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Optimising a Bidding Strategy for a Renewable Energy System with Batteries in the Nordic Markets

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Abstract

The Finnish power market is undergoing a rapid transformation driven by the increasing share of variable renewable energy sources (VRES), particularly wind and solar. This shift has resulted in increased price volatility, including frequent negative prices and occasional extreme spikes, highlighting the growing need for flexibility in the power system. Simultaneously, the reduced profitability of traditional energy arbitrage strategies has made participation in reserve markets, such as frequency containment reserves for disturbances (FCR-D), an increasingly important revenue stream for flexible assets such as battery energy storage system (BESS). As a result, determining how and when to participate in different electricity markets has become a more complex decision-making problem for asset owners.

This thesis addresses this challenge by developing a stochastic optimisation model for market bidding, aimed at maximizing the profits of a hybrid energy portfolio consisting of a solar power plant and a BESS. The model is designed to participate in both the day-ahead and up- and down-regulating FCR-D markets. The model considers uncertainty in day-ahead prices and FCR-D market prices, and solar power production using scenarios. A case study based on Finnish market conditions is conducted to evaluate the profitability of the proposed approach. Although bidding optimisation has been widely studied in the literature, studying pricing strategies remains relevant due to the evolving markets and the role of opportunity cost for zero marginal production, coupled with BESS. Moreover, relatively little research has focused on the Finnish context, particularly for a hybrid plant consisting of a solar plant and BESS.

The results demonstrate that the proposed bidding strategy improves profitability. Over a 30-day case study using 2024 data, the optimized system with the best price strategy increased profits by 5.58% compared to the naive strategy, with the greatest profit during summer due to higher solar production and favorable up-regulating FCR-D prices. The BESS enables load-shifting and helps reduce imbalances. Additionally, profit increased nearly linearly with battery size.

Keywords Electricity markets , Bidding optimisation, Stochastic programming, BESS

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Tiivistelmä

Suomalaiset sähkömarkkinat muuttuvat nopeasti lisääntyneen uusiutuvan tuotannon, etenkin aurinko- ja tuulivoiman johdosta. Tämän seurauksena hintojen vaihtelu on kasvanut, esimerkiksi negatiivisia hintoja ja ajoittaisia hintapiikkejä nähdän yhä useammin. Tämä korostaa joustavuuden tarvetta verkossa. Samanaikaisesti mahdolliset tuotot vuorokausimarkkinoilta ovat pienentyneet, korostaen tarvetta osallistua usealle markkinalle, esimerkiksi tajuusohjattuun käyttö- tai häiriöreserviin, etenkin joustavilla resursseilla. Tämän seurauksena päätöksenteko siitä, miten ja millä markkinoilla operoidaan on muuttunut entistä kompleksisemmaksi ongelmaksi.

Tämä dilomityö käsittelee tätä ongelmaa kehittämällä stoksatisen optimointimallin tarjousten tekemiseen. Tavoitteena on maksimoida tuottoja hybridilaitokselle, joka koostuu aurinkovoimalasta ja akusta. Malli on suunniteltu toimimaan vuorokausimarkkinoilla sekä ylös- ja alassäätö häiriöreservissä. Malli ottaa epävarmuuden markkinahinnoissa ja tuotannossa huomioon käyttämällä skenaarioita. Työssä on tehty kokeellinen tutkimus suomalaisilla markkinoilla, esitetyn metodin arvioimiseksi. Siitä huolimatta, että tarjousoptimointia on tutkittu laajasti, hintastrategioiden tutkiminen on edelleen relevanttia muuttuvien markkinoiden sekä hybridilaitosten vaihtoehtoiskustannusten johdosta. Tämän lisäksi tutkimus Suomalaisilla markkinoilla, etenkin aurinkovoimasta ja akusta muodostuvalle hybrilaitoksille, on ollut vähäistä.

Kokeelliset tulokset osoittavat, että ehdotettu tarjousoptimointi parantaa tuottavuutta. Valituilta kolmeltakymmeneltä päivältä vuodelta 2024, optimoiduilla tarjouksilla ja parhaalla hinta strategialla kasvu tuotoissa oli 5.58% verrattuna tilanteeseen, jossa systeemi oli optimoitu, mutta käytettiin naiivia hintastrategiaa. Parasta hintastrategiaa käyttämällä suurin kasvu tuotoissa nähtiin kesältä, suurimmaksi osaksi johtuen kasvaneesta tuotannosta ja lisääntyneistä tuotoista ylössäätävästä häiriöreservistä. Akun avulla voidaan toteuttaa kuormansiirtoa ja akku auttaa myös pienentämään tasevirheen määrää. Tämän lisäksi, tuotot lisääntyvät lähes lineaarisesti, kun akun kokoa kasvatetaan.

Avainsanat Sähkömarkkinat, tarjousoptimointi, stokastinen ohjelmointi, Akku

Preface

I would like to thank everyone who supported me throughout the thesis process. I am especially grateful to my advisor Helmi Hankimaa, who has given invaluable advise and feedback throughout the entire process. I would like to thank my supervisor, Professor Fabricio Oliveira for his guidance and expertise. Thank you to the entire Wind & Solar team at St1 Suomi Oy for the opportunity to write this thesis, and for your support and interest in the work throughout the process. I would also sincerely like to thank my family and friends, especially my partner Sebastian, for their endless encouragement throughout my studies and this thesis process.

I have thoroughly enjoyed my studies at Aalto University, where I have gained many found memories and now I look forward to learning more and applying the knowledge I have gained to meaningful challenges in the future.

Espoo, 27th of June 2025

Aurora Kauraala

Contents

Symbols and abbreviations

Abbreviations

aFRR	Automatic frequency restoration reserve
BESS	Battery energy storage system
DA	Day-ahead market
EH	Energy hub
ENTSO-E	European network of transmission system operators for electricity
EES	Energy storage systems
EV	Electric vehicle
FCR	Frequency containment reserve
FCR-D	Frequency containment reserve for disturbances
FCR-N	Frequency containment reserve for normal operation
FFR	fast frequency reserve
IDA1	Intraday auction one
mFRR	Manual frequency restoration reserve
MILP	Mixed-integer linear programming
MW	Mega watt
MWh	Mega watt hour
PV	Photovoltaic
RES	Renewable energy sources
RTE	Round-trip efficiency
SE1-SE4	Sweden power price areas
SCAD	Single day-ahead coupling
TSO	Transmission system operator
VPP	Virtual power plant
VRE	Variable renewable energy
XGBoost	Extreme gradient boosting

Symbols

Sets

S	Set of scenarios
T	Set for hours

Parameters

Γ_{ts}^{DA}	Day-ahead market price in hour t in scenario s (€/MWh)
Γ_{ts}^{UP}	Up-regulating FCR-D market price in hour t in scenario s (€/MWh)
Γ_{ts}^{DN}	Down-regulating FCR-D market price in hour t in scenario s (€/MWh)
β_{ts}^{sell}	Indicator whether bid is cleared to day-ahead market or not
β_{ts}^{UP}	Indicator whether bid is cleared to up-regulating FCR-D market or not
β_{ts}^{DN}	Indicator whether bid is cleared to down-regulating FCR-D market or not
P^{PCC}	Licensed power at the point of common coupling (MW)
π_s	Probability of scenario s
E	Rated capacity of the energy storage system (MW)
P^{BAT}	Rated power of charge and discharge of the energy storage system (MWh)
η_{CHA}	Charge efficiency of the energy storage system (%)
η_{DIS}	Discharge efficiency of the energy storage system (%)
$\hat{P}_{ts}$	Power production forecast available at gate closure for the day-ahead market per hour and per scenario (MWh)
C^{PV}	Rated capacity of the solar power plant (MW)
P^{FCR}	Upper limit for bids to the FCR-D markets (MW)

Decision variables

b_t^{sell}	Bid to sell power in the day-ahead market in hour t (MW)
b_t^{buy}	Bid to buy power in the day-ahead market in hour t (MW)
b_t^{DN}	Power bid in the down-regulating FCR-D market in hour t (MW)
b_t^{UP}	Power bid in the up-regulating FCR-D market in hour t (MW)
p_{ts}^{sell}	Power sold on the day-ahead market in hour t in scenario s (MWh)
p_{ts}^{buy}	Power bought on the day-ahead market in hour t in scenario s (MWh)
p_{ts}^{DN}	Capacity sold on the down-regulating FCR-D market in hour t in scenario s (MW)
p_{ts}^{UP}	Capacity sold on the up-regulating FCR-D market in hour t in scenario s (MW)
e_{ts}	Energy stored in the energy storage system in hour t in scenario s (MWh)
p_{ts}^{CHA}	Charging power in the energy storage system in hour t in scenario s (MW)
p_{ts}^{DIS}	Discharging power in the energy storage system in hour t in scenario s (MW)
p_{ts}^{PV}	Solar production in hour t in scenario s (MWh)
Δ_{ts}	Imbalance between market commitment and production in hour t in scenario s (MWh)
Δ_{ts}^{+}	Excess production in hour t in scenario s (MWh)
Δ_{ts}^{-}	Deficit production in hour t in scenario s (MWh)
i_t	binary variable indicating if power is purchased on the day-ahead market in hour t
j_{ts}	Binary variable indicating whether the battery is charging or discharging at time t

1 Introduction

The European electricity market has undergone profound structural changes over the past decade. Driven by political commitments to mitigate climate change, there has been a rapid expansion in variable renewable energy (VRE) generation, particularly wind and solar. Simultaneously, fossil-fuel power plants have increasingly been phased out, both due to policy pressure and reduced competitiveness against low-marginal-cost VRE. Renewable energy capacity, particularly wind and solar, has increased significantly in Finland. In fact, based on ongoing construction and investment plans, wind power generation in Finland is expected to reach up to twice the electricity consumption of 2022 by the late 2030s [1].

In addition to these trends, external shocks, such as geopolitical issues, have further destabilized the European power market [2]. Where electricity prices once followed relatively predictable patterns, extreme volatility is now common. Finland, especially, has extremely volatile day-ahead prices. In 2024, Finland had 724 hours of negative day-ahead prices. In contrast, in January of the same year, the Finnish spot-market reached an all-time high of 1896 €/MWh, which resulted from a combination of high demand, low wind generation, and unexpected plant outages.

To maintain grid stability, electricity supply and demand must be matched continuously in real time. This requirement becomes increasingly challenging as the share of VRE increases, introducing greater uncertainty and fluctuations in the power system [3]. Deviations between predicted and actual production are inevitable due to forecasting errors, unforeseen events and the stochastic nature of VRE production. Moreover, unlike traditional power plants, VRE do not inherently provide inertia, which stabilizes the grid by resisting frequency changes. To manage these challenges, transmission system operators (TSOs) operate reserve markets. These markets enable a real-time balance between supply and demand. As conventional thermal power plants are phased out, battery storage, demand-side response, and power electronics-based solutions are expected to play a growing role in providing reserve services [1].

Consequently, the role of battery energy storage systems (BESS) is expected to grow. In recent years, there has been an increase in the integration of energy storages in Finland. Utility-scale BESS has particularly grown, with about 0.2 GWh currently in operation and an additional 0.4 GWh planned. The progress has been supported by investments and legislative changes that eliminate obstacles, such as the double taxation of stored electricity. [1]

VRE producers face increasing challenges in maintaining profitability [4]. Since VRE generates electricity at zero marginal cost, producers often submit bids at zero price. Combined with auction-based pricing, this leads to the cannibalization effect. As a result, during periods of high renewable output, especially when electricity consumption is low, supply often exceeds demand, pushing market prices down, sometimes even into negative values. At the same time, the narrowing price spread between peak and off-peak hours further limits revenue opportunities. Consequently, participation in multiple markets and leveraging load shifting have become important for improving profitability. For BESS operators, the ability to strategically allocate capacity between markets is essential to maximize overall profitability.

The objective of this thesis is to develop a stochastic optimisation model for supporting bidding decisions in Finnish electricity markets for a portfolio consisting of a solar power plant and BESS, with the goal of maximizing the profits. The model is designed for players that participate in both the day-ahead and up- and down-regulating FCR-D markets and operates with an hourly time resolution. Scenario generation is used to account for uncertainties in the day-ahead market prices, up- and down-regulating FCR-D market prices, and solar power production. A case study is conducted to evaluate the expected profitability of a portfolio comprising a solar power plant and a BESS.

This thesis is structured as follows. Chapter 2 provides an overview of solar power and battery energy storage systems. Additionally, it introduces the reserve market products, particularly the up- and down-regulation FCR-D markets, their market designs, and the day-ahead market auction. Furthermore, the chapter presents modeling frameworks for bidding strategies, with a focus on stochastic optimisation. Chapter 3 presents the modeling assumptions and the formulation of the stochastic optimisation model for bidding. Chapter 4 describes the methodology used for scenario generation. Chapter 5 presents the results of the case study. Chapter 6 discusses the limitations of the model, outlines potential improvement, and concludes the content of this thesis.

2 Background

This thesis focuses on the optimal bidding strategy of a solar power plant with battery energy storage in the Finnish electricity markets, and thus, it is important to understand the technical and market environment in which such a system operates. Therefore, this chapter provides background on the relevant electricity markets, technologies, and prior research. Section 2.1 introduces the Nordic day-ahead market, which serves as the primary marketplace for electricity trading. Section 2.2 describes the Nordic reserve markets, with a focus on up- and down-regulating FCR-D markets. Section 2.3 presents the operating principles and characteristics of solar power, while Section 2.4 introduces battery energy storage systems and their role in energy markets. Finally, Section 2.5 reviews previous research on optimal bidding strategies.

2.1 Day-Ahead Market

The Nordic day-ahead market is the main platform for Finnish power companies to sell their energy. The market is operated by Nord Pool which operates in 15 countries including the Nordic and Baltic countries, the United Kingdom, among others [5]. In the day-ahead electricity market, supply and demand must always be balanced to ensure stability in the grid. Electricity producers and buyers submit their bidding curves to the day-ahead market by 12:00 CET, indicating how much electricity they are willing to sell or purchase and at what price. These bids are then processed through the Single Day-Ahead Coupling (SDAC) using a algorithm called Euphemia, which matches orders across the Europe taking into account network constraints. A market clearing price for each hour and bidding zone is determined according to the intersection of the supply and demand curves. The results, including the clearing prices and volumes, are published at 12:45 CET or later. Market prices are bound between -500 €/MWh and 4000 €/MWh [5].

The Nordic day-ahead market aims to determine a market-clearing price, or area price, for each participating bidding zone. Transmission limitations between bidding zones can lead to price differentiation, commonly referred to as area prices. Price separation between neighboring zones occurs when the transmission interconnection operates at maximum flow capacity. Countries may have multiple bidding zones, such as Sweden (SE1-SE4) [6]. Finland has not been divided into multiple bidding zones and functions as a single pricing area.

Through market-based pricing, it incentivizes producers to offer electricity at competitive rates while ensuring that demand is met through the least-cost generation resources available. The supply curves, which represent the willingness of generators to sell electricity at various price levels, intersect with the demand curves, which reflect the willingness of consumers to purchase electricity. An example of supply and demand curves can be seen in Figure 1.

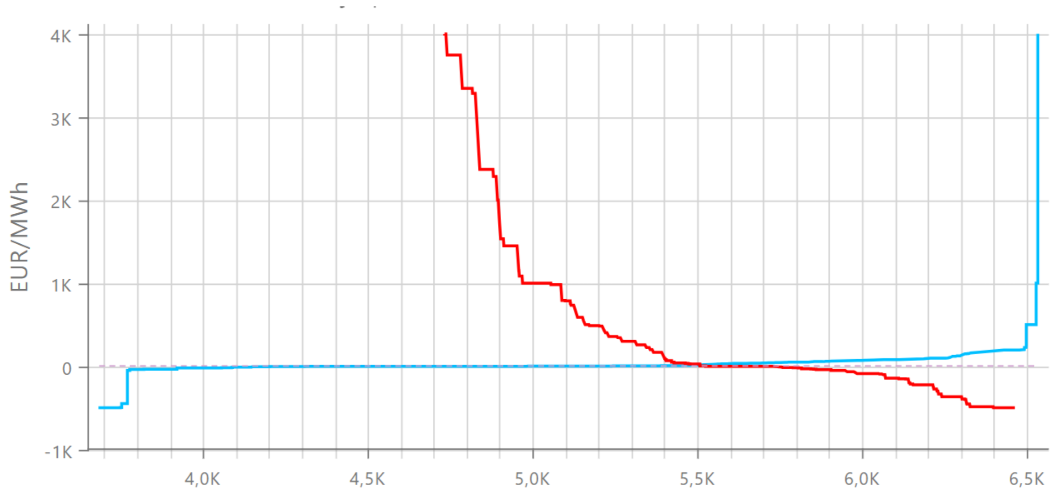

Figure 1: Aggregated bidding curve from Nordpool for one hour in Finland. The blue curve is the supply curve and the red curve is the offer curve. The market-clearing price for this hour was 12.52 €/MWh. [7]

Market prices are influenced by several factors, including fuel costs, generation mix, weather conditions, and network constraints. Market regulations [8] require participants to set the price of electricity they sell based on either the marginal cost of producing it or the opportunity cost. Opportunity costs reflect the potential benefit lost by choosing one option over another. Opportunity costs may be present due to opportunities to store energy, use it for own consumption, or bid it in subsequent markets. Accurately evaluating these costs is challenging, as it requires considering future market conditions and alternative uses of energy. Producers therefore develop bidding strategies based on forecasts of market prices, demand forecasts, and the availability of their generation assets. The marginal cost of renewable energy is effectively zero [9]. Thus, producers usually offer their production at zero price unless they have another use for it, such as energy storage.

If actual production deviates from daily commitments due to forecast errors or unforeseen events, market participants can adjust their positions through intraday trading. Moreover, BESS can help minimize imbalances by storing excess energy or supplying power when actual production falls short [10]. Balancing markets, managed by transmission system operators, provide a last resort mechanism for addressing real-time imbalances. The pricing structure in balancing markets often penalizes deviations, by imbalance settlement cost, from day-ahead commitments, reinforcing the importance of accurate forecasting and strategic bidding in the day-ahead auction.

2.2 Reserve Markets

Reserve markets play a critical role in maintaining the stability and reliability of the electricity system by balancing supply and demand fluctuations in real-time. These markets ensure that sufficient backup capacity is available to respond to grid disturbances, frequency deviations, and unexpected changes in electricity consumption or generation. The need for reserve capacity has grown significantly in recent years due to the increasing share of renewable energy sources, which introduce more variability in electricity supply into the power system. [11], [12]

In the Nordics, reserve markets are managed by each country's transmission system operator. In Finland, this responsibility lies with Fingrid. They operate the reserve markets and procure resources from the market. The Nordic transmission system operators are required to maintain a certain amount of reserves [13]. There are multiple reserve products and there is a market for each of them, each serving a different purpose. These include frequency containment reserves (FCR) for normal operation (FCR-N) and disturbances (FCR-D), automatic frequency restoration reserve (aFRR), manual frequency restoration reserve (mFRR), and fast frequency reserve (FFR). These reserve products differ in their purpose and technical implementation. The market places are presented in Figure 2. Some reserves are also divided into upward and downward regulation, depending on whether the aim is to increase or decrease the grid frequency. From the perspective of a power plant, upward regulation means increasing electricity supply to the grid, either by ramping up generation or by reducing consumption. Conversely, downward regulation involves reducing electricity supply or increasing local consumption to help bring the frequency down when it rises above the nominal level.

Figure 2: Reserve market places in Finland [14].

FCR-D is designed to mitigate significant frequency deviations caused by unexpected events such as power plant outages or sudden changes in demand. FCR-D is classified into up-regulating FCR-D and down-regulating FCR-D to account for both over- and under-frequency conditions. These reserves help maintain grid stability by rapidly adjusting power generation or consumption in response to deviations from the nominal 50 Hz frequency. The activation of FCR-D is based on real-time frequency measurements. Up-regulating FCR-D reserves are activated when the frequency falls below 49.5 Hz, and down-regulating FCR-D activates when it rises above 50.5 Hz.

Up-regulating FCR-D is activated in less than 10 seconds. Fingrid's obligation for 2024 was set at 295 MW, with a volume weighted average price of 12 €/MW in 2023. The minimum bid size for participation is 1 MW. The purpose of up-regulating FCR-D is to increase electricity production or decrease consumption when the grid frequency drops below 49.5 Hz, helping to restore balance [12]. Similarly, down-regulating FCR-D also activates in less than 10 seconds. In 2024, Fingrid's obligation for this reserve was 240 MW, with a 2023 volume weighted average price of 14 €/MW. Like up-regulating FCR-D, the minimum bid size is 1 MW. However, its role is the opposite: it is used to decrease electricity production or increase consumption when the frequency rises above 50 Hz, ensuring that the grid remains stable [12].

FCR-D is procured through both annual and hourly markets. In the annual capacity auctions producers commit to offering reserve capacity for a full year whereas in the hourly capacity auctions participants can submit bids daily. The gate closure time for the hourly market is 17:30 CET for the following day. Participants receive compensation for making their reserve capacity available, regardless of activations. Figure 3 shows the projected development of the need for FCR-D reserves. While the total demand for up- and down-regulating FCR-D in the Nordic region is expected to remain stable, Fingrid anticipates that their share of the reserve provision will increase in the coming years.

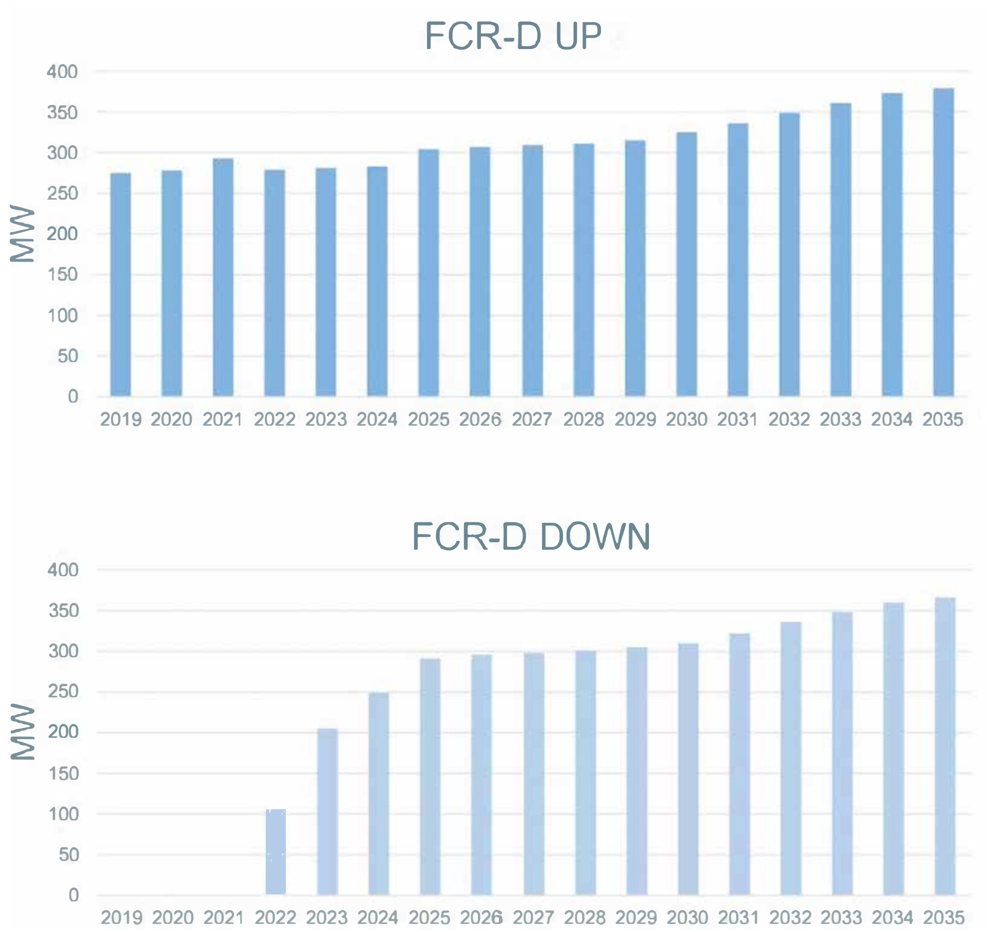

Figure 3: Upper figure presenting the projected demand for up-regulating FCR-D and bottom figure the projected demand for down-regulating FCR-D. Demand for FCR-D in Finland is expected to steadily grow during the upcoming years [15].

2.3 Solar Power

Solar energy is the radiant energy emitted by the Sun, which can be harnessed for various applications, including electricity generation with photovoltaic (PV) systems and heating with solar thermal energy. The Sun provides an enormous amount of energy, $1.7 \cdot 10^{22} J$ in 1.5 days, while the total annual energy use by humans is $4.6 \cdot 10^{20} J$, which means that available solar energy vastly exceeds global energy consumption [16]. Photovoltaic technology converts sunlight directly into electricity using semiconductor materials. When sunlight (photons) strikes a photovoltaic cell, it excites electrons, generating an electric current. This process, known as the photovoltaic effect, occurs in p-n junctions formed by semiconductor layers. A solar panel system consists of solar panels, inverters, transformers, mounting structures, tracking mechanisms, and wiring [17].

Over the years, various photovoltaic technologies have emerged, each with distinct characteristics, efficiencies, and costs. Silicon-based solar cells are widely used in commercial applications, accounting for about 90% of global solar panel production.

They are categorized into two main types, mono-crystalline and poly-crystal. Mono-crystalline silicon solar cells have an efficiency of approximately 20-25%. They offer high efficiency and performance, a long lifespan of over 25 years, and better performance in low-light conditions. Polycrystalline silicon solar cells have an efficiency of around 16-18%. Although multi-crystalline silicon solar cells are less efficient than mono-crystalline silicon solar cells, they dominate the global market because of their lower production costs [18]. With the growing demand for more efficient and cost-effective solar cells, new technologies are being developed. At the moment, gallium arsenide solar cells have the best efficiency of more than 30%. They provide high efficiency because of their superior absorption properties. However, they are very expensive to produce and rely on the limited availability of gallium [18].

Solar power is non-dispatchable and inherently intermittent [19]. Its output depends directly on weather conditions and time of day, which means it cannot be controlled in the same way as conventional power generation. Although solar power cannot be increased on demand, it is possible to curtail its production by disconnecting panels or limiting inverter output [20]. Curtailment can be implemented almost instantaneously, making it relatively fast and flexible in terms of downward regulation. Solar power is qualified to provide down-regulating FCR-D services in Finland [21].

The predictability of solar generation has improved with advances in weather forecasting and machine learning [22]. Day-ahead forecasts for solar power can reach reasonable accuracy, especially for clear-sky conditions. However, short-term variations due to cloud cover still present challenges. Another important consideration is how well solar power production aligns with electricity demand. In many regions, peak solar production occurs around midday, which often do not coincide with peak hours. Peak hours refer to periods of high electricity demand, typically in the early morning and in the late afternoon to evening when consumption rises again. Off-peak hours, on the other hand, occur during periods of lower demand, such as late at night or midday in some regions. Therefore, integrating solar energy effectively requires either flexible demand, energy storage, or complementary generation sources that can cover the gaps between production and consumption.

In recent years, most of Finland's solar power capacity has been rooftop photovoltaic and small-scale solar plants. However, large-scale solar power plants with a capacity exceeding one megawatt have been developed in Finland at a significant pace for about two years. By the end of 2024, the total capacity of utility-scale solar power in operation had surpassed 120 megawatts, with nearly half being completed in 2024 [23]. The growth of large-scale solar power in Finland is expected to accelerate, with investment decisions made by the end of 2024 bringing the projected installed capacity to approximately 450 megawatts by 2025 [24]. As shown in Figure 4, this capacity is expected to continue increasing rapidly.

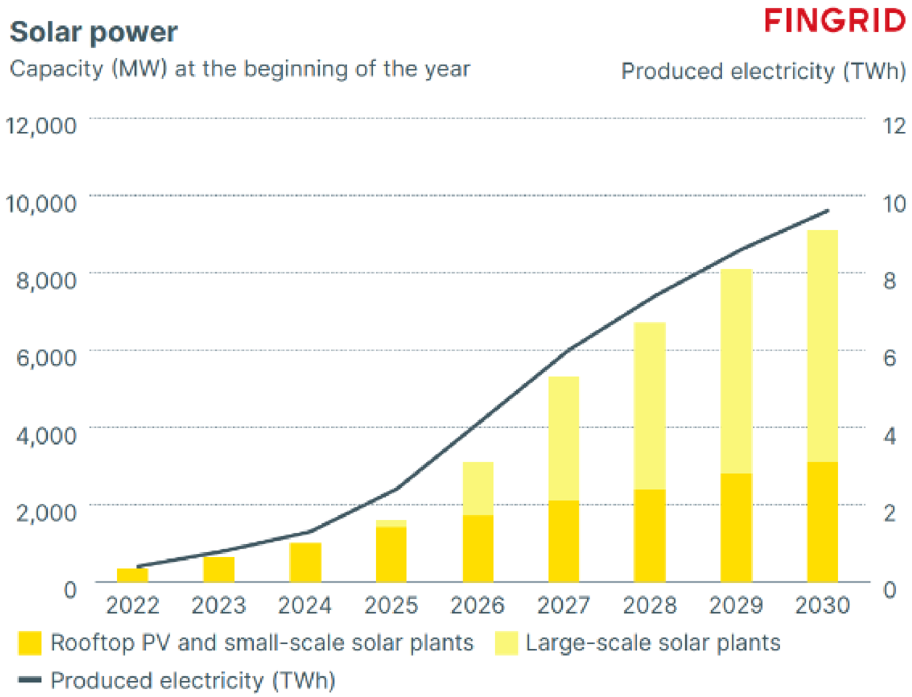

Figure 4: Projected development of solar power in Finland [25]. Especially the number of large-scale solar power plants are expected to grow.

2.4 Battery Energy Storage Systems

Solar energy production is inherently intermittent. Battery energy storage systems (BESS) help mitigate this variability by storing surplus electricity generated during peak production periods and supplying it during times of low solar output. They improve the resilience and reliability of power grids by facilitating the integration of intermittent renewable sources and serving multiple functions, including load leveling, energy management, backup power, voltage support, and grid stabilization. The combined use of solar power and batteries optimizes the utilization of renewable resources [26].

The increasing share of renewable energy, particularly wind and solar, amplifies the importance of energy storage [27], [28]. In regions with high renewable capacity, surplus electricity could be generated at no additional cost when supply exceeds demand. Energy storage systems enable capturing this surplus power.

Electricity demand fluctuates throughout the day, influencing electricity market prices, which tends to be higher during peak hours and lower during off-peak periods. This variation is due to differences in generation costs. During peak demand hours, electricity is often produced using flexible but expensive power sources such as oil- and gas-fired plants. These sources are not only expensive but also tend not to be environmentally friendly, which is why reducing their use is a key goal in the transition to cleaner energy systems. Conversely, when demand is low, these costly generators can be shut down. Energy storage systems (EES) can capitalize on this dynamic by storing cheaper electricity produced during off-peak hours and supplying it during peak periods [29].

Common metrics used to describe battery energy storage systems include rated power, battery capacity and round-trip efficiency (RTE). Rated power refers to the maximum continuous active power that the storage device can deliver or absorb during discharge and charge, respectively. It is important to distinguish this from the peak power, which represents the absolute maximum the device can handle for short durations and is typically higher than the rated value. Round trip efficiency is the ratio of energy retrieved from a battery to the energy initially put into it during a full charge-discharge cycle. It is a key performance metric for energy storage systems, as it determines how much energy is lost during the charging and discharging processes, directly impacting the overall effectiveness of the storage system. Battery capacity refers to the total amount of energy a battery can store and, for utility-scale batteries, it is typically measured in mega watts (MW) [30]. It is calculated by multiplying the discharge current by the discharge time. In large-scale applications like grid or industrial storage, a higher capacity means the system can provide power for a longer duration.

The high efficiency of lithium-ion technology makes it a preferred choice for grid-scale energy storage, electric vehicles (EVs), and portable electronics. The service life of lithium-ion batteries is around 5-15 years [31]. Lithium ion batteries generally exhibit a round-trip efficiency of 85%–95% [27], depending on factors such as battery chemistry, operating conditions, and aging.

2.5 Research on Optimal Bidding Strategy in Energy Markets

Different market participants employ various bidding techniques to maximize their revenue while mitigating risks. Some producers optimize their bid curves to account for potential intraday market opportunities, while others strategically allocate capacity between the day-ahead and reserve markets. The decision to offer capacity in the day-ahead market versus holding it for ancillary services depends on market price expectations and regulatory constraints.

Earlier research has demonstrated that bidding at true costs is optimal under certain market designs that allow, for example, the inclusion of fixed costs in addition to marginal costs [32]. However, the structure of modern electricity markets differs from those assumptions, and such optimality does not necessarily extend to today's market conditions. The problem is further complicated by nonlinear structure of offering, as revenue depends on the product of two variables, price and quantity. Thus, bidding strategy optimisation remains a challenging and actively researched topic. Many prior studies have focused on finding optimal bid quantities without considering bid prices [33]–[36]. However, there are some studies that utilize varying approaches to find both optimal bid volumes and prices [37], [38]. Authors of [37] presents a stochastic optimisation model to minimize operational costs for an electrical vehicle aggregator. Their results demonstrated that including both quantity and price in reserve bids is beneficial over bids based on quantity alone. However, their problem setting is different from this thesis, since the study does not consider any production of their own, and their objective is to minimize cost. In addition, imbalance is not penalized sufficiently, which can affect the results.

In a multi-market environment like the Nordic power system, where a generator can participate in several different electricity markets with varying price formation mechanisms, opportunity cost becomes a key factor in offer optimisation. Producers must consider not only the immediate profit from selling in the current market but also the potential profits they could earn in subsequent markets. This means that the price of electricity should reflect the expected value of alternative opportunities, especially when energy can be stored and sold later. In addition, uncertainty in renewable energy generation further complicates this decision making. As a result, modern producers must optimize their offers by weighing both the uncertainty in production and the opportunity cost of committing energy to one market over another.

There are various combinations of variable renewable energy (VRE) sources and battery energy storage systems, each with its own characteristics. However, similar methodologies can generally be applied regardless of the specific type of renewable energy or storage technology, since all VREs are inherently intermittent and most energy storage systems are capable of providing similar services, despite differences in their technical specifications. There are multiple ways of referring to a VRE and an energy storage unit that operate together, depending on the context and focus of the application. Common terms include hybrid power plant, co-located system, energy hub, aggregated resource, or virtual power plant (VPP).

The optimal bidding strategy for variable renewable energy and battery energy storage systems has been widely studied across different market settings and with varying focuses. Some studies concentrate on VRE sources like solar or wind [39], [40], while others examine BESS operating independently [41], relevant also to this thesis during winter months when solar production is minimal. In addition to stochastic optimisation, several other methods have been explored to optimize bidding strategies, including artificial intelligence-based approaches [42], machine learning and deep learning techniques [43], bidding curve optimisation [44], and robust optimisation [45]. Since this thesis considers a combined solar power plant and energy storage system participating in the day-ahead and FCR-D up- and down-regulation markets, the literature review in this section focuses on studies with similar settings and that utilize stochastic optimisation methods.

2.5.1 Bidding Optimisation

Stochastic programming is an optimisation approach designed to handle uncertainty in real-world decision-making [46]. It has proven to be highly effective in optimizing complex systems where key parameters are not known in advance, outperforming many traditional deterministic methods in both accuracy and efficiency. Unlike deterministic models, which rely on single-point estimates such as expected values to represent uncertainty, stochastic programming incorporates uncertainty directly within the optimisation problem. In stochastic optimisation, the optimal decision is determined by evaluating the model in multiple potential outcomes of the uncertain variables. As a result, the solution may not be the best one for one specific outcome, but it provides the best overall performance across scenarios before the realization of the uncertainties are observed.

A wide range of studies have applied stochastic optimisation to create optimal bidding strategies in electricity markets [35], [41], [47], [48]. Authors in [41] presents a mixed-integer linear programming (MILP) model to optimize the participation of BESSs in the Swedish FCR markets. The model is designed to maximize potential profit and also accounts for battery degradation. It considers participation in multiple FCR services, including FCR for normal operation (FCR-N) and FCR for disturbances (FCR-D) in both up- and down-regulation. From the case study on 2022 data, the results indicate that the highest profit comes from multi-market participation, with the largest share of that profit generated in the FCR-D markets.

Other studies that considered Nordic markets include [49], which introduced a stochastic model that accounts for the impact of wind power production and consumption on market prices. Two bidding algorithms were developed and evaluated within the Nord Pool electricity market. The authors of [50] developed a bidding strategy for wind power plants in the Nordic electricity market as a stochastic mixed-integer programming model, aiming to maximize expected profits while minimizing imbalance settlement costs.

The authors of [51] explore how over-installing renewable energy sources (RES), such as wind and solar, can increase producer profits. They introduced a scenario-based stochastic optimisation model for developing a bidding strategy that maximizes expected profits in the day-ahead and balancing markets. It also accounts for battery degradation and export capacity limits. Their simulation results show that the proposed stochastic approach can lead to higher profits than the deterministic method. In particular, it increased profits by 5.25% for a wind power producer and by 1.23% for a solar (PV) producer. The study also finds that using a battery energy storage system is economically beneficial if its cost is less than 200,000 €/MWh.

Several studies have focused on the development of optimal bidding strategies for standalone battery energy storage systems [52]–[54]. The authors of [52] propose an optimisation-based bidding strategy to determine optimal bids and estimate the revenue potential of BESS, operating alone or as part of a virtual power plant. The results show that with current BESS costs, participation in the aFRR market is not economically viable. However, projected cost reductions by 2025 could make BESS operations profitable, although still less profitable than participating in the FCR market.

2.5.2 Generating Scenarios for a Stochastic Optimisation Model

There are multiple ways to account for uncertainty in production and market prices. Stochastic optimisation is one way of modelling with uncertainty; other frameworks deal with uncertainty using a deterministic model and optimizing using the mean value [55], using robust optimisation [56], or using distributionally robust optimisation [57]. In this thesis uncertainty was modelled leveraging the stochastic programming framework, meaning that uncertainty was taken into account by modelling multiple scenarios for the uncertainty factors.

Stochastic optimisation models are used for decision making under uncertainty and thus require data to characterize the uncertain parameters. The quality of data directly impact the model's performance and the reliability of the results. The ways to include stochasticity in scenarios are, for example, Monte Carlo simulation [58], residual sampling [59], and artificial neural networks [60]. In this thesis the data for the stochastic program was created by sampling values from the distribution of residuals.

Several studies on stochastic optimisation have employed residual sampling as part of their scenario generation process [58], [61]. Authors of [58] presents a stochastic optimal bidding model for an Energy Hub (EH) that incorporates variable renewable energy sources and battery energy storage in day-ahead electricity and reserve markets. It utilizes a Monte Carlo sampling method to simulate uncertainties in wind power output. The authors of [61] develop a stochastic programming model to optimize day-ahead market bids for a demand response aggregator under price uncertainty. They use Monte Carlo sampling to generate electricity price scenarios, which are then reduced for computational efficiency. The model includes a risk constraint and is solved as a mixed-integer linear program. Results using Danish market data show that the stochastic approach better matched the decisions under perfect information better than if robust optimisation was used.

3 Model

This chapter presents a stochastic optimisation model for optimizing bidding in the day-ahead and FCR-D markets under price and production uncertainty in the Finnish markets. The imbalance settlement costs are also taken into account. The producer bids their production from the solar plant and a BESS. The BESS can provide load-shifting by charging during the hours with a lower day-ahead market prices and discharging when prices are higher in the day-ahead or FCR-D markets. Modeling assumptions are introduced in Section 3.1. Section 3.2 presents the model formulation.

3.1 Modeling Assumptions

The proposed model's objective function maximizes profit in all considered markets. The model is formulated as a stochastic optimisation model and operates with a 24-hour time horizon, covering the following day. The decisions comprise optimal bid quantities under production and price uncertainty. The decision making process is simplified by dividing it into two stages: day-ahead decision and operating day decisions. Day-ahead decisions include determining the optimal bid quantities for the day-ahead market and the up-regulating FCR-D markets. Thus, the producer does not observe the outcome of the day-to-day market before submitting offers to the FCR-D market. A simplification was made in assuming that only one bid, consisting of price and quantity, is submitted to the day-ahead market instead of a bidding curve. Operating day decisions include the operation planning of the solar power plant and BESS based on the specified solar production forecasting and cleared bids. Possible decisions include the solar power plant being curtailed, and the BESS's operation schedule can be altered. Operating day decisions are made to fulfill commitments and minimize imbalances. The producer is modelled as a price-taker, meaning that the volume bought or sold by the producer does not affect the market price.

For the FCR-D markets, the model assumes that the cleared capacity is never activated. Consequently, the model considers only the capacity fees for reserving capacity, while potential energy fees from actual activations are excluded. The minimum bid size of 1 MW to the FCR-D markets is assumed to be filled organically in this model. In addition, it is also assumed that solar power can be curtailed. Uncertainty in production and market prices are taken into account by scenario-based modeling.

3.2 Model Formulation

Objective function

The objective (1) is to maximize the expected market profit over three markets: the day-ahead, up-regulating FCR-D and down-regulating FCR-D markets, while penalizing imbalances between planned and actual production and consumption.

$$\max \sum_{s\in S}\sum_{t\in T}\pi_s\Big(\left((p_{ts}^{sell}-p_{ts}^{buy}\right)\cdot\Gamma_{ts}^{DA}+p_{ts}^{UP}\cdot\Gamma_{ts}^{UP}+p_{ts}^{DN}\cdot\Gamma_{ts}^{DN}\Big)$$
$$-\sum_{s\in S}\sum_{t\in T}\delta\left(\Delta_{ts}^{+}+\Delta_{ts}^{-}\right) \tag{1}$$

The objective function is formulated as a maximization problem, where p_{ts}^{sell},p_{ts}^{buy} are non-negative variables that denote the cleared quantities of sold and bought day-ahead bids. Variables p_{ts}^{UP} and p_{ts}^{DN} denote the cleared quantities of up-regulating and down-regulating FCR-D, respectively, in megawatts. Indices $t = \{1, \dots, T\}$ denote the considered time horizon, i.e., the 24 hours of the following day. The set of scenarios $S = \{1, \dots, |S|\}$, captures uncertainty in solar production, day-ahead market price and up-regulating FCR-D and down-regulating FCR-D markets prices. The parameter π_s denotes the probability of scenario s. The parameters Γ_{ts}^{DA}, Γ_{ts}^{UP}, and Γ_{ts}^{DN} represent the scenario-dependent market prices for the day-ahead market, up-regulating FCR-D, and down-regulating FCR-D, respectively, at time t under scenario s. Non-negative variables $\Delta_{ts}^{+} \geq 0$ and $\Delta_{ts}^{-} \geq 0$ represent the power imbalance for excess and deficit power at time step t of the scenario s. Imbalance is penalized by δ. Since balancing responsible parties are obligated to maintain a balanced position, a sufficiently large number δ is used to minimize imbalances in the model [62].

Constraints

Constraints (3)–(6) ensure that only accepted bids lead to actual power transactions, reflecting the stochastic nature of market liquidity. The approach to modeling uncertainty in market clearing is similar to that used in [63]. The acceptance of a bid at the price level in time t and scenario s is captured by binary parameters β_{ts}^{sell}, β_{ts}^{UP}, β_{ts}^{DN}, which indicate whether the bid is accepted based on the corresponding scenario-dependent market prices. Equation (2) presents the general logic applied to all β_{ts} parameters, demonstrated through the case of a selling bid in the day-ahead market. Parameter bp_{ts} represents the scenario-dependent bid price for day-ahead market.

$$\beta_{ts}^{sell} = \begin{cases} 1, & \text{if } \Gamma_{ts}^{DA} \geq bp_{ts}^{sell} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Non-negative variables b_t^{UP} and b_t^{DN} represent bids to up-regulating FCR-D and down-regulating FCR-D market. The cleared bid in each time period t and scenario s is described by the non-negative variables p_{ts}^{UP} and p_{ts}^{DN}, reflecting market-clearing under uncertainty.

$$p_{ts}^{UP} = b_t^{UP}\cdot\beta_{ts}^{UP} \qquad \forall t\in T, s\in S \tag{3}$$

$$p_{ts}^{DN} = b_t^{DN}\cdot\beta_{ts}^{DN} \qquad \forall t\in T, s\in S \tag{4}$$

Non-negative variables b_t^{sell} and b_t^{buy} represent selling and buying bids to day-ahead market. The actual power sold in each time period and scenario, p_{ts}^{sell}, depends on whether the selling bid is cleared, determined by the binary variable β_{ts}^{sell}. Conversely, buying denoted by non-negative variable p_{ts}^{buy} occurs only in scenarios where the selling bid is rejected, i.e., when the market price is lower than the selling bid price. This is captured by the complement $(1 - \beta_{ts}^{sell})$, which ensures that power is bought only when selling is not profitable.

$$p_{ts}^{sell} = b_t^{sell} \cdot \beta_{ts}^{sell} \qquad \forall t \in T, s \in S \tag{5}$$

$$p_{ts}^{buy} = b_t^{buy} \cdot \left(1 - \beta_{ts}^{sell}\right) \qquad \forall t \in T, s \in S \tag{6}$$

To prevent simultaneous buying and selling in the day-ahead market, a binary variable i_t is introduced to restrict bidding behavior. It ensures that at each time step t, the model can either place a buy bid or a sell bid, but not both. This logic is implemented in Equations (7) and (8).

$$b_t^{buy} \leq i_t^{buy} \cdot (P^{pcc}) \qquad \forall t \in T \tag{7}$$

$$b_t^{sell} \leq \left(1 - i_t^{buy}\right) \cdot (P^{pcc}) \qquad \forall t \in T \tag{8}$$

Constraint (9) guarantees that the total selling bids submitted for each hour remain within the capacity limits of the interconnection between the producer and the power grid. The capacity limit of the interconnection is represented by parameter P^{PCC}.

$$b_t^{sell} + b_t^{UP} \leq P^{PCC} \qquad \forall t \in T \tag{9}$$

Constraint (10) guarantees that the total buying bids submitted for each hour remain within the capacity limits of the interconnection between the producer and the power grid.

$$b_t^{buy} + b_t^{DN} \leq P^{PCC} \qquad \forall t \in T \tag{10}$$

Constraint (11) ensures that bidding does not exceed the power plant's capacity. Parameter C^{PV} represents the solar production capacity and parameter E denotes the BESS's capacity.

$$b_t^{sell} + b_t^{UP} \leq C^{PV} + E \qquad \forall t \in T \tag{11}$$

Constraint (12) ensures that the combined bought power from the day-ahead market and sold power to down-regulating FCR-D market cannot exceed the battery's capacity. Meaning that all energy received from the grid, whether through bought electricity from the day-ahead market or resulting from down-regulation commitments, must remain within the limits of the BESS's capacity.

$$b_t^{buy} \leq E - b_t^{DN} \qquad \forall t \in T \tag{12}$$

Constraints (13) and (14) restrict the amount that can be bid to the FCR-D markets. Parameter P^{FCR} represents the maximum capacity that can be offered to the FCR-D markets. This model assumes that reserve capacity is provided by the BESS and thus the amount of possible capacity to bid to reserve markets is limited.

$$b_t^{UP} \leq P^{FCR} \qquad \forall t \in T \tag{13}$$

$$b_t^{DN} \leq P^{FCR} \qquad \forall t \in T \tag{14}$$

Constraints (15) and (16) represent the solar production at time t of scenario s. Constraint (15) enforces that the solar production p_{ts}^{PV} is at most the scenario-dependent solar availability $\hat{P}_{ts}$. Equation (16) balances the energy flows by ensuring that the total power generated, from solar and energy discharged from the battery, denoted by the nonnegative variable p_{ts}^{DIS}, minus the energy used to charge the battery, denoted by the nonnegative variable p_{ts}^{CHA}, equals the cleared day-ahead commitments. Delta captures the excess or deficit generation in scenarios s if the market commitments are not met.

$$p_{ts}^{PV} \leq \hat{P}_{ts} \qquad \forall t \in T, s \in S \tag{15}$$

$$p_{ts}^{PV} + p_{ts}^{DIS} - p_{ts}^{CHA} = \left(p_{ts}^{sell} - p_{ts}^{buy}\right) + \Delta_{ts} \qquad \forall t \in T, s \in S \tag{16}$$

Predicting renewable energy generation with complete accuracy for the next day is not feasible due to the variability and unpredictability of these sources. As a result, any deviation between the scheduled schedule and the actual power generation of the power plant creates power imbalances during operating hours. These imbalances occur as either a surplus or a shortage of power, depending on whether the plant produces more or less than expected.

Excess and deficit production, Δ_{ts}, are penalized in the objective function. Constraint (17) represents the sum of positive and negative imbalances by nonnegative variables Δ_{ts}^{+} and Δ_{ts}^{-}.

$$\Delta_{ts} = \Delta_{ts}^{+} - \Delta_{ts}^{-} \qquad \forall t \in T, s \in S \tag{17}$$

The approach to modeling battery's energy level used in equations (18)-(20) is similar to the one in [60]. Constraint (19) represent the battery's charge at time step t of the scenario s. Constraint (18) represent the battery's charge at the first time step of the scenario s and constraint (20) denotes the battery's charge at the final time step of the scenario s. Non-negative parameters η_{CHA} and η_{DIS} denote the charging and discharging efficiencies of the battery, and variable e_{ts} denotes the energy level in the BESS at time-step t in megawatts. The variables p_{ts}^{CHA} and $p_{ts}^{DIS} \geq 0$ denote the charge and discharge power. A BESS ties together decisions made on different days, as it can store energy. It is assumed that the battery must have 60% charge at the end of the day to reflect its influence on the decisions and profits of the following day. In this way, each day can be modelled as an independent optimisation problem. If such a constrain was not imposed the model would empty the BESS at the end of the day.

$$e_{ts} = 0.6 \cdot E + \eta_{CHA} \cdot p_{ts}^{CHA} - \frac{1}{n_{DIS}} \cdot p_{ts}^{DIS} \qquad \forall t = 1, s \in S \tag{18}$$

$$e_{ts} = e_{(t-1)s} + \eta_{CHA} \cdot p_{ts}^{CHA} - \frac{1}{n_{DIS}} \cdot p_{ts}^{DIS} \qquad \forall t \in T \backslash \{1\}, s \in S \tag{19}$$

$$e_{ts} = 0.6 \cdot E \qquad \forall t = 24, s \in S \tag{20}$$

Constraint (21) enforces that the battery's energy level, denoted by the non-negative variable e_{ts}, remains below the rated capacity of the energy storage system.

$$e_{ts} \leq E \qquad \forall t \in T, s \in S \tag{21}$$

Constraints (22) and (23) enforces that the energy storage system cannot be charged or discharged with more power than its rated power. Additionally, a binary variable, j_{ts}, ensures the battery cannot be charged and discharged simultaneously.

$$p_{ts}^{CHA} \leq j_{ts} \cdot P^{BAT} \qquad \forall t \in T, s \in S \tag{22}$$

$$p_{ts}^{DIS} \leq (1 - j_{ts}) \cdot P^{BAT} \qquad \forall t \in T, s \in S \tag{23}$$

Constraint (24) ensures that in, each scenario s, the energy storage system has at least the amount of energy required to fulfill the commitment in the up-regulating FCR-D market.

$$e_{ts} \geq \frac{1}{\eta_{DIS}} p_{ts}^{UP} \qquad \forall t \in T, s \in S \tag{24}$$

Constraint (25) ensures that in each scenario s, the energy storage system has space to store the amount of energy required to fulfill the commitment in the down-regulating FCR-D market.

$$e_{ts} \leq E - \eta_{CHA} p_{ts}^{DN} \qquad \forall t \in T, s \in S \tag{25}$$

4 Scenario generation

This section outlines the methodology for creating price predictions for the FCR-D markets. Scenarios for the day-ahead market, up- and down- regulation FCR-D markets, as well as for solar production, are also created for the optimisation model to account for price and production uncertainty. The scenarios are generated by adding a residual value to the prediction. Section 4.1 presents the scenario generation for the day-ahead market prediction. Section 4.2 outlines the method for creating predictions and generating scenarios for the up- and down-regulating FCR-D markets. Section 4.3 presents the scenario generation for the solar production prediction.

4.1 Day-ahead Market-Price Scenarios

The generation of day-ahead market price scenarios begins with a prediction for the day-ahead market price. This price prediction model originates from the SKM Market Predictor platform [64]. The model outputs a single prediction for the Finnish day-ahead market price with hourly granularity.

To capture uncertainty around this forecast, the historical deviations between past predictions and actual market outcomes is analyzed. These deviations, referred to as residuals, represent the errors made by the forecasting model. A distribution is then fitted to these residuals. The Python package Fitter [65] is used for this purpose, as it tests a wide range of distributions and selects the best fit. In this case, the best-fitting distribution for the forecast errors was found to be the dgamma distribution, with parameters $\alpha = 0.6096, \theta = 24.58, loc = -0.56$. This distribution is illustrated in Figure 5.

Once the residual distribution is known, scenarios are generated by sampling residual values from it. For each hour, a residual value is drawn from the dgamma distribution and added to the corresponding forecasted price. This process is repeated for as many times as the desired number of scenarios. Each resulting scenario represents a possible realization of future day-ahead market prices.

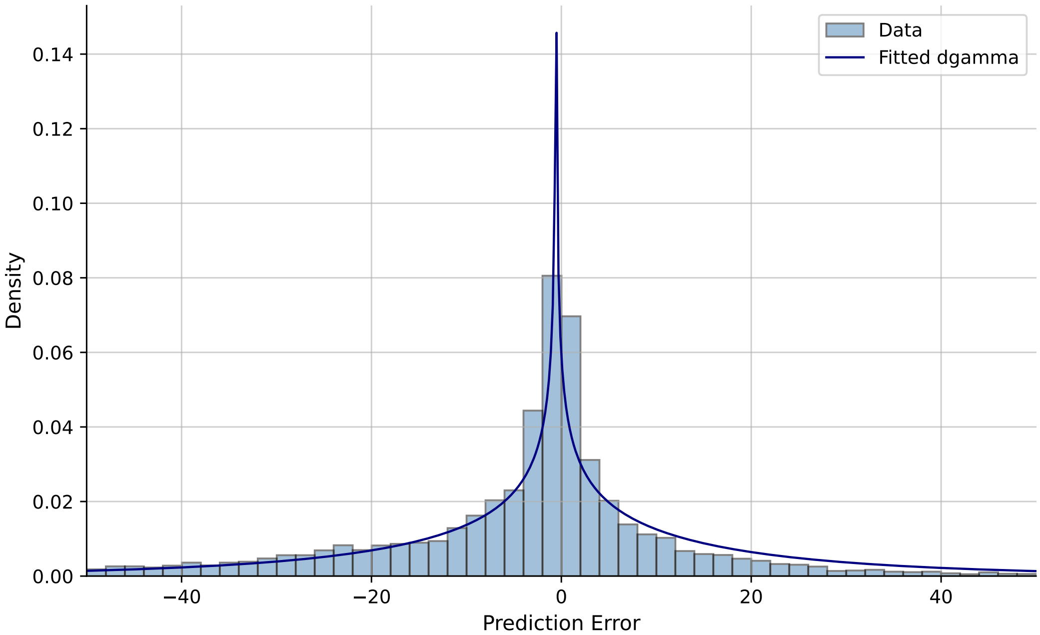

Figure 5: Fitter dgamma distribution for historical day-ahead market price prediction errors.

4.2 FCR-D Market-price Predictions and Scenarios

The prediction for the market price for FCR-D up and down markets are obtained by training an Extreme Gradient Boosting (XGBoost) regression model [66] using historical data from March 2024 to February 2025. Extreme Gradient Boosting regression model is a machine learning algorithm used to predict continuous outcomes. It works by building many decision trees one after another, where each new tree aims to correct the prediction mistakes made by the previous ones. This step-by-step improvement process is guided by gradient descent, which helps minimize prediction errors.

The features were selected based on factors expected to influence market prices and on information available prior to the FCR-D market gate closure. The chosen features to predict the market price for the XGBoost model are consumption prediction, lag 1-24 values for up- and down-regulating FCR-D market prices, renewable production prediction, non-renewable production, which is obtained by reducing renewable production from the production prediction, intraday trading transmission capacity between Finland and Estonia, Finland and SE1, and Finland and SE3 price zones. Information from markets that had gate closing time before FCR-D markets are also added as features. These features include the day-ahead market price, the bought volumes, and the marginal prices for the mFRR up and down markets. They also include the volume-weighted average price, traded volume, highest and lowest prices, and the last trade price from the first intraday auction market (IDA-1). Additionally, the hour, the day of the week, and the month are included as features. The features that were used and the sources are listed in Table 1.

The feature importances of the ten most important features are presented in Figure 6 and Figure 7 for the up- and down-regulating FCR-D market price predictions made with XGBoost, respectively. Feature importance represents which features have the most significant impact on a model's predictions. For a single decision tree, it is calculated based on how much each attribute's split point improves the performance metric, weighted by the number of observations the node is responsible for. These figures show that the load forecast for the following day is the most important feature for both price predictions, followed by the lag-1 prices. Some differences can be observed between the feature importances for the up- and down-regulating FCR-D prices, e.g., the renewable production prediction is more important in up-regulating FCR-D price prediction, while nonrenewable production is more important for down-regulating FCR-D price prediction. For the up-regulating FCR-D price prediction the importance score ranges from 6 to 408, the least important being the month. Similarly for down-regulating FCR-D price prediction the range is 8-397.

Table 1: Features and their data sources used in the XGBoost regression model for FCR-D market price predictions.

Feature	**Source**
Consumption prediction	Fingrid Open Data Portal
Lag 1–24 values of FCR-D up market prices	Fingrid Open Data Portal
Lag 1–24 values of FCR-D down market prices	Fingrid Open Data Portal
Renewable production prediction	Fingrid Open Data Portal
Non-renewable production	Fingrid Open Data Portal
Intraday trading capacity FI–EE	Fingrid Open Data Portal
Intraday trading capacity FI–SE1	Fingrid Open Data Portal
Intraday trading capacity FI–SE3	Fingrid Open Data Portal
Day-ahead market price	SKM Market Predictor
Bought volume in mFRR up market	Fingrid Open Data Portal
mFRR up market marginal prices	Fingrid Open Data Portal
Bought volume in mFRR down market	Fingrid Open Data Portal
mFRR down market marginal prices	Fingrid Open Data Portal
ID1 volume-weighted average price	SKM Market Predictor
ID1 volume	SKM Market Predictor
ID1 highest trade price	SKM Market Predictor
ID1 lowest trade price	SKM Market Predictor
ID1 last trade price	SKM Market Predictor
Hour	Fingrid Open Data Portal
Day of the week	Fingrid Open Data Portal
Month	Fingrid Open Data Portal

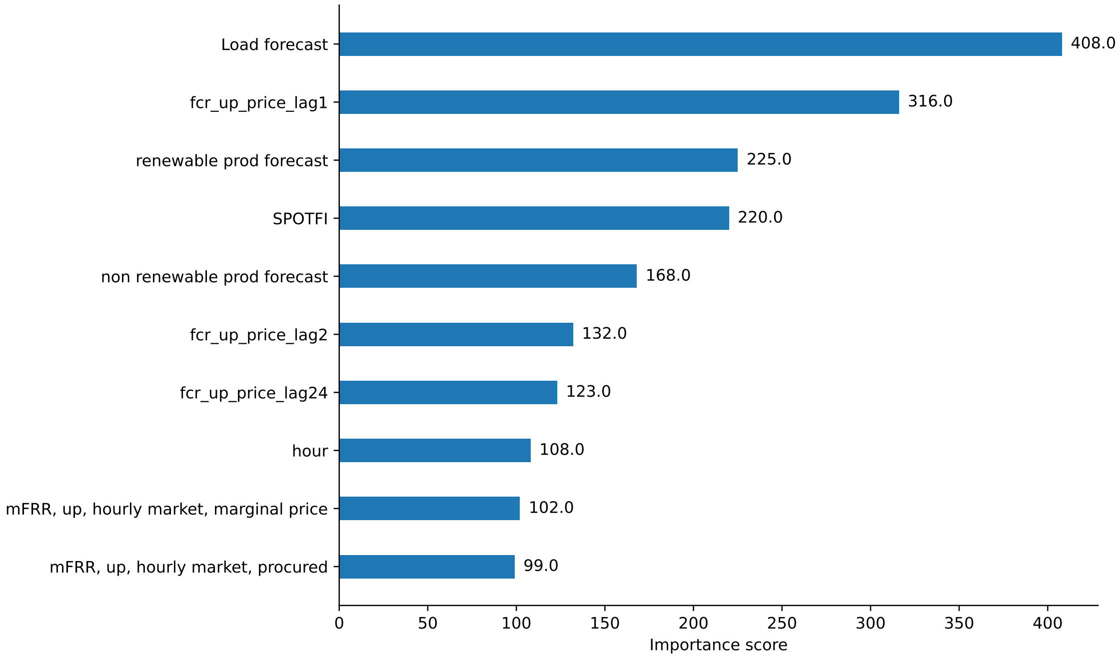

Figure 6: Feature importance for up-regulating FCR-D market price prediction.

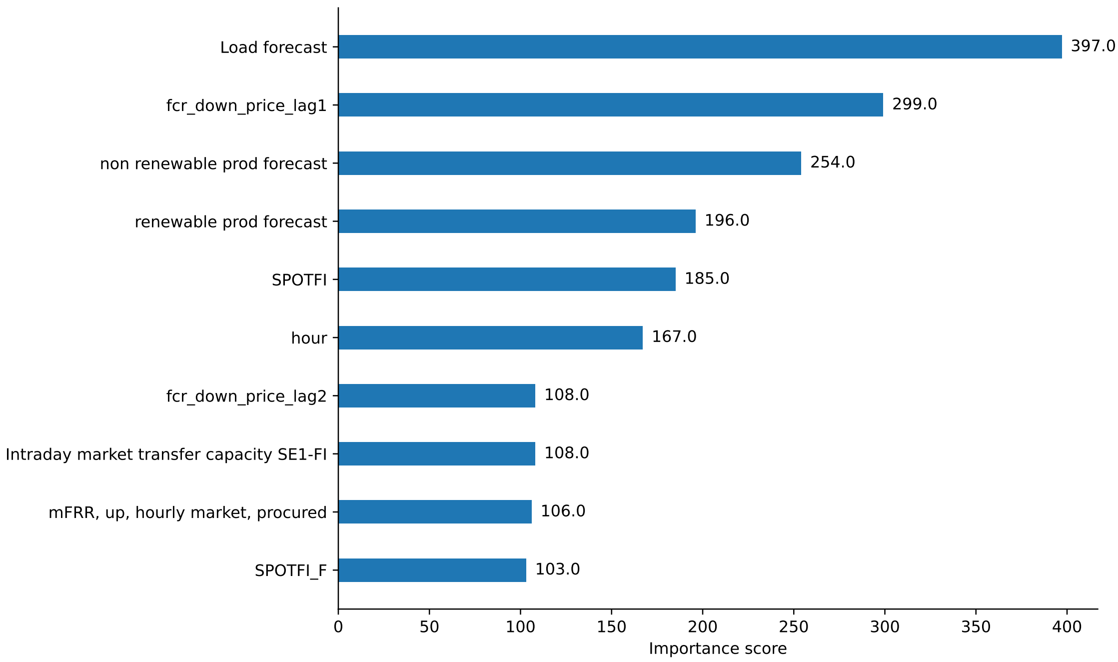

Figure 7: Feature importance for down-regulating FCR-D market price prediction.

Data from March 2024 to February 2025 was used to train the model. The training data had hourly granularity. A train-test split of 75/25, a learning rate of 0.1 and 100 estimators were applied. With these features, the R score for FCR-D down- and up-market price predictions were 0.781 and 0.710 respectively. The R value of 1 is the perfect correlation and 0 means that these is no correlations. Figure 8 shows the actual down-regulating FCR-D market price in blue and model predicted FCR-D down price in red. For these prediction indices the R value was 0.81. It can be seen that the prices are predicted relatively well by the model.

The R-score for FCR-D up price prediction is 0.710. Thus, the model predicts the prices fairly well. From Figure 9, it can be seen that for these 150 prediction indices the prediction was very accurate, with an R-value of 0.86. However, the prediction model occasionally struggles with predicting the height of price spikes.

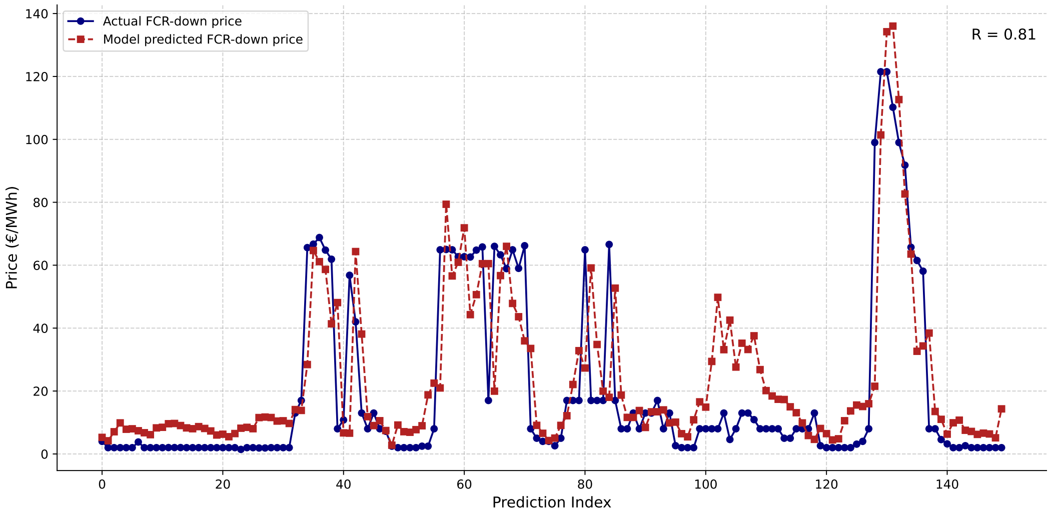

Figure 8: Down-regulating FCR-D market price prediction for 150 prediction indices.

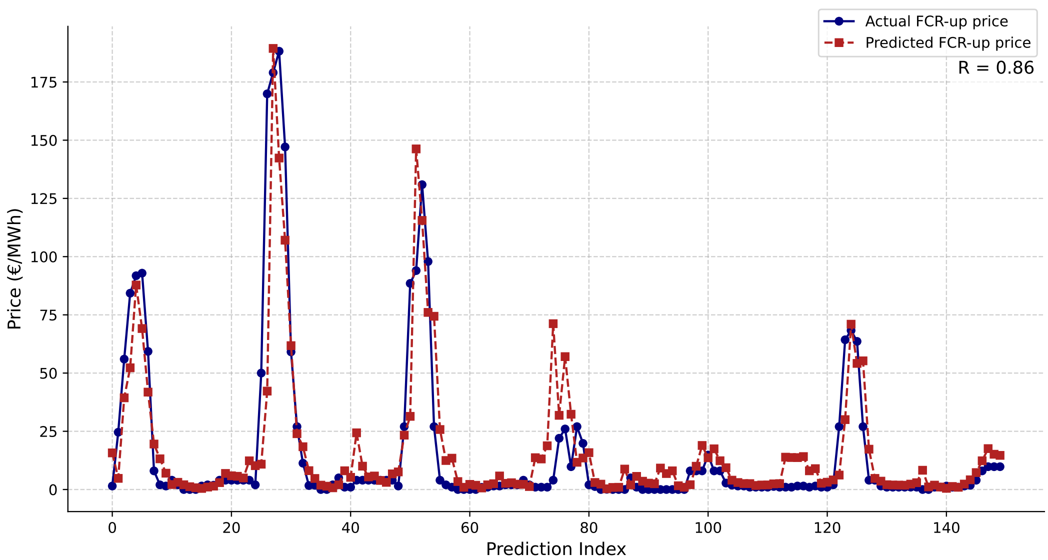

Figure 9: Up-regulating FCR-D market price prediction for 150 prediction indices.

After training the XGBoost models for the up- and down-regulating FCR-D market prices, they are used to produce hourly price forecasts for a given day. To generate a forecast for a specific day, the relevant input features, listed in Table 1, are provided to the models. Once the inputs are provided, the models outputs predicted hourly prices for up- and down-regulating FCR-D markets for the following day.

However, in order to account for uncertainty in these predictions and to generate realistic price scenarios for the model outlined in section 3, it is necessary to model the forecast errors. This is done by examining the historical residuals, the differences between the actual market prices and the model's predictions. A distribution is then fitted to these residuals with Python's Fitter package. Using the fitted distribution, residuals can be sampled and added to the predicted prices, thereby generating alternative plausible prices.

The best fitting distribution for the historical residuals for down regulating FCR-D price can be seen in Figure 10. The best fitting distribution for FCR-D down residuals was a skewcauchy distribution with parameters $\alpha = 0.328, \theta = 4.647, loc = 1.02$. For the up-regulating FCR-D market prices, the prediction residuals are best described by a t-distribution. The fitted distribution parameters are $\tau = 2.43, \nu = 1.07, \mu = 2.52$, as shown in Figure 11

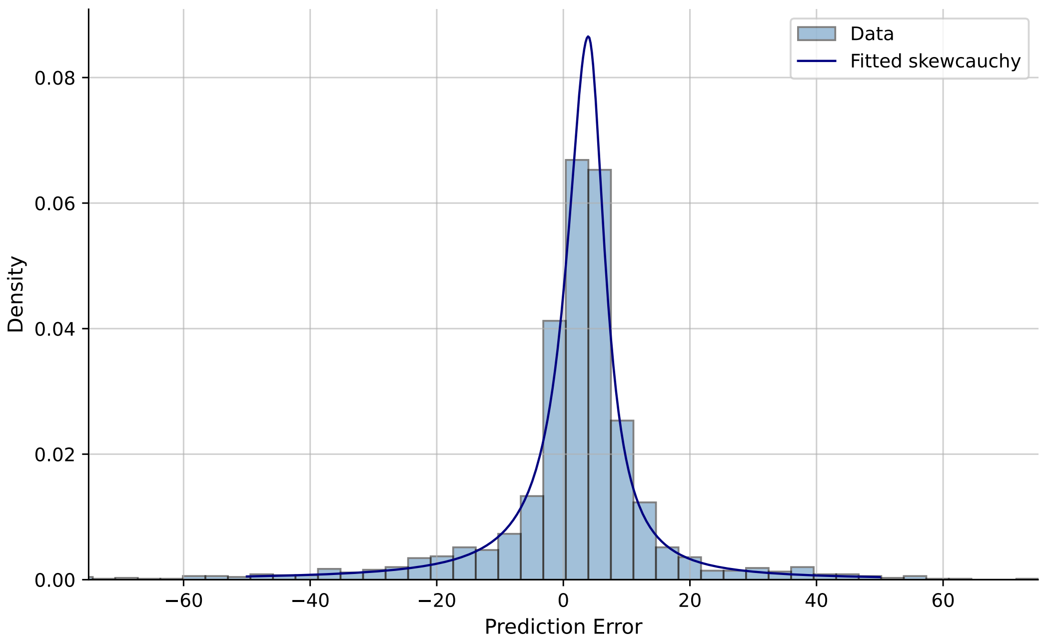

Figure 10: Fitted skewcauchy distribution to down-regulating FCR-D price prediction errors.

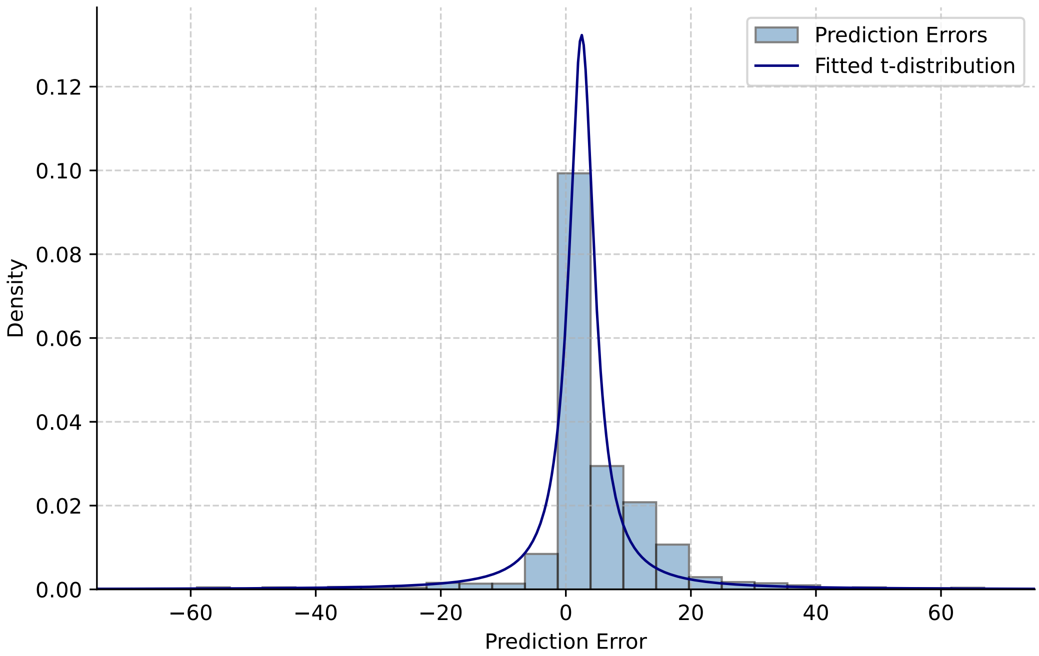

Figure 11: Fitted t-Distribution to up-regulating FCR-D price prediction errors.

Once the error distributions are fitted, the scenario generation process proceeds as follows. For each hour, a residual value is sampled from the fitted distribution and added to the model's predicted price. This is repeated for as many times as the number of desired scenarios. Each set of sampled residuals, when added to the forecast, results in one scenario that reflects a plausible realization of future prices under uncertainty.

4.3 Solar Production Scenarios

Solar production, as all renewable production, is inherently intermittent. Each hour, the producer faces production uncertainty. Factors affecting solar production are, for example, solar irradiance, weather conditions such as cloud cover and temperature, and the time of the day and the year. Thus, making accurate predictions is challenging. To account for this uncertainty in the model, scenarios for solar production are generated by introducing variation into the solar power forecast. Specifically, residual values, representing historical prediction errors, are added to the forecast to produce a set of plausible alternative production outcomes.

Access to prediction data for a specific solar power plant was not available. Therefore, solar production prediction data provided by Fingrid, covering the entire country, was used. The solar prediction was adjusted to the size of the modelled solar plant. The forecast is updated daily at noon and provides predictions for the following 72 hours. Similarly, actual measured production data from a specific solar power plant was not available. As a substitute, Finland's historical solar production data from ENTSO-E was used and scaled to reflect the size of the modelled solar plant. It should be noted that this data does not include any curtailment, so all production values are assumed to be unconstrained.

Solar production follows a strong daily cycle, typically peaking around midday and dropping to zero during the night. As a result, the magnitude and variability of prediction errors also vary by hour. For example, the uncertainty during midday, when production is high, can be larger in absolute terms than during the early morning or late evening when production is minimal. To reflect this time-dependent behavior of uncertainty more accurately, a separate residual error distribution for each hour of the day is constructed. This means that when generating production scenarios, the model samples residuals from the distribution corresponding to the specific hour being predicted. For instance, a residual added to a hour 10 forecast comes from the distribution fitted to historical prediction errors at hour 10. This approach allows the model to better capture the characteristics of production uncertainty throughout the day and avoids applying unrealistic residuals. The residual distribution for each hour is presented in Table 2.

Table 2: Best-fit distributions and parameters for each hour.

Hour	Distribution	Parameters
0	johnson s_u	a = 5.80, b = 0.50, loc = 1.67e-05, scale = 1.70e-08
1	weibull_max	c=0.36, loc=9.53e-29, scale=0.05
2	skewcauchy	a=-0.94, loc=-2.19e-07, scale=0.01
3	crystalball	beta=5.17e-07, m=1.27, loc=0.00, scale=1.89e-09
4	levy l	loc=0.02, scale=0.07
5	weibull_max	c=0.28, loc=3.57e-28, scale=2.11
6	gausshyper	a=1.63, b=0.57, c=1.03, z=0.73, loc=-9.46, scale=9.46
7	mielke	k=2.70, s=221.88, loc=-8.76, scale=8.72
8	laplace_asymmetric	kappa=2.43, loc=-0.39, scale=0.66
9	genhyperbolic	p=0.79, a=0.05, b=-0.02, loc=-0.08, scale=0.03
10	gennorm	beta=0.83, loc=0.34, scale=0.49
11	laplace	loc=0.70, scale=0.77
12	dgamma	a=1.53, loc=0.90, scale=0.56
13	laplace asymmetric	kappa=0.40, loc=1.44e-08, scale=0.60
14	genhyperbolic	p=0.74, a=8.93e-12, b=8.25e-12, loc=-6.07e-13, scale=1.29e-12
15	johnsonsu	a=-1.25, b=0.12, loc=-3.53e-09, scale=9.97e-09
16	cauchy	loc=0.00, scale=0.02
17	loglaplace	c=0.77, loc=-9.42e-27, scale=0.02
18	kappa3	a=2.26, loc=-7.32e-09, scale=0.01
19	gilbrat	loc=-0.00, scale=0.00
20	wald	loc=-0.00, scale=0.00
21	betaprime	a=0.13, b=2.01, loc=0.00, scale=0.40
22	betaprime	a=0.13, b=2.01, loc=0.00, scale=0.40
23	genextreme	c=1.29, loc=-0.00, scale=0.00

5 Case study

In this section, the model introduced in Section 3 is applied to evaluate how different bidding strategies affect the profits of a hybrid power plant consisting of solar power and a BESS, operating in the day-ahead and up- and down-regulating FCR-D markets. The model is run for 30 chosen days with a range of price strategies to identify which yield the highest profits. The analysis considers seasonal variation in profitability, examines the operational behavior of the BESS, and compares best pricing strategies to a naive baseline. Finally, the effect of the energy storage system's capacity on the optimal bidding strategy and profits is assessed.

5.1 Input Values and Process of Running the Model

The model is run with different price strategies for 30 days, all spaced 10 days apart. This time period covers the period from February 3^{rd} 2024 to December 17^{th} 2024. As input for the model, predictions for the day-ahead, up-regulating FCR-D, and down-regulating FCR-D market prices, as well as for solar production, are generated. For each of the 30 days, 10 scenarios based on these predictions were produced. In the model, the 10 scenarios were assumed to be equiprobable. The scenario generation process was outlined in Section 4. Other input parameters include the beta values that were computed based on the predicted price scenario and the price strategies. Charging and discharging efficiencies of 0.93 and 0.97, respectively, are used, resulting in a 0.902 round-trip efficiency, which is common for lithium-ion batteries [27]. The modelled power plant has a battery with a 10 MWh energy capacity and a 10 MW power rating which is the same as the maximum bid capacity to FCR-D markets. The solar park's capacity is 20 MW and the interconnection capacity is 30 MW.

To assess how different pricing strategies affect profits from a single day, a range of realistic prices is analyzed for each of the three markets. A single price strategy consists of three bid offer prices, a day-ahead, up-regulating FCR-D, and down-regulating FCR-D prices, respectively. Prices ranging from 0 €/MWh to 4 €/MWh were chosen for day-ahead bids and prices from 0 €/MWh to 10 €/ MWh for up- and down-regulating FCR-D bids. Bid prices of 0-4 €/MWh were chosen for the day-ahead bid because the marginal cost of solar power is effectively zero. Additionally, although the average day-ahead price in 2024 was 38.87 €/MWh, approximately 25% of the hours had prices below 4 €/MWh, which justifies lower bids to day-ahead market. Market regulation requires power producers to bid at their marginal cost or the opportunity cost. Thus, analyzing non-zero bid prices is justified because energy can be stored in the BESS and the company is also participating in reserve markets. Therefore, selling energy at low day-ahead prices may mean foregoing more valuable opportunities in reserve markets or during peak-price periods in day-ahead markets, which can be further capitalized through load-shifting. A higher bid price ensures that the bid is cleared on the day-ahead market when it exceeds the opportunity cost of these alternative revenue streams.

Bid prices between 0 €/MW and 10 €/MW were chosen for both up- and down-regulating FCR-D markets since it is likely that bids with these prices will be cleared in the market regularly. This choice was motivated by the fact that in 2024, the average FCR-D market clearing prices were 16.56 €/MW for down-regulation and 17.31 €/MW for up-regulation. However, a substantial share of hours, 68.15% for down-regulation and 71.56 % for up-regulation, cleared below 10 €/MW. Bidding at higher price levels would significantly reduce the likelihood of being cleared to these markets.

A set of pricing strategies was created by enumerating all combinations of bid prices for the day-ahead, up-regulating, and down-regulating FCR-D markets within the ranges described above. With 5 day-ahead bid prices, and 11 bid prices for both up- and down-regulating FCR-D, this procedure resulted in 5 x 11 x 11 = 605 pricing strategies. After generating the price strategies, which represent the prices used for bidding in the model, beta values are generated to account for uncertainty in market clearing. This is done by assessing whether the bids made with each price strategy would be accepted based on the market price predictions developed in Section 4. Betas are computed as described in Section 3 with constraint (2). Beta is one if the bid is cleared and otherwise beta is zero.

The model is run for 30 days of data and for each day the model is run for each of the 605 price strategies. For each strategy and day, the model is run twice: first to determine the optimal bidding quantities under uncertainty, and then to evaluate the resulting profit through an out-of-sample analysis. This makes it possible to find which pricing strategy results in the highest profit for each of the selected days. The process of running the model for one day and one price strategy is illustrated in Figure 12. In the first run, predictions for day-ahead market prices, up-regulating and down-regulating FCR-D market prices, and solar production are used to determine the optimal bid quantities for each market under uncertainty. In the second run, the profit resulting from the strategy obtained in the first run is analyzed. This is done by an out-of-sample analysis, where the model is run with values that are not included in the data set used in the optimisation of the model. Actual prices for day-ahead and up- and down-regulating FCR-D markets and the realized solar production are used. In the second run, the bids obtained from the first run are fixed, and new beta values are computed using the actual market prices, as previously described. During the out-of-sample analysis, the model optimizes the operation of the system to fulfill the commitments with minimal imbalances. There are often at least a few hours where imbalances are unavoidable during the day, which is common with variable renewable energy. However, the model minimizes imbalances by modifying both the schedule and the amount of energy the battery charges and discharges.

After the second run, once the imbalance quantity is acquired, the strategy given by the first run can be assessed. This is done by computing profits from each market by multiplying the cleared bid quantity with the corresponding market price. The imbalance settlement costs for the day in question are then calculated and subtracted from the profits. The imbalance settlement costs were retrieved from Fingrid's open data sets. Possible activation fees received by the company are not considered since Fingrid does not share data on FCR-D activations. Thus, it is assumed that the FCR-D commitments are not activated in the analysis of the results.

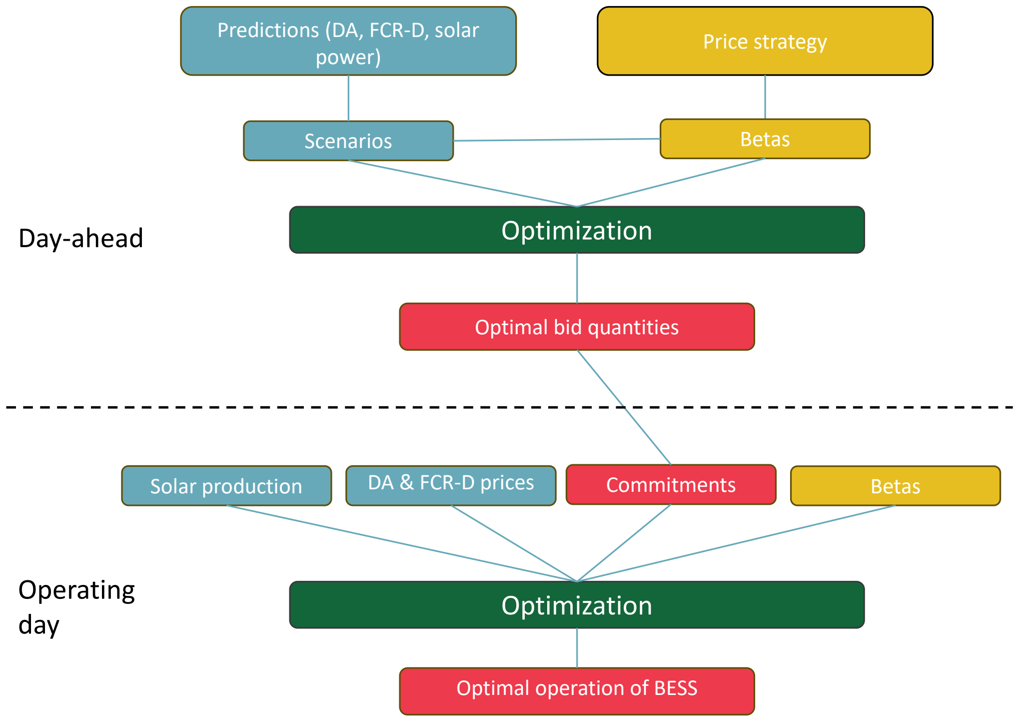

Figure 12: Illustration of the process of running the model for one price strategy and for one day.

5.2 Optimal bidding strategy for the observed 30 days

Breakup of the results from running the model for the chosen 30 days, as described before, are presented in Table 3. The table presents how the model allocates bids across different markets, showing the best price strategy, total profit, the bought and sold power from and to day-ahead market, and capacity bid to down- and up- regulating FCR-D markets for each day. Seasons of the year are separated by the dash lines.

Out of the chosen 30 days, only three days' best price strategy out of the observed price strategies was the naive one. The naive price strategy refers to bidding with the marginal price, which is effectively zero, on all the observed markets. In the best price strategy for each day, the day-ahead bid price took values between 0-4 €/MWh, which was the tested price range for the day-ahead market prices. Out of the chosen 30 days, 10 had bid price of 4 €/MWh, 10 had bid price of 2 €/MWh, 7 had bid price of 0 €/MWh and the remaining 3 had bid price of 1 €/MWh for the day-ahead market. Bid prices for both up- and down-regulating FCR-D markets range from 0 €/MW to 10 €/MW.

In the optimum strategy, the company operates on all of the considered markets on every day, except for one day when the company only sells power to day-ahead market and capacity to down regulating FCR-D market. The total amount of sold capacity to the up- and down regulating FCR-D markets were almost 3000 MW for each. The total power sold to the day-ahead market was 1965 MWh. In the optimum strategy the company buys power from the day-ahead market on 12 days. The amount ranges from under a megawatt to a bit over 20 megawatts. The most common amount to buy was 10 MWh, which equals to one full charge of the BESS.

Table 3: Price strategy, total profit and the bid quantities to the observed markets. A price strategy consists of bids to day-ahead market (€/MWh), up- and down-regulating FCR-D markets (€/MW).

Price Strategy	Total profit (€)	DA buy (MWh)	DA sell (MWh)	FCR-D down (MW)	FCR-D up (MW)
(4.0, 4.0, 10.0)	5578.82	0.000	60.309	142.290	70.657
(4.0, 0.0, 0.0)	7014.77	0.000	66.558	131.780	101.506
(4.0, 0.0, 0.0)	7728.25	0.000	32.942	144.137	101.360
(2.0, 6.0, 10.0)	20515.38	0.000	14.113	131.841	88.391
(0.0, 0.0, 0.0)	10384.82	0.000	83.785	160.408	76.359
(4.0, 3.0, 3.0)	7091.77	0.000	103.107	79.997	94.628
(4.0, 0.0, 0.0)	3766.49	0.000	96.189	155.280	72.433
(2.0, 6.0, 10.0)	15514.49	10.000	46.235	34.884	188.656
(2.0, 6.0, 10.0)	17552.14	0.000	111.747	3.021	196.639
(2.0, 2.0, 2.0)	29867.36	0.000	130.997	16.311	217.106
(4.0, 3.0, 0.0)	6678.78	0.000	145.366	91.235	100.799
(0.0, 2.0, 0.0)	2223.98	20.000	62.700	113.656	82.631
(1.0, 4.0, 4.0)	4555.46	20.753	60.283	33.656	113.951
(0.0, 0.0, 0.0)	4617.74	10.000	140.133	99.257	142.582
(2.0, 3.0, 0.0)	3513.78	0.753	74.374	54.420	153.250
(2.0, 7.0, 0.0)	4850.70	10.000	66.909	116.129	110.361
(2.0, 6.0, 10.0)	7564.69	10.000	18.841	21.532	190.146 9
(2.0, 9.0, 0.0)	7621.15	0.000	89.380	146.712	0.000
(0.0, 0.0, 0.0)	4408.51	25.699	58.926	112.263	109.509
(0.0, 2.0, 2.0)	4742.59	15.699	82.215	88.602	123.093
(4.0, 0.0, 3.0)	5185.00	0.000	69.437	83.606	62.253
(4.0, 0.0, 0.0)	9990.78	10.000	33.950	98.801	136.590
(4.0, 0.0, 2.0)	4052.06	15.691	35.488	72.950	137.767
(2.0, 0.0, 7.0)	8564.94	0.000	38.359	133.548	101.748
(0.0, 10.0, 2.0)	3408.36	4.301	50.509	164.302	19.400
(3.0, 8.0, 2.0)	10125.23	0.000	35.340	157.848	49.179
(1.0, 2.0, 5.0)	7358.49	0.000	50.608	68.602	14.453
(0.0, 10.0, 2.0)	11197.06	0.000	30.376	80.624	58.200
(4.0, 0.0, 0.0)	1753.76	0.000	31.961	159.478	64.199
(2.0, 3.0, 9.0)	2434.52	0.000	43.450	81.158	14.625
Total	239861.85	152.90	1964.59	2978.33	2992.47

Table 4 presents the breakup of the profits for the chosen 30 days. Moreover, it presents how the profits are divided between seasons. The total profit, out of which imbalances were reduced, was 239 861 €. Approximately 21.77 % of the profit came from the day-ahead market, around 46.30 % came from up regulating FCR-D market and around 31.92% came from down-regulating FCR-D market. Since the capacity sold to up- and down-regulating FCR-D markets were about the same, this result implies that the model was able to capture better prices from the up-regulating FCR-D market than from the down-regulating FCR-D market.

Table 4: Seasonal breakdown of day-ahead, up-regulating FCR-D profit, and down-regulating FCR-D profit.

Season	**DA Profit (€)**	**FCR-D down (€)**	**FCR-D up (€)**
Spring	14 143.26	32 090.73	15 846.29
Summer	16 673.42	3 204.27	56 514.52
Autumn	14 348.57	17 030.20	21 116.16
Winter	7 051.00	24 244.07	17 599.34
Total	**52 216.25**	**111 076.31**	**76 569.27**

5.3 Comparing Best Pricing Strategies to a Naive One

To understand how much profits can be increased Table 5 presents daily profits that the company would have obtained with the naive strategy and with the best pricing strategy. Moreover, the absolute and perceptual differences between the two are presented on a daily level. Out of the 30 days, on 22 days there was an increase in profits when the best pricing strategy was used.

The biggest increase between an optimal price strategy for a day and the naive (0.0,0.0,0.0) strategy was on 30.06.2024 when the percentage increase was 124.12% and absolute increase was 2522.84 €. The average daily increase out of the observed days was 11.40%. The total profit from the 30 days was 5.58% better with the optimized price strategies than what it would have been if the naive strategy was used.

Table 5: Comparison in profits between naive and best pricing strategy with absolute and percentual differences of the profits.

Day	Naive strategy profit (€)	Best strategy profit (€)	Absolute difference (€)	% Difference
1	5498.72	5578.82	80.09	1.46
2	7014.77	7014.77	0.00	0.00
3	7728.25	7728.25	0.00	0.00
4	19800.11	20515.38	715.26	3.61
5	10384.82	10384.82	0.00	0.00
6	7054.13	7091.77	37.64	0.53
7	3766.49	3766.49	0.00	0.00
8	14863.12	15514.49	651.37	4.38
9	16466.73	17552.14	1085.41	6.59
10	29867.36	29867.36	0.00	0.00
11	6253.84	6678.78	424.94	6.79
12	1612.35	2223.98	611.62	37.93
13	2032.63	4555.46	2522.84	124.12
14	4617.74	4617.74	0.00	0.00
15	3453.76	3513.78	60.01	1.74
16	4511.09	4850.70	339.61	7.53
17	7500.10	7564.69	64.59	0.86
18	7220.05	7621.15	401.10	5.56
19	4408.51	4408.51	0.00	0.00
20	4380.45	4742.59	362.14	8.27
21	3977.07	5185.00	1207.93	30.37
22	9919.31	9990.78	71.46	0.72
23	3789.24	4052.06	262.82	6.94
24	8257.88	8564.94	307.06	3.72
25	3048.63	3408.36	359.72	11.80
26	9489.99	10125.23	635.24	6.69
27	5649.22	7358.49	1709.27	30.26
28	11154.90	11197.06	42.15	0.38
29	1753.76	1753.76	0.00	0.00
30	1718.62	2434.52	715.90	41.66

5.4 The Effect of Seasons on the Profit

Season affects market prices, power consumption, and generation. In Finland, winter brings high electricity demand due to heating and low solar output, leading to higher day-ahead prices, while summer sees lower demand and abundant hydro and solar generation, often resulting in lower or even negative prices. Wind power generation is often higher in winter, and hydropower peaks during spring. In the FCR-D markets, down-regulation prices peak in spring (22.04 €/MWh on average during 2024) and are lowest in summer (5.39 €/MWh on average during 2024). On the other hand, up-regulation prices are highest in summer (36.03 €/MWh on average during 2024) and lowest in winter (9.03 €/MWh on average during 2024), reflecting seasonal differences in flexibility and reserve availability. Therefore, relying on a single price strategy for the entire year may be suboptimal.

For the purposes of this modelling, seasons are defined as follows: spring spans from March to early May, summer from May to the end of July, autumn from August to the end of October, and winter includes November through February. This classification is chosen to reflect solar production, which peaks in June, rather than adhering to traditional definitions.

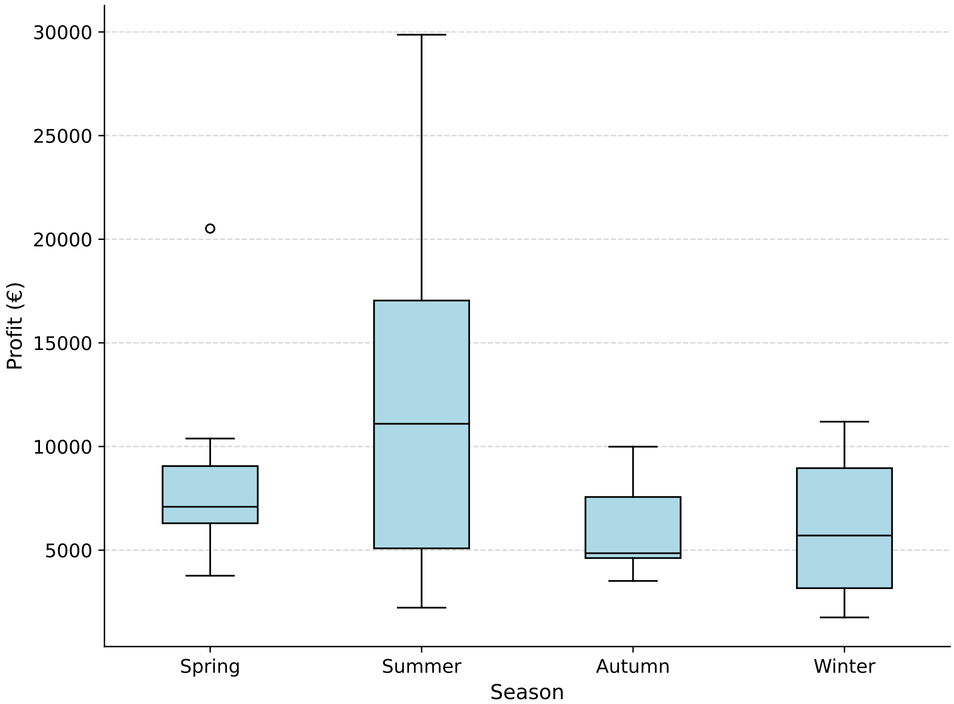

Figure 13: Box plot of seasonal average profits.

Figure 13 contains a box plot where the horizontal line in the middle of the box represents the median profit. The area between the bottom edge of the box and the median corresponds to the 25^{th} to 50^{th} percentile, while the area between the median and the upper edge represents the 50^{th} to 75^{th} percentile. Values between the upper and lower whiskers fall within the typical range of the data, excluding outliers, which are visualized as circles.

From Figure 13, it can be seen that profits are highest during summer and lowest during autumn. In addition, the variation in profits is greatest during the summer. The least variation in profits occurs during spring and autumn. Table 6 shows the total profit of the company with the naive strategy and with the best price strategy in different seasons. The absolute increase and percentual increase is also stated in the Table. It shows that the percentual increase in total profit on summer is the highest with 7.44% increase. The second highest increase was in the total profits from winter when the percentual increase was 6.49%.

Table 6: Seasonal comparison of naive and best price strategies.

Season	**Naive strategy (€)**	**Best strategy(€)**	**Absolute Difference (€)**	**% Difference**
Spring	61 247.29	62 080.30	833.01	1.36%
Summer	71 095.99	76 392.21	5 296.22	7.44%
Autumn	50 088.08	51 894.94	1 806.86	3.61%
Winter	49 762.24	52 994.42	3 232.18	6.49%

5.5 Operation of BESS

During the day-ahead stage, the model creates a schedule for charging and discharging so that bids to the markets can be fulfilled. During the operating day stage, the BESS can reschedule charging and discharging based on cleared bids and specified solar production. The BESS can adapt its behavior in several ways on the operating day: it can initiate charging or discharging during hours that were originally inactive, adjust the amount of energy charged or discharged, or even perform the opposite of the day-ahead plan, for example, discharging when charging was scheduled, or vice versa. These operational adjustments enable the BESS to respond to deviations between predicted and actual solar generation, thereby minimizing imbalances.

Figure 14 and 15 illustrate how the BESS adapts its operation on the operating day compared to the original day-ahead plan. In Figure 14, the charging schedule shows that while the day-ahead plan scheduled charging during specific hours, the operating day behavior differs both in timing and magnitude. For example on hour 5, the BESS is charging, which was not planned in the day-ahead schedule and on hour 7 the charging power is 3 instead of the 10 that was originally planned. Similarly, Figure 15 presents the discharging schedule, where the operating day actions deviate from the planned discharging hours and quantities.

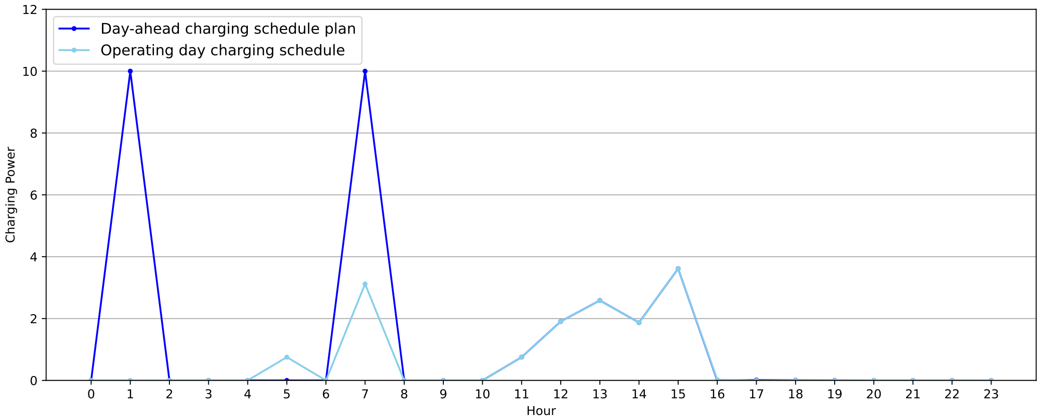

Figure 14: Day-ahead charging schedule plan in dark blue and operating day charging schedule in light blue.

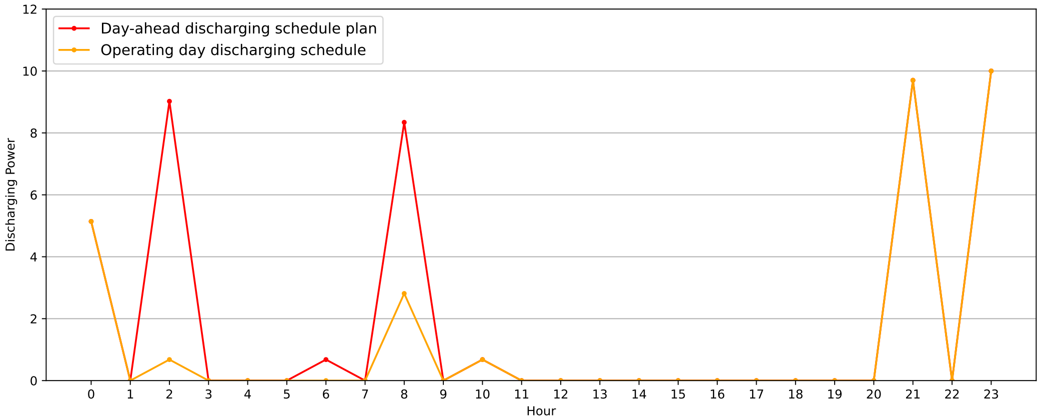

Figure 15: Day-ahead discharging schedule plan in red and operating day discharging schedule in orange.

5.6 Seasons Effect on the Operation of the Hybrid Power Plant

The operation of the BESS varies by season. Since the company operates a solar power plant, solar production fluctuates throughout the year, which in turn affects how the BESS is operated. Additionally, as previously mentioned, electricity demand and consumption, and consequently market prices, also change with the seasons. The average operation of the BESS during different seasons are presented in Figures 16, 17, 18 and 19 for spring, summer, autumn and winter respectively. Each figure has charging power in orange, discharging power in blue, bought power from day-ahead market in green and solar power production in gray. Each figure has different scale on y-axis. Due to the modeling choice represented with constraints (18) and (20), it is assumed that the BESS' state of charge is 60% at the end of the day, which affects the average charging and discharging values on that hour.

Figure 16 shows the average charging schedule during spring. The BESS typically discharges during the early hours of the day and begins charging more actively from around 7 a.m. until approximately 3 p.m. This pattern reflects load-shifting behavior: the BESS charges during the daytime, when solar production is higher and market prices are generally lower, and discharges later in the afternoon (around 4–5 p.m.), when solar production ceases and demand, and thus prices, tend to rise. In spring, it is also common for the BESS to discharge in the evening. During the observed spring days, the company did not purchase power from the day-ahead market to charge the BESS.

The average charging schedule during summer is shown in Figure 17. In summer, solar production is at its peak, and the BESS is used more. Compared to spring, the BESS is charged more earlier in the day. In addition to charging from solar, power is also purchased from the day-ahead market during the day and evening when prices are lower, allowing for discharge at later hours when higher prices can be captured. As in spring, the BESS performs load-shifting throughout the summer.

Figure 19 presents the average BESS operation schedule during autumn. Compared to spring and summer, the charging and discharging pattern aligns more closely with the solar production curve. The BESS typically discharges around 4 p.m., as solar generation begins to decline, indicating that load-shifting is also taking place during autumn. In the evening hours, when solar production is no longer available, the BESS is more frequently charged with power purchased from the day-ahead market than during the spring and summer months. Finally, Figure 19 presents BESS's average operation during winter. The operation appears more stochastic and does not follow the solar production curve, which is considerably lower during the winter months. Charging typically occurs around midday and afternoon, while discharging is more common during the evening.

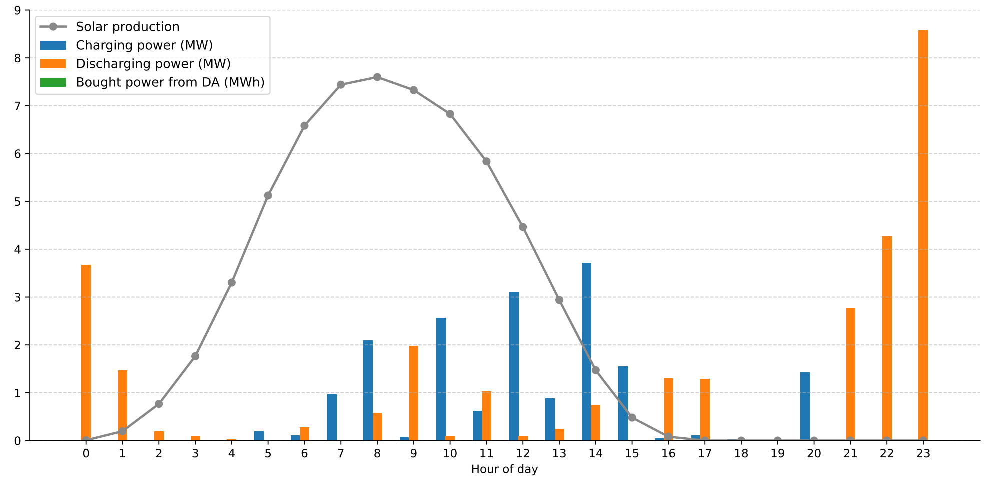

Figure 16: Average operation of the hybrid power plant during spring.

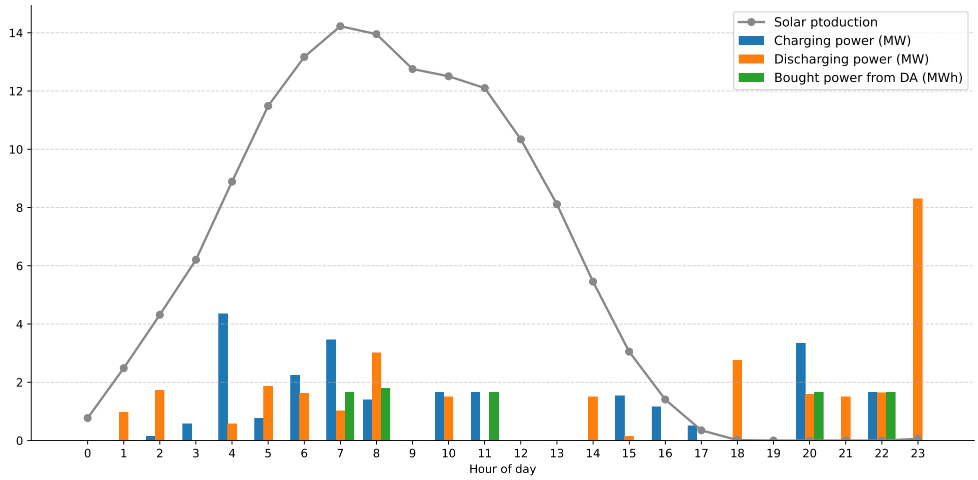

Figure 17: Average operation of the hybrid power plant during summer.

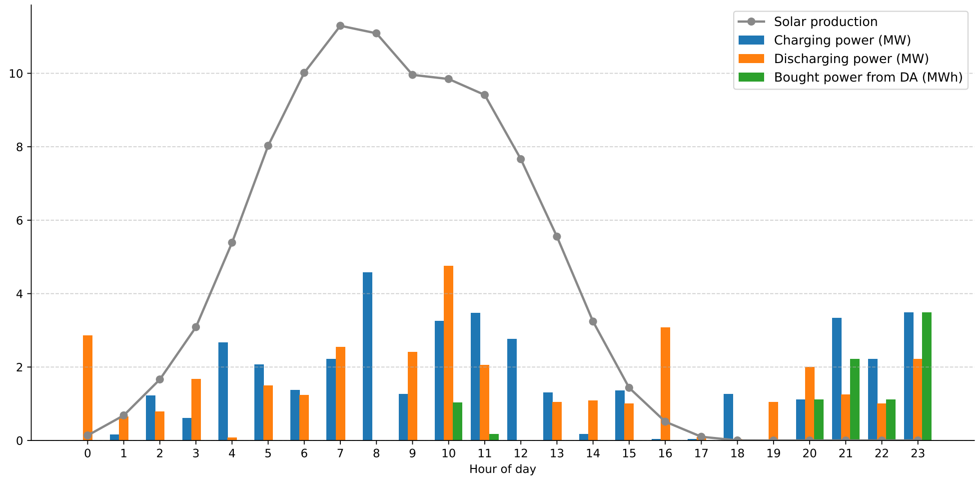

Figure 18: Average operation of the hybrid power plant during autumn.

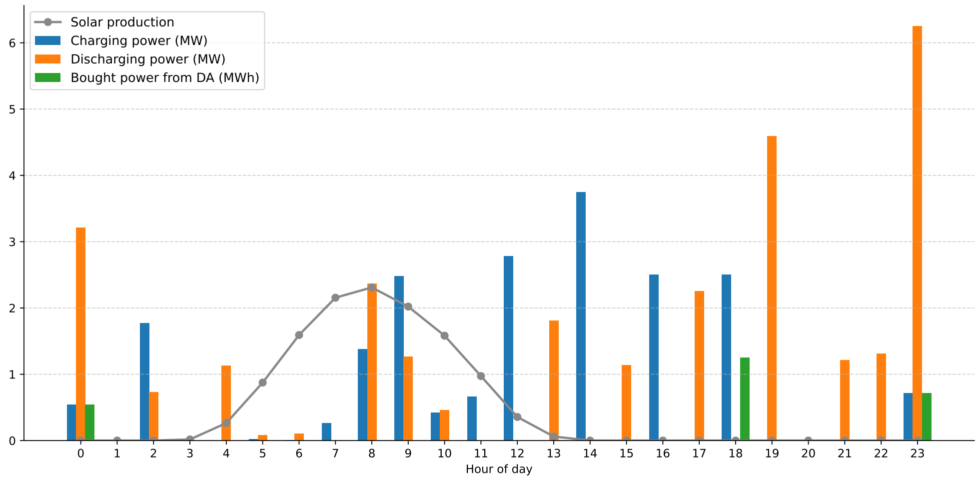

Figure 19: Average operation of the hybrid power plant during winter.

A summer day is used to illustrate BESS operation during the season when solar power production is at its highest and most of the profit is generated. While average values are presented in Figure 17, deeper insight into BESS operation during high-activity periods can be gained by examining a specific summer day, as important variations in charging and discharging behavior may be obscured by the averaging process. Although Figure 20 represents just a single day, it is indicative of the typical BESS operation pattern observed throughout the summer.

On the observed day, the BESS begins by charging with power purchased from the day-ahead market and discharges it in the following hour. As solar production increases, the BESS charges again and discharges on hour 5. Later in the day, another charge–discharge cycle occurs, by using power from the day-ahead market. Additionally, the BESS performs load-shifting by charging at 3 p.m. and discharging at 4 p.m.

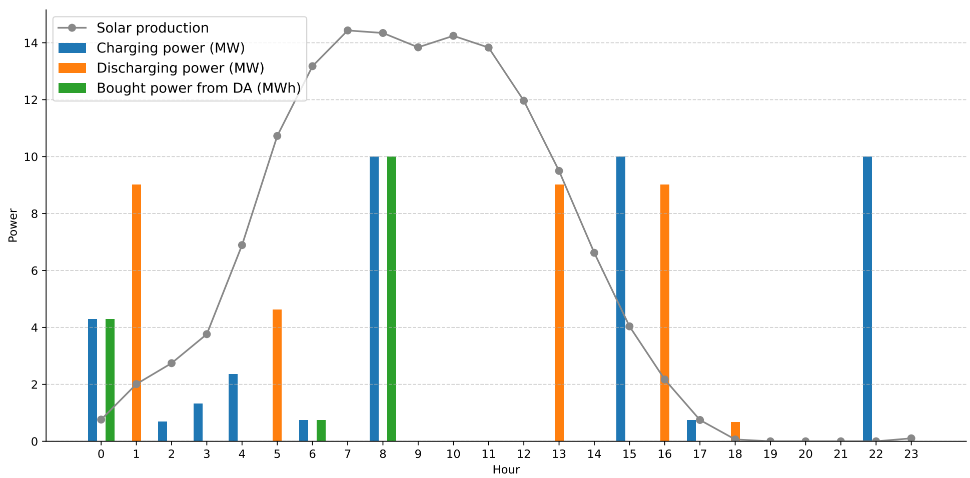

Figure 20: A battery's operation schedule presented on a summer day.

5.7 Effect of Battery Capacity on Optimal Bidding Strategy

To analyze how profits and best price strategies vary with different BESS capacities, the model is run for the same day using battery capacities ranging from 1 to 20 MW. The profits are then evaluated using the optimal pricing strategy for each battery capacity. While results are shown for a single day, similar increases in profit and changes in the optimal bidding strategy were observed across other days as well.

The results are presented in Table 7. The table presents the profit, increase in profit compared to a one size smaller BESS and the optimal price strategies for each battery size. It can be seen that the profits increase linearly with the size of the battery. However, the increase is a bit steeper with BESS sizes 1-5 MW. The increase in profit per 1 MW additional battery is in range 377.13-543.25 € for battery sizes 1 - 20 MW and the average increase in profit is 424.00 €/MW for the observed day. From Table 7 it can also be seen that optimal bid prices change only slightly when battery capacity increases. The down-regulating FCR-D bid price stays constant at 3.0 €/MW regardless of the battery capacity. Similarly, the day-ahead bid price does not change as the battery capacity increases. The up-regulating FCR-D bid price changes slightly with battery capacities. It alternates between 0 €/MW and 2 €/MW.

The payback period for different battery sizes is presented in Figure 21. It is assumed that the cost of a BESS is 200 000 €/MW and increases linearly with the capacity. It can be seen that as the BESS size increases, the rate of increase for the payback period slows down. This means that for a larger BESS it takes comparatively fewer days to pay back for itself compared to smaller installations.

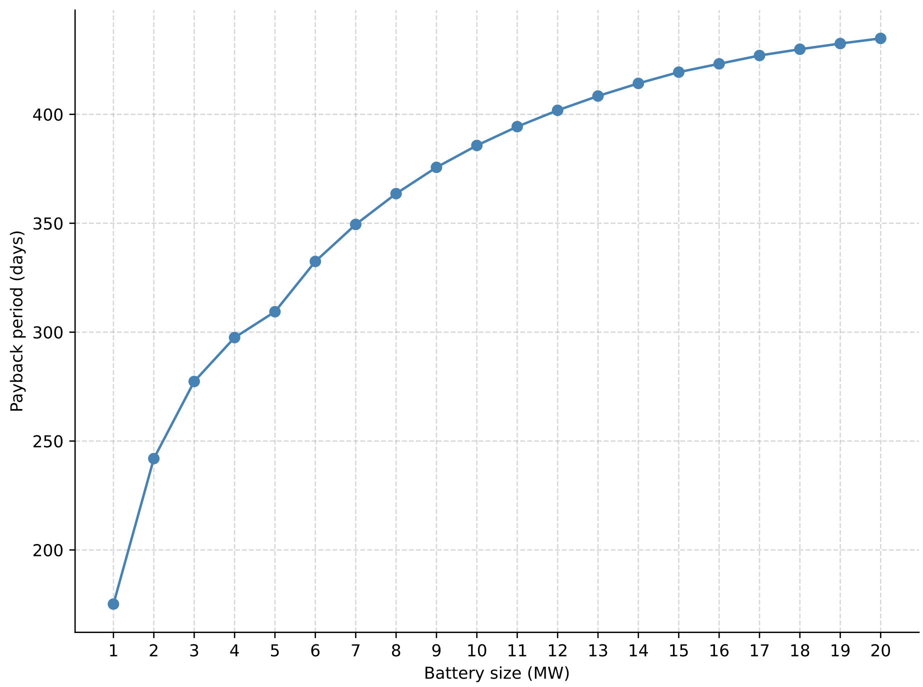

Figure 21: The figure presents the payback period in days with increasing BESS sizes.

Table 7: Best price strategies and corresponding profits for battery sizes from 1 to 20 MW. A price strategy consists of bids to day-ahead market (€/MWh), up- and down-regulating FCR-D market (€/MW). The last column shows the profit difference compared to the previous battery size.

Battery capacity (MW)	**Price strategy**	**Profit (€)**	**Increase in profit (€/1 MW)**
1	(4.0, 2.0, 3.0)	1141.85	
2	(4.0, 2.0, 3.0)	1653.25	511.40
3	(4.0, 0.0, 3.0)	2163.26	510.01
4	(4.0, 2.0, 3.0)	2688.97	525.71
5	(4.0, 0.0, 3.0)	3232.22	543.25
6	(4.0, 2.0, 3.0)	3609.35	377.13
7	(4.0, 2.0, 3.0)	4006.16	396.81
8	(4.0, 2.0, 3.0)	4400.35	394.19
9	(4.0, 0.0, 3.0)	4791.33	390.98
10	(4.0, 0.0, 3.0)	5185.00	393.67
11	(4.0, 0.0, 3.0)	5578.67	393.67
12	(4.0, 0.0, 3.0)	5972.33	393.66
13	(4.0, 0.0, 3.0)	6366.00	393.67
14	(4.0, 0.0, 3.0)	6759.67	393.67
15	(4.0, 0.0, 3.0)	7153.33	393.66
16	(4.0, 0.0, 3.0)	7561.35	408.02
17	(4.0, 2.0, 3.0)	7962.15	400.80
18	(4.0, 2.0, 3.0)	8374.06	411.91
19	(4.0, 2.0, 3.0)	8785.98	411.92
20	(4.0, 2.0, 3.0)	9197.89	411.91

6 Conclusion

This thesis presented a stochastic optimisation model designed to maximize the profits of a Finnish market participant operating a solar power plant and a BESS. The model focused on bidding strategies in the day-ahead market and in both up- and down-regulating FCR-D markets. In addition, scenario generation methods were used to form estimates to account for uncertainty in day-ahead market prices, up- and down-regulating FCR-D market prices and solar power production. The scenarios were used to find the optimal bidding strategy in a case study in the Finnish context and on data from 2024. The model was used to analyse how much the profits could be increased by a better price strategy instead of the naive strategy. Moreover, seasonal differences in profits were analyzed. Finally, the effect of the capacity of the energy storage system on the optimal bidding strategy and profits were analyzed.

The results show that with an optimal bidding strategy for day-ahead and up- and down-regulating FCR-D markets, a producer can get higher revenue than just by bidding with the zero marginal cost. The improvement was dependent on the season and the size of the BESS. Over the 30 chosen days in 2024, the total profit was increased 5.58% when the optimized price strategy was used every day, compared to if the naive strategy was utilized. The profit gains were seasonally dependent: the largest increase in profits occurred during summer (7.44%), primarily due to higher solar production and increased profits from up-regulating FCR-D market. It was shown that the BESS enables load-shifting and alters its behavior on the operating day to minimize imbalances caused by the prediction errors. The results also showed that profits increase nearly linearly with battery size, with an average gain of 424 € on the observed day per additional MW.

The results show that the BESS schedule on the operating day often deviates from the schedule determined on the day-ahead. These deviations include changes in the timing and magnitude of charging and discharging, and in some cases, even reversing the planned operation. Thus, the BESS can react to unexpected deviations in solar production. By adjusting its operation in real time, the BESS helps minimize imbalances and increases the profitability of the hybrid power plant. Seasonal analysis reveals how BESS operation is shaped by the variability of solar production and shifts in electricity market prices. In spring and summer, high solar output and favorable FCR-D market prices enable efficient load-shifting, with the BESS charging during daylight hours and discharging during peak price periods. Summer, in particular, represents the most active and profitable period for the hybrid power plant, as it combines high solar availability with strategic bidding. In contrast, autumn and especially winter present more constrained conditions, with the BESS relying more on market purchases and exhibiting less predictable operational patterns due to limited solar input. This thesis did not account for BESS degradation. These results could differ if battery degradation had been taken into account, as it can influence the optimal operation of the power plant [67]. Furthermore, when charging the BESS with solar production, fluctuations in solar power production can lead to additional degradation, which were also not considered in this thesis [68].

There are several areas in which the current model and methodology could be improved or extended in future work. First, improvements in scenario generation could lead to better profit. More accurate forecasting of solar power production could reduce imbalances between predicted and actual solar production and thus reduce imbalance settlement costs. Moreover, in addition to using different solar residual distributions for each hour of the day, scenario accuracy could be further improved by tailoring these distributions to different seasons, better capturing seasonal variation in forecast errors. Similarly, more precise market price predictions could allow the model to allocate the bids across markets more precisely to capture the best price available. Secondly, the current model relies on a limited set of predefined price strategies. While these provided a reasonable basis for optimisation, it is possible that the true optimal price strategy is outside the tested combinations. Incorporating a broader range of price strategies, or implementing a search algorithm could lead to finding better price strategies. Another limitation is that the solar production and prediction data used in this thesis does not originate from an actual operating solar power plant. Although it reflects realistic patterns, the use of real production data could increase the validity and reliability of the results. Additionally, the requirement for the BESS to have a 60% state of charge at the end of the day may have influenced the results. Lastly, this thesis analyzes only 30 individual days, which limits the robustness of the results. More reliable insights could be obtained by extending the analysis, e.g., to a full year. With a limited number of days, random events can have large impact on the results, especially when comparing seasonal differences.

Regarding practical applicability, the framework developed in this thesis offers valuable insights, but the results may not fully reflect the profits that could be achieved in reality. For example, the simplifying assumption that bids to the day-ahead and FCR-D markets are submitted simultaneously can effect the outcome. Additionally, this thesis focused on the day-ahead market and up- and down-regulating FCR-D markets. Participation in other markets, such as aFRR, or intraday markets, could potentially yield different outcomes. Including these markets in future work could provide a more comprehensive view of market opportunities for hybrid systems. Lastly, the results may change once the 15-minute time resolution is implemented in the Finnish day-ahead market, as it could enable more precise scheduling and better alignment between solar production, battery operation, and market participation.

Despite its limitations, this thesis demonstrates the value of optimizing bidding strategies across multiple markets and leveraging load shifting, as the model effectively utilizes the BESS to enhance the value of zero-margin solar generation and improve overall profitability by minimizing imbalance settlement costs. This multi-market approach can increase profit and improve the overall economic viability of a VRE system coupled with BESS. These results are valuable given the challenges of maintaining profitability for variable renewable energy sources in the current Finnish day-ahead market.

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