under varying demand levels (high, medium, and low), with details provided in Table 7.4, are explored. The transfer capability of Line 1 is capped at 20 MW, whereas Line 2 maintains a capacity of 100 MW.

**DA Market Clearing without FCR-N:**
- **Low Demand Scenario:** The line flow stays below the NTC, avoiding congestion. This results in outcomes similar to those in scenarios without transmission constraints.
- **Medium Demand:** During DA clearing, the ST unit at Bus 1 imports 20 MW via Line 1, while the TH unit at Bus 2 can export through Line 2. Consequently, the prices at Buses 2 and 3 are capped at $15/\text{MWh}$, reflecting the TH unit’s variable cost. However, the ST unit at Bus 1, as a price-setter, raises the price to the DA market cap $200/\text{MWh}$ due to Line 1’s congestion.
- **High Demand:** With increasing demand, the situation persists; the TH unit continues as the marginal producer for Buses 2 and 3, while the ST unit at Bus 1 sets the price.

**DA Market Clearing with FCR-N:**
- **Low Demand:** The ST unit bids zero in the DA market, and along with the NST unit, fulfills the demand. However, as the NST unit’s dispatch in the FCR-N market is limited by its DA dispatch, the ST unit becomes the marginal producer and price-maker in the FCR-N market.
- **Medium Demand:** The constrained Line 1 places the ST unit as the marginal producer at Bus 1 and the TH unit at Buses 2 and 3 in the DA market. In the FCR-N market, the ST unit bids below the TH unit’s variable cost to be dispatched.
- **High Demand:** In this scenario, the TH unit remains the marginal producer at Buses 2 and 3 in the DA market. In the FCR-N market, due to the TH units’ limited capacity, the ST unit emerges as the marginal producer and again sets the price to the market cap.

In this case, the bid prices and volumes of the ST unit are depicted in Fig. 7.5 in a new situation. The analysis considers scaling of total DA demands (comprising 50 MW for ST, 50 MW for NST, and 70 MW for TH nodes, each having generation capacities of 100, 50, and 100 MW respectively) and FCR-N demands of 20 MW by percentages ranging from 0% to 130%.

When the total demand is below 57 MW, the NST unit is capable of meeting the entire DA demand. In this scenario, the DA market bid prices are set at 0 €/MWh. For total demands of 76 MW or higher, the NST unit contributes 50 MW in the DA market. The responsibility for generating the remaining demand falls on the ST and TH units. In response, the ST unit bids at the DA market cap price (200 €/MWh) in the DA market and at $c_{\text{FC}}$ in the FCR-N market, adjusting its bid volume as needed. This variation in bid volumes leads to distinct
prices for each bus. Due to the NTC limitation of 20 MW on Line 1, the prices at different buses diverge, with $\lambda_{1}^{DA}$ being set at 15 €/MWh and $\lambda_{2}^{DA}$ at 30 €/MWh.

Table 7.4: Generation Portfolio and Market Clearing Prices in Case II

<table>
<thead>
<tr>
<th>Network</th>
<th>Demand</th>
<th>Generation</th>
<th>( \lambda )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DA FCR-N</td>
<td>DA FCR-N</td>
<td>DA FCR-N</td>
</tr>
<tr>
<td></td>
<td>[MWh]</td>
<td>[MW]</td>
<td>[MWh]</td>
</tr>
<tr>
<td>w/ Net.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>(50,50,70)</td>
<td>NA</td>
<td>(30, 50, 90)</td>
</tr>
<tr>
<td>M</td>
<td>(50,50,40)</td>
<td>NA</td>
<td>(30, 50, 60)</td>
</tr>
<tr>
<td>L</td>
<td>(4.5,25)</td>
<td>NA</td>
<td>(0, 34, 0)</td>
</tr>
<tr>
<td>w/o FC</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>(50,50,70)</td>
<td>20</td>
<td>(30, 50, 90)</td>
</tr>
<tr>
<td>M</td>
<td>(50,50,40)</td>
<td>20</td>
<td>(30, 50, 60)</td>
</tr>
<tr>
<td>L</td>
<td>(4.5,25)</td>
<td>20</td>
<td>(24, 10, 0)</td>
</tr>
</tbody>
</table>

i) (ST, NST, TH) different values for each bus; ii) (x)=(x,x,x) same for all buses; iii) FCR-N market demand is not bus-specific; H: High; M: Medium; L: Low; NA: Not applicable; w/ Net.: with NTC limits; w/o Net.: without NTC limits; Bold: marginal producer in bus 1; Underline: marginal producer in buses 2 and 3.

Figure 7.5: (Upper) Bids of the ST unit, (Middle) Cleared prices of each market and nodes and (Lower) stacked generation of all units in Case II with scaled total demand.

In this case study, the effect of congestion on the transmission line was evaluated. Findings indicate that the strategic bidding behavior of the unit aims to...
congest the line, leveraging its market power to elevate the price at its node.

### 7.3.3 Case III (HPP Market Interaction considering Water Value)

In this case study, the interaction of HPPs with markets when taking into account the value of stored water is examined. The structure and numerical outcomes for the power system and water network are depicted in Fig. 7.6. This includes three HPPs: an ST unit at bus 1, an NST unit at bus 2, and a TH unit at bus 3, with water flowing from bus 1 to bus 2.

The strategic actions of the target plants are explained in this study. Congested transmission lines, previously explored in Case II, are not the focus here. For simplicity, $C_l$ is set to 200 MW, sufficient to prevent congestion. The water flow time from station 1 to station 2, $\tau_j$, as the delay of water flow between units, is assumed to be zero. The impact of water value on the strategic behavior of the ST unit is assessed by assigning a high value to the water in this case study.

**Parameters:** Various ID price scenarios and load levels are considered to evaluate the response of the ST unit under different conditions. The other parameters remain constant, as illustrated in Fig. 7.6. Water inflow to units one and two, $V_{1t}$ and $V_{2t}$, are 10 and 20 HEM\(^2\) respectively; FCR-N demand, $D_{tw}^\text{FC}$, is 20 MW; thermal costs, $c_n^\text{DA}$ and $c_{ntw}^\text{FC}$, are 48 and 50 €/MWh; future electricity price, $\lambda_f^\text{F}$, is 26 €/MWh; and the expected future production equivalent, $\mu_j^\text{F}$, is 0.9 MWh/m\(^3\).

**Results:** As indicated in Fig. 7.6, the ST unit endeavors to maximize revenue by discharging as much water as possible, while the market operator aims for efficient water usage and conservation in the NST unit reservoir. A proper decision-making framework is needed to determine the optimal market for selling:

**Time Step 1:** At this stage, strategic unit 1 bids at thermal cost prices in the DA market, competing with Thermal Unit 3 to be cleared first. It procures 30 MW from the ID market, influenced by the advantageous ID and DA price relationship. Consequently, the settled prices reflect the thermal costs, with the market operator optimizing water usage, thereby meeting demand through the TH and ST units in the DA market. The ST unit limits discharge and conserves water for future use due to the lower ID price.

**Time Step 2:** In the subsequent phase, the expected ID market price exceeds thermal costs, leading Strategic Unit 1 to shift from buying to selling 15 MW to the ID market. The market operator, valuing the water highly, still dispatches the TH unit to conserve water in the NST unit. This causes the ST unit to raise prices to the market cap in both markets, a preferable strategy compared to dispatching the NST unit.

**Time Step 3:** In the final phase, demand exceeds the TH and ST units’ capacity, necessitating the NST unit’s activation. The NST unit’s generation capacity allows it to participate in the FCR-N market, shifting the ST unit’s role

\(^2\)Hour equivalent (HE): It is the amount of water flow of 1m\(^3\)/s during 1 hour.
from a price maker to a price taker in this market. The cleared FCR-N market
price aligns with the TH unit’s production cost, set at 50 EUR/MWh.

This case study demonstrates the intricate strategic behavior of the ST unit
while the value of stored water and ID trading are considered. The ST unit can
use the ID market trading capabilities to adjust its strategy to discharge water
in the case of high or low prices. The ID price is low, it tries to buy from the
ID market and save water for the future and when the ID price is high, it sells
the power to the ID market, and increases the cleared prices in its node; hence,
maximizing its sell to the DA market.

Figure 7.6: Schematic and numerical results in Case III. Water flow: dotted arrow;
Electric power flow: solid arrow; WI: water inflow; \(m_{n0w} = 300 \text{ m}^3\).
7.3.4 Case IV: Market Power Exercise

The focus of this case study is to evaluate the dynamics of participating in the DA, ID, and FCR-N markets over an extended period, specifically 24 time steps (\( N_T = 24 \)), as depicted in Fig. 7.7.

Initially, the study presents the profiles of demand and expected ID prices. These profiles include variations in ID prices during periods of both low and high demand, ensuring a comprehensive analysis.

The study then shifts to examining the prices and power dispatch scenarios when the water value is relatively low (\( \lambda_{w}^F = 20\,€/\text{MWh} \)). Notably, during higher demand intervals, such as time steps 7-9, there is a noticeable increase in DA market prices. This increase is primarily attributed to the limited capacity of NST and TH units, positioning the ST unit as a price maker during these intervals. A similar pattern is observed in FCR-N prices, especially at bus 1, where the ST unit’s activities and susceptibility to line congestions are pronounced.

In its strategic engagement with the ID market, the ST unit adopts a tactical approach. It buys from the ID market when DA prices are low yet demand is high, particularly during time steps 3 to 5. Conversely, it sells to the ID market during periods of low demand but high ID prices, which occurs around time steps 11 to 13. To streamline the presentation of data, a new variable, \( p_{1t}^{DA} = \sum_{s,n=1} p_{nstw}^{DA} \), is introduced to condense information.

![Figure 7.7: Numerical results in Case IV (Market Power Exercise).](image-url)
7.3.5 Case V: Large Scale Analysis

In Case V, the study utilizes the IEEE 118-bus system, featuring a network of 186 lines, a load capacity of 4,242 MW distributed across 118 buses, and a generation capacity of 4,377 MW located in 18 buses. The results of this analysis are depicted in a boxplot, as shown in Fig. 7.8.

A notable observation from the study is the volatility of FCR-N market prices, particularly during the early periods, from $t = 1$ to 7. During these times, the demand in the DA market tends to be on the lower side. This volatility in the FCR-N market contrasts with the behavior observed during periods of higher demand in the DA market, specifically from $t = 10$ to 19. In these intervals, there is a significant drop in FCR-N market prices, reflecting the dynamic interplay between demand in the DA market and pricing in the FCR-N market.

![Boxplot results in Case V (Large Scale).](image)

In Case V (Large Scale), the analysis of cleared prices in the FCR-N market, represented as $\lambda^{FC}_{tw}$, is conveyed through Probability Density Functions (PDFs) as illustrated in Fig. 7.9.

*Firstly*, the figure offers probabilistic insights into the price ranges at various time steps, highlighting when certain price ranges are most likely to occur. For example:
1. There is a high probability of prices exceeding 48 €/MW at $t = 1$.
2. Conversely, the likelihood of prices falling below 12 €/MW is greatest between time steps 9 and 21. *Secondly*, an examination of the shapes of the PDFs reveals the following information. The PDF at $t = 13$ is narrow, indicating a consistent
price range below 36 €/MW. In contrast, the PDF at $t = 1$ is broader, suggesting a wider price fluctuation range between 6 and 60 €/MW. Therefore, $t = 13$ demonstrates a more predictable and stable pricing scenario in the FCR-N market compared to $t = 1$.

Therefore, the use of PDFs is instrumental for power plants in managing temporal price risks. Decisions made on this basis are statistically significant and reliable, as they are grounded in the analysis of available historical data through these PDFs. This approach offers a comprehensive understanding of potential price fluctuations and aids in strategic decision-making for energy market participation.

![PDF of cleared prices of FCR-N market $\lambda_{tw}^{FC}$ in Case V for different time steps; PPD: Posterior predictive distribution; OD: Observed data (x-axis is the FCR-N prices in €/MW.)](image)

Similarly, PDF of the cleared FCR-N market prices are shown in Fig. 7.10. There are relatively higher prices in 2017 and 2019 with higher probability in 2019.

### 7.4 Conclusion

The strategic operation of HPPs in sequentially cleared electricity markets, including day-ahead, intraday, and frequency-regulation markets, has been examined. This study aids the HPPs in optimally trading across multiple markets while efficiently managing water resources for electricity generation. Various conditions have been considered in the study of the power plants and markets to explore aspects like market clearing, the exercise of market power, and the valuation of water. Historical market data have been utilized to create realistic scenarios for uncertain parameters. Consequently, the PDFs of the cleared prices have been
calculated, which are essential for power plants engaging in intraday and FCR-N market trades. This analysis showed the indicative signal to the operators regarding the high-profit scenarios in the FCR-N market.

Figure 7.10: PDF of cleared prices of FCR-N market $\lambda_{tw}^{FC}$ in Case V in different years; PPD: Posterior predictive distribution; OD: Observed data.
Part III

Market Design Challenges: A Long-Term Study
Chapter 8

Reserve Dimensioning Methodology for the Multi-Area Reserve Capacity Markets

In this chapter, the benefits of adopting a dynamic methodology for dimensioning Frequency Restoration Reserves (FRR) within the Nordic Load Frequency Control (LFC) block are studied. A new model for multi-area FRR dimensioning is introduced that is consistent with the latest approach recommended by Nordic TSOs. This model presents a practical solution for dynamic, multi-regional FRR dimensioning, showcasing its relevance and applicability in current energy system operations. The content of this chapter is extracted from the following paper:


8.1 Introduction

The evolving dynamics of electricity markets in Europe are increasingly being influenced by the growing reliance on variable renewable energy (VRE) sources. The dependence of these sources on meteorological conditions introduces complex challenges in maintaining equilibrium between the supply and demand of energy.

European TSOs play a pivotal role in ensuring the availability of operational reserves to sustain a balance between power generation and consumption. Discrepancies arise when there are instantaneous deviations from the pre-planned, hourly constant power output schedules in the day-ahead (DA) market. These imbalances, resulting from unexpected events, inaccurate forecasts, and varia-
tions within trading intervals, are managed through the deployment of rapid-response reserves like Fast Frequency Response and Frequency Containment Reserves, along with Frequency Restoration Reserves (FRR) which were introduced in Chapter 2. Simplistically, rapid-response reserves are used to momentarily maintain the power balance, whereas FRR is utilized to manage the energy balance throughout each quarter-hour. The adequacy of FRR is crucial for maintaining this balance reliably; for instance, in the Nordic Load-Frequency Control (LFC) block, this reliability level is expected to be 99% of the time \[119,120\]. As the interconnectivity of European electricity markets intensifies to support more VRE integration, it becomes imperative for TSOs to enhance coordination both in dimensioning and procuring FRR capacity, and in activating FRR energy.

In the Nordic LFC block, the dimensioning of FRR capacity currently follows a static method where the necessary automatic FRR (aFRR) and manual FRR (mFRR) capacities are predetermined for extended durations (like seasons or years). This method does not take into account expected short-term operational conditions such as anticipated VRE generation, electricity demand, and available transmission capacities. In contrast, a dynamic dimensioning approach would involve determining FRR capacity closer to real-time, thereby incorporating these expected short-term conditions. As VRE penetration increases, there are stronger incentives for dynamically dimensioning FRR to ensure that the volumes of FRR capacity procured are more in line with short-term operational realities. Studies have shown that in a single-area power system, a dynamic approach to FRR dimensioning can sustain the desired reliability levels continuously and could reduce the need for reserve capacity, thereby lowering balancing costs \[121\]. However, this has not been thoroughly examined in a multi-area setting to date. This chapter aims to contrast the requirements for FRR capacity under both dynamic and static dimensioning approaches within a multi-area framework. The focus is on the availability of information regarding expected operational conditions at the time of FRR dimensioning. A multi-area FRR dimensioning model is introduced, suitable for both static and dynamic methods. This model is applied to a case study of the Nordic LFC block, with aFRR and mFRR sized sequentially in accordance with a novel methodology proposed by Nordic TSOs in \[122\].

In the context of Europe, the TSOs within a Load-Frequency Control (LFC) block are obligated to create Frequency Restoration Reserve (FRR) dimensioning strategies in accordance with Article 157 of the System Operation Guideline (SOGL) \[120\]. This directive necessitates that the FRR dimensioning methodology must fulfill both a deterministic and a probabilistic criterion. The deterministic criterion mandates that the FRR capacity should be sufficient to compensate for the failure of any single system component. On the other hand, the probabilistic criterion requires that the FRR capacity should be capable of addressing imbalances within the LFC block with a 99% probability. Additionally, TSOs must take into account any geographical constraints that might affect the distri-

\[1\] The Nordic LFC block is synonymous with the Nordic synchronous area
8.1. INTRODUCTION

Figure 8.1: Map with the Nordic LFC block highlighted in blue. Orange arrows represent AC interconnections while orange lines represent HVDC interconnections.

bution of FRR within the LFC block. Such constraints are present in the Nordic LFC block, leading to its division into 11 distinct LFC areas. A representation of the Nordic LFC block can be seen in Fig. 8.1.

As highlighted in [123], the diversity of power systems necessitates distinct reserve dimensioning methods, tailored to each system’s unique challenges and resources. Consequently, European TSOs develop specialized FRR dimensioning strategies for their systems, adhering to the stipulations of Article 157 in SOGL. Within the Nordic LFC block, a unified methodology for FRR capacity allocation and dimensioning across all Nordic LFC areas has been put forward [122]. This proposed method aims to reduce the overall Nordic FRR capacity requirement while considering the transmission constraints among LFC areas. The process involves sequential dimensioning and allocation of FRR capacity, initially focusing on FRR needed for handling reference incidents (RIs), followed by FRR for normal imbalances (NIs). The methodology is designed to ensure that the transmission capacity reserved for RIs is not utilized in the dimensioning process for NIs. In line with the probabilistic requirement of Article 157 in SOGL, a chance-constrained optimization method for FRR dimensioning is recommended, where the chance constraints reflect the likelihood of insufficient reserves [124]. This strategy aims to enhance the sharing of FRR across Nordic LFC areas, thus reducing the overall FRR capacity requirement in the Nordic LFC block. A technique to precisely solve such an extensive chance-constrained optimization problem is proposed in [125].

The Central European LFC block has predominantly concentrated on developing dynamic FRR dimensioning methods for individual LFC areas. A prevalent

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2These LFC areas are equivalent to the Nordic bidding zones
CHAPTER 8. RESERVE DIMENSIONING METHODOLOGY FOR THE MULTI-AREA RESERVE CAPACITY MARKETS

approach is to use imbalance probability distributions, determined by expected operating conditions, to size reserve capacity so that system imbalances are met with a specified probability. Historical imbalances and corresponding operating conditions are analyzed using machine learning techniques such as artificial neural networks [126], k-means clustering [127], or k-nearest neighbour algorithms [128] to derive these probability distributions. The Belgian TSO has recognized the effectiveness of such dynamic methods over traditional static approaches and has thus recommended their implementation [129]. However, these methods are primarily designed for single-area power systems and do not account for reserve sharing among different LFC areas.

Numerous studies have introduced dynamic reserve dimensioning methodologies within a multi-area framework, where reserve allocation is integrated with the power system dispatch. Such methods are detailed in various publications, including [130-133]. However, these models base the necessity for reserves on the predetermined power system dispatch, creating a mutual dependency. This approach is not directly applicable to the Nordic region, where FRR procurement is not co-optimized with the day-ahead (DA) market. Consequently, these methodologies may not be suitable to evaluate the advantages of dynamic FRR dimensioning in the market structure discussed in this chapter.

In their work, the authors of [124] apply a chance-constrained optimization strategy for static dimensioning and allocation of FRR within the Swedish LFC areas, reflecting current practices in the Nordic LFC block. This approach, however, can be adapted for dynamic dimensioning, provided that relevant data are accessible. One of the primary objectives of this chapter is to modify this methodology for dynamic reserve dimensioning. Additionally, it is aimed to align this approach with the recent guidelines recommended by Nordic TSOs [122], ensuring that it sequentially dimensions FRR for both reference incidents (RIs) and normal imbalances (NIs).

8.2 Information Accessibility and FRR Neccesity

The primary rationale behind preferring dynamic over static dimensioning of FRR lies in the increased availability of operational condition-related information closer to the time of FRR dimensioning. This ensures the procurement of FRR capacity volumes that are matched to the expected operational conditions. This section delves into the key factors that influence the requirement for FRR capacity in a context involving multiple areas.

There are four principal factors that shape the dimensioning of FRR: available transmission capacities (ATCs), reference incidents (RIs), deterministic normal imbalances (DNIs), and stochastic normal imbalances (SNIs). The ATCs play a crucial role in limiting the transfer and balancing of imbalances across LFC areas, thereby defining the level of self-sufficiency required in each area regarding FRR capacity. Knowledge of ATCs post-day-ahead market clearance, where inter-
area transmission gets finalized, enables optimal FRR allocation for those specific conditions. Conversely, in the absence of this information, FRR allocation needs to be more conservative. Despite this, ATCs can be reasonably estimated once the net transfer capacities (NTCs) and generation/demand forecasts are available.

RIs relate to the potential loss of the most significant component in each LFC area, in both upward and downward capacities. The magnitude of RIs is contingent on the planned output of each component, which is possible to find out post-DA market clearing. Without this information, FRR should be capable of covering the loss of any component operating at full capacity. Planned component downtimes, if known in advance, can reduce the RI magnitude.

DNIs and SNIs constitute two distinct categories of normal imbalances. DNIs can be accurately calculated from planned power system dispatch, assuming the non-inclusion of re-dispatch mechanisms like intraday trading. They stem from the ramping limitations of dispatchable generation and High Voltage Direct Current (HVDC) interconnectors. These limitations result in imbalances during trading period transitions, as these entities take time to adjust their outputs to new levels, leading to DNIs. If intraday trading is excluded and ramping speeds are known, DNIs can be precisely determined after DA market clearance.

SNIs, on the other hand, arise from uncertainties in real-time output, primarily due to forecast errors and intra-hourly variations in electricity consumption and Variable Renewable Energy (VRE) generation. It is not possible to find these imbalances post-DA market clearance due to the unpredictable nature of prediction errors and trading period fluctuations. However, the potential deviation, particularly from VRE generation, is lower if the expected VRE generation is low. Thus, different forecasted generation levels imply varying ranges of potential SNIs, influencing the required FRR capacity accordingly. The extent of information availability across different case studies will be further explored in Section 8.6.

8.3 Developed Model for Dimensioning FRR

This section presents an overview of the developed model for FRR dimensioning. The model is utilized in this study to evaluate the impact of information availability on the requirements for FRR capacity. It appears that there are no significant obstacles to adapting this model for dynamic, multi-area FRR dimensioning in real-world applications. A schematic representation of the entire dimensioning process is depicted in Fig. 8.2. The setup of the model aligns with the methodology proposed in [122], which initially focuses on minimizing the total FRR capacity needed for reference incidents in the LFC block, followed by minimizing the total FRR capacity for normal imbalances. The model is capable of being entirely reliant on simulated imbalance data, thereby enabling assessments of future FRR capacity needs. In this study, the model begins by simulating the hourly power system dispatch over a year, as indicated in Box 1 of Fig. 8.2. Prac-
tically, this data could also comprise actual historical or planned power system dispatch data.

Following this, as shown in Box 2, the FRR capacity required for RIs is dimensioned and allocated, taking into consideration the size of RIs and ATCs. Next, potential NI scenarios are simulated based on the hourly power system dispatch. These NIs are then adjusted based on the ATCs after RI-dimensioning (ATC*). Subsequently, NIs are separated into a short-term component and a slower component, which determines the NIs to be managed by automatic FRR (aFRR) and the total FRR, respectively. This process of simulation, adjustment, and categorization of NIs is illustrated in Box 3. Box 4 and Box 5 then involve the dimensioning of aFRR and total FRR capacities, respectively, based on the categorized NIs and the remaining ATCs post-imbalance adjustment (ATC**). Finally, the manual FRR (mFRR) capacity required in each LFC area is calculated as the difference between the total FRR capacity and the aFRR capacity, as shown in Box 6. The procedural details encompassed in Box 1 and Box 3, as well as the RI data in Box 2, are elaborated upon in Section 8.4. The methodologies for FRR dimensioning in Box 2, Box 4, Box 5, and Box 6 are detailed in Section 8.5.

8.4 Methodology for Imbalance Scenario Simulation

This section focuses on the methodology for simulating imbalance scenarios, which serve as foundational inputs for the optimization models that determine and allocate FRR capacity. The primary motive for simulating imbalances lies in the ability to dissect and manage the influence of various components on the total imbalances within each LFC area. Such granularity is essential because the uncertainty levels associated with potential imbalances from different components can vary based on the available information. Utilizing historical data would only provide access to the aggregate imbalances of an LFC area, hiding the contributions from individual components. To enhance understanding, each subsection here is linked to the corresponding sections in Fig. 8.2, thus providing a clear connection between the theoretical framework and the visual representation of the process.

8.4.1 Simulation of Hourly Power System Dispatch (Box 1)

In this research, the power system dispatch for a full year has been simulated to dimension the FRR for that period. The Open Dispatch Model Nordic (ODIN) is utilized for this simulation. ODIN calculates the cost-optimal hourly power system dispatch in Northern Europe, considering the power system structure, electricity demand, and meteorological data. A comprehensive explanation of ODIN’s functionalities and parameters is available in [13]. For this study, ODIN was executed using the power system design from 2019 and meteorological data.
8.4. METHODOLOGY FOR IMBALANCE SCENARIO SIMULATION

from 2016. It is important to note that in practical applications, ODIN’s output could be substituted with actual historical or planned power system dispatch data.

8.4.2 Simulation of Reference Incidents (Box 2d)

According to the guidelines, each TSO should maintain at least the minimum mFRR capacity to address one reference incident in any of their LFC areas. There is also the possibility of sharing mFRR capacity between different LFC areas and TSOs [120]. In this approach, the occurrence of the largest possible RI in any LFC area is considered, such as the loss of a major generator, consumer, or HVDC interconnector. The specific dimensions of these RIs are documented in [135].
8.4.3 Simulation of Normal Imbalances (Box 3a)

Normal imbalances are characterized as instantaneous divergences from planned dispatch schedules and require analysis at a finer temporal resolution than an hour [136]. Therefore, simulation of NIs operates on a 1-minute time scale. As outlined in Section 8.2, DNIs are a consequence of ramping limitations in dispatchable generation and HVDC interconnectors. DNIs are nonexistent outside of these ramping periods. The duration of the ramping period between two consecutive hours is calculated based on planned outputs and known ramping speeds, as detailed in equation (8.1). The list of sets in this section is as follows: \( Z \) is the set for LFC areas \((z_1 \ldots z_N)\), indexed \( z \), \( \mathcal{W} \) is the set for scenarios \((1 \ldots W)\), indexed \( \omega \), \( \mathcal{L} \) is the set for positive unidirectional transmission interconnections, indexed \( l \), \( \mathcal{H} \) is the set for hours \((1 \ldots H)\), indexed \( h \), \( \mathcal{M} \) is the set for minutes \((1 \ldots M)\), indexed \( m \), \( \mathcal{M}_h \) is the set for minutes inside hour \( h \), indexed \( m \), \( \mathcal{D} \) is the set for technologies causing deterministic imbalances, indexed \( d \) and \( \mathcal{S} \) is the set for technologies causing stochastic imbalances, indexed \( s \).

\[
R_{d,h \rightarrow h+1} = \frac{|P_{d,h+1}^{plan.} - P_{d,h}^{plan.}|}{r_d}, \forall h \in \mathcal{H} \setminus \{H\} \ d \in \mathcal{D} \tag{8.1}
\]

The assumption in the model is that the ramping period is symmetrically distributed around the trading period shift, dividing the time equally before and after the shift. This assumption allows for a straightforward method to calculate the actual output at a minute-level resolution during the ramping periods. This one is achieved by employing linear interpolation based on the planned output and the duration of each ramping period associated with a trading period shift. For the periods outside the ramping intervals, the actual output at a minute resolution is simply set to be equal to the planned output.

To formalize this concept, a function is introduced, denoted as \( HD(\cdot) \), which is responsible for computing the actual minute-resolution output. It either applies linear interpolation or sets the output to the planned dispatch level, depending on whether the time point in question falls within a ramping period. The calculation of DNIs is then based on this function, as articulated in equation (8.2).

\[
\delta_{d,m}^{det.} = HD(P_{d,h}^{plan.}) - P_{d,h}^{plan.}, \forall m \in \mathcal{M}_h, h \in \mathcal{H}, d \in \mathcal{D} \tag{8.2}
\]

As previously mentioned in Section 8.2, SNIs are primarily the result of forecast errors and fluctuations in VRE generation and electricity consumption. To simulate multi-area SNIs, particularly from wind power generation, the model proposed in [137] has been utilized, which operates on planned hourly generation data. In this study, the same model is applied to simulate SNIs arising both from VRE generation and electricity consumption. Given that solar power contributions were relatively minor in the Nordic countries in the year 2019, a single aggregated VRE time series for the analysis has been employed. However, in
scenarios where solar power is more prevalent, it is better to use separate time series for wind and solar power.

The simulation of day-ahead forecast errors employs a multivariate autoregressive moving average model (ARMA(\cdot)). This model captures the spatial, temporal, and forecasted generation/demand level correlations in forecast errors. For each technology contributing to SNIs, the vector of actual output for each area in hour \( h \) \( (\bar{P}^{\text{real.}}_{s,h} = [P^{\text{real.}}_{s(z_1),h} \ldots P^{\text{real.}}_{s(z_N),h}]) \) is derived using the corresponding vector of planned output for that hour \( (\bar{P}^{\text{plan.}}_{s,h}) \). The process of calculating the actual output is formalized in equation (8.3):

\[
\bar{P}^{\text{real.}}_{s,h} = \bar{P}^{\text{plan.}}_{s,h} - \text{ARMA}(\bar{P}^{\text{plan.}}_{s,h}), \forall h \in H, s \in S \quad (8.3)
\]

The model enhances hourly data to minute resolution through cubic spline interpolation (\( CS(\cdot) \)), adding a high-frequency variability component modeled by an autoregressive process (\( AR(\cdot) \)). This approach captures intra-hourly variability, essential for accurately simulating SNIs. SNIs are calculated using this refined data, as outlined in equation (8.4).

\[
\delta^{st}_s,m = CS(P^{\text{real.}}_{s,h}) + AR(CS(P^{\text{real.}}_{s,h})) - P^{\text{plan.}}_{s,h}, \forall m \in M_H, h \in H, s \in S \quad (8.4)
\]

8.4.4 Simulation of Normal Imbalance Netting (Box 3b)

After generating the SNIs and DNIs, the subsequent step in the model involves simulating imbalance netting. Imbalance netting is the process where a positive imbalance in one LFC area compensates for a negative imbalance in another, conditional on the availability of adequate transmission capacity. In our model, it is assumed that imbalances are netted in a manner that minimizes the total unserved energy across the LFC block.

To achieve this, a modified version of the linear optimization problem that is utilized for imbalance netting, as detailed in [136], has been employed. The optimization problem is structured to ensure that power is transferred between LFC areas only when it contributes to reducing the total amount of unserved energy in the LFC block. The specifics of this problem involve balancing the various imbalances across different areas, considering the limitations and capacities of the transmission network, and adhering to the objective of minimizing the overall impact of imbalances on the system.

\[
\min_{\Gamma \geq 0} \sum_{m \in M}(\sum_{z \in Z}(\tau^u_{z,m} + \tau^d_{z,m}) + \lambda_1 \sum_{l \in L} f_{l,m}) + \\
\lambda_2 \sum_{m \in M\setminus\{M\}} \sum_{z \in Z}(\tau^\Delta^+_{z,m} + \tau^\Delta^-_{z,m}) \quad (8.5a)
\]
CHAPTER 8. RESERVE DIMENSIONING METHODOLOGY FOR THE
MULTI-AREA RESERVE CAPACITY MARKETS

\[
\begin{align*}
\text{s.t.} & \quad \sum_{d \in D_z} \delta_{z,m}^d + \sum_{s \in S_z} \delta_{z,m}^s + \tau_{z,m}^u - \tau_{z,m}^d = \\
& \quad \sum_{l \in (L_z)} f_{l,m} - \sum_{l \in (\cdot, L_z)} f_{l,m} \quad \forall \ m \in \mathbb{M}, \ z \in \mathbb{Z} \\
& \quad f_{l,m} \leq ATC_{l,m} \quad \forall \ l \in \mathbb{L}, \ m \in \mathbb{M} \\
& \quad (\tau_{z,m+1}^u - \tau_{z,m+1}^d) - (\tau_{z,m}^u - \tau_{z,m}^d) \leq \tau_{z,m}^{\Delta^+}, \ \forall \ z \in \mathbb{Z}, \ m \in \mathbb{M} \setminus \{M\} \\
& \quad (\tau_{z,m}^u - \tau_{z,m}^d) - (\tau_{z,m+1}^u - \tau_{z,m+1}^d) \leq \tau_{z,m}^{\Delta^-}, \ \forall \ z \in \mathbb{Z}, \ m \in \mathbb{M} \setminus \{M\}
\end{align*}
\]

Where \( \Gamma = \{\tau_{z,m}^{u/d}, f_{l,m}, \tau_{z,m}^{\Delta^+/\Delta^-}\} \) is the set of non-negative decision variables. \( r_{z}^{u/d} \) is the upward/downward reserve capacity in area \( z \) \([\text{MW}]\), \( p_{z,\omega}^{u/d} \) is the activated upward/downward reserve energy in area \( z \) in scenario \( \omega \) \([\text{MWh}/5 \text{ min or h}]\), \( f_{l,\omega} \) is the transmission over the interconnection \( l \) in scenario \( \omega \) \([\text{MWh}/\text{h or 5 min}]\), \( \tau_{z,m,\omega}^{u/d} \) is the upward/downward unserved energy in area \( z \), during minute \( m \) or in scenario \( \omega \) \([\text{MWh/minute or 5 min or h}]\), \( \tau_{z,m}^{\Delta^+/\Delta^-} \) is the positive/negative minute-to-minute change of unserved energy in area \( z \), minute \( m \) \([\text{MWh/minute}]\).

The objective function, represented by \((8.5a)\), aims to minimize the total unserved energy, alongside the energy transmission and the minute-to-minute variations in unserved energy. The weighting coefficients are arranged as \( \omega \)\([\text{MWh}, 5 \text{ min or h}]\), \( \delta \)\([\text{MWh/min, 5 min or h}]\), \( \tau_{z,m}^{\Delta^+} \), and \( \lambda_2 \), ensuring that the primary focus is on minimizing unserved energy, followed by reducing transmission and then smoothing out the minute-to-minute changes in unserved energy. The reduction in transmission is targeted to prevent unnecessary strain on the transmission network, and minimizing minute-to-minute changes is intended to yield a more stable imbalance time series. The power balance within each zone is maintained by the constraint \((8.5b)\), while the transmission limits are set by \((8.5c)\). The constraint \((8.5d)-(8.5e)\) are used to calculate the values of minute-to-minute changes in unserved energy. Following the process of imbalance netting, the normal imbalances that are relevant for FRR dimensioning, denoted as \( \delta_{z,m}^{NI} \), are determined. This calculation takes into account the netted imbalances across different zones and time periods, thereby providing a more refined and realistic assessment of the NIs that need to be managed by the FRR.

\[
\delta_{z,m}^{NI} = \tau_{z,m}^d - \tau_{z,m}^u \quad \forall \ z \in \mathbb{Z}, \ m \in \mathbb{M}
\]

Additionally, the model calculates the remaining transmission capacities for the AC interconnections \( (ATC_{l,m}^{pre}) \) as per equation \((8.7)\). This calculation considers the pre-netting ATC of the interconnections during the same time period \( (ATC_{l,m}^{pre}) \), as well as the actual transmission over these interconnections \( (f_{l,m}) \) and the transmission occurring in the opposite direction \( (f_{-l,m}) \). This same principle is applied when computing \( ATC^* \) from the initial ATC after the dimensioning of reference incidents.

\[
ATC_{l,m}^{pre} = ATC_{l,m}^{pre} - f_{l,m} + f_{-l,m} \quad \forall \ l \in \mathbb{L}, \ m \in \mathbb{M}
\]
8.5 Methodology for Dimensioning and Allocating FRR

This section outlines the process of dimensioning and allocating FRR across LFC areas in response to specific imbalances and ATC data. These processes correspond to box 2, 4, 5, and 6 in Fig. 8.2. Adhering to the approach outlined in [122], the dimensioning of FRR-RI and FRR-NI is conducted in a sequential manner. Nonetheless, the underlying methodology for dimensioning both FRR-RI and FRR-NI remains largely similar.

This section initially details the general approach employed for FRR dimensioning. Following this, the specifics of the sequential dimensioning process for FRR-RI and FRR-NI will be elaborated upon. This sequential approach ensures that FRR resources are allocated efficiently and effectively, taking into consideration the unique requirements and constraints of different LFC areas, while also addressing the distinct challenges posed by RIs and NIs. The objective is to achieve an optimal balance that ensures system stability and reliability across all areas.
8.5.1 General Methodology for FRR Dimensioning (Box 2a, 4a, 5a)

The use of chance-constrained optimization for probabilistic reserve dimensioning in multi-area power systems, as suggested in [124], forms the basis of the general FRR dimensioning methodology. This approach balances the need for reserves against the probabilistic nature of power system imbalances, especially in a multi-area context. The general formulation for this chance-constrained reserve dimensioning problem is as follows:

\[
\min_{\Gamma \geq 0} \sum_{z \in \mathbb{Z}} \left( r_z^u + r_z^d \right) \quad (8.8a)
\]

s.t.

- \( p_z^{u,\omega} - p_z^{d,\omega} + \delta_z^{u,\omega} + r_z^{u,\omega} - r_z^{d,\omega} = \sum_{l \in (L_z, \ldots)} f_{l,\omega} - \sum_{l \in (\ldots, L_z)} f_{l,\omega} \quad \forall \ z \in \mathbb{Z}, \omega \in \mathcal{W} \quad (8.8b) \)
- \( p_z^{u/d,\omega} \leq r_z^{u/d,\omega} \quad \forall \ z \in \mathbb{Z}, \omega \in \mathcal{W} \quad (8.8c) \)
- \( f_{l,\omega} \leq ATC_{l,\omega} \quad \forall \ l \in \mathbb{L}, \omega \in \mathcal{W} \quad (8.8d) \)
- \( \mathbb{P}_\omega \left[ \sum_{z \in \mathbb{Z}} \tau_z^{u/d,\omega} \leq 0 \right] \geq 1 - \epsilon^{u/d} \quad (8.8e) \)

In this context, \( \Gamma = \{ r_z^{u/d}, p_z^{u/d}, f_{l,\omega}, \tau_z^{u/d} \} \) denotes the set of non-negative decision variables. The objective function (8.8a) aims to minimize the total reserve capacity. To ensure power balance in each area for every scenario, the condition (8.8b) is applied. Additionally, the activation of reserves is restricted so as
8.5. METHODOLOGY FOR DIMENSIONING AND ALLOCATING FRR

not to exceed the reserve capacity, as outlined in (8.8c), and the transmission is similarly limited to not exceed the ATC for each unidirectional interconnection, as stated in (8.8d). The chance constraints, which guarantee that the reserves are adequate for at least a certain proportion of the scenarios, are incorporated in (8.8e). The acceptable proportion of scenarios where the upward/downward reserves are insufficient is defined by the parameters $\epsilon_{u/d}$. In the baseline case study, these parameters are set to $\epsilon_{u/d} = 0.01$, adhering to the guidelines cited in [120].

The model is further refined by introducing binary decision variables ($\pi_{u/d}$), which indicate whether the upward/downward reserves are insufficient in a given scenario. This leads to the reformulation of the problem as a mixed integer programming (MIP) problem. The modification involves replacing the constraint (8.8e) with a new set of constraints, taking into account $W$, the total number of scenarios:

\[
\begin{align*}
\tau_{z,\omega}^u & \leq \pi_{u,\omega} \cdot \max(0, -\delta_{z,\omega}) \quad \forall \ z \in \mathcal{Z}, \omega \in \mathcal{W} \quad (8.9a) \\
\tau_{z,\omega}^d & \leq \pi_{d,\omega} \cdot \min(0, \delta_{z,\omega}) \quad \forall \ z \in \mathcal{Z}, \omega \in \mathcal{W} \quad (8.9b) \\
\sum_{\omega \in \mathcal{W}} \pi_{u/d,\omega} & \leq \epsilon_{u/d} W \quad (8.9c) \\
\pi_{u/d,\omega} & \in \{0, 1\} \quad \forall \ \omega \in \mathcal{W} \quad (8.9d)
\end{align*}
\]

When addressing a large number of scenarios, solving the MIP problem in its original form can be a formidable computational task, potentially unfeasible. However, a reformulation of this MIP problem, introduced in [125], presents an efficient solution. This reformulated approach is capable of providing exact solutions within a reasonable computational timeframe, even for a very large number (over 10,000) of scenarios. Therefore, in this chapter, the method described in [125] is applied to solve the reserve dimensioning problems (exact reformulation is excluded here and readers are encouraged to the source paper for more details).

A limitation of the approach in [125] is its exclusion of second-stage variables (such as reserve activation, unserved energy, and transmission) from the problem. Hence, the information provided from the solution is the dimensioned reserve capacities ($r_{z,u/d}^*$) in each area and the binaries indicating insufficient reserves ($\pi_{u/d,\omega}^*$). For the sequential dimensioning methodology discussed in the subsequent subsection, knowing the transmission in each scenario is crucial to compute the adjusted ATC* for imbalance netting following FRR-RI dimensioning. Additionally, the initial problem formulation does not account for how the allocation of reserve capacity influences these second-stage variables. It is conceivable that an alternative solution, with the same total reserve capacity as the original problem, could lead to a more efficient system balance. This efficiency improvement might manifest in reduced transmission network usage, lower un-
served energy, or more cost-effective reserve activation. Although this chapter
does not delve into the specifics of which technologies provide reserve capacity,
the focus is on minimizing transmission and unserved energy. To achieve this, and
to obtain transmission details for each scenario as well as to reallocate reserves,
the following linear optimization problem is solved:

\[
\begin{align*}
\min_{\Gamma \geq 0} & \quad \sum_{\omega \in \mathbb{W}} \left( \sum_{z \in \mathbb{Z}} (\tau_{z,\omega}^u + \tau_{z,\omega}^d) + \gamma \sum_{l \in \mathbb{L}} f_{l,\omega} \right) \\
\text{s.t.} & \quad p_{z,\omega}^u - p_{z,\omega}^d + \delta_{z,\omega} + \tau_{z,\omega}^u - \tau_{z,\omega}^d = \\
& \quad \sum_{l \in (\mathbb{L}_z, \ldots)} f_{l,\omega} - \sum_{l \in (\ldots, \mathbb{L}_z)} f_{l,\omega} \quad \forall \ z \in \mathbb{Z}, \omega \in \mathbb{W} \\
& \quad p_{z,\omega}^{u/d} \leq \pi_{z,\omega}^{u/d} \quad \forall \ z \in \mathbb{Z}, \omega \in \mathbb{W} \\
& \quad f_{l,\omega} \leq ATC_{l,\omega} \quad \forall \ l \in \mathbb{L}, \omega \in \mathbb{W} \\
& \quad \tau_{z,\omega}^{u/d} \leq \pi_{\omega}^{u,d} M \quad \forall \ z \in \mathbb{Z}, \omega \in \mathbb{W} \\
& \quad \sum_{z \in \mathbb{Z}} \tau_{z,\omega}^{u/d} = \sum_{z \in \mathbb{Z}} r_{z,\omega}^{u/d} 
\end{align*}
\] (8.10a)

In this optimization problem, \( \Gamma = \{r_{z,\omega}^{u/d}, p_{z,m}^{u/d}, f_{l,m}, \tau_{z,m}^{u/d}\} \) is defined as the set of non-negative decision variables. The goal, as specified in the objective function (8.10a), is to minimize the total amount of unserved energy and transmission. A small value for \( \gamma \), significantly less than 1, is chosen to prioritize minimizing unserved energy over transmission, reflecting the likely higher costs to the TSO. If costs for reserve activation are known or can be estimated, the objective function can be adjusted to include the minimization of these activation costs.

The constraints for maintaining power balance, adhering to transmission lim-
its, and abiding by reserve activation limits remain consistent with those in (8.8).
The quantity of upward/downward unserved energy is constrained to be positive
only in specific scenarios, as delineated in (8.10c). Here, the parameters \( \pi_{\omega}^{u,d} \) are
based on the outcomes of the previously conducted reserve dimensioning prob-
lem. The total upward/downward reserve capacity is required to match that of
the earlier solved reserve dimensioning problem, as mandated by (8.10f). How-
ever, there is flexibility in the allocation of reserve capacity across different areas,
provided that the reserves are adequate for scenarios where \( \pi_{\omega}^{u,d} \) equals 0.

### 8.5.2 Procedure for Sequential FRR Dimensioning (Box 2, 4-6)

This section delves into the method for sequentially dimensioning FRR-RI and
FRR-NI. It is important to note that the capacity allocated for the activation
of FRR-RI should not overlap with the capacity used for imbalance netting or
the activation of FRR-NI. Additionally, the dimensioning of FRR-NI involves a
two-step process to appropriately allocate capacity for aFRR and mFRR, thereby determining the specific requirements for each type of capacity. This subsection provides a detailed overview of the sequential FRR dimensioning methodology as adopted in this study.

**FRR-RI Dimensioning**

Since RIs are typically addressed by mFRR alone, it is unnecessary to separate the FRR-RI capacity into aFRR and mFRR components. Likewise, distinguishing between fast and slow imbalances is not required, and using hourly resolution data suffices to model a series of discrete events. The data for FRR-RI dimensioning is based on RIs outlined in Section 8.4.2, using hourly ATCs calculated from ODIN. Section 8.6 will discuss the utilization of RI and ATC data across various scenarios of information availability. In certain scenarios, multiple RI situations will be analyzed using the same hourly ATC values. As depicted in Fig. 8.2, the goal is to forward the adjusted ATC data (ATC*), post FRR-RI dimensioning, to the imbalance netting phase. The ATC* data should represent a single value for each hour. Therefore, it is crucial to determine which RI scenario’s ATC* data to use each hour. To avoid overestimating the capacity for imbalance netting and reserve sharing, the selected data corresponds to the "worst-case scenario," defined as the scenario that results in the highest overall usage of transmission interconnections. An algorithm, detailed in Algorithm 1, has been developed to select the hourly ATC* data that will be forwarded for imbalance netting, based on the identification of the worst-case scenario.

**Algorithm 1** Algorithm for worst-case (WC) RI scenario at each hour

1. $ATC^* \leftarrow$ Input data from ODIN (ATC data)
2. $RIs \leftarrow$ List of all possible RIs
3. $Opt \leftarrow$ Optimal results from (8.10) with all RIs
4. for $\delta$ in $RIs$ do
   5. $f_\delta \leftarrow$ Select transmission ($f$) in $Opt$, with RI $\delta$
   6. $\tilde{f}_\delta \leftarrow \sum_{l \in L} f_{l,\delta}$
   7. Append $(\delta, \tilde{f}_\delta)$ to $OptResults$
5. end for
6. $WC \leftarrow \delta$ where $\arg\max (\tilde{f}_\delta) \in OptResults$
7. Compute $ATC^{**}$ with (8.7) and $f_{WC}$

**Dimensioning of FRR-NI**

Following the dimensioning of FRR-RI, the resultant ATC* data are employed for netting the simulated NIs. These netted NIs undergo a sampling process. The procedures for imbalance simulation, netting, and sampling are as outlined
in Section 8.4. Post these steps, the data with a 5-minute resolution for ATC** (ATCs after netting), slow imbalances, and short-term imbalances are used. This data serves as the input for FRR-NI dimensioning. The use of ATC** and im- balance data in different scenarios of information availability will be elaborated in Section 8.6. The initial phase in FRR-NI dimensioning involves sizing and allocating the aFRR capacity, utilizing ATC** and short-term imbalances. This process follows the optimization problems detailed in Section 8.5, resulting in the optimal allocation of aFRR capacity for upward and downward adjustments $(r_{u/d,aFRR}^{z})$.

Subsequently, the overall FRR-NI capacity is sized and allocated, considering ATC** and slow imbalance data. It is important to note that aFRR capacity is included within the total FRR-NI capacity. Therefore, the total FRR-NI capacity allocated in each LFC area must at least equal the aFRR capacity. However, due to the methods employed in imbalance sampling, along with FRR dimensioning and allocation, a scenario where this is not the case cannot be completely ruled out. To address this, additional constraints are incorporated into the optimization problems (8.8) and (8.10) to ensure compliance:

$$r_{u/d}^{z} \geq r_{u/d,aFRR}^{z} \forall z \in Z$$

Upon finalizing the dimensioning stages for both aFRR and total FRR-NI, the required mFRR capacity for each LFC area is easily computed. This is achieved by deducting the aFRR capacity from the total FRR-NI capacity within each LFC area, as expressed below:

$$mFRR_{u/d}^{z} = FRR_{u/d}^{z} - aFRR_{u/d}^{z} \forall z \in Z$$

8.6 Exploring Different Scenarios of Information Availability

This section delves into the influence of varying degrees of information availability on the dimensioning of FRR capacity. Analysis encompasses three distinct scenarios: a Static case where FRR capacity is determined on an annual basis, a Dynamic Pre-Day-Ahead (Pre-DA) case where this capacity is calculated daily prior to the day-ahead market clearing gate-closure time, and a Dynamic Post-Day-Ahead (Post-DA) case where the calculation is performed daily following the closure of the DA market. The intent of examining these scenarios is not to endorse a particular approach as the definitive method but to explore how different levels of information availability affect the requirements for FRR capacity.

In Fig. 8.4, the timelines for these three scenarios are illustrated. The figure employs specific symbols to represent key concepts: $T_c^{L}$ denotes the lead time, which is the duration from the point of FRR dimensioning until the operating hour $t_n, \forall n \in [0, 24]$. The symbols $T_d^i, T_s^i$, and $T_u^i$ signify the decision-to-realization latencies for DNIs, SNIs, and ATCs, respectively. These parameters
Figure 8.4: Timelines of different market setups for dimensioning the reserve capacities: (a) Static (b) Dynamic Pre-DA (c) Dynamic Post-DA. The time of FRR dimensioning is shown by the cross sign.

indicate the time taken from FRR dimensioning to the availability of actual value information. Additionally, $\delta$ is used to represent a unit of market time.

In the Static methodology, the dimensioning of FRR capacity is carried out on an annual basis. This strategy necessitates sufficient capacity to address imbalances throughout the year. Initially, FRR-RI is sized considering one random RI for each hour across the year, accompanied by corresponding ATCs. Consequently, the scenario set $\mathcal{W}$ for FRR-RI dimensioning comprises 8760 scenarios. Following this, FRR-NI is sized utilizing modeled DNIs and a simulated scenario of SNIs per hour, along with corresponding ATCs*. With a 5-minute resolution in the data, the $\mathcal{W}$ set for FRR-NI dimensioning encompasses $8760 \times 12 = 105,120$ scenarios. Executing the FRR dimensioning model using the Static approach for a year takes about 165 minutes, employing Gurobi 10.0 in Python 9.3 on a 32 GB RAM laptop for optimization problem solving.
In the *Dynamic Pre-DA* framework, FRR is sized daily prior to the DA market clearing. It is presumed that forecasts for VRE generation and consumption for DA market clearing are accessible, but information on DNIs, RIs, and ATCs remains unknown. FRR-RI dimensioning initially occurs by processing upward and downward RI for each LFC area, considering the ATCs for each hour in the preceding 20 days. This results in the $W$ set containing $20 \times 24 \times 22 = 10,560$ scenarios for FRR-RI dimensioning (22 refers to the reference incidents in 11 bidding zones for both upward/downward directions). Subsequently, FRR-NI is sized based on the modeled DNIs from the last 20 days and 20 simulated potential SNI scenarios for the upcoming day, with each day’s DNIs paired with a unique SNI scenario. ATCs* for each day are determined using the worst-case RI detection algorithm, as detailed in Section 8.5.2. Given the 5-minute resolution data, the $W$ set comprises $24 \times 12 \times 20 = 5,760$ scenarios for FRR-NI dimensioning. The daily execution of the FRR dimensioning model with the *Dynamic Pre-DA* approach takes approximately 3.5 minutes.

The *Dynamic Post-DA* strategy involves daily FRR dimensioning post the DA market clearing. Implementing this approach can be challenging due to the condensed timeframe for FRR dimensioning and procurement. Nonetheless, it provides insights into the impact of information availability on FRR dimensioning. Similar to the *Dynamic Pre-DA* approach, VRE generation and consumption forecasts are assumed available, but ATCs and DNIs are known at this stage. While in practice, the size of RIs would be known, the absence of individual plant-level data in the ODIN model leads us to assume RIs of similar size as in previous approaches. Initially, FRR-RI is sized by processing all potential RIs for each of the 24 hours of the upcoming day, along with known ATCs. Thus, the $W$ set includes $24 \times 22 = 528$ scenarios for FRR-RI dimensioning. Then, FRR-NI is sized based on the derived DNIs for the next day and 20 simulated potential SNI scenarios for the same day. Each SNI scenario is merged with the same DNIs, considering that DNIs are assumed known post-DA market clearing. Also, the respective ATCs* are uniform across scenarios, determined by the worst-case RI detection algorithm. With data at a 5-minute resolution, the $W$ set for FRR-NI dimensioning includes $24 \times 12 \times 20 = 5,760$ scenarios. The daily execution of the FRR dimensioning model with the *Dynamic Post-DA* approach takes about 2.5 minutes.

Table 8.1 summarizes the level of information availability for the four parameters influencing FRR dimensioning across these three approaches. The designation "X" indicates knowledge limited to a historical probability distribution, "XX" signifies the availability of DA forecasts allowing for a narrower probability distribution based on these forecasts, and "XXX" indicates precise real-time knowledge of a parameter.
8.7 Results and Discussion

This section presents and analyzes the results from a case study, including two sensitivity analyses.

8.7.1 Impact of Information Availability

A key finding of this research is the influence of information availability on the dimensioning of FRR. Three different approaches, as detailed in Section 8.6, were examined. Fig. 8.5 illustrates the annual requirement for both upward and downward FRR in the Nordic region under these different approaches. In the Static approach, the FRR requirement remains constant throughout the year. However, in the Dynamic approaches, the FRR requirement fluctuates based on operational conditions. It is observed that the Dynamic approaches generally necessitate less upward FRR capacity than the Static approach, while the requirement for downward FRR capacity is higher. Particularly, the Dynamic Post-DA approach shows a marginally reduced need for FRR capacity, especially in terms of upward FRR, compared to the Dynamic Pre-DA approach. This suggests that import capacity is often more constrained than export capacity in LFC areas with significant imbalances. The more accurate knowledge about ATCs in the Dynamic Post-DA approach seems to particularly lessen the need for upward reserves (needed when net production or import must increase), more so than downward reserves (needed when net consumption or export must increase).

Fig. 8.6 displays heatmaps illustrating the average requirement for both upward and downward total FRR capacity in each LFC area for the various setups investigated. These heatmaps reveal that a substantial portion of upward reserve capacity is typically allocated to Finland and southern areas in the Nordic system. This pattern aligns with the general direction of electricity flow towards these regions, reinforcing the observations made earlier. Furthermore, the Dynamic approaches appear to reduce the need for upward FRR capacity notably in Finland, eastern Denmark, and southern Sweden.

Fig. 8.7 presents duration curves that compare the daily upward and downward reliability of FRR-NI across the various approaches examined in this study. The concept of daily reliability is quantified as the proportion of times each day when all LFC areas experience no unserved energy. This figure highlights a
significant advantage of dynamic FRR dimensioning: it adjusts the daily FRR capacity requirements in response to forecasted operational conditions to achieve the targeted 99% reliability for each day.

In contrast, the Static approach demonstrates a different reliability profile. While it maintains a reliability level above 99% for the majority of days, there are approximately 20% of days where the reliability falls below the 99% target, with some days exhibiting substantially lower reliability. It is important to note that the Static approach is designed to ensure only an average yearly reliability of 99%, rather than guaranteeing this level on a daily basis. This discrepancy underscores the limitations of a static approach in adapting to daily variations in operational conditions, compared to the more flexible and responsive dynamic methods.

### 8.7.2 Impact of Reserve Re-Allocation

A contribution of this study is the incorporation of a reserve re-allocation strategy into the methodology previously established [125]. Table 8.2 provides a comparative analysis of the effects of reserve re-allocation on several key metrics. This comparison is based on the aFRR dimensioning process using the Dynamic methodology.

---

The unserved energy and transmission without re-allocation was obtained by solving (8.10) with fixed zonal reserve capacities.
Figure 8.6: Showing the average total FRR capacity per LFC area in the different investigated cases. Top row left to right: Upward FRR with Static, Dynamic Pre-DA and Dynamic Post-DA approach. Bottom row left to right: Downward FRR with Static, Dynamic Pre-DA and Dynamic Post-DA approach.

Figure 8.7: Duration curves showing the daily reliability for FRR-NI with the different dimensioning approaches.

*Pre-DA approach* over a period of 31 simulated days, both with and without the implementation of reserve re-allocation.

The data reveals that reserve re-allocation results in only a marginal change in the expected unserved energy. However, it significantly impacts the utilization of the transmission network during reserve activation, where the usage is decreased by over fourfold due to the re-allocation process. This indicates a more efficient distribution of reserves across the network, leading to reduced congestion and enhanced system efficiency.

While introducing reserve re-allocation does extend the computational time required for reserve dimensioning, the increase is not substantial enough to pose practical difficulties, except potentially in scenarios involving a significantly larger number of scenarios. This suggests that the benefits of reserve re-allocation, particularly in terms of enhanced network efficiency and reduced congestion, can be achieved without compromising the feasibility or efficiency of the reserve dimensioning process.
Table 8.2: Average daily expected unserved energy, transmission and dimensioning time with/without reserve re-allocation

<table>
<thead>
<tr>
<th>Re-allocation?</th>
<th>$\tau^u$ [kWh]</th>
<th>$\tau^d$ [kWh]</th>
<th>$f$ [kWh]</th>
<th>Time [s.]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>190</td>
<td>475</td>
<td>4704</td>
<td>29</td>
</tr>
<tr>
<td>No</td>
<td>191</td>
<td>477</td>
<td>21 349</td>
<td>6</td>
</tr>
</tbody>
</table>

8.7.3 Sensitivity Analyses

This section delves into two sensitivity analyses focused on exploring the effects of varying reliability levels and reduced ATCs. Both analyses utilize data from a 15-day period and apply the Dynamic Pre-DA approach.

Reliability Index

In the baseline scenario, the security level is set at 99% ($\epsilon = 0.01$). Altering this value has a consequential impact on the required FRR capacity. Table 8.3 details the average upward FRR requirements for each control area, which encompasses the aggregation of all Load Frequency Control (LFC) areas within a single country, across three distinct security levels.

The findings indicate that even a slight reduction in the security level, by a few percentage points, leads to a substantial decrease in the need for FRR capacity. This reduction is particularly notable in the requirements for FRR-RI and aFRR. Conversely, setting the security level to allow no unserved energy ($\epsilon = 0.00$) results in a significant increase in the demand for both FRR-RI and aFRR capacity.

These observations underscore the critical nature of accurately solving chance-constrained optimization problems. Achieving the precise solution is essential to avoid either over-dimensioning or under-dimensioning FRR capacity, which can have significant operational and economic implications for the power system.

Table 8.3: Upward FRR capacity for all control areas considering different reliability indexes (MW)

<table>
<thead>
<tr>
<th>Control Area</th>
<th>$\epsilon = 0.00$</th>
<th>$\epsilon = 0.01$</th>
<th>$\epsilon = 0.03$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FRR RI</td>
<td>aFRR</td>
<td>mFRR</td>
</tr>
<tr>
<td>SE</td>
<td>349</td>
<td>729</td>
<td>518</td>
</tr>
<tr>
<td>NO</td>
<td>1000</td>
<td>630</td>
<td>295</td>
</tr>
<tr>
<td>DK</td>
<td>600</td>
<td>307</td>
<td>81</td>
</tr>
<tr>
<td>FI</td>
<td>1221</td>
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<td>361</td>
</tr>
<tr>
<td>Total</td>
<td>3171</td>
<td>2041</td>
<td>1254</td>
</tr>
</tbody>
</table>
8.8 Conclusion

In this chapter, the advantages of applying a dynamic approach to the dimensioning of FRR within the Nordic LFC block have been explored. A novel model for multi-area FRR dimensioning has been developed, aligning with the recent methodology proposed by Nordic TSOs. This model holds practical applicability for dynamic, multi-area FRR dimensioning.

The simulation studies conducted reveal that dynamic dimensioning effectively reduces the requirement for upward FRR capacity. However, there is a slight increase in the average need for downward FRR capacity when compared...
to the static reserve dimensioning approach. The primary advantage of the dynamic method lies in its capacity to adjust FRR requirements in line with anticipated operating conditions, thereby ensuring the attainment of a specified daily reliability level.

A significant finding is that conducting FRR dimensioning post-Day-Ahead market clearing, when more detailed information about operating conditions is accessible, leads to a reduction in upward FRR capacity requirements in the simulated scenarios. However, the practical implementation of such a dynamic dimensioning approach faces several computational and regulatory hurdles that need to be addressed.

The results from these case studies underscore the potential benefits of enhancing the forecasting of expected operational conditions, especially in the context of adopting a dynamic approach to FRR dimensioning. Improved forecasting could further optimize reserve requirements, contributing to the efficiency and reliability of the power system operations. This research indicates a promising direction for future developments in reserve dimensioning and management in the Nordic LFC block and potentially in other regions with similar operational dynamics.
Chapter 9

Efficient Long-Term Market Design for Low-Carbon Generation Assets

9.1 Introduction

The EU electricity market system has been successful in ensuring reliable energy supply, affordable prices, and supporting the transition to decarbonization. However, recent years have seen a significant rise in energy prices and volatility, particularly due to Russia’s invasion of Ukraine, which disrupted global energy markets. This led to higher energy bills for consumers [138], despite the decreasing costs of renewable energy. Emergency measures were implemented at EU and national levels to mitigate the crisis, but they exposed weaknesses in the market design, such as consumer vulnerability to price spikes and dependence on imported fossil fuels. To better understand the dynamics of the EU’s energy mix, Fig. 9.1 illustrates the gross production level of main assets by fuel type in the region. The figure provides valuable insights into the contribution of various energy sources to the overall energy supply.

Europe cannot afford to rely solely on market mechanisms to drive investments based on scarcity pricing. Instead, it needs to take proactive steps to stimulate investment in flexibility technologies, treating it as a “no-regret” option similar to the approaches taken with grid infrastructure or hydrogen development.

This issue has led to the integration of renewables into electricity markets and the allocation of public support through auctions. This combination of competitive auctions and remuneration schemes, which link support payments to electricity prices, has created additional revenue volatility for onshore and offshore wind and solar energy projects in Europe [139]. Before 2014, onshore wind and solar photovoltaic (PV) projects had a little track record and policies like feed-in tariffs provided protection against electricity price risks and guaranteed high returns for investors. However, the introduction of competitive auctions and remuneration schemes changed this situation [140].
CHAPTER 9. EFFICIENT LONG-TERM MARKET DESIGN FOR
LOW-CARBON GENERATION ASSETS

In response to the challenges posed by the energy crisis and to leverage the growing importance of renewables, the European Commission President announced a reform of the electricity market design in March 2023 [10]. The reform aims to enhance the efficacy of the European energy sector, achieve climate neutrality, and support the competitiveness of Europe’s net-zero industry. According to the Agency for Cooperation of Energy Regulators (ACER), the current market system has delivered approximately €34 billion in annual savings.

The proposed changes to EU legislation, such as the Electricity Regulation, Electricity Directive, and REMIT Regulation aim to reduce reliance on fossil fuel prices and create a buffer between short-term markets and consumer electricity bills. Key measures include incentivizing longer-term contracts, boosting the power purchase agreements (PPAs) market, stabilizing electricity prices, and preventing excessive revenues for energy producers. The proposal requires the use of two-way contracts for difference (CfDs) for new low-carbon investments with public funding and aims to improve forward electricity markets. These changes are expected to have a significant impact on the energy sector and promote a more sustainable and stable electricity market for consumers. In the United Kingdom (UK), the primary subsidy mechanism employed to achieve these goals is CfD which is awarded through competitive auction processes. Under the CfD, owners of renewable energy assets are guaranteed a fixed price (£/MWh) for the electricity they generate over a 15-year contract period [141]. When formulating CfDs, policymakers and regulators generally aim to achieve two primary objectives: (1) to provide economic incentives for investments in renewable energy sources in alignment with predetermined political deployment targets and (2) to facilitate the seamless integration of renewable energy into power markets, minimizing any potential distortions in market dynamics.

Once a renewable producer and the government have entered into a CfD contract, the producer can continue selling their power on the day-ahead market or

![Figure 9.1: Gross production level of main assets in the energy mix by fuel type in EU](image)
any other market of their choice. The CfD payments are determined through a separate financial settlement, which takes into account the relative levels of the floating (reference) market price and the fixed strike price. If the strike price exceeds the reference market price, the government or CfD party pays the difference to the renewable producer as a *payout*. Conversely, if the strike price falls below the reference market price, the renewable producer must pay the difference between the two prices to the government as a *clawback*.

The most commonly used remuneration schemes in Europe include the one-sided CfD contract in Germany and the Netherlands and the two-sided CfDs used in the UK and Denmark. These schemes guarantee producers a minimum support price equivalent to their bid in the support auction. However, the rules regarding excess revenues when the electricity price exceeds the support price differ between the one-sided and two-sided CfDs. With one-sided CfDs, producers can keep the excess revenues, while with two-sided CfDs, they are required to pay these revenues back to the government. This difference in remuneration rules leads to variations in revenue volatility during the support contract period. In other words, investors can speculate on higher electricity prices when using one-sided CfDs, while two-sided CfDs eliminate this incentive \[142\].

Administrative Strike Prices (ASPs) define the highest possible price per MWh that a project utilizing a specific technology can receive for generating electricity as the strike price in the CfD remuneration calculation. These ASPs serve as a limiting factor even if an auction results in a higher clearing price. Fig. 9.2 presents the ASPs applicable to different technology types for their respective allocation rounds (AR) in the UK \[4\]. These application rounds started from 2014 with auctions in different years.

ASPs differ from the levelized cost of electricity generation. ASPs are set

---

1Gasification and Pyrolysis, known as Advanced Conversion Technologies (ACTs), are included in the CfD scheme under the category of 'fuelled technologies'. A generating station qualifies as an eligible ACT station if it produces electricity through the utilization of Advanced Fuel, which is either gas or liquid derived from the Gasification or Pyrolysis of Biomass or Waste.
higher or lower based on several factors considered in CfD party calculation. ASRs are increased to account for costs not included in the standard levelized costs, such as CfD top-up payments adjusted for transmission losses. Also, if a generator sells power through a PPA at a discount to the market price or faces other transaction costs, ASRs are increased to compensate for these route-to-market costs. Furthermore, if the CfD contract duration is shorter than the project’s operating life, and post-contract revenues from wholesale markets are lower than the levelized cost, ASRs are increased to offset this difference. Project life revenues after the CfD contract’s expiration are also factored into the ASP calculation. The auction results of all previous allocation rounds are depicted in Fig. 9.3. In the fourth allocation round, AR4, a total of 93 projects, amounting to 10.8GW in capacity, successfully secured contracts at an average price of £41/MWh in 2012 values (£56/MWh at present – July 2023).

Notably, offshore wind emerged as the most cost-effective and significant technology, securing contracts for 7.0GW of new capacity at a record-low price of £37/MWh in 2012 prices (£50/MWh in current value). In addition, 2.2GW of new solar capacity obtained contracts at an average rate of £46/MWh (£62/MWh today). Similarly, onshore wind secured 0.9GW at £42/MWh (£60/MWh today), and an additional 0.6GW of “remote island wind” was contracted at £46/MWh (£62/MWh today). This particular auction round stood out as the largest to date (July 2023), with a capacity nearly double that of the third round and three times the capacity of the second round. Moreover, it was notable for its competitive pricing, boasting a capacity-weighted average price of £41/MWh in 2012 prices.

The combined capacity of 10.8GW is projected to produce approximately 45TWh of electricity, accounting for roughly 14% of the current power generation in the UK. This amount of energy would be sufficient to meet the electricity needs of over half of UK households or fulfill all the extra demand required for running
electric vehicles by the end of the decade.

In theory, one-sided CfD can ensure revenue stability if they guarantee a sufficiently high floor support price. However, the auction process for one-sided CfDs has faced various challenges that resulted in zero bids for offshore wind projects [142]. Some reasons can be identified for this issue: (1) The failure of these auctions can be attributed to factors such as the auction design decisions made by governments. For example, the Dutch government’s choice to conduct only zero-bid auctions and select winners based on qualitative criteria had an impact on the outcome. Another instance is the 2021 auction for the 800–1000MW Thor offshore wind farm in Denmark [143], where multiple zero bids were received, and a lottery draw was used to determine the winning bidder. Although this auction was for a two-sided CfD, the Danish Energy Agency included a clause that set a maximum limit on the CfD payments from the winning bidder to the government. Once the maximum amount of 2.9 billion DKK or 390 million EUR (2021 prices) was reached, the bidder was no longer obligated to make further payments to the government [144]. This effectively transformed the scheme from a two-sided CfD to a one-sided CfD. Consequently, the bidders for the Thor project speculated on the potential profits they could earn by selling electricity outside the government-backed remuneration scheme. (2) Project sponsors anticipate a rise in wholesale electricity prices in the future, coupled with expected cost reductions through the utilization of larger turbine sizes. These factors lead to lower production costs and create an expectation of increased profitability. (3) The presence of zero bids incorporates a real-option element due to the significant time gaps between the auction award and the actual implementation of the project [145]. Successful bidders in offshore wind projects typically took an average of 25 months from the auction award date to reach their project hurdle rate. This extended timeline provides project sponsors with the opportunity to reassess market conditions and financing arrangements, allowing them to potentially cancel the awarded contract if deemed necessary. In Germany, for instance, the non-realization penalties for the initial successful zero-bid projects amounted to approximately 2.5% to 3.8% of the total project development costs. Consequently, bidders faced the prospect of significant earnings while bearing a comparatively smaller downside risk in the form of penalty payments [145].

In order to ensure the financial viability of their projects, sponsors may resort to securing alternative revenue stabilization mechanisms prior to reaching a project hurdle rate. One such mechanism involves entering into corporate PPAs with companies that possess a credit rating [146]. These companies, including Amazon, Google, and Facebook, which were the top three off-takers of renewable electricity globally in 2020, have a significant long-term demand for electricity. By establishing these agreements, projects can secure the necessary financing through project financing, which is the prevailing method for financing offshore wind assets in Europe [147]. However, the financing terms for projects supported by corporate PPAs are heavily influenced by the contracted volume of project electricity production under the PPA and the creditworthiness of the off-taker.
Investors in offshore wind projects have demonstrated a willingness to submit negative bids in order to secure the rights for development. In a notable example, the UK government conducted its Offshore Wind Leasing Round 4 in 2021 and received option fees amounting to an annual sum of 879 million GBP for the rights to develop offshore wind sites until the second auction phase for CfD contracts \[148\]. Similarly, in the case of the Hollandse Kust West auction held by the Dutch government in 2022, a portion (10\%) of the auction scoring criteria was based on a one-time payment made by bidders to acquire the development rights for the project. This payment was capped at a maximum of 50 million EUR. Additionally, starting in 2023, the German government will introduce auctions that require bidders to make an unlimited one-time payment for the rights to develop offshore wind sites \[149\].

One of the impacts of negative prices on system operation is initiated through the duration of CfD contract. On July 3rd, 2023, the GB electricity market was characterized by an unprecedented stretch of negative prices lasting for 15 consecutive hours, starting from 2 AM and concluding at 5 PM. This remarkable event has significant implications for power stations operating under renewable CfDs, as their operations exceed the prescribed 6-hour limit, thereby rendering the CfD inactive and depriving them of associated payments. Consequently, it makes sense for wind farms to shut down, and that is what system operators did.

Fig. 9.4 displays how different support mechanisms affect the Levelized Cost of Electricity (LCOE) for onshore wind in Germany. It shows that merchant generation, which carries the highest risk, results in the highest LCOE and, consequently, the highest expenses for consumers. Conversely, two-sided CfDs offer the lowest LCOE. It is predicted that by 2030, adopting two-sided CfDs over a pure merchant model for renewable energy sources deployment could lead to annual savings of 3.4 billion EUR for consumers. The cost difference between a two-sided CfD and a sliding premium is less pronounced\(^2\). Nevertheless, during periods of high wholesale prices, sliding premiums can generate significant extra income for RES investors, leading to increased costs for consumers. In contrast, with CfDs, the net cost to consumers remains stable regardless of wholesale price fluctuations.

\section{9.2 Literature Review}

Contemporary methodologies seek to fundamentally rectify the distortions resulting from conventional CfDs. The pivotal advancement in these methodologies is the separation of payment calculations from the production volumes of the asset. By ensuring that payments are not based on actual production but are in-

\(^2\)In a feed-in premium (FIP) scheme, electricity generated from renewable energy sources (RES) is generally marketed on the electricity spot market, and producers of RES are awarded a premium in addition to the market price for their electricity output. This premium can be \textit{fixed}, meaning it remains constant regardless of market price fluctuations, or it can be \textit{sliding}, adjusting in response to changes in market prices.
instead derived from independent variables, such as meteorological measurements, they circumvent the distortions introduced by injection-based CfD specifications. Nonetheless, it is essential to acknowledge that these strategies have yet to be deployed and assessed in any setting, hence their efficacy in real-world scenarios remains undetermined. Here, several variations are investigated that have been proposed to address the limitations of conventional CfD contracts as the main support schemes in the UK.

### 9.2.1 Long Lasting Negative Prices

Several support schemes aim to address the issue of incentives for electricity generators to produce even when prices fall below their variable costs, particularly in situations with negative prices. One approach to tackle this problem is by setting CfD payments to zero for electricity generated during negative price periods. While this eliminates the incentive to produce during such periods, it introduces a new challenge. Generators now face significant revenue uncertainties, as their overall earnings depend heavily on the frequency of negative prices, which is beyond their control. To manage this risk, some countries implement this fix only if negative price periods persist for multiple hours (e.g. six consecutive hours in UK [150]). For instance, in Germany, the initial minimum duration for a negative price period was set at six hours, but it was later reduced to four hours [151]. Starting from 2027, it will be further reduced to just one hour. However, there are drawbacks to such rules. They introduce bidding uncertainties, as generators must anticipate the occurrence and length of negative price periods during the bidding stage. A miscalculation in this regard can lead to costly outcomes.
9.2.2 Long Reference Period

Several implemented CfDs employ a distinct underlying approach that deviates from the use of hourly spot prices. Instead, they utilize a reference price, typically represented by the weighted or unweighted average spot prices over monthly or yearly intervals. One example is the German market premium, which employs a one-sided downside-cap CfD. Similarly, the Danish hybrid CfD also follows this approach. The timeframe over which prices are averaged is commonly referred to as a "reference period.”

By extending the reference periods for calculating CfD payments, the generator can take benefit from intra-period price differences, thereby reintroducing incentives. As a result, dispatch and maintenance activities are optimized during these periods to capture the highest prices. Investment decisions are also influenced by the aim of producing during the hours with the highest prices within the reference periods. While yearly reference periods provide seasonal incentives, monthly reference periods do not offer such incentives. They solely encourage optimizing production timing within specific periods rather than across them.

9.2.3 Capability-based CfD

An approach proposed by Elia \[152\] suggests that subsidy payments (and corresponding repayments) should be decoupled from the actual production of a plant and instead be based on the plant’s production potential. The payment is calculated by taking the feed-in tariff (i.e., the bid) and subtracting the reference market price, which corresponds to the hourly spot market prices. The resulting value is not multiplied by the actual production of the plant but by the production potential (without any curtailment) in the respective hour. Therefore, the definition of the plant’s production potential is of particular importance for the achievable revenue of the operators and must be determined with special care.

The production potential should calculate the theoretically achievable generation for each plant, taking into account the plant’s capacity as well as specific meteorological, topographical, and technical conditions. Under normal operating conditions, the production potential should approximately correspond to the actual feed-in. Deviations between the production potential and the actual feed-in occur particularly when the plant is regulated down (where network-related curtailments are compensated) or is out of operation due to maintenance or defects. According to Elia \[152\], suitable calculation methods can be derived from the methodology used to determine lost production. In Germany, various methods of varying accuracy exist for this purpose. The most accurate method, known as peak billing, uses weather data measured at the plant (wind speed or solar radiation) and determines the production potential based on a power curve. The simplified peak billing allows the use of reference values from other identical plants or weather data near the plant instead of plant-specific values.
9.2.4 Financial CfD

In their study [153, 154], the authors introduced financial CfDs as an alternative. These contracts resemble traditional CfDs in their long-term nature and technology-specific focus on generation patterns such as wind, solar, and nuclear power. Under this contract, the government makes fixed hourly payments to the generator. In return, the generator reimburses the government with the hourly spot market earnings, applicable to wind and solar power. It is essential to note that these revenues are not the actual earnings of the specific asset but are calculated based on a reference generator, serving as a benchmark. However, similar to forwards, these financial CfDs separate payments from actual generation. This contract still suffers from lower price responsiveness as the total payment to generators is fixed no matter how the market prices develop per day. More detailed analyses are stated in section 9.4.2.

9.2.5 Volatility CfD

Fluence [155] proposes the implementation of a volatility CfD to de-risk investments in energy storage and other flexible technologies in Europe. The volatility CfD aims to create investment certainty and level the playing field for storage assets. Under this proposal, the volatility CfD provides long-term contracted revenue to flexible asset owners based on wholesale market volatility. The revenue guarantee, known as the strike price, is linked to a pre-defined level of volatility in the day-ahead market, with a 10-year term. To allocate the volatility CfDs, annual auctions are conducted to select the lowest-cost assets, ensuring fair competition. The volume of CfD auctions is determined by the national regulator, considering the flexibility needs of the electricity system.

Settlement of the volatility CfD occurs monthly, with flexibility assets providing a benchmark revenue based on actual market volatility. If the actual volatility is lower than the strike price, the CfD owner receives a payment, while higher volatility results in a payment from the owner. Projects still optimize their operations across different markets to achieve profitability. While the bi-directional payment flows are tied to day-ahead wholesale market volatility, the awarded assets are not obligated to participate in the DA market. Instead, the DA market serves as a benchmark for payments within the volatility CfD framework. This approach recognizes the versatility of flexibility assets, which can operate in different market segments. By incentivizing flexibility assets to operate in the market segment that generates the highest revenue, the volatility CfD optimizes the overall energy system. Prices in the system reflect scarcity, and by allowing flexibility assets to optimize across various markets, they contribute to the efficient functioning of the energy system. Requiring these assets to participate exclusively in a specific market could limit their ability to support different segments where their deployment would be most beneficial.
9.2.6 Yardstick Financial CfD

The author in [156] proposes a new financial CfD that not only provides a separation between the physical generation and CfD payment, but also ensures efficient investment in the right location. In other words, the yardstick payment is highly correlated with predicted hourly output but independent of the actual output. In this contract, locational marginal price is used for congestion management and addressing the locational distortions. It also includes an extra term related to the premium of the system average capacity factor and actual on-site capacity factor which is claimed to reward areas with a low correlation with the system average. This contract will be investigated in detail in section 9.4.2. Table 9.1 summarizes the positive and negative impacts of the different CfD contract approaches.

9.3 Problem Statement

The conventional CfD contracts, despite their advantages in stabilizing revenues and increasing the bankability of renewable energy projects, present certain problems that need to be addressed. Firstly, the choice of reference price, which determines the revenue for the producer, is often based on longer-term averages rather than real-time market prices. This introduces a risk for producers, as they may be exposed to price fluctuations and potentially miss out on capturing market upside during periods of high prices.

Another issue lies in the settlement of CfD contracts, where the payment is tied to the actual measured output of the renewable energy asset. While this approach aligns with the traditional method, it limits the flexibility for alternative settlement arrangements, such as predetermined production profiles or fixed baseloads. Producers bear more risk when the settlement deviates further from the actual output.

Furthermore, conventional CfDs are designed in a manner that lacks the opportunity for renewable energy producers to benefit from favorable market conditions and higher prices. The absence of mechanisms to retain market upside limits the financial gains for producers and may hinder their ability to fully capitalize on advantageous market trends.

The clawback feature in CfDs, which triggers the repayment of excess payments if market prices fall below the strike price, differentiates them from sliding premium schemes. However, this aspect also adds complexity and further risk to the contract. The differentiation between CfDs and sliding premiums becomes crucial as market dynamics shift, with lower strike prices and higher market prices. Clear delineation and understanding between these mechanisms are essential for effective policy-making and industry engagement.

Overall, conventional CfD contracts suffer from issues related to the choice of reference price, settlement arrangements, the limited market upside for producers, and the complexity introduced by the clawback mechanism. Addressing these
Table 9.1: Summary of Different Approaches and Their Impacts

<table>
<thead>
<tr>
<th>Approach</th>
<th>Positive Impacts</th>
<th>Side Effects</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Lasting Negative Prices</td>
<td>Price responsiveness</td>
<td>Dependency of the lifetime revenue to the negative prices</td>
<td>[153]</td>
</tr>
<tr>
<td>Long Reference Period</td>
<td>Improve maintenance scheduling</td>
<td>Day-ahead distortion</td>
<td>[153]</td>
</tr>
<tr>
<td>Suspended Distortive Payment</td>
<td>Capping the payment to government in clawback</td>
<td>Revenue uncertainty (dependency to frequency of low prices)</td>
<td>[143]</td>
</tr>
<tr>
<td>Capability-based CfDs</td>
<td>Less distortion in merit-order</td>
<td>Market data manipulation of potential production. Mute signal for the investment</td>
<td>[152, 157]</td>
</tr>
<tr>
<td>Financial CfDs</td>
<td>Purely financial contract</td>
<td>Lack of solution for locational distortions, low price responsiveness</td>
<td>[153]</td>
</tr>
<tr>
<td>Volatility CfDs</td>
<td>Hedge against DA market volatility</td>
<td>Conditional over asset’s production (any market)</td>
<td>[155]</td>
</tr>
<tr>
<td>Yardstick Financial CfD</td>
<td>Reduce locational signal distortion</td>
<td>Problem in cost recovery based on the energy limited CfD duration</td>
<td>[156]</td>
</tr>
</tbody>
</table>

problems will be crucial in refining CfDs and maximizing their potential as a financial tool for renewable energy generation.

As it was stated earlier, investors need to hedge the revenue through participation in different market setups apart from CfD payments if the unit is not fully hedged in the CfD contract. Fig. 9.5 shows the revenue streams for a typical market actor participating in different market setups. Here the reference price for CfD contracts is based on the day-ahead energy prices.

In this figure, at different time steps, varying revenue stacks are observed that
may either fall below or exceed the project’s hurdle rate. For instance, in hours 1 and 4, despite the requirement to pay clawbacks to the government, the project hurdle rate is achieved in hour 4 due to revenue from other market arrangements, a scenario not replicated in hour 1. During hour 3, the positive CfD payout renders the trade profitable despite the low electricity price, whereas, in hour 5, this threshold is not reached. This trading pattern underscores the significance of efficient dispatch in achieving project objectives, especially concerning the two-sided CfD payments. The existing modifications made to CfDs do not effectively address all the issues associated with conventional CfDs. While these tweaks may address certain risks, such as volume risk and inefficient retrofit and repowering choices, they fail to address other risks in a consistent manner. In the following section, the problems with conventional CfDs are elaborated in detail.

9.3.1 Problems with Conventional CfDs

Traditional CfDs share aspects with financial derivatives, but their binding to specific assets is distinct. This linkage restricts secondary market trading without associated asset sales and may lead to asset dispatch manipulation to influence payments. Notably, conventional CfDs present two main challenges: incentivizing a “produce-and-forget” mentality and causing intraday and balancing market disruptions.

Produce-and-Forget Issue

Traditional CfDs encourage power generators to prioritize maximizing production. These contracts are similar to the conventional feed-in tariffs that separate the generator’s revenues from any market incentives. With revenues per MWh always matching the strike price, there are some distortions as follows:
• **Investment Dynamics**: These CfDs do not encourage the selection of system-friendly renewables, such as high-efficacy wind turbines or adaptable solar panels. Therefore, the incentive for optimal, sustainable resource utilization and plant design is lacking.

• **Repowering and Retrofit Decisions**: Investment decisions in energy assets, encompassing maintenance, retrofit, and repowering, are influenced by conventional CfDs, which tend to suppress spot price fluctuations and thus, distort market signals. This can lead to suboptimal investment during energy crises and overinvestment during surpluses, as stakeholders might prioritize adhering to existing contracts instead of optimizing for current market conditions. Even in the context of wind turbine repowering, the finite nature of conventional CfDs might discourage upgrading to more efficient units to maintain the benefits of existing contracts.

• **Maintenance Schedules**: The absence of incentives for generators to strategically time maintenance activities during low-demand periods may lead to suboptimal scheduling decisions, potentially exacerbating supply-demand imbalances.

• **Power Dispatch Challenges**: Traditional CfDs do not drive generators to amplify production during high-price durations or to curtail during low-price intervals. For instance, wind, solar, and nuclear plants should reduce outputs when prices fall beneath their operational costs. But with conventional CfDs, they might continue production, even when prices go negative. This is especially problematic for technologies with fluctuating variable costs. Thermal power plants, reservoir hydropower, and storage plants are especially vulnerable. These adaptable generators need a price-driven operation for viability. Encouraging consistent electricity production can nullify their worth as adaptable resources. This problem magnifies when CfDs dominate more of the market.

Enhanced CfD specifications have addressed certain “produce-and-forget” challenges inherent in conventional CfDs by implementing longer reference periods, such as monthly or yearly. Utilizing average spot prices within these extended periods, as exemplified in the German market premium and Danish hybrid CfD, restores some incentives for generators by no longer muting intra-period price variances. Consequently, generators are motivated to optimize dispatch and maintenance to capture peak prices and make investment decisions that focus on producing during high-priced hours within these reference intervals. However, these modified CfDs present their own set of issues:

• **Partial Incentive Alignment**: Although improved, they only partially rectify misaligned incentives since price variances across different reference periods are flattened, lacking stimulation for seasonal production adaptation or responsiveness to varied annual price scenarios.
Day-Ahead Market Disturbances: The equalized CfD payments per MWh throughout a reference period can distort day-ahead market bids. Generators may manipulate their bids based on the CfD payments, much like tax or subsidy implications, potentially leading to strategic withholding of generation during low-price periods or excessive generation even when prices are negative.

Volume Risks

Volume risk refers to the uncertainty associated with the amount of electricity that a renewable energy project will produce over a given period. This risk is particularly pronounced for renewable energy sources such as wind and solar, where output can vary significantly due to factors beyond the control of operators, such as weather conditions, seasonal variations, and unexpected equipment downtime. Key aspects of volume risk include:

- Intermittency: Renewable energy sources like wind and solar power are intermittent, meaning their output can fluctuate widely depending on weather conditions. This variability can lead to significant deviations from projected energy production levels.

- Forecasting Errors: Predicting the exact amount of electricity that will be generated by renewable sources involves uncertainties. Forecasting errors can result in either underproduction or overproduction relative to the contracted amounts in the CfD, affecting revenues and costs.

- Technical Performance: Equipment performance issues, maintenance requirements, and aging infrastructure can also lead to variability in production volumes, further exacerbating volume risk.

Price Risks

Price risk refers to the uncertainty and potential financial impact associated with fluctuations in electricity market prices. Under a two-sided CfD, the generator is typically paid the difference between a predetermined strike price and the actual market price of electricity. Conversely, if the market price exceeds the strike price, the generator may be required to pay back the difference. This mechanism exposes participants to price risks in various ways:

- Market Price Volatility: Electricity prices in wholesale markets can be highly volatile, influenced by factors such as fuel prices, demand fluctuations, policy changes, and the overall mix of generation capacity. High volatility can lead to significant variations in CfD payments.

- Price Cannibalization: As more renewable energy enters the market, periods of high renewable production can lead to “price cannibalization,” where the
9.3. PROBLEM STATEMENT

Market price of electricity drops due to oversupply, particularly during windy or sunny periods. This can reduce the revenue for renewable projects under CfDs, as the market price may frequently fall below the strike price.

- **Regulatory and Policy Changes**: Changes in energy policy, market rules, or support mechanisms can also lead to shifts in electricity prices, affecting the value of CfD payments. For example, changes in carbon pricing, subsidies for other forms of generation, or adjustments to market access rules can impact market prices.

**Regulatory Risks**

Regulatory risk, particularly in the context of renewable energy and support mechanisms like two-sided CfDs, refers to the uncertainty and potential financial implications for market participants due to changes in government policies, regulations, or legal frameworks. This risk is a critical factor for investors, developers, and operators in the renewable energy sector, as it can significantly impact the feasibility, profitability, and overall attractiveness of renewable energy projects.

To mitigate regulatory risk, stakeholders in renewable energy projects often engage in thorough due diligence, including scenario analysis and stress testing against potential regulatory changes. Long-term contracts and hedging strategies can provide some protection against future regulatory shifts. Active engagement with policymakers and participation in industry associations can also help influence the development of supportive and stable regulatory frameworks.

**9.3.2 CfD Revenue Calculation**

In order to understand the reasoning behind different distortions by conventional CfDs, it is required to catch up the basic calculations of the CfD payment. Suppose \( q_{i,h} \) is the physical selling quantity of a unit \( i \) at hour \( h \), \( \lambda_h \) is the spot price of the market at hour \( h \), \( c_{i,h} \) is the marginal cost of the production of unit \( i \) at hour \( h \), \( R_h \) is the reference price for CfD contract at hour \( h \) and \( SP \) is the strike price of the CfD contract. Given the above notation, the net income of the unit \( i \) at hour \( h \) is as follows:

\[
\text{Rev}_{i,h}^{\text{Tot}} = \text{Rev}_{i,h}^{\text{energy}} + \text{Rev}_{i,h}^{\text{CfD}} = q_{i,h}[\lambda_h - c_{i,h}] + q_{i,h}[SP - R_h] \tag{9.1}
\]

Where, \( \text{Rev}_{i,h}^{\text{energy}} \) is the revenue from selling energy to the market operator with the day-ahead energy market price and \( \text{Rev}_{i,h}^{\text{CfD}} \) is the compensation through the CfD market which could be positive, where the strike price is above the reference price or negative, vice versa. In the \( \text{Rev}_{i,h}^{\text{energy}} \) calculation the marginal cost of energy production is deducted from the payment. This value in most cases of renewable assets is negligible.
9.3.3 Reference Price Considerations

To calculate the reference price in 9.1, different approaches might be taken based on the underlying contract design. Here, two cases in the intermittent renewable generation domain have been investigated: Positive and Negative Intermittent Market Reference Prices (IMRP).

Positive IMRP

The calculation of CfD Generator payments hinges on the difference between the market reference price (MRP) and the CfD’s strike price. There are two types of MRPs: the Baseload Market Reference Price (BMRP) and the Intermittent Market Reference Price (IMRP). The applicable MRP and the prices for electricity sales are determined by the CfD contract. The BMRP is seasonally calculated using a traded volume weighted average of forward season data, provided daily by the London Energy Brokers’ Association (LEBA). The resultant BMRP is published biannually on the EMRS website. In contrast, the IMRP for Intermittent Technologies is derived from the GB day-ahead hourly price calculated by the weighted average of the two market price indexes, EPEX Spot and N2EX as follows:

\[
IMRP_h = \frac{\sum_{i=1}^{N_s} \lambda_{i,h} V_{i,h}}{\sum_{i=1}^{N_s} V_{i,h}}
\]  

(9.2)

Where:

- \(\lambda_{i,h}\) represents the day-ahead hourly price for trading hour \(h\) and price source \(i\).
- \(V_{i,h}\) is the day-ahead hourly volume traded at hour \(h\) for price source \(i\).
- \(N_s\) denotes the total number of price sources, which includes EPEX Spot and N2EX among others.

If there is only one published price for the day-ahead market through each of the resources, the published price would be the final reference price.

Negative IMRP

Negative Pricing terms apply to both baseload and intermittent generators under the CfD contract, but not every CfD includes these provisions. The contract determines one of two versions of negative pricing. In the first version, negative IMRP occurs when the IMRP falls below £0/MWh for six consecutive hours or more. In the second version, negative IMRP is considered when being below...
9.3. PROBLEM STATEMENT

£0/MWh for one hour or more [150]. For these hours, the pricing difference is limited to the strike price.

When the IMRP is negative based on the second version, the CfD payment for each contract is calculated as follows:

$$\text{Rev}_i,h^{\text{CfD}} = \min(SP - IMRP_h, SP) \times q_{i,h}$$  \hspace{1cm} (9.3)

The \( \min \) operator in the above equation limits the CfD revenue to the strike price when the negative IMRP scheme is activated. The negative price rule introduces a challenge due to increased balancing costs, named the secondary “herding” effect. This occurs because all CfD units react identically and simultaneously. Consequently, if all CfD units exit the system at once in response to negative pricing rules, it not only causes operational problems but also substantially increases the costs associated with maintaining system balance. This problem had a cost of around £12 million on December 28 and 29, 2022 in the UK [158].

9.3.4 Distortions in intraday and balancing markets

A subsequent issue with traditional CfDs is the impact they have on intraday and balancing markets, resulting from the use of the day-ahead price as the contract’s underlying element. Once the auction is cleared, the price for the hourly CfDs payment becomes fixed and known to the generator. From this point forward, it acts as an opportunity cost and is factored into pricing, much like any other variable cost component. This situation carries consequences for the ensuing market phases, specifically the intraday and balancing markets. This effect manifests clearly during high-price and low-price hours:

High-Price Periods

When the day-ahead price is higher than the strike price, generators have to pay the difference per MWh generated. However, suppose the intraday or imbalance price is lower than the value of this payment. In that case, it might be economical for generators to reduce their production and buy power on the intraday market to meet their obligations, even though this may not be the most efficient outcome for the market as a whole. To further illustrate this issue, the following example has been provided. Consider a generator unit that has a CfD contract with a strike price equal to 80 €/MWh and it is subjected to a day-ahead price of 200 €/MWh. The generators must pay 120 €/MWh for every MWh they produce in that hour. If the intraday or balancing market price falls to 119 €/MWh, two scenarios can be imagined:

a) Generator Produces Power

When the generator produces power, the costs involved are as follows:
• **Cost to Generator:** Operational cost (assumed to be 0 €/MWh for simplicity) + CfD Payment (120 €/MWh).

• **Total Cost:** 120 €/MWh.

Under this scenario, the generator is obligated to pay 120 €/MWh for every MWh produced to fulfill the CfD agreement, ignoring operational costs for simplicity.

b) **Generator Curtails Production and Buys from Intraday Market**

If the generator decides to curtail production and instead buys power from the Intraday Market, the cost structure changes:

• **Cost to Generator:** Intraday Price (119 €/MWh).

• **Total Cost:** 119 €/MWh.

Instead of generating power and paying the CfD, the generator can buy power for 119 €/MWh on the intraday market. It is important to mention that this curtailment could be intentional or unintentional. In the intentional case, for the sake of having less cost of paying back CfD in this case, the unit could intentionally curtail its output to buy it from the intraday market. However, due to the intermittent nature of renewable energy generation and wrong weather forecasting, the unit might have no enough generation which leads to the above situation in which it is required to buy the remaining power for the other market setups. In this case, artificial demand has been created which might even increase the price further up.

The decision-making process of the generator, when faced with the option to produce power or curtail production and buy from the intraday market, can be analyzed from three different perspectives:

i) **Economically Rational Decision for the Generator**

Choosing the cheaper option (Scenario b) is the economically rational decision for the generator. Despite having the capacity to generate power, the generator opts to curtail its output and buy from the intraday market to minimize costs.

ii) **Inefficiency**

The decision to buy power from the intraday market, rather than producing it, leads to inefficiency. Energy production capacity, especially that which is low-carbon and low-cost, is not utilized due to financial incentives. This results in buying power from potentially higher-cost and higher-carbon sources. In the
9.3. PROBLEM STATEMENT

absence of a CfD contract, the unit could generate electricity to help solve the system deficit, as indicated by high price signals.

iii) Market Distortion

The decision to curtail production and buy power from the intraday market introduces several distortions in the market:

1. Supply: Curtailment reduces power supply in the intraday market, potentially driving prices up as supply tightens.

2. Demand: By buying in the intraday market to avoid CfD payments, the generator artificially increases demand.

3. Overall Impact: Both the reduction in supply and the artificial increase in demand introduce price distortions. This misalignment of supply and demand fundamentals affects market stability and price signals, leading to broader implications for market efficiency.

Low-Price Hours

In periods of low pricing, a converse situation unfolds, with governments extending payments to generators. These financial aid functions act similarly to a subsidy. During these instances, power plant operators subtract the received payment from their ideal balancing or intraday market bids, resulting in placing bids that are ineffectually lower than their own variable costs. To further illustrate this issue, the following example has been provided. Consider a generator unit that has a CfD contract with a strike price equal to 80 €/MWh and it is subjected to day-ahead price of 60 €/MWh. The generators receive 20 €/MWh for every MWh they produce in that hour. If the intraday or balancing market price falls to -10 €/MWh, two scenarios can be imagined:

a) Generator Produces Power

- Cost to Generator: Operational cost (assumed to be 0 €/MWh for simplicity) + CfD Payment (80 €/MWh - 60 €/MWh = 20 €/MWh).

- Total Revenue: 20 €/MWh.

The government compensates the generator 20 €/MWh to fulfill the CfD agreement, disregarding operational costs for simplicity.
b) Generator Buys from Intraday Market

- **Cost to Generator**: Intraday Price (-10 €/MWh).
- **Total Revenue**: 10 €/MWh.

Instead of generating power and receiving the CfD, the generator has the option to buy power at -10 €/MWh from the intraday market.

The analysis of this case can be explained from three perspectives:

1. **Economically Rational Decision for the Generator**: Choosing the option with higher revenue (Scenario a) is the economically rational decision for the generator. Despite negative prices on the intraday market, the CfD payment makes production financially favorable.

2. **Inefficiency**: Even when it may not be economically efficient or beneficial from a system-wide perspective to generate power (e.g., due to an oversupply), the generator produces power to capitalize on the CfD payment.

3. **Market Distortion**:
   a) **Supply**: Opting to generate power, especially in conditions where curtailment production would be more logical from a systemic perspective, further saturates an already oversupplied market, exacerbating negative prices.
   b) **Demand**: The generator’s incentive to bid lower in the intraday market (e.g., -20 €/MWh) to achieve what could be obtained through the CfD payment leads to further reductions in intraday prices, indicating inefficient market distortion.

Utilizing real-time (balancing) prices instead of day-ahead prices as the underlying would prevent the distortions in the intraday/balancing markets. Nonetheless, this approach could prompt risk-averse generators to offload all production into the system imbalance instead of disclosing their available generation during the day-ahead stage, thereby jeopardizing operational system security. In instances where generators are shielded from short-term prices through CfDs, price volatility is amplified, sometimes resulting in notable market distortions, such as negative pricing scenarios. A relevant example unfolded in the Dutch market in spring 2023, where the distortion from a support scheme impacted market outcomes, leading to a scenario where a second day-ahead auction was necessitated due to reaching the technical lower price limit. Notably, if all generation units, including wind and solar, were exposed to wholesale price incentives, they would feasibly curtail at 0 €/MWh. This would not only mitigate support costs and system stress but also facilitate the continued operation of thermal plants, averting the resource-intensive processes and physical costs associated with their shutdown and subsequent startups.
9.4. CASE STUDY AND SIMULATION RESULTS

9.4 Case Study and Simulation Results

In this section, different case studies have been performed to show quantitatively how the two main proposals for the CfD contracts can help to remove some of the distortions in the conventional CfDs.

9.4.1 Benchmark Study

In this case, the conventional CfD has been considered to perform the analysis on a typical date with two different scenarios of electricity price. The first one is a date with all positive prices and in the second one, some hours during the date, the prices are negative.

Positive Price Period

In this case study, the objective is to establish a benchmark scenario for the CfD payments. Within the framework of a conventional CfD agreement, during periods when the reference price \( \lambda_h \) exceeds the predetermined strike price (SP), there ensues a transfer of funds from the generating entity to the CfD counterparty, and conversely, when the reference price falls below the strike price. Consequently, the net revenue derived from the CfD contract remains constant across all time intervals. For the purpose of simplification in this analysis, the marginal costs associated with generation are assumed to be negligible.

Table 9.2 and Fig. 9.6 show the details of the calculations for a single day in this scheme.

Figure 9.6: Flow of the money in the CfD contract in the case of positive reference price \( (\lambda_h \text{ and } R_h \text{ are overlapping}) \)
Table 9.2: Hourly Revenue from DA Market, CfD, and Total Revenue with Reference Price

<table>
<thead>
<tr>
<th>Hour</th>
<th>Revenue from DA Market (€/MWh)</th>
<th>Revenue from CfD (€/MWh)</th>
<th>Total Revenue (€/MWh)</th>
<th>Reference Price (€/MWh)</th>
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</table>

**Negative Price Period**

In the scenario under consideration, there are instances where the reference prices are negative values for certain periods. According to prevailing regulations [150], should the reference prices remain negative for a duration of six consecutive hours, they are to be treated as zero. In the case study illustrated in Fig. 9.7, it is observed that during these intervals, the net revenue for the generating entities does not remain uniform, as the financial clawback to the government surpasses the compensation disbursed to the generator units. Consequently, within this context, the CfD agreement fails to serve as an effective revenue stabilization mechanism for the generators.

Table 9.3 elucidates the payment and revenue details for a specified sample date. An analysis of the total revenue indicates that during periods of positive
reference hours, the financial transactions are structured in such a manner that they yield a consistent revenue stream for the generators. However, during intervals of negative reference hours, the generators’ revenue is not hedged, if it generates (Case I), leading to scenarios where they may incur a net loss in total revenue. However, if it does not generate in hours with a negative DA market price (Case II), the total revenue would be zero as the CfD payment itself depends on the generation. The best case here is to include non-production-based CfD methods which will keep the total revenue steady even if the unit does not generate.

Fig. 9.8 illustrates the fluctuating reference price data over a span of two years in the UK electricity market [159]. It reveals that for the majority of the time, prices remained above zero, indicating that the negative impacts of the hours with negative prices are generally insignificant. Nevertheless, it is noteworthy that there were approximately 100 hours during the last two years where the reference prices dipped below zero and this number will increase in the future as the penetration level of renewable energy assets increases.

9.4.2 Previously Proposed Methods

Yardstick Locational CfD

This section aims to articulate how the Yardstick Locational Contract for Difference (CfD) can be leveraged to maintain incentives within the spot market [156].

Efficient Dispatch The fundamental premise of the Yardstick Locational CfD is that payment is calculated as $(s - p_{rh})\theta_{rh}k$, irrespective of the generation
Table 9.3: Hourly Revenue from DA Market Cases I and II, CfD, and Total Revenue with Reference Price

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<th>Revenue from CfD (€/MWh)</th>
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status, thereby promoting efficient dispatch. In this formula, $s$ is the strike price, $p_{rh}$ is the reference price which is the wholesale day-ahead market for location $r$ and hour $h$, $\theta_{rh}$ is the capacity factor of the unit in location $r$ and hour $h$, and $K$ is the installed capacity of the unit. This section delves into evaluating the efficacy of this approach.

Consider the scenario illustrated in the Fig.9.9. Based on the interplay of strike price, avoidable cost, and market price levels, various outcomes are conceivable. A unit intending to bid under these diverse scenarios is hypothesized:

**Point A:** At this point, the bid value is higher than the market price. If one asset bids at this value, it will not be dispatched. In this case, only the CfD
Point B: At this point, the bid value is lower than the market price, so the bid will be accepted for dispatch. The total revenue of the unit in this case would be:

\[
\text{Rev}_B = \text{Rev}^{DA}_B + \text{Rev}^{CfD}_B = (p_{r,1} - c)\theta_{r,1}k + (s - p_{r,1})\theta_{r,1}k = (s - c)\theta_{r,1}k, \quad (9.5)
\]

which is higher than \( \text{Rev}_A \). Thus, it shows that the generators are incentivized to bid based on the true cost \( (c) \) using the financial CfD contract.

Point C: There are two situations at this point as the market price is below the avoidable cost of the unit:
• **Do Not Generate:** In this case, there is no revenue from the DA market, and the total revenue would be from the CfD:

\[
\text{Rev}_c = \text{Rev}_c^{\text{CfD}} = (s - p_{r,2})\theta_{r,2k}.
\]  

(9.6)

• **Generate:** In this case, the revenue would be

\[
\text{Rev}_c = \text{Rev}_c^{\text{DA}} + \text{Rev}_c^{\text{CfD}} = (p_2 - c)\theta_{r,2k} + (s - p_{r,2})\theta_{r,2k},
\]

in which \(\text{Rev}_c^{\text{DA}} \leq 0\) and the unit has the risk of losing \((p_2 - c)\theta_{r,2k}\) if it generates. Thus, it has no incentive to generate, which is aligned with merit-based dispatch when the market price is lower than the avoidable cost of the unit.

**Point D:** At this point, the generator’s bid is higher than the market price, and it will not be dispatched (like Point A). Also, based on the CfD payment regulation, if the reference price is negative, it will be considered as zero. Thus, the revenue in this case is:

\[
\text{Rev}_D = \text{Rev}_D^{\text{CfD}} = s\theta_{r,2k}.
\]

(9.8)

**Point E:** There are two situations in this case based on the dispatch decision of the generator:

- **Do Not Generate:** In this case, the revenue would be the same as Point D.
- **Generate:** In this case, the total revenue would be:

\[
\text{Rev}_E = \text{Rev}_E^{\text{DA}} + \text{Rev}_E^{\text{CfD}} = (p_3 - c)\theta_{r,3k} + s\theta_{r,3k},
\]

(9.9)

which is lower than the case when the unit does not generate. Thus, there is no incentive for the unit to generate, which is compliant with the system need in the case of very low market prices.

These case studies have shown that the proposed CfD contract will provide efficient dispatch signals for the units, and the system would benefit from cost-effective dispatch.

**Locational Distortions** In this section, the analysis is to know how this method can be used to remove locational distortions. First, limiting the length of the contract by the number of full operation hours instead of a time-limited contract can remove the distortion of over-rewarding the high resource areas. The provided illustration visually represents the comparison between two types of locations, ”Central” (i.e. normal or low wind profile) and ”Windy”, in terms of their subsidy-related metrics. It assumes that:

**Subsidy Limit by Energy Production:** The subsidy limit is defined as a fixed amount of energy production in Megawatt-hours (MWh) per Megawatt
(MW) of capacity. In this case, it is set to 30,000 MWh per MW. This assumption implies that once a location produces this amount of energy, the subsidy ends.

**Different Energy Production Rates:** The "Central" and "Windy" locations have different annual energy production rates. The Central location produces 2,000 MWh per MW per year, while the Windy location produces 3,000 MWh per MW per year. This difference reflects the varying efficiency or potential of different locations, with windy areas typically generating more power due to stronger or more consistent winds.

**Subsidy Duration Based on Production:** The duration for which the subsidy is available differs between locations and is directly tied to how quickly they reach the subsidy limit. The Windy location reaches this limit faster due to its higher production rate.

**Discount Rate for Present Value Calculation:** A discount rate of 3.5% is used to calculate the present value of the total subsidy for each location. This rate is critical in determining the present value of future cash flows, reflecting the time value of money. The discount rate chosen reflects a moderate assumption about the cost of capital or the opportunity cost of investment.

Considering the above case study, the following result could be interpreted:

**Years to Reach Subsidy Limit:** The bar chart segment (in blue) in Fig.9.10 displays the number of years each location takes to reach the subsidy limit. The "Central" location requires 15.0 years, while the "Windy" location takes only 10.0 years.

**Present Value of Total Subsidy:** This part of the chart (in orange) illustrates the present value of the total subsidy for each location. The "Central" location has a present value of approximately 23,875, whereas the "Windy" location has a slightly higher present value of about 25590.

This visualization aids in understanding the differences in subsidy dynamics based on the location and its resource potential, with the "Windy" location reaching the subsidy limit faster and having a higher present value of the total subsidy compared to the "Central" location.

After limiting the contract based on a fixed number of full operating hours, this contract can be completed to remove the incentive to locate in regions of high resource while retaining the incentive to locate where the local resource has a lower correlation with the country average. In this contract, the CfD revenue payment compensates \((s - p_{r,h})\theta_{r,h,k} + a_h k\) during hour \(h\) at site \(r\) over a span limited to \(T\) hours, where \(T\) fulfills the condition that \(\sum_{h=1}^{T} \theta_{v,h} = N\), and \(a_h\) is defined as the \(\sum_{h=1}^{H} (\theta_{s,h} - \theta_{r,h}) p_h H\), will be effective for both the allocation of resources and location optimization, regardless of production status. In this equation, \(K\) represents capacity, \(\theta_{r,h}\) denotes the predicted capacity factor at site \(r\) for hour \(h\), \(\theta_{v,h}\) is the actual recorded output per MW at the VRE site during hour \(h\), \(\theta_{s,h}\) is the average capacity factor for the system, \(H\) refers to the total number of hours or settlement periods annually, \(N\) is the fixed length of the contract in terms of full operational hours, \(s\) is the set strike price, and \(p_h\) stands
CHAPTER 9. EFFICIENT LONG-TERM MARKET DESIGN FOR LOW-CARBON GENERATION ASSETS

Consider a 10MW wind turbine that needs to be installed in three different locations. Table 9.4 demonstrates the results of a study for one year with a limit of full operating hours to 30000 MWh/MW and an average system capacity factor of 0.42. The data on the electricity prices is for the SE3 bidding zone in 2023. The distributions of the forecast capacity factor for one year in each location are depicted in Fig. 9.11.

This analysis shows that based on the normal CfD payment Location A has the higher average locational capacity factor and seems to be more profitable to install wind units. This locational distortion through the CfD payment motivates the investors to install their units with a higher capacity factor and could result in an extra need for transmission networks in highly congested areas. But, as
Table 9.4: Specifications of the three different locations in the yardstick locational CfD

<table>
<thead>
<tr>
<th></th>
<th>Location A</th>
<th>Location B</th>
<th>Location C</th>
</tr>
</thead>
<tbody>
<tr>
<td>System Capacity Factor</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
</tr>
<tr>
<td>Full operation time (h)</td>
<td>7507</td>
<td>7522</td>
<td>7500</td>
</tr>
<tr>
<td>Base CfD payment (€)</td>
<td>380976</td>
<td>303700</td>
<td>151344</td>
</tr>
<tr>
<td>Locational incentive (€)</td>
<td>-198122</td>
<td>143762</td>
<td>823403</td>
</tr>
<tr>
<td>Total CfD Payment (€)</td>
<td>182581</td>
<td>447461</td>
<td>974747</td>
</tr>
</tbody>
</table>

the new location term ($a_h$) is added to the base CfD payment it removes the motivation to install in higher capacity factors and removes this distortion. As the results show, although the base CfD payment is higher in Location A, the final payment after taking into account the locational incentive motivates the investors to invest in Location C which in turn removes the incentive to solely allocate in high capacity factor areas.

**Benchmark-based Financial CfD (b-FCfD)**

In this contract, which was briefly discussed in section 9.2.4, there are two types of payment transactions:

**Remuneration to the Generator (GOV-to-GEN Income):** The state provides a stable hourly compensation to the contractual partner, which remains unaffected by production levels or market prices. This compensation rate is established through a competitive bidding process during the initial procurement stage and remains consistent throughout the contract’s duration, with potential adjustments for inflation.

**Compensation to the State (GEN-to-GOV Levy):** In return, the generator reimburses the state with the hourly economic gains (contribution margin) of a standard reference generator. These standard gains are calculated as the excess of the day-ahead market price over predefined benchmark costs (if positive, otherwise zero), multiplied by the hourly production of the reference generator. For wind and solar energy sources, where production costs are negligible, these profits are equivalent to their total revenue. The reference generator is crucially distinct from the actual asset pledged as security for the contract. Through these mutual payments, depending on the choice of the reference model, the payments to the state approximately equal the real sales revenues, leaving the capacity payments as profit for the producer.

The benefit for wind and solar power generators with this hedging strategy is that it focuses on securing their total revenue rather than revenue per megawatt-hour, thereby mitigating risks associated with production volume, such as variability in wind conditions. Additionally, seasoned developers have the expertise to fine-tune their asset generation pattern, maintenance timing, and operational
management to maximize profitability. Since the financial hedge is external, any extra gains achieved through these optimizations are fully retained by the developers, unlike in conventional CfD models where such advantages might be offset by the CfD’s differential calculations.

Thus, in this contract, the total payment to the generator remains constant during the contract period. However, the locational distortion remains as different locations based on the capacity factors of the reference generator provide different incentives for the investor for the decision-making process. Table 9.5 shows the results of a simple case study based on the previous input data of three different locations but considering benchmark-based CfD payment. As the results show, if there is a different payment transaction between the unit and the government agency, the total payment would be the same for different locations. This is the nature of the model to stabilize the revenue for the different investors; hence, it does not provide a locational incentive for the market participants compared to the Yardstick locational CfD which is a negative point.

<table>
<thead>
<tr>
<th>Location A</th>
<th>Location B</th>
<th>Location C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gov-to-Gen Payment</td>
<td>5.52</td>
<td>5.52</td>
</tr>
<tr>
<td>Gen-to-Gov Payment</td>
<td>-2.62</td>
<td>-2.10</td>
</tr>
<tr>
<td>Merchant Market Sales</td>
<td>2.62</td>
<td>2.10</td>
</tr>
<tr>
<td>Total CfD Payment</td>
<td>5.52</td>
<td>5.52</td>
</tr>
</tbody>
</table>

**Reference Model Discussion** The definition of the reference model in the b-FCfD is crucial for the opportunity and risk profile of the operator, as it directly affects the net revenue. Currently, the reference model in [153] is not yet detailed but describes only possible approaches for establishing a reference plant pool. This leaves a significant aspect of this contract open.

The characterization of the reference model depends greatly on how technology- and location-specific the reference is chosen. Choosing the price of the day-ahead market as a reference would pose a high deviation risk for the operators but also provide a high optimization potential. This option could be attractive for operators who significantly differ in their production performance from the market average values and are capable of efficiently controlling their production. A more narrowly defined reference, based on actual measurement data of the plants or mathematical models reliant on local weather data, would reduce the risk for operators but also limit the optimization potential. This could be appealing for plant operators seeking stability and predictability in their revenues who prefer to take fewer risks.
Further Challenges  An additional challenge to be addressed is whether b-FCfD qualifies as a financial derivative, which would subject it to corresponding financial market regulation. The argument against this classification is that b-FCfDs are not directly about trading financial derivatives but about subsidy payments. This question arises independently of the previously mentioned effect of the b-FCfD, which is not influenced by its characterization as a financial product. If classified as a financial derivative, the use of this subsidy instrument would be significantly complicated, especially for smaller players.

Moreover, financial future products require collateral backing. For typical future products, only liquid capital is accepted as collateral. This poses significant challenges for producers, which is why future products can only be held in the portfolio to a limited extent. To circumvent this difficulty, [153] suggest creating regulations that allow the renewable energy plant itself to be used as collateral. The practical implementation of this aspect also needs to be clarified.

This situation highlights the complexity of integrating innovative financial instruments like the b-FCfD into existing regulatory frameworks. The balancing act involves providing enough flexibility for these instruments to be effective and accessible, especially for smaller entities, while ensuring that they comply with the necessary financial regulations to maintain market stability and protect stakeholders. The following concerns are raised in this type of contract:

- **Inadequate Consideration for Variability and Specificity:**
  - **Uniformity and Technological Issues:** The model may not fully account for technological variances and location-specific challenges, thereby failing to accommodate the distinctive performance characteristics and hurdles of different energy resources (like wind versus solar).
  - **Impediment to Innovation:** The strict adherence to predefined benchmarks might inadvertently curb innovative endeavors, as producers might prioritize meeting existing standards over exploring and investing in novel technologies and operational methods.

- **Regulatory and Bureaucratic Challenges:**
  - **Government Involvement:** The heightened role of regulatory bodies or government in managing technology-specific auctions and defining reference parameters could introduce bureaucratic inefficiencies and potentially slow decision-making processes.
  - **Market Distortions:** The regulatory framework might unintentionally favor specific technologies or scales based on how reference plants and auctions are defined, disrupting market dynamics and potentially hindering the growth of certain technologies or regional developments.

- **Financial and Operational Implications for Producers:**
CHAPTER 9. EFFICIENT LONG-TERM MARKET DESIGN FOR LOW-CARBON GENERATION ASSETS

- **Economic Consequences:** Producers may face financial strains due to penalties for underperforming against reference plants, even when factors are beyond their control, such as resource variability or unforeseen operational challenges.

- **Operational Focus Misalignment:** The model may inadvertently foster a system-gaming mentality, where producers optimize operations to meet or slightly exceed reference plant metrics, possibly neglecting other important aspects like sustainability, long-term advancements, or exploring beyond the existing benchmarks.

### 9.4.3 Contract Criteria Analyses

In order to correctly assess the quality and effectiveness of any CfD contract, this section provides a comprehensive study investigating six qualitative metrics and three design options to manipulate. This comparative analysis helps the decision-makers to correctly assess all proposed methods and future options.

#### Qualitative Metrics

The following criteria are defined to assess different aspects of each CfD design.

**Optimal Dispatch**  Under the traditional CfD framework, electricity generators lack the motivation to adjust their output in response to fluctuating market prices. Specifically, during periods of high electricity prices, there is no incentive for generators to increase production, and conversely, when prices fall below production costs, the current model does not encourage a decrease in output. This issue is particularly relevant for wind, solar, and nuclear plants, which, under existing CfDs, continue to produce electricity even when market prices dip below their variable costs or turn negative. This approach not only undermines the economic rationale for flexible generation assets, including those powered by fossil fuels, hydrogen, reservoir hydroelectricity, and storage technologies but also diminishes their value by not utilizing their capability to adjust output based on the balance of demand and supply.

To address these inefficiencies, a reformed CfD model should incentivize optimal utilization of energy assets, promoting a system-friendly approach that aligns generation with real-time market conditions. This means encouraging power plant owners to produce electricity when prices are above their short-term variable costs and to reduce or halt production when prices are not favorable. Such incentives should be effective not only in the day-ahead market but also in real-time operations, ensuring that decisions on electricity generation are guided by current price signals.
Optimal sitting and locational distortion removal Most renewable developers are awarded contracts that span several years from the time of commissioning, irrespective of the contract’s nature—be it set administratively, auctioned, or categorized as a Feed-in Tariff (FiT), CfD with FiT, a Feed-in Premium (FiP), or a Premium Feed-in Tariff (PFiT). Given that the contract strike price typically exceeds the average market price, offering a positive premium, developers are further incentivized to choose locations with high wind or solar exposure. This preference aligns with the aim of maximizing generation potential, though it might not always coincide with achieving the lowest system cost when considering both investment and transmission expenses.

Optimal maintenance schedule Under the traditional CfD framework, there is a significant misalignment between maintenance scheduling incentives for generators and the optimal management of the energy system’s demand and supply balance. Nuclear power generators, for instance, might opt to schedule maintenance activities during winter months, driven by the availability of cheaper engineering teams, rather than aligning these schedules with periods of low demand. This approach overlooks the potential benefits of conducting maintenance when the energy system experiences reduced strain, thereby ensuring higher availability during peak demand periods.

Similarly, intermittent renewable energy sources, such as wind and solar, face a perverse incentive structure. Due to the correlation between imbalance settlement costs and spot prices, these generators may find it financially advantageous to undertake maintenance during times of high spot prices. This strategy aims to sidestep elevated imbalance costs but contradicts the broader objective of maintaining energy supply during high-demand periods. Ideally, maintenance for these renewables should be planned for times when demand is low, ensuring that their contribution to the grid is maximized when it is most needed. The current CfD model inadvertently encourages practices that could compromise the efficiency and reliability of the energy system, highlighting the need for a revised approach that better aligns maintenance scheduling with the overarching goals of energy sustainability.

Intraday and balancing market distortions The conventional CfD mechanism introduces distortions in the intraday and balancing markets, primarily due to its reliance on the day-ahead price as the foundational reference for determining the hourly CfD payment. Once the day-ahead auction clears, the price for the hourly CfD payment becomes fixed and known to the generator. This fixed price then acts as an opportunity cost for the generator, influencing their behavior in the same way as any other variable cost component would. The distortion introduced by the conventional CfD affects these markets in different ways depending on whether the market is experiencing high-price or low-price hours which was discussed numerically in section 9.3.4.
Incentive to participate in forward contracts  CfDs can reduce the incentives to participate in forward contracts by addressing the limitations inherent in forward and futures contracts, particularly for low-carbon generators like wind and solar power producers. Forward contracts, including futures, play a vital role in electricity markets by allowing utilities to hedge against price risks. These contracts are settled based on the difference between the spot price at the settlement period and the forward price agreed upon at the contract’s initiation. CfDs offer a tailored solution to the limitations of forward contracts in the electricity market, particularly benefiting renewable energy investments. They address the short-time nature issue of forward contracts by offering longer durations that align with the decades-long lifespan of assets like wind farms and solar panels. Furthermore, unlike futures contracts, CfDs do not require the posting of margins, which reduces the financial burden on liquidity-constrained renewable energy firms. These features make CfDs a more attractive and practical option for hedging price risks in long-term low-carbon generation investments. It is proposed by [160] to incorporate opportunities for commercial Power Purchasing Agreements (PPAs) within the framework of CfDs tenders addressing an important aspect of market dynamics in renewable energy financing and trading. By allowing the establishment of commercial PPAs before a developer enters into a long-term CfD with the state, this approach can have several significant effects on forward markets and the broader energy market.

Cost recovery  The intermittent generation assets usually require a large amount of investment in the beginning which needs to be recovered through a properly designed financial contract. Usually, the financial forward contract spans over 1-3 years which is not attractive for the developers. However, the CfD can provide long-term financial contract if properly designed. Some CfDs are time-limited which is a fixed contract for a specific time no matter how the generation portfolio develops over time while some other contracts are energy-limited in which the support is provided until the asset reaches to a specific energy production limit. In any case, it needs to be estimated that whether the contract can provide a sufficient hedge for the developers to invest in specific assets.

Volume and price risks  One of the main features of any CfD contract is to hedge the price for the developers. The price hedge is implemented through payment transactions to and from the government. However, the volume risk is not necessarily hedged as the wind speed in the case of wind power varies during the contract period. This imposes a revenue risk for the developer. For example, in the low-wind years, the revenue would be lower because the low volume in this case is no longer balanced out with higher prices in the market.
CfD Designs Tools

**Reference prices** Reference prices are one of my main keys in designing a proper CfD design. The resolution of these prices can vary from hourly to monthly and yearly values depending on the structure of the CfD design. The use of monthly or yearly average spot prices, either weighted or unweighted, as the reference price in CfDs provides a nuanced incentive structure for renewable energy generators. In markets like Germany and Denmark, this approach helps to determine CfD payments over longer periods, which in turn encourages generators to optimize their operations. In the UK market, these prices are calculated based on the weighted average of two electricity market price indexes, as explained in section 9.3.3. Since CfD payments are based on these longer reference periods, generators are exposed to intra-period price fluctuations. This exposure motivates generators to optimize dispatch and maintenance schedules to benefit from higher prices within these periods. Additionally, it influences their investment decisions, pushing them towards technologies and practices that allow them to generate power during higher-priced hours. This strategy ensures that generators are not just passively receiving payments but are actively engaged in improving their efficiency and output to align with market demands, thereby enhancing the overall efficiency and sustainability of the power market. In general, the methodology of selecting the reference prices has a considerable impact on the effectiveness of the each proposed approach.

**Quantity** The premium between the strike price and the reference prices is multiplied by the a term related to the energy production or capability of the underlying unit. Conventional CfDs are based on the energy production while the new methodologies are promoting the capacity-based factor to improve the price-responsive of the contracts to the energy prices. These new designs have different approaches in setting the capacity values:

- **Fix Payment per MW:** In this model, the quantity is set based on the installed capacity of the unit no matter how it is operated or where it is located. This approach can avoid distorting the dispatch decisions but only if properly designed [16].

- **Capability-based:** As the first approach, quantity can be determined based on the capability of unit in a generation. The production potential should calculate the theoretically achievable generation for each plant, taking into account the plant’s capacity as well as specific meteorological, topographical, and technical conditions [152], [156].

- **Reference Unit method:** This is a methodology for establishing an hourly generation profile closely aligned with the production of contracted assets, without replicating the exact output of the contracting party. It maintains a high correlation to the specific asset, ensuring its effectiveness as a proxy
hedge. The closer the asset’s actual production is to the reference, the more efficient the hedge becomes[153].

**Duration** The length of the contract is a key factor in determining the risk level of the investor when deciding on different solutions. The time-limited approach has a fixed contract length for the whole contract time like conventional CfD contracts in UK. In this type of contract, the revenue hedge is expected to last for a pre-defined period (for example, 25 years). In the energy-limited contracts, the CfD payments are expected to last until the unit reaches to a specific energy generation limit in its lifetime.

In the following section, a comparative study has been performed to evaluate the effectiveness of each proposed method.

Table 9.6: Comparative analysis of the proposed CfD mechanism and their specifications with respect to the defined metrics

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>Optimal dispatch</strong></td>
<td>Not Included</td>
<td>Guaranteed by the application of the capacity factor quantity calculation</td>
<td>Guaranteed by removing the dependence over energy production</td>
<td>Guaranteed by its financial nature</td>
</tr>
<tr>
<td><strong>Optimal sitting</strong></td>
<td>Not Included</td>
<td>Guaranteed by the inclusion of locational indexed term to the CfD payment</td>
<td>Not included</td>
<td>Not included</td>
</tr>
<tr>
<td><strong>Maintenance Scheduling</strong></td>
<td>Not Included</td>
<td>Proper maintenance considering price signals</td>
<td>Payment continue even if unit is not available</td>
<td>Not included</td>
</tr>
<tr>
<td><strong>Balancing and Intraday Distortion</strong></td>
<td>Not Included</td>
<td>No distortion due to not being connected to actual generation</td>
<td>No distortion due to not being connected to actual generation</td>
<td>No distortion due to not being connected to actual generation</td>
</tr>
<tr>
<td><strong>Forward Market Incentive</strong></td>
<td>Not Included</td>
<td>Its financial settlement nature addresses the needs for participation in Forward markets</td>
<td>Its financial settlement addresses the needs for participation in Forward markets</td>
<td>Not included</td>
</tr>
<tr>
<td><strong>Cost recovery</strong></td>
<td>considered</td>
<td>Not necessarily guaranteed</td>
<td>Guaranteed given the acceptance of the basis risk</td>
<td>Not included</td>
</tr>
<tr>
<td><strong>Price and volume risks</strong></td>
<td>Only price risk</td>
<td>Only price risk</td>
<td>Price and volume risks quarantined</td>
<td>Only price risk</td>
</tr>
<tr>
<td><strong>Regulatory risks</strong></td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td><strong>Design Tools</strong></td>
<td><strong>Reference Price</strong></td>
<td>Weighted average of day-ahead market indexes</td>
<td>Wholesale energy market price</td>
<td>Wholesale energy market price</td>
</tr>
<tr>
<td><strong>Quantity</strong></td>
<td>Metered energy generation</td>
<td>Locational hourly capacity factor</td>
<td>Generation level of reference generator</td>
<td>Metered energy generation</td>
</tr>
<tr>
<td><strong>Duration</strong></td>
<td>Typically 25 years</td>
<td>Energy-limited</td>
<td>Time-limited</td>
<td>10 years</td>
</tr>
</tbody>
</table>
9.5 Discussion and Policy Implications

The analysis of the CfD contracts within the electricity sector (especially UK setups), as presented in section 9.4.3, underscores the complexity and multifaceted nature of designing CfD mechanisms that are both effective and efficient. Through an exploration of six qualitative metrics and three design options, this study has illuminated the inherent challenges and opportunities that policymakers and market participants face in optimizing CfD contracts for the evolving energy landscape.

At the heart of the debate on CfD design is the recognition that there is no singularly "correct" approach that universally applies to all contexts. Each contract design embodies a distinct set of advantages and drawbacks, necessitating a careful and nuanced consideration of the specific goals and circumstances of the energy market in question. The ideal CfD structure, therefore, is one that is tailored to address the unique dynamics and needs of the market it serves, balancing the trade-offs between responsiveness to price signals, risk mitigation, and the promotion of renewable energy sources.

One of the central dilemmas in CfD design is the tension between the desire for revenue certainty and the need for price responsiveness. Traditional CfD models, while providing a strong hedge against market volatility and thus promoting investment in renewable energy, often do so at the expense of operational flexibility. These contracts typically lack incentives for generators to adjust their output in response to real-time market conditions, potentially leading to inefficiencies such as overproduction during periods of low demand or underutilization of flexible generation assets.

Conversely, a CfD structure that is highly responsive to price signals can encourage more efficient dispatch and investment decisions, aligning generation more closely with market demand and reducing systemic costs. However, this increased responsiveness often comes at the cost of reduced revenue certainty for generators, potentially deterring investment in new capacity, especially in capital-intensive technologies like wind, solar, and nuclear power.

The policy implications of these findings are profound. Policymakers must navigate these trade-offs with a clear understanding of their priorities for the energy sector, whether that be maximizing efficiency, encouraging the adoption of renewable energy, ensuring system reliability, or managing the costs of the transition to a low-carbon economy. This balancing act requires not only a deep understanding of the technical aspects of CfD design but also a keen sense of the market dynamics and future trends in energy production and consumption.
Part IV

Closure
Chapter 10

Concluding Remarks and Future Work

10.1 Conclusions

With the increasing integration of renewable energy assets into power systems, there is a great need to rethink the electricity market design to facilitate this integration. The proposed EU electricity market reform in 2023 was one of the main indications that such a change is required. This thesis performed a qualitative and quantitative analysis of different aspects of market designs to provide an understanding of the impacts of different setups on the profitability and operationality of the electricity market. This study has been divided into two main subsections: Short-term and long-term electricity markets, with the main focus on the Nordic electricity market considering lots of hydropower plants. Chapter 1 - 3 explains the introduction and basic electricity market and mathematical background required to understand the thesis content. The following list seeks to express the main conclusions from the rest of the chapters in this thesis:

- Chapter 4 introduces two primary methodologies—machine learning and statistical approaches—to establish an optimization framework for the strategic planning and operation of generation assets within the Nordic electricity market. This is achieved through a three-stage stochastic optimization model. The model incorporates an enhanced version of the long-short term memory (LSTM) model for generating price scenarios, alongside the utilization of the GAMLSS framework to accurately model the uncertainty associated with Active-Time Duration (ATD) in manual Frequency Restoration Reserves (mFRR) balancing energy offers. This method markedly enhances the precision of electricity price forecasts across various market phases. The model proposed in this chapter is used to form the main analysis in Chapter 5.

- Chapter 5 presents a new multi-stage stochastic optimization model designed...
specifically for Hydro Power Plants (HPPs) operating in European electricity markets. It seamlessly incorporates the LSTM architecture for accurate electricity price predictions and employs the GAMLSS method to precisely capture the ATD in balancing energy bids. This model adeptly navigates the complexities of the day-ahead, Frequency Containment Reserve for Normal operation (FCR-N), and mFRR markets, enabling the development of more effective and profitable bidding strategies for HPPs. The results of the modeling demonstrate a robust framework that allows HPP operators to increase their revenue by engaging in capacity-based markets, such as FCR-N and mFRR capacity markets. Moreover, by applying the proposed ATD approach, the model yields more realistic outcomes compared to simplistic bidding strategies that assume full activation of balancing bids, thereby enhancing the strategic positioning of HPPs in the market.

• Chapter 6 outlines a new strategy for addressing the uncertainties in the optimal planning and operation of cascaded HPPs within sequential electricity markets. The strategy, named SARO, aims to guide HPP operators in optimally distributing their resources among day-ahead energy, mFRR capacity, and energy markets. This distribution is carefully planned to consider the uncertainties related to both current and future electricity prices, as well as the active-time duration for accepted mFRR energy offers. A notable result from the evaluation of SARO is its enhanced capability for revenue generation, outperforming traditional stochastic optimization techniques. Even under the most cautious SARO strategy, the generated revenue significantly exceeds that obtained through conventional methods.

• Chapter 7 delves into the strategic management of HPPs in sequentially cleared electricity markets, encompassing day-ahead, intraday, and frequency-regulation markets. It provides guidance for HPPs to optimize their trading across these markets while managing their water resources for electricity production effectively. The research considers a range of conditions affecting power plants and markets, including market clearing processes, market power exertion, and water valuation. One of the findings is in the case of transmission line congestion. Findings indicate that the strategic unit’s bidding behavior aims to congest the line intentionally, leveraging its market power to elevate the price at its node. Another result of the strategic maneuvers of the Strategic unit, navigating the intricate balance between the value of stored water and Intraday (ID) market dynamics. The ST unit uses ID market trading to fine-tune its water discharge strategy, aligning with current market prices. It conserves water for future utilization by buying from the market when ID prices are low and seeks to maximize revenue by selling electricity at higher prices as ID prices rise.

• Chapter 8 demonstrates the benefits of a dynamic approach to Frequency Restoration Reserve (FRR) dimensioning in the Nordic Load Frequency Con-
10.2. FUTURE WORK

In the context of the escalating integration of renewable energy resources within power systems, it becomes imperative to reconsider the design of electricity markets to support such integration effectively. The European Union’s electricity market reform proposed in 2023 serves as a pivotal signal that such transformation is indispensable. This thesis has endeavored to conduct both qualitative and quantitative assessments of various market designs, aiming to elucidate the implications these designs hold for the market’s profitability and functionality.

The subject of short-term electricity markets is expected to become increasingly relevant in the future, against the backdrop of a shifting energy paradigm characterized by enhanced demand-side participation, the variability of renewable energy sources, and the integration and coordination of diverse energy carriers. This shift underscores the urgency of facilitating the energy transition and optimizing social welfare, thereby showing new prospects and challenges for the enhanced cross-border integration of markets. The imperative to improve the coordination between sequential markets and devise market designs that support such coordination is more pressing than ever. Given the distinctive attributes of each electricity market, shaped by regional specifics such as production, consumption, and grid characteristics, a universal solution remains a bit hard to achieve. However, the insights gained from specific electricity market experiences can lay...
the foundation for the development of electricity markets in other regions of the world.

Future research directions could delve into the effects of stochastic wind power generation, acknowledging its growing contribution to the energy mix. Additionally, the challenge of predicting and managing variations in water inflow to each reservoir, influenced by unpredictable weather conditions, suggests a need for advanced modeling approaches to ensure effective hydropower management. In the context of strategic bidding and modeling, stochastic modeling and new scenario generation techniques can be employed to model the interaction of the intraday market and the value of the stored water with the bidding behavior of the strategic actors. On the problem of FRR dimensioning, new computational methods need to be investigated to fasten the process of solving the chance-constraint optimization or propose new relaxation methods to find the optimal solution with an acceptable accuracy level. Also, following the future trends toward the integration of EU markets, the possibility of procurement at the EU level using the cross-border interconnection is a feasible study that paves the way for the lower cost of provision of ancillary services. Finally, following the guidelines on the future market design by the European Union, the more practical implementation of the CfD market needs to be investigated. Especially, the design of reference prices is a challenge given the context of local market setups in each country and ideas of using market indexes like mFRR and aFRR capacity market to form a more informed reference price for the CfD contract design needs to be fully investigated.
References


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