



Vaasan yliopisto
UNIVERSITY OF VAASA

Amjad Hossain

**Optimizing Pricing Strategies to Maximize Profits
for Balancing Service Providers in FCR-N and FCR-D
Reserve Markets**

School of Technology and Innovations
Master's Thesis in Smart Grids Programme

Vaasa 2025

UNIVERSITY OF VAASA**School of Technology and Innovations**

Author:	Amjad Hossain		
Title of the thesis:	Optimizing Pricing Strategies to Maximize Profits for Balancing Service Providers in FCR-N and FCR-D Reserve Markets		
Degree:	Master of Science in Technology		
Discipline:	Smart Grids		
Supervisor:	Professor Hannu Laaksonen		
Instructor:	Elahe Doroudchi (Postdoctoral Researcher)		
Year:	2025	Pages:	56

ABSTRACT:

The goal of this thesis is to determine how a 1 MW battery can profit in Finland's frequency reserve markets with smart pricing strategies. It consists of two markets: FCR-N, run continuously and FCR-D which is brought in when there are unusual fluctuations in frequency.

This work looks at how different pricing methods can change the profit a battery system earns. Using real data from Fingrid's 2024 frequency reserve markets, a battery operating model was run to provide the findings reported in this master's thesis. For FCR-N, two control methods were examined: a straightforward rule based one and an advanced approach using practical logic that responds to changes in prices and frequency. The easy-to-use model earned more profit, yet the market rules were better followed with the improved logic.

A review of FCR-D was included, though a lack of activation data results in imprecise and less trustworthy findings.

This study demonstrates that using a good strategy and precise information, battery systems may do well in FCR-N. Future work on the model could add battery aging as a factor, make the controlling system more complex and include the complete set of FCR-D activation data.

KEYWORDS: Fingrid, Reserve market, FCR-N, FCR-D, pricing strategy, battery, frequency control, profit simulation, market data, energy storage

Contents

1	Introduction	7
2	Literature Review	8
2.1	Overview of Frequency Containment Reserve (FCR) Markets in Finland	8
2.2	Technical and Market Rules for BSPs	9
2.3	Profit Modeling and Optimization in Reserve Markets	9
2.4	Battery and Technical Modeling in Reserve Market Applications	12
2.5	Bidding Strategies in Frequency Reserve Markets	13
2.6	Gaps and Future Work	15
3	Data Sources and Description	17
3.1	FCR-N (Frequency Containment Reserve for Normal operation)	17
3.1.1	FCR-N Hourly Market Bids	17
3.1.2	FCR-N hourly market prices	18
3.2	FCR-D Upward (Frequency Containment Reserves for Disturbances Upwards Regulation)	19
3.2.1	FCR-D upward bids	19
3.2.2	FCR-D upward market prices	20
3.3	FCR-D Downward Regulation (Frequency Containment Reserves for Disturbances Downwards Regulation)	21
3.3.1	FCR-D downward bids	21
3.3.2	FCR-D downward market prices	22
3.4	Spot Prices and Frequency Data	23
4	Methodology	25
4.1	Data Preprocessing	25
4.1.1	Real-time frequency	25
4.1.2	Historical frequency	25
4.1.3	FCR-N methods	26
4.2	Battery Operation Model	29
4.3	Profit Calculation Logic	30
4.4	FCR-N Strategy Simulation	31

4.5	FCR-D Strategy Simulation	32
4.6	Assumptions and Tools	33
5	Results	34
5.1	FCR-N Simulation: Version 1 and Version 2	34
5.1.1	Version 1 – Frequency-Based Battery Simulation	34
5.1.2	Version 2 – Spot Price-Based Battery Simulation	37
5.2	FCR-N Profit Comparison (Version 1 vs Version 2)	41
5.2.1	FCR-D Upward	41
5.2.2	FCR-D Downward	42
6	Discussion	44
6.1	FCR-N: Strategy Logic Comparison	44
6.2	FCR-D: Initial Results and Data Limitations	45
7	Conclusion	46
8	References	47
	Appendices	51
	Appendix 1. Python Code for FCR-N Market (Version 1)	51
	Appendix 2. Python Code for FCR-N Market (Version 2)	54

Figures

Figure 1. FCR-N Hourly Market Bids Yearly data with Forecast.	20
Figure 2. FCR-N Hourly Market Prices Yearly data with Forecast.	21
Figure 3. FCR-D Upwards Hourly Market Bids Yearly data with Forecast.	22
Figure 4. FCR-D Upwards Hourly Market Prices Yearly data with Forecast.	23
Figure 5. FCR-D Downwards Hourly Market Bids Yearly data with Forecast.	24
Figure 6. FCR-D Downwards Hourly Market Prices Yearly data with Forecast.	25
Figure 7. FCR-N Simulation (V1) Sos and Hourly Profit January to March	36
Figure 8. FCR-N Simulation (V1) Sos and Hourly Profit April to July	37
Figure 9. FCR-N Simulation (V1) Sos and Hourly Profit August to September	38
Figure 10. FCR-N Simulation (V1) Sos and Hourly Profit October to December	39
Figure 11. FCR-N Simulation (V2) Sos and Hourly Profit January and March	40
Figure 12. FCR-N Simulation (V2) Sos and Hourly Profit April to June	41
Figure 13. FCR-N Simulation (V2) Sos and Hourly Profit July to September	42
Figure 14. FCR-N Simulation (V2) Sos and Hourly Profit October and December	42

Tables

Table 1. FCR-N Yearly Profit Comparison (Version 1 vs Version 2)	43
Table 2. FCR-D Yearly Upward Profit Comparison (Version 1 vs Version 2)	44
Table 3. FCR-D Yearly Downward Profit Comparison (Version 1 vs Version 2)	45

List Of Abbreviations

API	Application Programming Interface
BESS	Battery Energy Storage System
BSP	Balancing Service Provider
CSV	Comma-Separated Values
FCR	Frequency Containment Reserve
FCR-N	Frequency Containment Reserve for Normal Operation
FCR-D	Frequency Containment Reserve for Disturbances
FFR	Fast Frequency Reserve
Hz	Hertz
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt-hour
MWh	Megawatt-hour
MW	Megawatt
SOC	State of Charge

1 Introduction

It is necessary that Finland's electricity system is always in balance. Any difference between production and power use results in a change in the frequency of the grid. Such behavior can injure equipment and bring about blackouts. Instead, Fingrid secures additional power, called reserves, bought from a number of different agencies. Batteries, factories, and energy service companies are some of the providers that offer these reserves. The job is to react fast when the grid frequency goes too high or too low. Fingrid makes use of two primary types of frequency reserves:

- I. FCR-N is constantly at work, handling little frequency adjustments.
- II. FCR-D is used when the frequency goes too far off from the normal level.

In the markets each day, companies make offers to participate and join the trading of these two energy reserves. The more successful a company's pricing strategy, the greater its profit will be. That is the central message of this thesis. The objective is to see which approach can help a 1 MW battery earn money in these markets using actual 2024 prices from Fingrid and to identify the best pricing strategy.

This research mainly examines FCR-N, as this market is constantly active and full simulation can be performed with its available data. Usually, FCR-D is checked, but not thoroughly, due to a lack of needed activation data. Income generated by the battery in FCR-D is not fully reliable without knowing the exact time each asset was activated.

This thesis follows the given structure: First, it outlines the Finnish reserve markets and describes how batteries are used. After that, the author explores what scholars in the field have reported. Next, the structure of the battery, the types of analyses done and the simulation approach are clarified. After that, the results are presented and analyzed side by side for the control logics. The closing sections explain what the results show, draw conclusions and outline possible ways to improve this work in the future.

2 Literature Review

2.1 Overview of Frequency Containment Reserve (FCR) Markets in Finland

Stable and balanced electricity flow is required in Finland and other Nordic countries at all times. A difference between electricity generation and consumption allows the frequency of the grid to vary. If lightning occurs, it may harm machinery and interrupt the power supply. To prevent this, Fingrid, Finland's transmission system operator, gets backup energy from several companies. Among those companies are Balancing Service Providers (BSPs), including battery owners, industries, aggregators, and energy producers.

Fingrid uses three major reserve products to keep the grid stable:

- I. For normal situations, measurements make up FCR-N.
- II. When frequency falls below the baseline, it is an FCR-D Up.
- III. If the frequency rises suddenly, turn FCR-D to Down.

FCR-N is active at all times, while FCR-D Up and Down comes on when the frequency moves outside the usual limits (49.9–50.1 Hz). Renewable power products are traded through two different markets: one for annually signed reserve contracts and another for daily bids. The night before the delivery date is often the bidding deadline. Rules governing who may participate and how quickly a response must respond are specific to each reserve product.

Batteries meet the speed requirements set by Fingrid and can switch on and off quickly. Lenders are legally required to test and clear an operating firm before issuing letters of credit. Fingrid makes sure that the batteries will be able to supply the agreed power for the expected time. To be considered for FCR-N, a battery should deliver full power for a

steady one hour. For FCR-D, have to train a minimum of 20 minutes and there's an extra buffer of energy in the other direction.

Through its data, Fingrid (2022) stated that a 1 MW capacity in the FCR-N market tends to earn about €189,000 annually, with FCR-D Down feasible to earn even more at up to €275,000. How many numbers are available depends on market prices, accepted bids and whether the unit was started. 2024 hourly price data from Fingrid was used in this thesis to measure the possible profit for a 1 MW battery considering the FCR-N market. FCR-D information is part of the background, but a lack of activation data does not allow for its full modeling.

2.2 Technical and Market Rules for BSPs

To participate in reserve markets, a BSP must meet a number of technical conditions. It is required that, in real time, the unit reports the SOC value to Fingrid for batteries. A core purpose of FCR-D is to have complete activation within just 30 seconds from the start. There are size requirements too: the smallest bids accepted for FCR-N is 0.1 MW and the smallest bid accepted for FCR-D is 1 MW. The rules governing these markets are all explained in the public documents published by Fingrid on the reserve market.

In 2024, Fingrid changed the way pricing is done in FCR markets from pay-as-bid to marginal pricing. All those able to sell get the same price which is the highest bid accepted by the market. As a result of this change, BSP bids will be affected and earnings may vary. When making profit calculations, will use the pricing from the 2024 Fingrid market.

2.3 Profit Modeling and Optimization in Reserve Markets

In years past, several studies have examined the possibility for batteries to earn a profit by participating in reserve markets in the Nordic region. One of Alizadeh's(2017) first

papers was about deciding how much of Finland's FCR-N and FCR-D storage capacity should be used. An algorithm was used to calculate the most profitable settings which were kept within the official limitations on state of charge and how much power each charger could use at once. Results suggested that optimizing battery charging gave the business a bigger profit in FCR-D than a fixed charging plan.

Viiil (2024) examined a different version of this idea where a wind park and battery functioned as a team. Combining wind and batteries using a MILP model increased profits up to 18.76% in both FCR-D Up and FFR markets. It also demonstrated that including a battery allows better wind power use, mainly when prices in the spot market are down.

Larrabure (2022) also focused on how a set of electric vehicles can combine forces in the FCR-D market. A rolling optimization algorithm was used to change the bidding strategy each hour. The results indicate that this control method can ensure EV fleets stay within their requirements while maximizing earnings by bidding into the flexible capacity reserve for distributed generation.

Hameed et al. (2023) investigated the Nordic FCR-N market and discovered that prices in this sector are harder to forecast than traditional energy market prices. Studies also showed that places with comparable education systems such as Finland and Sweden, do not always share the same price trends which means forecasting is not always simple. Since this is a thesis-level industry, the prediction of prices plays a role in how firms decide on their bids.

The Finnish FCR-N market saw Alderwerelt (2024) use a combined system of batteries and flywheels. The flywheel supported the system during quick and short changes and the battery was for the larger, longer changes in power. As a result of this, the battery was worn down less and lasted more than twice as much time. Because of this strategy, the system could bid in the market without facing major risks.

Brugger and Wunderlich (2023) studied how to project FCR-D prices in Sweden. A model was selected that uses time series along with LASSO to predict what prices would be. The goal was to help buyers and sellers decide on better bidding prices. Because FCR-D prices may show a lot of randomness, the study added extra steps to filter out any noisy data before doing predictions. It lets battery operators plan better offers, mainly in markets where prices often fluctuate.

Thingvad et al. (2024) developed a model that helps batteries make their own decision about when to participate in FCR-N, FCR-D, or energy arbitrage. It was found that moving between markets based on price, limits set by regulations, and the state of the batteries works best. Profit could increase by as much as 105% when the model was used instead of concentrating sales in just one market all year. It shows that using bidding strategies in real time or every hour helps a lot.

Thingvad et al. (2023) looked at how switching between FCR-N and FCR-D every hour affects the financial side of transportation in a different article. As a result, charging the battery less often allowed it to go through 51% fewer charge/discharge cycles, helping lower both aging and maintenance fees. At the same period, the company's profits rose by 22%. Applying the code is useful for this thesis because it will also test hourly switching logic using Fingrid's 2024 data.

At the end, Stockholm Exergi (2024) presented a bidding model that blends reserve bidding, energy arbitrage and peak shaving. Price forecasts helped the model choose in which hour the battery would work as a service. The study found that switching electricity use to off-peak times brings in extra money, without breaking performance standards. Since the rules in Finland's reserve markets are similar to those studied in Sweden, the ideas from the study can easily be applied there.

2.4 Battery and Technical Modeling in Reserve Market Applications

Battery energy storage systems (BESS) are finding popularity as methods to support the power grid, mainly through the services FCR-N and FCR-D. This means understanding how far batteries can go, how charging and discharging occur, what losses are suffered, how aging happens, and what restrictions Fingrid has set, such as those related to state of charge (SOC).

Eloranta (2024) investigated how the rules in this sector influence the expenses incurred by batteries operating in Finland's FCR-N market. Based on the research, if not careful with charging and discharging, the battery gets used more often than it should. The study shows that adjusted bidding according to actual regulations and market changes can save money and offer a way to earn income.

Hankimaa (2023) demonstrated a process where a battery was included with a wind power system. The model experimented with placing bids into the FCR-D and FFR markets. The research found that when wind and battery are used together, guided by a good optimization model, the profit level can be increased. This way of thinking can also be used to figure out the right time and spot for installing batteries.

Laine-Ylijoki (2024) examined the use of a 1 MW battery for wind turbine balancing and connecting to the FCR market in Finland. Wind output was balanced using one model and reserve market bidding was done with another. In particular, when examined in FCR-N, the profits produced on the reserve market are better and can be recovered within five years or less.

Oksanen (2017) and Ruokosuo (2018) analyzed the ways flexible loads and demand-side resources might be used on reserve markets. The study found out that joining many small resources through aggregation can fulfill the technical criteria of reserve markets. The same principle can work for smaller batteries, because blending assets may allow Fingrid to meet its bid size requirement.

The study Repo (2020) examined a method that improves reserve market participation for a collection of energy assets. Fingrid data from previous years was used to test the model and the tests confirmed that opting for the best market one hour at a time can increase revenue by as much as two to three times.

Saulny (2017) tested a virtual version of Fortum's 2 MW / 1 MWh "Batcave" battery in Finland's FCR-N hourly market. He set up tests in two ways: one keeping the battery involved and one making its power available only when hydropower is implementing its schedule. The analysis found that the highest income was made by keeping the battery drained nonstop, but this put the greatest strain on the battery. It is suggested that a backup source, like hydropower or an optimized battery may be needed when electricity demand is low.

The author also investigated how a global firm can manage its electricity costs by using both the day-ahead and reserve markets like FCR-N and FFR (Laitila, 2020). He designed a tool for working out the best combination of investment strategies. According to the study, using part of the electricity on the reserve market might make energy cheaper. This involves using the battery when prices are low, according to Fingrid data.

The study all agree that battery modeling isn't only concerned with cost. The model needs technical rules, market restrictions, a worry about degradation and smart methods to know when bidding is best. The thesis then explores how to earn more in FCR-N using a 1 MW battery and real data and rules from Fingrid 2024.

2.5 Bidding Strategies in Frequency Reserve Markets

How a storage battery bids influences both what it makes in reserve markets and how dependable it performs during actual usage. Many studies have looked into smarter

methods for making bids and planning in energy markets, since rules for reserves in Nordic countries can vary hourly.

Casla et al. (2022) built a comprehensive model to represent batteries used in Swedish FCR-N and FCR-D markets. The model works in two steps: predicting what will happen and handling actual changes, along with battery wear, charging expense and risky pricing. This thesis can benefit from this paper since it teaches how to set safe bid prices using data from the past and the market.

Sandvik (2024) will compare the results of batteries in the FCR-N, calculating prices based on Norwegian and Swedish markets. The finding was that batteries lacked profitability in Norway compared to Sweden, where a bigger battery could turn a profit. It proves that local prices are key and that hourly data such as the Fingrid data using is useful for choosing the best approach.

Dias and Jaumard (2024) considered whether more than one telecom base station with extra battery power could be coordinated to offer FCR-D services. Small battery projects were organized into a model to enable submission of a bidding size above 0.1 MW. The model found a way for batteries to earn via the FCR-D market by organizing bids across regions and at different times.

Valle (2024) considered an electric vehicle (EV) hooked up to a home energy system. Results revealed that bidding in the FCR-N market by using a rolling horizon strategy saved money for the household and made the EV available for transport. Dr. Schlegel is using a technique very similar to what this thesis simulates with the 1 MW battery.

Sørdalen (2022) modeled many small batteries regulated by separate agents. Agents submitted their own projections, but also shared details with a central coordinator who made bids in the reserve market. Using this type of flexible bidding let users earn more

and gave them the chance to change their service if needed. This technology shows once again that better bidding strategies can lead to greater profit.

The research shows that smart bidding should take market prices, how the system is activated, technical boundaries and risk into consideration. The thesis recommends using actual 2024 Fingrid data and modeling batteries one hour at a time to plan how to profit in the reserve market.

2.6 Gaps and Future Work

Even though research on batteries supporting FCR-N and FCR-D markets has increased, not all points have been fully explored yet. Most existing models operate on the assumption of constant power usage or average prices, while actual data on price or frequency is not included. By applying reinforcement learning, Strömer et al (2022). It showed that setting marginal pricing in the Swedish FCR-N market might lead to huge price rises if everyone acts strategically. Results demonstrate that including batteries and wind power could keep prices under control, but it needs the rulebooks to ensure equal bidding opportunities. That is, how the market is built can influence whether battery owners succeed and are treated fairly.

Hellgren (2024) added that this technique rarely fits the constantly changing frequency of electricity grids. Bastan and Sepoudi demonstrated in their work that managing the battery's SoC is not easy for vehicles linked in FCR-N. It turned out that using both markets together helps generate more income, but also makes the system more risky if the battery doesn't have enough energy left. It's necessary to address this, since most previous studies only use computer simulations that don't cover the limits of SoC, a motor's activation history or its response to actual frequencies.

In contrast, Juslin (2021) did things another way by blending a battery with a Kaplan hydropower turbine in Finland. The main goal of his research was to decrease turbine

damage from FCR-N cycles. He demonstrated that a small battery (20% of their offer) would reduce control actions by a massive 97% yet actual rewards depended on the size of the battery, how well the turbines worked together and the frequency of switching on or off. Using this system leads to many positive outcomes, but it is not yet possible to include hourly pricing or flexible bidding in detailed profit calculations.

Currently, the bulk of research either assumes everything goes to plan or explores outcomes over the years. Even now, there is not enough use of actual hourly prices, strict tracking of battery states and Fingrid standards in researching how a 1 MW battery might run successfully in FCR-N. FCR-D is even less studied because it is hard to find accurate frequency data in the correct ranges. The thesis looks at these issues by using 2024 Fingrid data for the FCR-N market and plans for future research on FCR-D.

3 Data Sources and Description

This thesis presents data collected from Fingrid's open data platform that deals specifically with the Finnish electricity reserve market. The main use of data from 2024 which covers the prices in the market, the volume of bids, spot prices and information on system frequency. The use of these datasets makes it possible to understand how reserves are involved in the market and when specific services might become involved.

Market hourly prices and bids are taken for the three types of reserve products in the study:

3.1 FCR-N (Frequency Containment Reserve for Normal operation)

3.1.1 FCR-N Hourly Market Bids

FCR-N bids let energy providers show how support can be provided to the electricity grid. Because these providers can supply energy rapidly, a swift response is possible if the frequency strays slightly from 50 Hz. Every day, Fingrid gathers the bids and matches how much to buy to the hourly system demand.

The graph demonstrates what amount of power was put into the FCR-N market every hour during 2024. The original blue bids are shown as dots and the orange dashed line is the average for the whole day. Over time the money available changes a lot. About 90% of the time, the bid amount is between 100 MW and 140 MW. The data shows that more patients were referred in April when there could have been others seeking help too. During those months, the amount of bids goes down just a bit. This chart depicts the times when the market had higher activity and the quieter times.

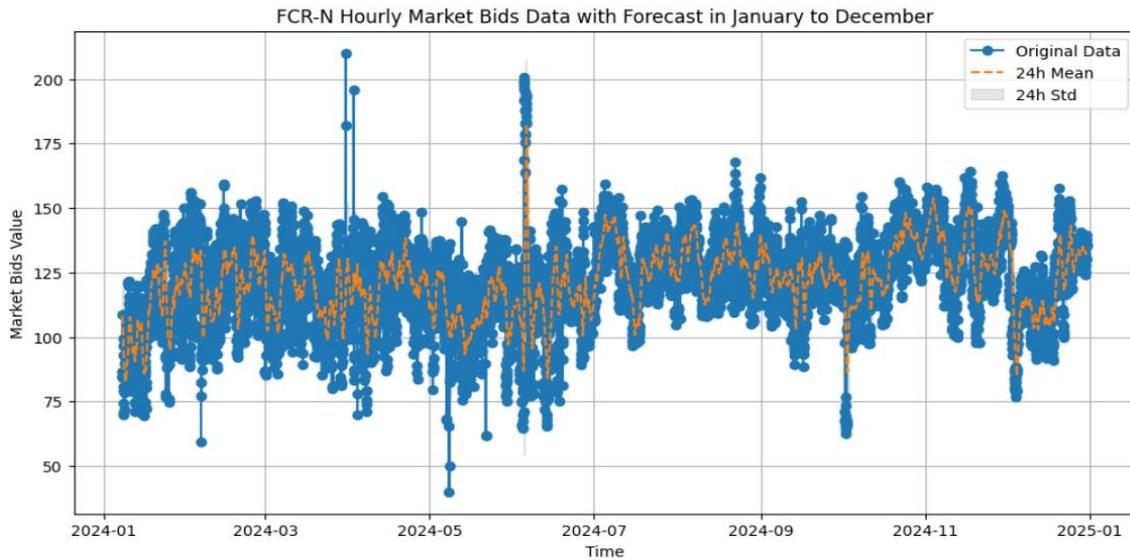


Figure 1. FCR-N Hourly Market Bids Yearly data with Forecast.

3.1.2 FCR-N hourly market prices

Show how much Fingrid must pay for reserve power every hour to maintain the stability of the electricity system. The daily price is based on the highest accepted bid for that day. Every evening, prices are released to be used the next day. The frequency remains stable within a range of 50 ± 1 Hz thanks to FCR-N.

It demonstrates the way prices of books, electronics and clothing went up hourly in 2024. A blue dot represents the price for one hour and the orange dashed line marks the average price over the previous 24 hours. Prices were very high in the period from February to May, with many days recording more than 400 €/MW and one day close to 500 €/MW. Once May ended, the average cost went down and stayed lower. Although a few larger surges occurred in November, the levels did not go as high. There was little change in prices during December. During the early months of 2024, the price trend was positive which might provide benefits to investors with stored bitcoin. Prices in the market remained steady and lower during the last half of the day.

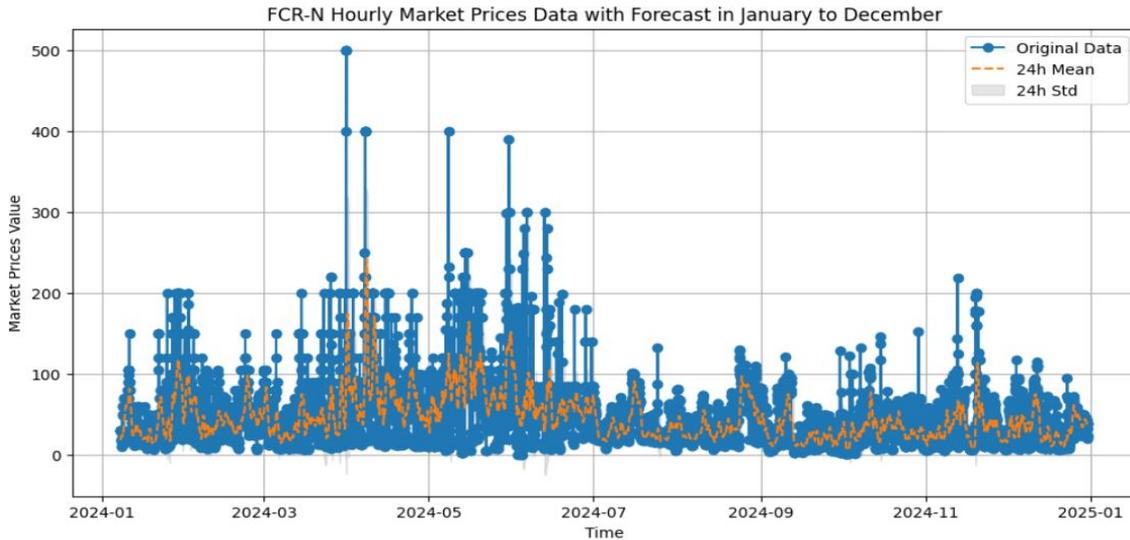


Figure 2. FCR-N Hourly Market Prices Yearly data with Forecast.

3.2 FCR-D Upward (Frequency Containment Reserves for Disturbances Upwards Regulation)

3.2.1 FCR-D upward bids

When the FCR-D triggers, energy providers will bid to increase the electricity frequency. This means that the frequency reduced below 49.9 Hz but has not yet crossed 49.5 Hz. Every day, Fingrid collects bids and determines how much it will purchase during each hour. The amount of money paid depends on what the electricity system requires.

The graph explains how much power from FCR-D was sent to the market every hour in 2024. The blue dots are errors made every hour and the orange line highlights the average over 24 hours. Volumes of new wind energy offers were very high in the early months, especially during January and February when most offers reached beyond 200 MW each. Following that, there was a small decrease in prices over spring and early summer. From July though October, the commodities were priced more steadily, with less severe declines. The pattern in November and December was for irregular bids and

a gradual decline toward year's end. It illustrates the level of activity in the market and the reserve resources that were accessible to solve frequency disturbances over the year.

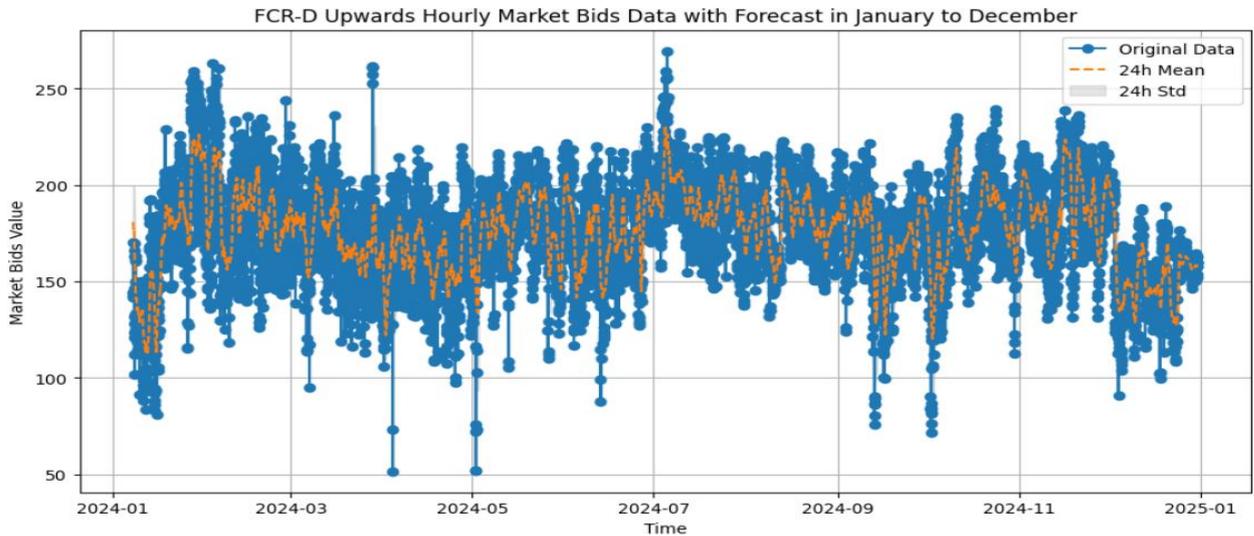


Figure 3. FCR-D Upwards Hourly Market Bids Yearly data with Forecast.

3.2.2 FCR-D upward market prices

FCR-D prices at the top of the market demonstrate the compensation for every hour of reserve power used in restoring a frequency drop. Utility Power is needed if the frequency is between 49.5 Hz and 49.9 Hz. Prices are set by using the highest price bid for that hour and are shared online the day before.

The graph shows the prices and at what times changed throughout the year 2024. The blue dots show prices by the hour and the orange dashed line tells what the average price was during the day. During March through June, many price spikes appear, the highest of which cost over 500 €/MW. The increased rates may be because people are looking for insurance during those months or there are fewer insurance providers. Starting in July, the prices decrease a lot and stay at a low level for most of the rest of the year. Although there are more cases in October and November, the rise isn't nearly as high as in the spring and summer. The graph demonstrates that FCR-D prices per unit went up

especially in the first half of the year, so providers probably made more money then. Prices stayed low during the second half and the market generally remained steady.

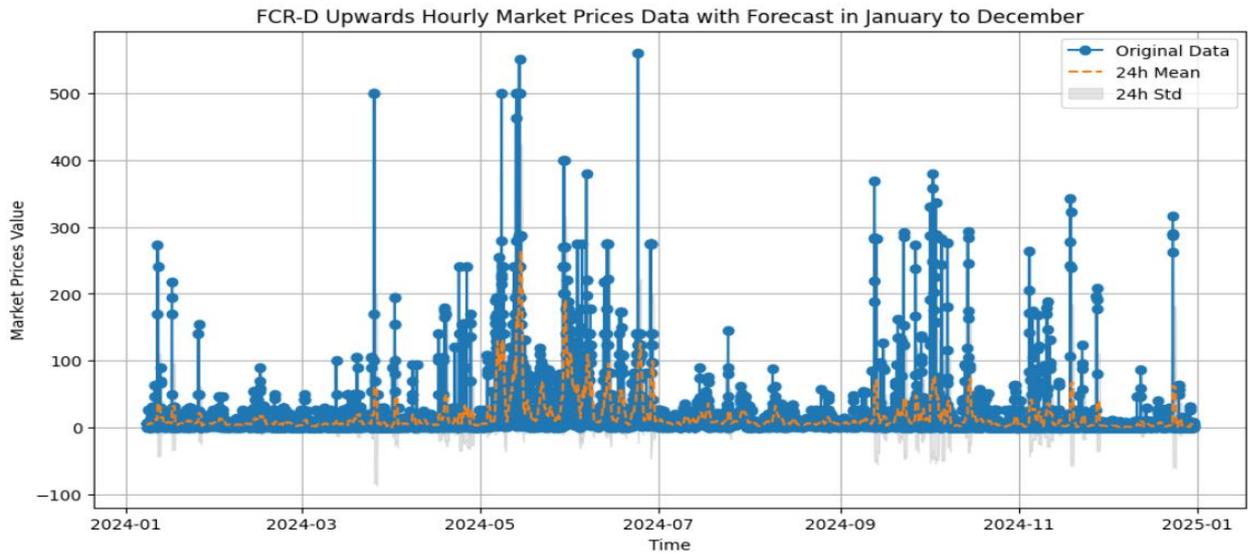


Figure 4. FCR-D Upwards Hourly Market Prices Yearly data with Forecast.

3.3 FCR-D Downward Regulation (Frequency Containment Reserves for Disturbances Downwards Regulation)

3.3.1 FCR-D downward bids

During disturbances in the grid, FCR-D bids allow energy providers to help raise the frequency of electricity. If the frequency falls between 49.9 and 49.5 Hz, something happens. Every day, Fingrid takes a look at the bids and figures out the amount to buy for each hour. The size of the option is determined by what the electric system requires.

It demonstrates the available power entering the FCR-D market from upstream sources each hour in 2024. The hourly bids are shown with blue dots and the orange dashed line shows the average for the entire day. There were very high bid volumes from the start, mainly in January and February, when lots of projects were valued at more than 200 MW.

During spring and a part of early summer, numbers decreased for a period. From July until October, there were fewer extreme changes in value. During November and December, auction volumes were less concentrated and fell a little toward the end. The graph illustrates the market's behavior all year long and when more or less reserve was available to help correct frequency issues in the system.

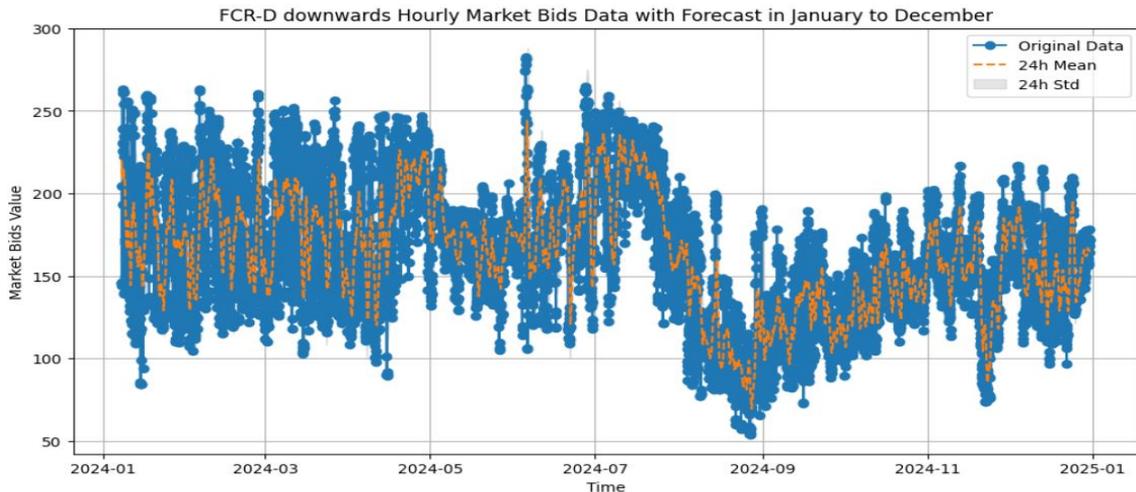


Figure 5. FCR-D Downwards Hourly Market Bids Yearly data with Forecast.

3.3.2 FCR-D downward market prices

Reveal how much Fingrid pays for reserve power to stop the frequency of electricity from rising. This service use if the frequency is more than 50.1 Hz and less than 50.5 Hz. Prices are set using the highest accepted offer of the hour and posted the evening before the event.

The price movements are shown one hour at a time for the whole year of 2024. A blue dot means one hour's price and the orange dashed line displays the average price over the last 24 hours. In the first months of the year, January to April, prices saw many large spikes, reaching up to 250 €/MW. Prices suddenly dropped a lot in April and stayed reduced through most of the summer. During the last quarter of 2021, energy prices rose once more, but did not reach the highs seen at the start of the year. It can be observed

on the graph that prices for FCR-D went down at the start of the year and then dropped through the summer, before climbing again toward the final part of the year. Many of the biggest shifts in price occurred in the winter and spring, suggesting the system needed more downward support then.

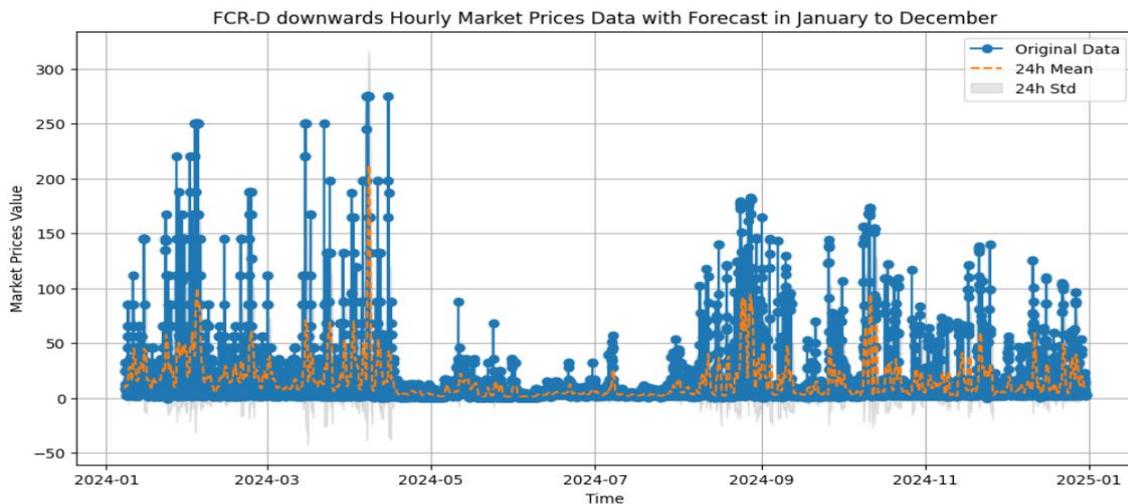


Figure 6. FCR-D Downwards Hourly Market Prices Yearly data with Forecast.

3.4 Spot Prices and Frequency Data

The studies used day-ahead prices from the main electricity market to examine how compare with prices from the reserve market. Thanks to this information, the battery decides the best way to try to make a profit from the energy it trades.

The information from Fingrid about grid condition made it possible to decide how soon would need extra capacity. Scientists could obtain both continuous frequency and discontinuous frequency data.

- I. It sends out news every three minutes to display the current value. It can track changes in it, but it's not suitable for detailed study.

- II. The system provides 10 readings per second. The data is collected each day and each month from substations in Finland and kept in CSV format. With it, the events in the system every hour.

The grid's frequency was kept mostly normal which points to more regular running for FCR-N. Nevertheless, FCR-D was almost never caused by these events where the frequency was too low. Therefore, FCR-D outcomes in this study depend only on market bid prices and not on how much the phones are used.

All the data was saved as CSV and I used Excel and Python to deal with it. The set of data was compiled to design the battery models and to generate the graphs and summaries shown in the coming sections.

4 Methodology

4.1 Data Preprocessing

All the data included in this thesis came from downloads on Fingrid's open data service. The majority of the data collected such as spot prices, FCR-N and FCR-D prices and reserve market bids, was already published on an hourly schedule. These were simple to combine and match since used the hourly time samples from the same year, 2024. Still, the frequency data came in two forms and extra work was needed to handle them.

4.1.1 Real-time frequency

Update information from this dataset is provided every 3 minutes, taken directly from Fingrid's control system. Although it provides live information on system frequency, the time steps are not fine enough to use for digital simulation. Only trends were analyzed from this data, as it was not involved in either battery selection or profit estimates.

4.1.2 Historical frequency

This collection of data is more appropriate for analysis. Data sampling happens 10 times every second and the measurements are taken at 400 kV substations in Finland. Monthly folders store the data and every day's data is saved in a separate CSV file. Doing so let's study how commonly the frequencies appear within the activation ranges of the power station reserves. All of the files were brought together, cleaned and turned into hourly averages in preparation for their use. There were small mistakes because of weak communication, but the mistakes did not seriously affect the main results.

4.1.3 FCR-N methods

For FCR-N, two methods were used to calculate profit:

4.1.3.1 First method – Simple price-based logic

The battery acts according to a basic rule that checks the price of electricity in the FCR-N market and the spot price. It makes sure that the grid frequency is stable. This way of thinking is put into a linear programming model to help the battery figure out when it should charge or discharge for the highest profits.

Market prices and technical considerations are used in a linear programming model to determine how much the battery should charge or discharge. The idea is to purchase energy when the cost is lower and sell it when the rate is higher to get the most profit every hour. It has an objective to be achieved, variables used in the decisions, parameters to help define the objective, and set constraints.

i. Objective Function

$$\text{Maximize Profit}_{\text{hourly}} = c_1 \cdot (P_{\text{FCR-N}} - P_{\text{spot}}) \cdot P_{\text{charge}} - c_2 \cdot P_{\text{FCR-N}} \cdot P_{\text{discharge}}$$

- The first part gives profit from charging at a lower price and getting paid the FCR-N price.
- The second part shows cost (or negative profit) from discharging, where energy is sent out and the battery gets paid at the FCR-N price.

ii. Variables

- P_{charge} : How much power (kW) the battery charges per hour
- $P_{\text{discharge}}$: How much power the battery discharges per hour
- SOC_t : The battery's state of charge (MWh) at time t

- c_1, c_2 : Control values that turn on charging or discharging
- $c_1 = 1$ if charging is allowed
- $c_2 = 1$ if discharging is allowed

iii. Parameters

- P_{FCR-N} : Price in the FCR-N market (€/kWh)
- P_{spot} : Spot market electricity price (€/kWh)
- η : Battery efficiency (e.g., 0.9)
- P_{max} : Maximum charging or discharging power (e.g., 1000 kW)
- SOC_{min}, SOC_{max} : Minimum and maximum charge levels
- Δt : Time step (1 hour)

iv. Constraints

- **Battery energy update:**

$$SOC_{t+1} = SOC_t + \eta \cdot P_{charge} \cdot \Delta t - (1/\eta) \cdot P_{discharge} \cdot \Delta t$$
- **SOC limits:**

$$SOC_{min} \leq SOC_t \leq SOC_{max}$$
- **Charging and discharging limits:**

$$0 \leq P_{charge} \leq c_1 \cdot P_{max}$$

$$0 \leq P_{discharge} \leq c_2 \cdot P_{max}$$
- **Only one action at a time:**

$$c_1 + c_2 \leq 1$$

v. How Charging and Discharging Are Decided

- If frequency is above 50 Hz and spot price is lower than or equal to FCR-N price, then:
 Charging is allowed $\rightarrow c_1 = 1, c_2 = 0$

- If frequency is below 50 Hz and spot price is higher than or equal to FCR-N price, then:
Discharging is allowed $\rightarrow c_1 = 0, c_2 = 1$
- If neither condition is met, then the battery does nothing $\rightarrow c_1 = 0, c_2 = 0$

4.1.3.2 Second method – Frequency-based logic

The battery does not rely solely on prices to make decisions in this approach. It responds by adjusting to shifts in the frequency of the grid. When the frequency reaches a value greater than 50 Hz, there is excessive energy present and the battery starts working to help bring things back into balance. A frequency below 50 Hz signals that the amount of energy is low, so the battery supplies what is needed to keep the grid humming. The battery now behaves as a true power source. It is sometimes explained using a linear programming model. The purpose is to earn the maximum profit within the technical limits of battery capacity, power usage and efficiency.

I. Objective Function

$$\text{Maximize Profit}_{\text{hourly}} = c_1 \cdot (P_{\text{FCR-N}} - P_{\text{spot}}) \cdot P_{\text{charge}} - c_2 \cdot P_{\text{FCR-N}} \cdot P_{\text{discharge}}$$

- The first part shows the profit from charging the battery when the spot price is low and selling that energy at the FCR-N price.
- The second part shows profit from discharging energy into the grid at the FCR-N price.

The variables, parameters, and constraints used here are the same as in Section 4.1.3.1. The only difference is how the battery decides whether to charge or discharge.

II. Charging and Discharging Are Decided

- If frequency > 50 Hz
 $c_1 = 1$ (battery can charge)
 $c_2 = 0$

- If frequency < 50 Hz
 $c_1 = 0$
 $c_2 = 1$ (battery can discharge)
- If frequency is exactly 50 Hz or there's no need to act
 $c_1 = 0, c_2 = 0$

The battery examines the spot price also: it does not charge when the spot price exceeds the FCR-N price and it does not discharge when the price is too low. That's why the battery is efficient, responding to both changes in frequency and energy prices and rejects operations that won't be profitable.

4.2 Battery Operation Model

Used a simulation of a battery storage system to study how pricing works in the FCR-N market. It is assumed that the battery has storage capacity of 1 MWh and a maximum output of 500 kW. It means the battery can exchange up to 500 kW of energy, going from full to empty or back, in an hour. The model progresses hour by hour, relying on authentic market and frequency information from 2024. When first plugged in, the battery's SOC is at 50%, making it half full.

The battery model operates based on a principle: it charges using electricity when the spot price is lower than the FCR-N price and releases energy when the spot price exceeds the FCR-N price. At the same time, the system frequency's behavior during the hour affects this kind of action. Frequency can determine if the battery will respond or not.

Two sets of control logic were used to run the battery simulation:

For the first version, the battery either charges or discharges at a fixed speed. If the frequency goes above 50 Hz, the system sends a signal to charge the battery, but only if

there is still space available and the spot price is not higher than FCR-N. If the frequency falls under 50 Hz, the unit makes a discharge signal, provided that the battery has not completely discharged. With this system, energy output or input is planned and the hourly swing is measured using prices and the total amount of energy required.

Unlike the previous model, the power supplied by the battery is flexible. However, the charger or discharger will respond depending on how the frequency changes hour to hour. Those areas where the frequency change is greater have a stronger power flow. As a result, in the simulation, the battery gets disturbed more by big frequency changes and remains calm when the grid is steady. Spot price and FCR-N price are compared following the same pricing rule to check the profitability of the action.

The energy level in the battery is continually followed throughout each year for both versions. Every hour, the battery's state of charge is updated and the results are recorded. In the simulation, we do not consider efficiency decreases, battery aging or other technical issues. The goal is to see if price-based charging and discharging will function as expected. Profit and state of charge were plotted to see the results when all steps were run with Python.

This model shows why there are opportunities to profit from the differences between the spot market and FCR-N prices. That different choices in logic can produce different results from the same battery and data.

4.3 Profit Calculation Logic

Profit in this simulation results from the amount the battery charges or discharges and the difference between the spot price and the FCR-N market price for every hour. Any time the spot price is under the FCR-N, making the battery purchase price higher, this saves money by having excess energy. If sales are not done under good conditions, then losses can occur.

Basically, the hourly profit is decided by the battery's energy change and the variation in prices between markets. If it doesn't make sense to trade (because of the price or battery situation), nothing happens and no profit record is kept.

For each hour, the simulation is analyzed to look for these conditions. It determines if charging or discharging can be done using the frequency and prices in the energy market. After every step, the battery's SOC is updated to keep it from exceeding its maximum level. A battery cannot be charged more than its recommended levels and power should never go over 500 kW.

Every hour's profits are set aside and accumulated to the total profit over a period. This makes it possible to observe the battery's performance as the simulation continues. The final result demonstrates the impact of the set prices on profit, as well as the most and least profitable work time periods.

4.4 FCR-N Strategy Simulation

The simulation with the FCR-N used two logic versions to explore how a battery could profit from changes in prices and market frequency. Both cars utilized data and a battery from 2024 and were generally the same, but charged and discharged power differently.

The battery in the first tests could not change the amount of power it used for discharging and recharging. The reasoning was straightforward: the battery could charge if the frequency was 50 Hz or over and the spot was less than the FCR-N, plus there was enough room in the battery. If power decreased below 50 Hz, the battery might run out, but only if there was still some energy. The approach checked the frequency direction only and made choices without altering the power flow.

With Version 2, the logic began to work more actively. Whenever the frequency went up or down between hours, the battery changed its power output. A higher rate of movement meant the battery delivered more power. Consequently, the model showed how the battery would probably act in different grid scenarios.

Hourly data for the entire year of 2024 was used to test both versions. Each year, the research results were reviewed in January to March, April to June, July to September and October to December. This allowed analysis of how changing conditions and frequencies affected battery profit in each season.

It is believed that Version 2 gives a closer portrayal of operational reality because it responds to real changes on the grid. It also demonstrates how, even with the same battery and market, adaptable tactics may produce various financial results.

4.5 FCR-D Strategy Simulation

The same process for using batteries in FCR-N was adopted for the FCR-D upward and downward markets. The target was to measure how much profit was possible by comparing prices in the reserve market and the spot market. This simulation, though, avoided the true FCR-D situation, as the activation frequency was mostly eliminated.

Only when the system frequency is no longer within its usual limits does FCR-D services begin to operate. The frequency has to fall between 49.5 Hz and 49.9 Hz for upward regulation and must increase between 50.1 Hz and 50.5 Hz for downward regulation. Most cases did not see these abnormalities in 2024. Because of this, only limited testing time was available to make sure the battery could be activated.

Since activation data was not included, the FCR-D model was run just using the accessible market information. Hourly market rates, bids given by energy consumers and spot

prices were all recorded. As more frequency data becomes available, a more reliable simulation for FCR-D will be possible.

4.6 Assumptions and Tools

To make the model clear and simple, this thesis used a few basic assumptions when developing the simulation. We established a straightforward way of handling both charging and discharging. Whether the battery was charged or discharged depended on the price margin and the way the frequency went up or down. It operated with simple control methods and did not involve predictions.

No consideration was given in the model for the way batteries age or the energy lose. All the calculations show the battery was functioning perfectly all the time, rather than the battery's efficiency decreasing with age. Besides, both buyers and reserve sellers didn't face any extra expenses, including fees or running costs.

The analysis and simulations were performed chiefly with Python. Some of the libraries employed are pandas for process data, NumPy for calculations and Matplotlib for graph representation. The early uses of Excel included reviewing and clearing the first data, along with organizing the datasets prior to simulation.

Using these resources, the simulation ran smoothly and provided clear information for studying battery performance and profits.

5 Results

Simulation results for the FCR-N and FCR-D reserve markets are presented in this chapter. Because the simulations for this market use actual data, the main priority is given to FCR-N. Both a simple logic version (Version 1) and a version with more accurate battery behavior (Version 2) of the FCR-N simulation were tested. Each one is looked at one by one in the following section.

The results from the FCR-D project are also described briefly. The revenue numbers came up from running the simulation, but cannot put trust in them completely. The researchers explained that information needed to check if the battery would have been activated truly wasn't present. In addition, the FCR-D section is added to demonstrate progress and help plan future developments.

5.1 FCR-N Simulation: Version 1 and Version 2

5.1.1 Version 1 – Frequency-Based Battery Simulation

With Version 1, the battery powers the model in a basic mode. A battery charges its energy if the frequency is higher than 50 Hz and it discharges if it's less than that. Payment is only made when the current price is less than or equal to what was originally paid. The battery's size is 1000 kWh and it can charge or discharge 500 kW in an hour. The profit is found by comparing the amount of energy charged or discharged and the price between those times. Exploring limits in this model ignores how a battery acts under normal conditions. It shows how much profit could be earned if the battery system operated under ideal conditions.

See the graph above to observe battery behavior during the initial months of 2024. Up top, the SOC indicates the amount of charge in the battery. Many times, the battery charge went as high as 1.0 or as low as 0.0 which meant this version often included lots of both full charging and discharging.

Find the hourly profit at the bottom of the chart. In late January and mid-February, profits were highest for the company. There were many periods with only little profit and almost no times when the logic made unprofitable trades. The earnings over the past three months came to €12,035.77, proving that the company can generate profit under the right circumstances.

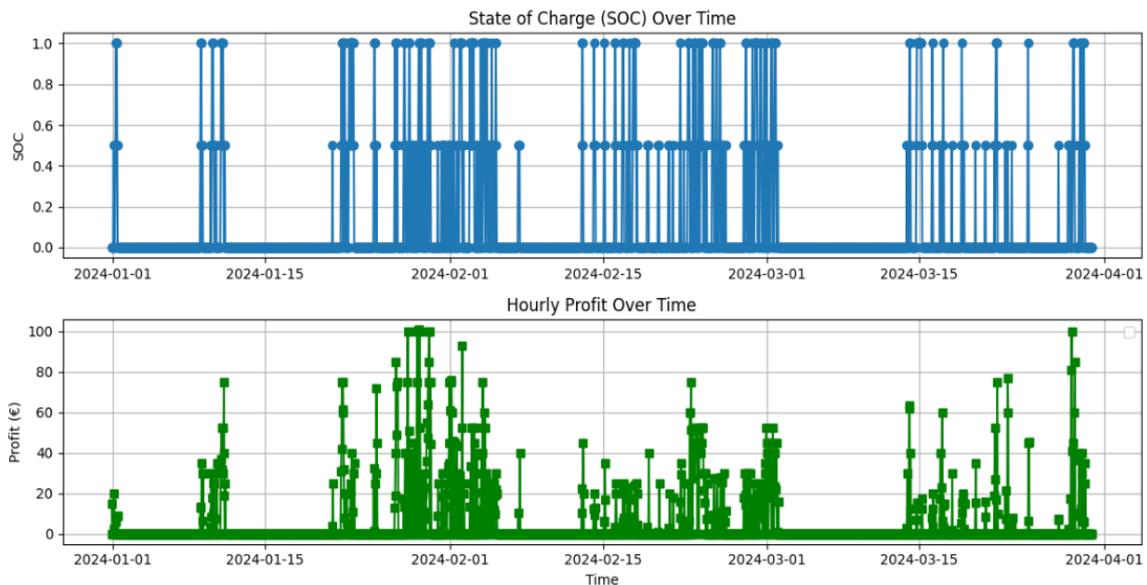


Figure 7. FCR-N Simulation (V1) Sos and Hourly Profit January to March

This graph records the battery activity that took place in the second quarter of 2024. At the top, the battery's SOC goes frequently from being empty to full, much as it did in the first quarter. The charge cycle happened since the battery was both filling and draining. The earnings for the battery are shown in the lower graph and notice many profitable hours, some going even higher than €200. Due to this, the market was more profitable during those hours. The company made €29,936.60 in profits during April to June, about

twice as much as the income during the first quarter. This result demonstrates that the market was in very good condition.

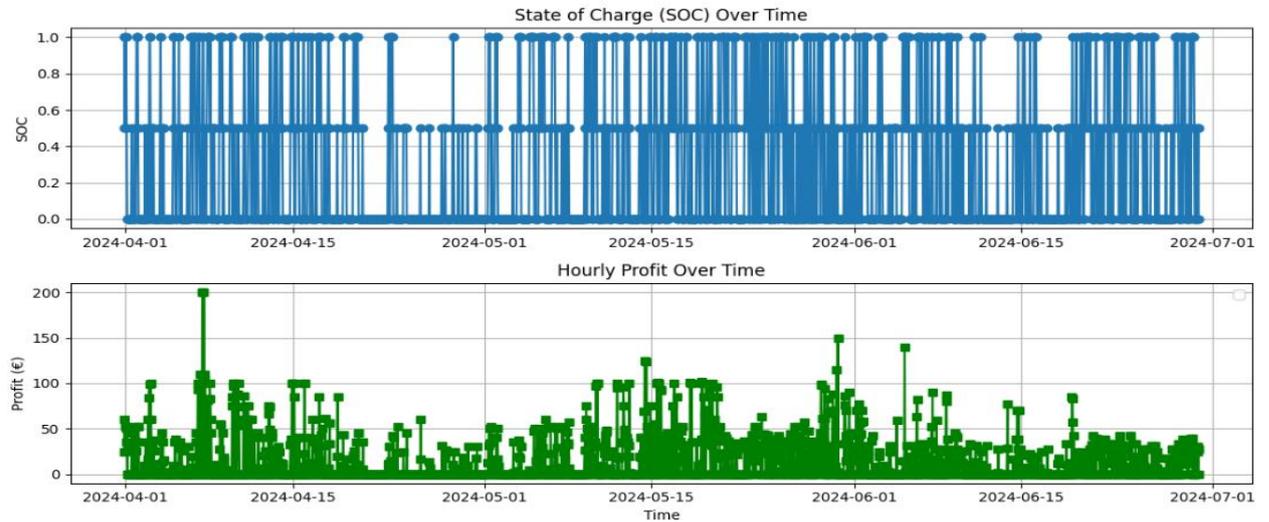


Figure 8. FCR-N Simulation (V1) Sos and Hourly Profit April to July

During July, August and September 2024, the battery made a total of €14,633.87. Whereas the income was lower this quarter, the vehicle was still able to use its battery all through the period. It showed that the battery repeatedly charged and lost power, based on how the state of charge shifted. While July and August brought more predictable profit, this seems to show that overall market conditions were pulling back from before.

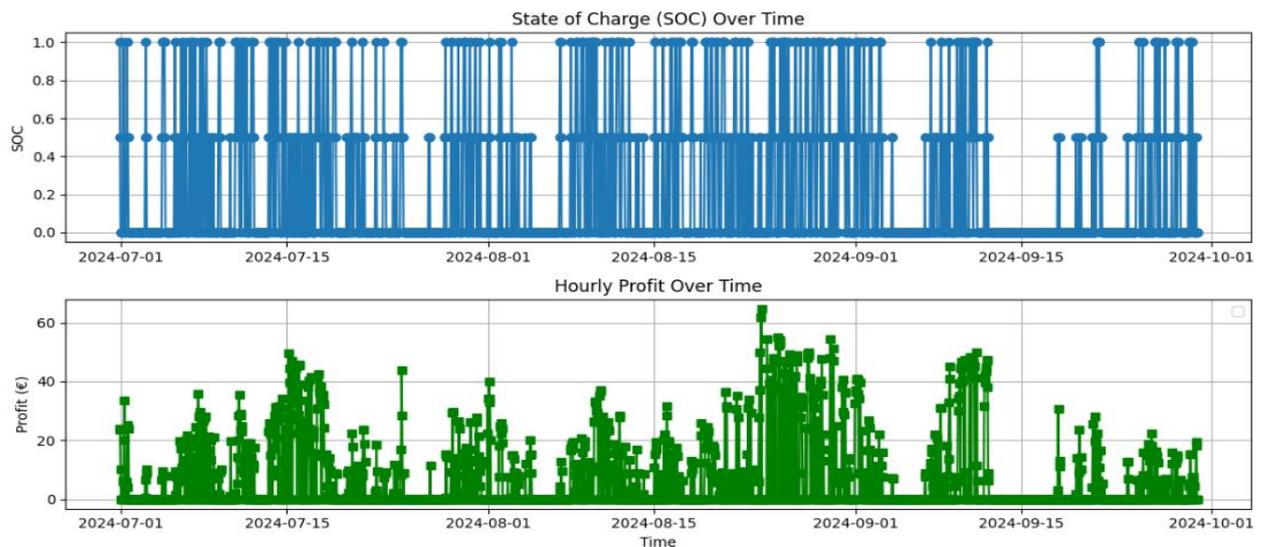


Figure 9. FCR-N Simulation (V1) Sos and Hourly Profit August to September

Over the period of October to December 2024, the battery earned €12,041.74. Profit remained at about the same level throughout the three months and there were no sudden increase. Prices did not fluctuate as much in this quarter as in previous quarters. Regularly, the battery charged and discharged according to the same simple way it always had. The results for this period were nearly identical to the first quarter, showing that earnings can change with market changes despite following the same system.

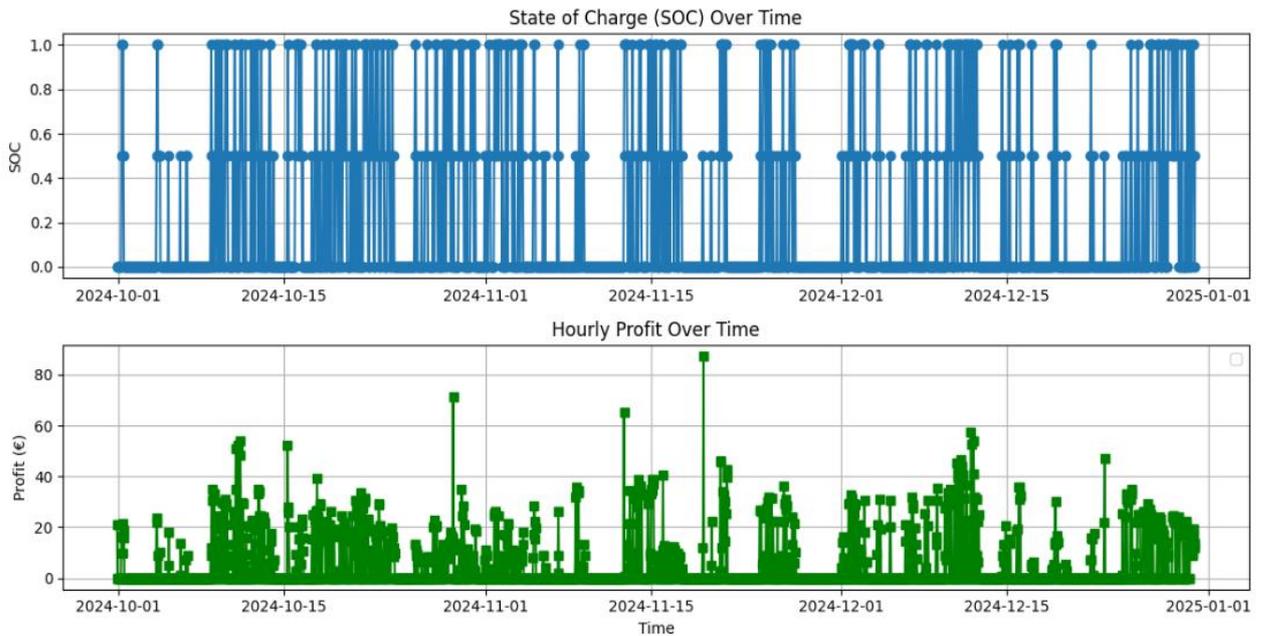


Figure 10. FCR-N Simulation (V1) Sos and Hourly Profit October to December

5.1.2 Version 2 – Spot Price-Based Battery Simulation

In this version, handling power with the battery is more accurate than it was in the first one. The device is charged by the FCR-N when the spot price is lower and discharged when the spot price goes above FCR-N. With a 1000 kWh capacity, the battery lets charge or discharge as much as 500 kW every hour. It always checks the energy level and won't let it get too high. The version use does not charge too much and only takes an action if it fits with the prices. Each hour, the profit is found by looking at how much battery capacity there is after charging or discharging. It allows me to observe the battery's responses to events that would happen in the real world.

Between January and March 2024, the battery earned a profit of €3,419.86 thanks to Version 2 logic. It can be observed from the top graph that the SOC increases at a slower rate than in Version 1. It was safe with charging and would avoid staying either very full or very empty for too long. We can tell from the bottom graph that profit per hour was less overall and more widely dispersed. The battery completed its charging or discharging only when the price was right. Even though the gain was smaller than in Version 1, this choice is safer and represents a more realistic way to trade.

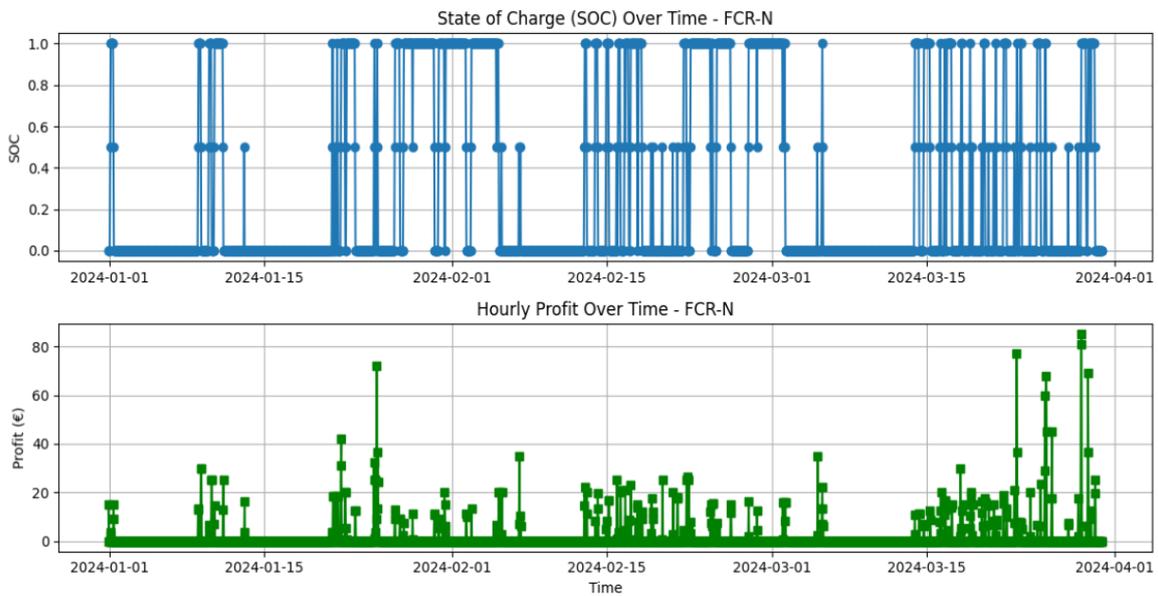


Figure 11. FCR-N Simulation (V2) Sos and Hourly Profit January and March

In April, May and June of 2024, the battery earned €9,600.19. There are higher levels of profit activity displayed on the graph, mainly in May and early June. Changes in price did not affect the performance much and the battery was used optimally. It appears that when the conditions were favorable, the logic shown in Version 2 gave better results.

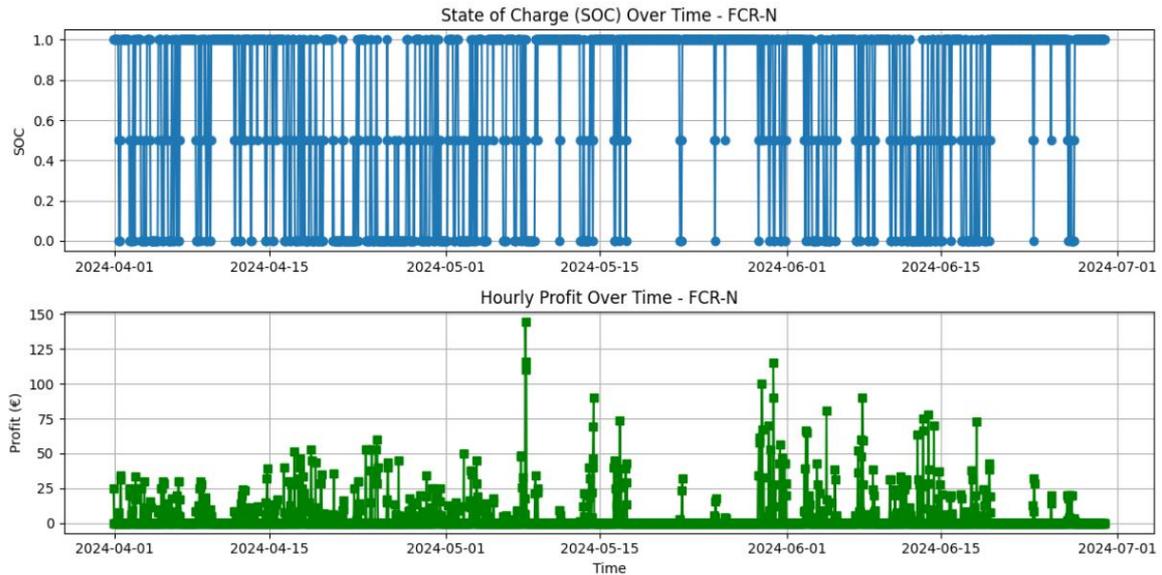


Figure 12. FCR-N Simulation (V2) Sos and Hourly Profit April to June

During the July to September quarter, the battery made €2,771.45, slightly lower than the quantities produced in the earlier quarter. Sales data show that profits were down and less intense, indicating the market did not work in their favor. Although the battery worked, according to the SOC graph, it didn't provide enough opportunities to earn much money anymore. Even though the basic idea is the same, the final result depends a lot on how costs and prices change over time.

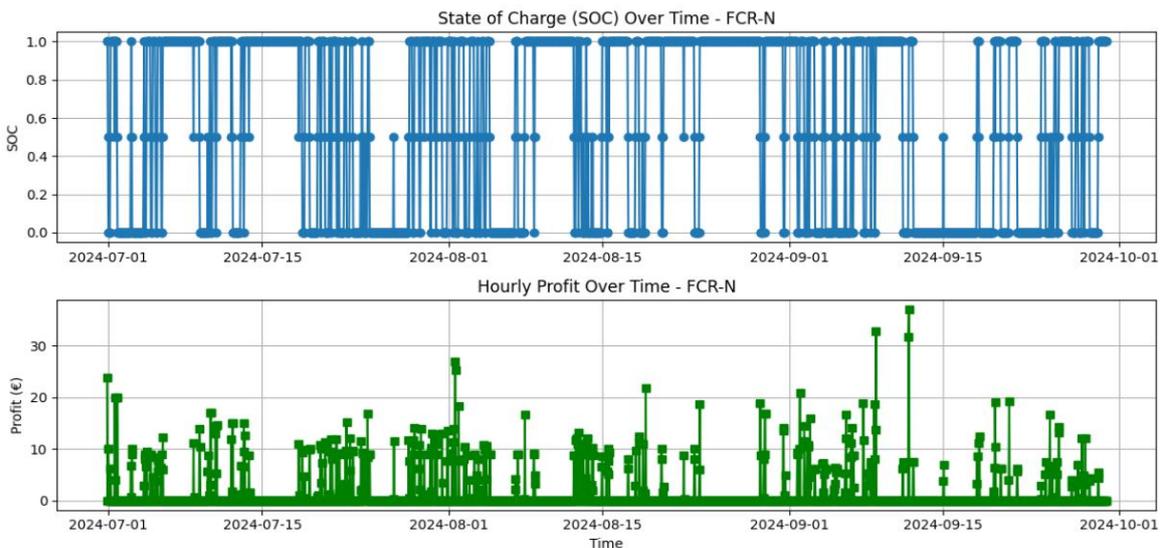


Figure 13. FCR-N Simulation (V2) Sos and Hourly Profit July to September

Between October and December 2024, the battery brought in €3,222.18. Mid-November was the main source of the company's profits, as shown by the graph. Besides that, the values remained lower and relatively stable. Even though the battery was active, the difference between spot and FCR-N wasn't quick enough to earn valuable gains. The outcome proves that the optimal charging time can be very different even with identical battery logic due to market fluctuations and timing.

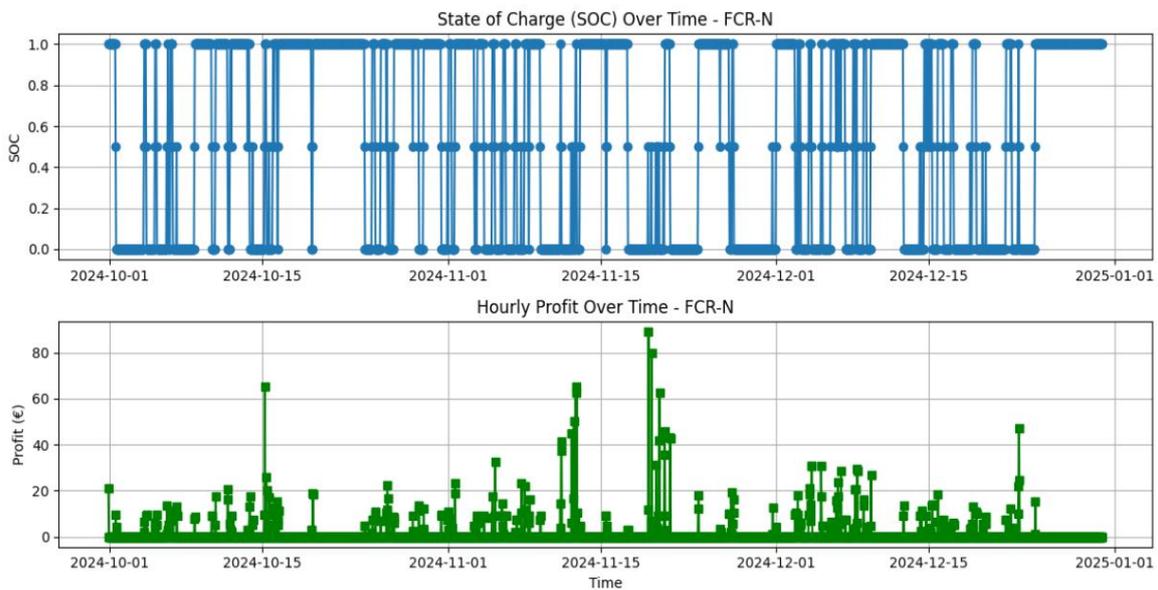


Figure 14. FCR-N Simulation (V2) Sos and Hourly Profit October and December

Version 1 brought in more profit or nearly €68,648, because it always used basic logic without restrictions. In Version 2, we made sure the simulator followed real battery rules such as maximum charging and discharging. Because of that, its profit became more consistent, at about €38,027. When we look at the two quarters, the biggest difference came in the second quarter with Version 1 making much more money than Version 2. It proves that actual battery planning should account for realistic logic.

5.2 FCR-N Profit Comparison (Version 1 vs Version 2)

Version 1 brought in more profit or nearly €68,648, because it always used basic logic without restrictions. In Version 2, we made sure the simulator followed real battery rules such as maximum charging and discharging. Because of that, its profit became more consistent, at about €38,027. When we look at the two quarters, the biggest difference came in the second quarter with Version 1 making much more money than Version 2. It proves that actual battery planning should account for realistic logic.

Table 1. FCR-N Yearly Profit Comparison (Version 1 vs Version 2)

Quarter	Profit – Version 1 (€)	Profit – Version 2 (€)
January to March 2024	12,035.77	3,419.86
April to June 2024	29,936.60	9,600.19
July to September 2024	14,633.87	2,771.45
October to December 2024	12,041.74	3,222.18
Total	68,647.98	38,027.36

5.2.1 FCR-D Upward

When Version 1 is selected, the battery is synchronized with the model's frequency. Under 50 Hz, it delivers energy and collects the profits from the rising FCR-D price. Above 50 Hz, the battery will charge. The miners continue to do this each hour, without looking at the current spot price. Overall, the version made €18,893.21.

In Version 2, the battery compares the FCR-D price going up and the spot price to make its decision. Only when the FCR-D price is greater than the spot price, it begins to discharge and make more money than it spends. If earnings are not possible at the moment,

it prefers to wait or trade when the exchange rate is decreasing. A total of €30,349.76 was raised using this version.

FCR-D Upward Profit Comparison (Version 1 vs Version 2):

Table 2. FCR-D Yearly Upward Profit Comparison (Version 1 vs Version 2):

Quarter	Profit – Version 1 (€)	Profit – Version 2 (€)
January to March 2024	2,194.72	775.40
April to June 2024	9,850.91	10,016.37
July to September 2024	3,409.01	2,301.00
October to December 2024	3,438.57	2,082.11
Total	18,893.21	30,349.76

5.2.2 FCR-D Downward

In Version 1, the frequency determines the amount of battery power used. When the electricity's frequency goes above 50 Hz, it charges the battery and it discharges when the frequency drops below 50 Hz. There's no requirement to check price tags. Total profit from the calculation was €15,860.73.

For Version 2, the way the battery works is determined by the price range. If the FCR-D downward price is higher than the spot price, it receives power, but if the spot price exceeds it, it transfers power out. The approach is to check both the bid and the ask prices before engaging in trade. The profit from this method was €21,192.92.

FCR-D Downward Profit Comparison (Version 1 vs Version 2):

Table 3. FCR-D Yearly Downward Profit Comparison (Version 1 vs Version 2):

Quarter	Profit – Version 1 (€)	Profit – Version 2 (€)
January to March 2024	7,160.09	2,962.36
April to June 2024	1,446.34	2,349.36
July to September 2024	3,467.30	2,757.40
October to December 2024	3,787.00	2,527.34
Total	15,860.73	21,192.92

6 Discussion

6.1 FCR-N: Strategy Logic Comparison

It is clear from the FCR-N market that the way the battery uses its strategy greatly affects how much profit the market brings in. Version 1 followed a simple set of steps. Without checking for any technical limits, the battery responded to any price changes in the market. This year, the business achieved its largest yearly profit: about €68,648.

For Version 2, Experiments were designed with greater control. It restricted how much power could enter or leave the energy level, measured energy reserves and compared rates before rolling out a decision. In this version, though profit was lower, the approach proved to be simpler to use in everyday cases.

The biggest change happened in the second quarter, when Version 1 made noticeably more income than Version 2. It can be observed here that the outcome depends a lot on the way the logic is built.

Version 1 made more money, but Version 2 gives results that are easier to use when planning. It shows that specifying the rules carefully is necessary to ensure the results used for planning can be depended on.

6.2 FCR-D: Initial Results and Data Limitations

The market between FCR-D and assets was explored with testing of both upswing and downswing trends in both logic variations. The findings seem to point toward earning income, but there are vital details missing that keep me from totally trusting the results.

Both tests showed that Version 1 reacted to changes in frequency. When the frequency went below 50 Hz, the battery's energy was used to buy when the market rose. Above 50 Hz, it headed lower in the market. The analysis in this version did not factor in how much the products cost or how cost-effective the products were. With Version 2, both brands were now shown with price comparison. When FCR-D prices increased above the spot price, the battery started working in a way that avoided unprofitable actions.

With Version 2, more money was earned, whether the stock rose or fell, compared to Version 1: €30,350 versus €18,893 tops and €21,193 instead of €15,861 bottoms. It proves that a basic filter on prices can help improve results. However, neither version includes what really activates the system: actual activity patterns in the brain. While strategies were made by counting standardly used frequencies per hour, for real use, decisions are taken when a frequency exceeds a given limit for a certain time. Detailed checks of this sort are not part of our presentation.

As a result, the reported results may appear more positive than what would actually happen in real operation. Without activation data, it is not possible to accurately estimate how often the battery would be used. Therefore, the final analysis should be repeated using updated and complete data, as the current results are only an example.

Because the study did not feature natural activation, the present results from FCR-D are meant for early evaluation. In subsequent experiments, the structure of this strategy can be tested using actual performance data. It helps us get better results and better understand the ways these choices shape actual profits in FCR-D markets.

7 Conclusion

This thesis explored the ways in which a 1 MW battery could make a profit by providing services within the Finnish FCR-N and FCR-D reserve markets. The purpose was to see which pricing approach works best for battery-based energy adjustment companies by testing on real 2024 data from Fingrid.

Two approaches to controlling the FCR-N were tested in this market. The model without real-world restrictions made the highest profit of nearly €69,000, but this is the basic version. Version 2 was the more serious model; it obeyed arcane technical rules such as limits on charging and state of charge and was sold for about €38,000. While the results from this version were less, but depend on them more easily in practice. From this part of the thesis, it is clear that if batteries are used in reserve markets, their owners should plan well and use logic that works in practice.

The results for FCR-D appeared encouraging, mainly because the algorithm tests both market prices and technical factors. In fact, a lack of real usage details meant the model made only limited estimates of battery usage. For this reason, the FCR-D gives only preliminary results. In the future, a comprehensive analysis with real activation can be done using the FCR-D.

Overall, this thesis contributes by looking at Fingrid data to demonstrate the profit impact of different pricing strategies. It also points out that using strategies in line with the market's real rules becomes especially important in a fast-moving environment. The early data from FCR-D are helpful for beginning future research on this subject. It is possible to further improve these models by considering battery life, using more advanced forecasting and handling bid rolling in the future.

The work enables battery operators and aggregators to know how to join the reserve market, using facts, logical rules and fair ideas.

8 References

Kempitiya, T., Sierla, S., De Silva, D., Yli-Ojanperä, M., Alahakoon, D., & Vyatkin, V. (2020). An Artificial Intelligence framework for bidding optimization with uncertainty in multiple frequency reserve markets. *Applied Energy*, 280, 115918.

<https://doi.org/10.1016/j.apenergy.2020.115918>

Lunde, G. A., Damm, E. V., Gade, P. A., & Kazempour, J. (2025). Aggregator of electric vehicles bidding in nordic FCR-D markets: A chance-constrained program. *IEEE Transactions on Power Systems*.

<https://doi.org/10.1109/TPWRS.2025.3558868>

Fingrid, *Reserve Products and Reserve Marketplaces*, 2023.

<https://www.fingrid.fi/en/electricity-market/reserves/>

Fingrid, *Balance Services Market Information*, 2024.

<https://www.fingrid.fi/en/electricity-market/balance-service/>

Alavijeh, N. M., Khezri, R., Mazidi, M., Steen, D., & Tuan, L. A. (2024). Optimal Scheduling of Battery Storage Systems in the Swedish Multi-FCR Market Incorporating Battery Degradation and Technical Requirements. *arXiv preprint arXiv:2406.07301*.

<https://doi.org/10.48550/arXiv.2406.07301>

Herstad, T. R., Kazempour, J., Mitridati, L., & Zwart, B. (2024). Bidding in Ancillary Service Markets: An Analytical Approach Using Extreme Value Theory. *arXiv preprint arXiv:2412.02308*.

<https://doi.org/10.48550/arXiv.2412.02308>

Åkesson, N. E. J. (2024). Optimization of Electricity Resources on the Swedish Electricity Market.

<http://lup.lub.lu.se/student-papers/record/9177224>

Larrabure Mercado, O. I. (2022). *Optimization for the Power Reserve Market* (Master's thesis, Universitat Politècnica de Catalunya).

<http://hdl.handle.net/2117/376368>

Hameed, Z., Pollitt, M., Kattuman, P., & Træholt, C. (2023). Frequency markets and the problem of pre-dictability.

<https://doi.org/10.17863/CAM.93378>

van Alderwerelt van Rosenburgh, P. D. (2024). Enhancing Battery Energy Storage in the Finnish FCR-N Market with Flywheel Technology.

<http://hdl.handle.net/20.500.12380/307972>

Wunderlich, F. L., & Brugger, S. (2023). Forecasting Swedish FCR-D Prices using Penalized Multivariate Time Series Techniques.

<http://lup.lub.lu.se/student-papers/record/9133997>

Viiil, J. (2024). Revenue Maximization of a Wind Park and Battery Storage: Investigation of Frequency Power Reserve Markets through Mixed Integer Linear Programming.

<https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1911802&dswid=-972>

Ehrlin, E. (2024). Profit Optimization of Battery Energy Storage Systems.

<https://www.diva-portal.org/smash/record.jsf?dswid=4917&pid=diva2%3A1884154>

Thingvad, A., Hameed, Z., Ziras, C., & Nouredine, A. F. (2024, June). Optimal Scheduling of Limited Energy Reservoir Technologies in Nordic Ancillary Services and Energy Markets. In *2024 International Conference on Renewable Energies and Smart Technologies (REST)* (pp. 1-5). IEEE.

<https://doi.org/10.1109/REST59987.2024.10645417>

Thingvad, A., Ziras, C., Le Ray, G., Engelhardt, J., Mosbæk, R. R., & Marinelli, M. (2022, July). Economic value of multi-market bidding in nordic frequency markets. In *2022 International Conference on Renewable Energies and Smart Technologies (REST)* (Vol. 1, pp. 1-5). IEEE.

<https://doi.org/10.1109/REST54687.2022.10023471>

Alizadeh, M. (2017). Multi-objective optimisation of community battery energy storage capacity exploitation.

<https://urn.fi/URN:NBN:fi-fe2017121255754>

Eloranta, A. (2024). Analyzing Battery Energy Storage System Operation on the Finnish Reserve Markets—The Cost Components and Their Relative Significance to Yearly Cash-flows.

<https://urn.fi/URN:NBN:fi:aalto-202411217350>

Hankimaa, H. (2023). Optimising energy and reserve offers in the Nordic markets under uncertainty.

<https://urn.fi/URN:NBN:fi:aalto-202308275171>

Laine-Ylijoki, J. (2024). Techno-Economic Analysis of Battery Energy Storage Systems in Wind Power Plants and Reserve Markets.

<https://urn.fi/URN:NBN:fi:aalto-202408255727>

Oksanen, S. (2017). Participation in ancillary service and physical electricity markets with flexible demand resources.

<https://urn.fi/URN:NBN:fi:aalto-201707045985>

Repo, O. (2020). Electricity Market Optimization and Value Gain for Power Resources Through a Conceptualized Platform.

<https://urn.fi/URN:NBN:fi:aalto-2020122056404>

Ruokosuo, K. (2018). Participation of consumers in the Finnish electricity sector-an analysis of profit potentials and subsequent market impacts.

<https://urn.fi/URN:NBN:fi:aalto-201812146544>

Saulny, N. (2017). Operation and profitability of batteries in electricity reserve markets.

<https://urn.fi/URN:NBN:fi:aalto-201707046003>

Laitila, J. (2020). Power procurement and consumption optimization in a global industrial company.

<https://urn.fi/URN:NBN:fi-fe2020062445640>

Sørdalen, A. P. (2022). *Optimal integration and control of distributed batteries for multiple grid services* (Master's thesis, NTNU).

[no.ntnu.inspera 108943276 50798153.pdf](https://no.ntnu.inspera/108943276_50798153.pdf)

Valle, A. E. (2024). *Multimarket Services for an Electric Vehicle-Considering Activation of Frequency Containment Normal Operation Reserves* (Master's thesis, NTNU).

[no.ntnu.inspera 187763641 46798909.pdf](https://no.ntnu.inspera/187763641_46798909.pdf)

Sandvik, S. A. (2024). *Comparative analysis of the Swedish and Norwegian reserve market* (Master's thesis, NTNU).

<https://hdl.handle.net/11250/3168769>

Casla, I. M., Khodadadi, A., & Söder, L. (2022). Optimal day ahead planning and bidding strategy of battery storage unit participating in nordic frequency markets. *IEEE Access*, 10, 76870-76883.

<https://doi.org/10.1109/ACCESS.2022.3192131>

Dias, L., & Jaumard, B. (2024). Providing frequency containment reserve with cellular network power infrastructure. *IEEE Access*.

<https://doi.org/10.1109/ACCESS.2024.3420179>

Strömer, S., Poplavskaya, K., & Damsgaard, N. Improving the Efficiency of the Swedish Balancing Market for Frequency Containment Reserve. Model-Based Analysis of Possible Measures. *Model-Based Analysis of Possible Measures*.

<https://doi.org/10.1016/j.egy.2022.09.079>

Hellgren, J. Optimizing Concurrent Trading in Day-Ahead and Balancing Electricity Markets Using Safe Action Reinforcement Learning. *Available at SSRN 4980599*.

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4980599

Juslin, A. (2021). Complementing a Kaplan hydropower turbine with a battery energy storage: BESS sizing for shared FCR-N market participation and reduction of turbine control movements.

<https://urn.fi/URN:NBN:fi-fe202103026350>

Appendices

Appendix 1. Python Code for FCR-N Market (Version 1)

The simulation relied on this Python script for a battery working on frequency. It does real-time charging and discharging by monitoring frequency, spot prices and FCR-N prices. Data cleaning, calculation of hourly profit and charts to represent state of charge and profit are all part of the code. Prices are converted to €/kWh, energy in kWh, and power in kW.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

fcr_path = "C:\Frequency Containment Reserve for Normal operation, hourly market
prices 1 to 3 month.xlsx"
spot_path = "C:\Spot price 1 to 3 month.xlsx"
freq_path = "C:\Frequency - real time data 1 to 3 month.xlsx"
fcr_data = pd.read_excel(fcr_path, sheet_name='Data')
spot_data = pd.read_excel(spot_path, sheet_name='Sheet1')
freq_data = pd.read_excel(freq_path, sheet_name='Data')
fcr_data['startTime'] = pd.to_datetime(fcr_data['startTime']).dt.tz_localize(None)
spot_data['Time'] = pd.to_datetime(spot_data['Time']).dt.tz_localize(None)
freq_data['startTime'] = pd.to_datetime(freq_data['startTime']).dt.tz_localize(None)
fcr_data.rename(columns={fcr_data.columns[2]: 'P_FCR_N'}, inplace=True)
spot_data.rename(columns={'Price (snt/kWh)': 'P_spot'}, inplace=True)
freq_data.rename(columns={freq_data.columns[2]: 'frequency'}, inplace=True)
fcr_data['P_FCR_N'] = fcr_data['P_FCR_N'] / 1000
spot_data['P_spot'] = spot_data['P_spot'] / 100
freq_data.set_index('startTime', inplace=True)
hourly_freq = freq_data['frequency'].resample('H').mean().reset_index()
merged = pd.merge_asof(
```

```

fcr_data[['startTime', 'P_FCR_N']].sort_values('startTime'),
spot_data[['Time', 'P_spot']].sort_values('Time'),
left_on='startTime', right_on='Time',
direction='nearest'
)
merged = pd.merge_asof(
    merged.sort_values('startTime'),
    hourly_freq.sort_values('startTime'),
    on='startTime',
    direction='nearest'
)
battery_capacity = 1000
power_flow = 500
SOC = [0.5]
P_level = [battery_capacity * SOC[0]]
profit = []
for i in range(len(merged)):
    f = merged.loc[i, 'frequency']
    P_FCR_N = merged.loc[i, 'P_FCR_N']
    P_spot = merged.loc[i, 'P_spot']

    if f > 50:
        c1, c2 = 1, 0
        P_charge = power_flow if SOC[i] < 1 and P_spot <= P_FCR_N else 0
        P_discharge = 0
    else:
        c1, c2 = 0, 1
        P_charge = 0
        P_discharge = -power_flow if SOC[i] > 0 else 0
    new_P_level = P_level[i] + P_charge + P_discharge

```

```

new_P_level = np.clip(new_P_level, 0, battery_capacity)
new_SOC = new_P_level / battery_capacity
P_level.append(new_P_level)
SOC.append(new_SOC)
hourly_profit = c1 * (P_FCR_N - P_spot) * P_charge - c2 * P_FCR_N * P_discharge
profit.append(hourly_profit)
results = merged.copy()
results['SOC'] = SOC[1:]
results['P_level'] = P_level[1:]
results['Profit'] = profit
results['P_charge'] = [500 if p > 0 and f > 50 and ps <= pf else 0 for p, f, ps, pf in zip(profit,
merged['frequency'], merged['P_spot'], merged['P_FCR_N'])]
results['P_discharge'] = [-500 if p < 0 else 0 for p in profit]
print(" Total Profit (€):", round(sum(profit), 2))
print("\n Most Profitable Hour:")
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
plt.plot(results['startTime'], results['SOC'], marker='o')
plt.title("State of Charge (SOC) Over Time")
plt.ylabel("SOC")
plt.grid(True)
plt.subplot(2, 1, 2)
plt.plot(results['startTime'], results['Profit'], marker='s', color='green')
plt.title("Hourly Profit Over Time")
plt.ylabel("Profit (€)")
plt.xlabel("Time")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()

```

Appendix 2. Python Code for FCR-N Market (Version 2)

In the FCR-N market, a Python code was created to model how batteries are charged and discharged. It calculates and records profit using FCR-N and current spot market prices, keeps track of the SOC and displays summary results and plots too. Prices are converted to €/kWh, energy in kWh, and power in kW.

```
#import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

fcr_path = "C:\Frequency Containment Reserve for Normal operation, hourly market
prices 1 to 3 month.xlsx"
spot_path = "C:\Spot price 1 to 3month.xlsx"
fcr_data = pd.read_excel(fcr_path, sheet_name='Data')
spot_data = pd.read_excel(spot_path, sheet_name='Sheet1')
fcr_data['startTime'] = pd.to_datetime(fcr_data['startTime']).dt.tz_localize(None)
spot_data['Time'] = pd.to_datetime(spot_data['Time']).dt.tz_localize(None)
fcr_data.rename(columns={fcr_data.columns[2]: 'P_FCR_N'}, inplace=True)
spot_data.rename(columns={'Price (snt/kWh)': 'P_spot'}, inplace=True)
fcr_data['P_FCR_N'] = fcr_data['P_FCR_N'] / 1000 # €/MW → €/kWh
spot_data['P_spot'] = spot_data['P_spot'] / 100 # snt/kWh → €/kWh

merged = pd.merge_asof(
    fcr_data[['startTime', 'P_FCR_N']].sort_values('startTime'),
    spot_data[['Time', 'P_spot']].sort_values('Time'),
    left_on='startTime', right_on='Time',
    direction='nearest'
)

battery_capacity = 1000 # kWh
power_flow = 500 # Max charging/discharging per hour
SOC = [0.5] # Initial SOC
```

```

P_level = [battery_capacity * SOC[0]]
profit = []
P_charge_list = []
P_discharge_list = []
for i in range(len(merged)):
    P_FCR_N = merged.loc[i, 'P_FCR_N']
    P_spot = merged.loc[i, 'P_spot']
    current_level = P_level[i]
    P_charge = 0
    P_discharge = 0
    if P_spot < P_FCR_N and current_level < battery_capacity:
        P_charge = min(power_flow, battery_capacity - current_level)
    elif P_spot > P_FCR_N and current_level > 0:
        P_discharge = -min(power_flow, current_level)
    new_P_level = current_level + P_charge + P_discharge
    new_P_level = np.clip(new_P_level, 0, battery_capacity)
    new_SOC = new_P_level / battery_capacity
    P_level.append(new_P_level)
    SOC.append(new_SOC)
    charge_profit = (P_FCR_N - P_spot) * P_charge
    discharge_profit = P_FCR_N * (-P_discharge)
    hourly_profit = charge_profit + discharge_profit
    profit.append(hourly_profit)
    P_charge_list.append(P_charge)
    P_discharge_list.append(P_discharge)

results = merged.copy()
results['SOC'] = SOC[1:]
results['P_level'] = P_level[1:]
results['Profit'] = profit

```

```
results['P_charge'] = P_charge_list
results['P_discharge'] = P_discharge_list

total_profit = round(sum(profit), 2)
best_idx = results['Profit'].idxmax()
worst_idx = results['Profit'].idxmin()
best_time = results.loc[best_idx, 'startTime']
worst_time = results.loc[worst_idx, 'startTime']

print(" Total Profit (€):", total_profit)
print("\n Most Profitable Hour:")

plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
plt.plot(results['startTime'], results['SOC'], marker='o', label='SOC')
plt.title("State of Charge (SOC) Over Time - FCR-N")
plt.ylabel("SOC")
plt.grid(True)

plt.subplot(2, 1, 2)
plt.plot(results['startTime'], results['Profit'], marker='s', color='green', label='Profit (€)')
plt.title("Hourly Profit Over Time - FCR-N")
plt.ylabel("Profit (€)")
plt.xlabel("Time")
plt.grid(True)

plt.tight_layout()
plt.show()
```