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Optimisation of Battery Energy Storage System in the Estonian Energy Markets

Master's Thesis (15 ECTS)

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Tartu 2024

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Abstract:
Energy markets are distinctive markets with their specific challenges, obligations, and opportunities. The characteristics of electricity as a commodity constrain the way it can be traded. An important factor is that energy that we use to power everything from our refrigerators to medical equipment needs to be in balance. Balance means that the supply and demand of electricity must be roughly equal at any given moment. This balance is crucial for ensuring stable frequency, as the frequency at which the electricity oscillates must remains constant. Deviations from that frequency can lead to power quality issues and disruptions. Therefore, the system balance is an imperative - it must be fulfilled or there can be damage to the grid that distributes electricity. Ensuring balance has historically not been an issue - whenever we needed, we could burn more coal, oil or other fuels to create more energy. However, how we produce energy has come under scrutiny over time, with more and more focus being placed on lowering the impact of our activity on the environment. Greener energy sources, such as wind energy and solar energy, are largely out of our direct control - we cannot make the sun shine or the wind blow. This means that we need assets that can ensure that the grid is always in balance. One option that can alleviate this issue, is a Battery Energy Storage System (BESS). A BESS is able to charge and discharge large amounts of energy. It can help us balance the market by shifting the supply and consumption from one point of time to another. As the renewable energy already holds a significant amount of the Estonian energy market, then it is necessary to analyse whether there already is an economic incentive for building such a system. That is, whether the current market allows for the owner of BESS to make a profit when using it as a tool for energy arbitrage - for buying energy when prices are low and selling when prices are high. For our analysis we will be looking at the day-ahead (DA) and manual frequency restoration reserve (mFRR) markets, which are currently available in Estonia and whether a BESS can be profitable on these markets. We will treat this question as an optimisation task, whereby we have to decide when to buy and when to sell energy on the market. We will demonstrate that given our assumptions, operating a BESS is profitable on the Estonian energy markets whereby we will show that most of the profit comes from the mFRR market.

Keywords:
Battery Energy Storage System, energy market, optimisation, manual frequency restoration reserve, day-ahead market

CERCS:
P160 - Operation research P170 - Computer science T140 - Energy Research

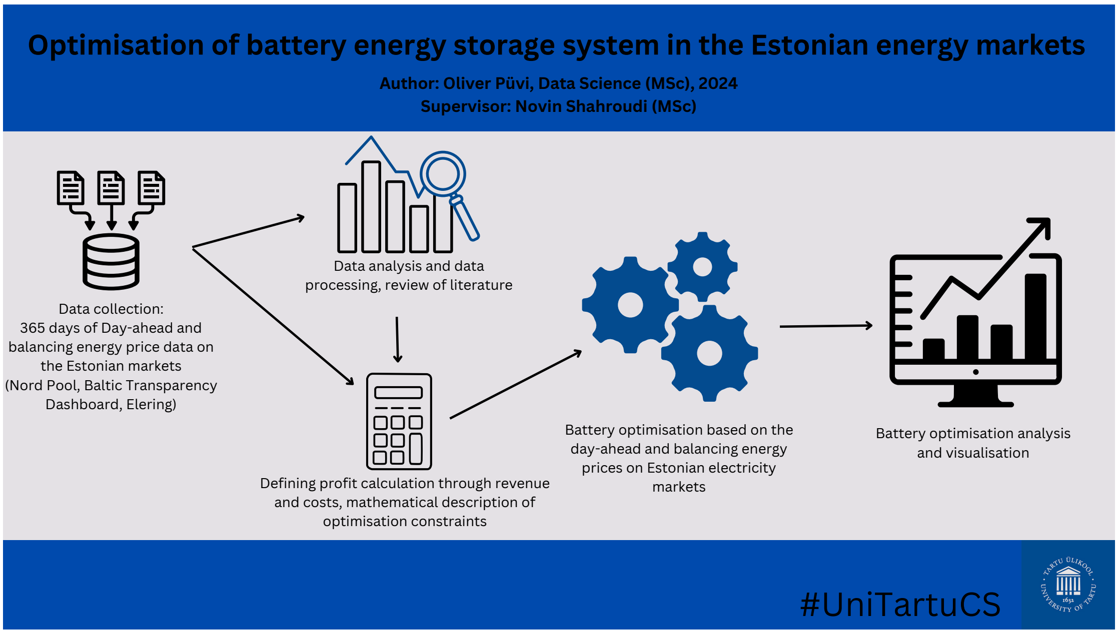


Figure 1. Graphical abstract

Suursalvesti Optimeerimine Eesti Elektriturgudel

Lühikokkuvõte:

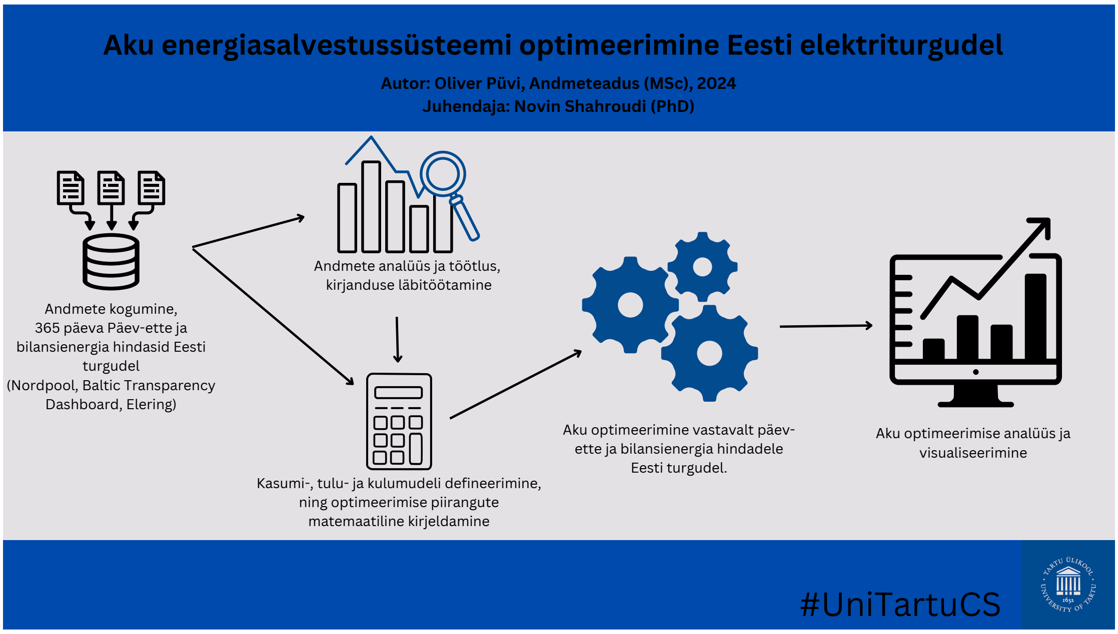
Energiaturud on eriomased turud, millel on oma katsumused, kohustused ja võimalused. Elektri omadused piiravad sellega kauplemise võimalusi. Oluline tegur on, et energia, mida me kasutame pea igal pool külmikutest meditsiiniseadmeteni välja, peab olema bilnasis. Bilanss ehk tasakaal tähendab antud kontekstis, et elektrienergia tootmine ja tarbimine peavad igal hetkel olema ligikaudu võrdsed. See tasakaal on stabiilse sageduse tagamiseks oluline, kuna elektri võnkesagedus peab elektrivõrgus püsima muutumatuna. Vastasel juhul võib ette tulla elektritoite häireid, ning elektrivõrk võib kannatada saada. Tasakaalu tagamine pole ajalooliselt olnud mure – vajadusel oleme saanud põletada rohkem kivisütt või muid kütuseid, et toota rohkem elektrienergiat. Seejuures oleme ajapikku hakkanud hoolima ka sellest kuidas ja millest me elektrit toodame. Üha enam keskendutakse tootmise keskkonnamõju vähendamisele. Rohelisemad energiaallikad, nagu tuuleenergia ja päikeseenergia ei ole aga enamasti meie kontrolli all – me ei saa sundida päikest paistma või tuult puhuma. See tähendab, et rohelise energia osakaalu suurendamiseks peame leidma viisi kuidas elektrienergia kindlus ja stabiilsus tagada. Üks lahendus antud probleemile on energiasalvestussüsteem ehk suur aku. Taoline süsteem on võimeline elektrivõrku laadima ja elektrivõrgust tarbima suures koguses energiat. Aku saab seega aidata meil turgu tasakaalustada, kuna seda saab kasutada elektrivõrgu koormamise ja mahakoormamise ühest perioodist teise nihutamiseks. Kuna taastuvenergial on juba praegu märkimisväärselt suur osa Eesti energiaturust, siis on tarvis analüüsida, kas sellise süsteemi ehitamiseks on olemas ka majanduslik stiimul. See tähendab, kas praegune turg võimaldab aku omanikul kasumit teenida kasutades seda energiaarbitraaži vahendina – energia ostmiseks, kui hinnad on madalad, ja müümiseks, kui hinnad on kõrged. Antud teesis anaüüsime aku kasumlikkust turgudel, mis Eestis olemas on - päev-ette turul ja manuaalse sageduse taastamise reservi turul. Me käsitleme seda küsimust optimeerimisülesandena, mille käigus otsustame, millal energiat turult osta ja millal turule müüa. Näitame, et meie eelduste kohaselt saab aku olla Eesti energiaturgudel kasumlik, ning et suurem osa sellest kasumist tuleb manuaalse sageduse taastamise reservi turult.

Võtmesõnad:

Energiasalvestussüsteem, aku, energiaturg, optimeerimine, manuaalse sageduse taastamise reserv, päev-ette turg

CERCS:

P160 - Operatsioonianalüüs P 170 - Arvutiteadus T 140 - Energeetika



Joonis 2. Graafiline abstrakt

Contents

1 Introduction

The governing trends in European energetics put a strong focus on reducing emissions. As a result we are seeing a rapid rise in the proportion of green renewable energy in our energy markets. By some estimates the proportion of renewables will rise to around 80-90% by 2050 [1]. However, the more popular renewable energy sources such as photovoltaic (solar) power, and wind power pose problems of their own as well.

First problem is that most systems that generate energy from renewable energy sources have limitations to how much their production can be increased in a given hour. Examples of such energy systems are wind parks (WP) and solar parks (SP) - pieces of land dedicated to producing energy from either wind (by wind turbines) or from solar energy (by photovoltaic systems - i.e. solar panels). The limit to their production is not only imposed by their size and technological aspects, but also by external factors - by the amount of wind or sunshine [2]. This means that if there is a need to increase production, then given that the WP or the SP has no supporting systems such as a battery, then it is impossible to increase its production. In turn, if the prognosis of the power generated by these energy sources is mistaken, then there is an imbalance risk in the grid - in the energy delivery system of a region. Imbalance in the grid means that the instantaneous supply and demand are not in balance (equal to each other), and thus the frequency in the grid is not on the level that it is supposed to be. This can negatively impact the grid itself, as the systems that distribute energy are built to operate at a certain frequency. Therefore the grid needs to be in balance - the demand and production must be equal as we cannot allow the frequency in the grid to deviate [3] from what the grid itself is built to tolerate. When the installed capacity[1] in the grid mostly consists of SP and WP, then, for example, an unexpected error in weather prediction can have a grave impact. It would not be possible to scale up the production of other parks to make up for the loss that the lack of sunshine creates in power generation. Because of this limitation these same parks cannot ensure the smooth functioning of the balancing market. That is, the balance in the grid cannot be solely guaranteed by assets that themselves depend on the factors such as weather. Thus, renewable energy sources leave the electricity grid vulnerable to weather, that at times can behave in an unexpected manner.

Besides the intermittency caused by the uncertainty in weather, there is always a danger that of a mismatch between the peak of the load and peak of supply.[4]. This means that even if the installed capacity of renewable energy sources is sufficient to cover the demand, then in practice this only holds if the period of high demand coincides with the period of high production. As opposed to the previous problem, this can lead to long-term

[1] Installed capacity refers to the maximum power that the energy production systems connected to the grid can generate.

inconsistency issues within the grid as it creates a situation whereby it is difficult to keep the grid in balance in the first place. This means that balancing the grid, even if there would be no prediction errors, would be difficult. For example for SP we expect high production periods to centre around midday, when the sunshine is strongest. Although midday is considered to fall among the peak hours [5], then the volumes sold at that time still fall short of the volumes sold right before the start and right after the end of the working hours [6] (before 9:00 and after 17:00). This means that the peak of SP power output usually does not coincide with the peak of demand (Fig 3). On the other hand, wind production is not as cyclical, which means that whether it meets the peak demand or not is irregular.

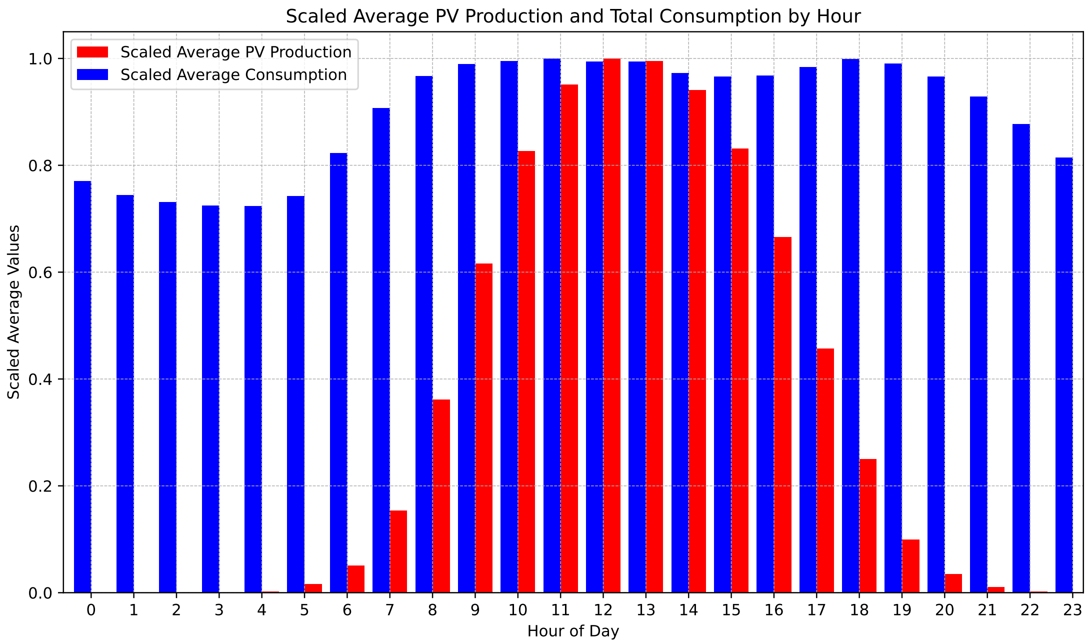


Figure 3. The average solar power production and the average consumption for each hour of the day in 2023. Graph is created using solar production and total consumption data from Elering [7]. The values are scaled by dividing with the highest average value of the corresponding data.

One solution that does not necessitate the coexistence of power stations that use non-green, non-renewable energy sources (e.g. coal-fired power stations) with WP and SP, is a grid-scale Battery Energy Storage System (BESS). Such a system can be operated virtually as a large, chargeable battery. BESS can charge when the supply is greater than demand and it can supply energy to the grid when the demand is higher than supply. Thus it can help fill in the gaps that the renewable energy sources leave as it can shift the time at which the produced energy is supplied to the grid and it can time its consumption. For example, it can do so by charging at times when WP can produce more than needed and by discharging when the demand is higher than what the WP can produce [8]. This would solve the second problem we posed. In addition, since BESS can be quickly ramped up or down (i.e. used to increase supply or demand) based on the need as long as it is not empty, then it solves the first problem we presented as well. That is, our BESS can also be used to instantaneously balance the demand and supply in the grid that reduces the intermittency caused by renewable energy sources[9].

Although currently renewable energy covers only a third of the demand in Estonia [10], it is essential to set such a system up to ease our transition from non-renewable energy sources to renewable energy sources. In other words, in order to be able to be more reliant on renewable energy sources, we must also have the capability to shift the supply from one period to another - something that we have not had to worry about, as this function has been covered by the non-renewable energy sources. The capability to transfer energy generation from one period to another must be ensured before it actually becomes the necessity as the damage of not being able to balance the grid might be irreversible. That preemptive approach can already be seen in the multitude of batteries being built in Estonia right now [11] [12]. Although such a system is necessary, the question becomes, whether BESS can also be profitable in the current energy markets for its owner. Is it profitable for the enterprise that controls and owns the battery? Is there an economic incentive for producers/suppliers to build grid-scale batteries that support the growth of renewable energy? That is to say, is the current balancing market set up such, that it allows for us to prepare for the growth of renewable energy usage, and whether there is incentive for private capital to cover this need?

In this thesis we will be retrospectively looking at how a BESS could have been operated on the Estonian electricity markets in 2023. We will be simulating participation in two primary markets currently operating in Estonia - the day-ahead (DA) market and manual frequency restoration reserve (mFRR) market. Since our thesis focuses on whether BESS can be a financially incentivised endeavour, rather than a necessity that must be guaranteed by the governing bodies of the market, then the goal of this thesis is to analyse the profitability of such a battery for its owner through optimising the BESS on Estonian energy markets. Similar optimisations have been done before on other DA markets for example in the US [13] [14], and in Denmark [15], and on the frequency markets for example in Latvia [16] and Germany/Spain [17]. However, it has not been done for the Estonian day-ahead (DA) and manual frequency restoration reserve (mFRR) markets.

In Section 2 we will first explain the energy markets with our main focus on the energy markets available in Estonia. In that section we will explain the day-ahead and intraday market, manual frequency restoration reserve, and imbalance settlements. We will then lay the ground for our optimisation in Section 3, whereby we will provide the mathematical formulation of our optimisation. In Section 4 we give an overview of the data that we will be using, and how we processed the data, as well as how we developed mock predictions that we used in our optimisation instead of actual price predictions. Finally, in Section 5 we will get to the optimisation itself. We will look at different scenarios and will then also analyse the results of our optimisation with conclusions in Section 6.

2 Energy markets in Estonia

The Estonian energy market operates in a similar manner to the energy markets in other European states. Electricity can be traded over the counter (OTC) or it can be sold and bought on the open market [3]. Our sole focus is on the open market. Currently there are 3 different markets for selling electricity in Estonia - the intraday (ID) market, day-ahead (DA) market, and manual frequency restoration reserve (mFRR) market, where the latter is considered a balancing market. In addition there are imbalance settlements for when a market participant cannot fulfill the obligations they have taken - when they have sold energy that they are unable to supply to the grid or when they have bought energy that they will not use. The way these markets operate, and the entity responsible for the market to function differs between markets and between countries. Therefore, let us dive deeper into these markets and also into imbalance.

2.1 Day-ahead market

In Estonia, just as in all of our neighbouring states except Russia, the day-ahead (DA) market maker is Nord Pool (NP)[2]. This means that NP is the mediator between different participants in the market. The energy suppliers provide the offers of volumes and the prices at which they would sell, and the consumers provide their bids of volumes and prices at which they would buy the specified volumes of electricity to the NP. NP will then match the supply side and the demand side to form the price of electricity for each trading period in the following day. For every trading period they release a supply and demand curve which features all the bids and all the offers in that given market to showcase how the price is formed (Example in Fig 6).

NP divides its participants into separate bidding zones. In most cases these market zones coincide with state borders. However, Norway and Sweden are divided into five and three market areas respectively. The other states that use NP as the DA market maker besides the aforementioned two are Finland, Latvia, Lithuania, Poland, Germany, Denmark, Netherlands, Belgium, France, Austria and Estonia (Fig 4).

The DA market is by far the largest market out of the aforementioned three markets (DA, ID, balancing), with 1030 TWh traded on NP in 2023 alone [19]. The participants in the DA market are free to offer electricity in any of the bidding zones offered as long as they can ensure that electricity is transferred to that market area. Whereas in some countries the granularity of the DA market is 15 minutes (e.g. Denmark [20]), then in Estonia it is 1 hour. This means that the seller offers to deliver a certain amount of energy in that period - for example 20MWh over 1 hour in Estonia, or respectively 5MWh over 15

[2]Nord Pool's website: `https://www.nordpoolgroup.com`

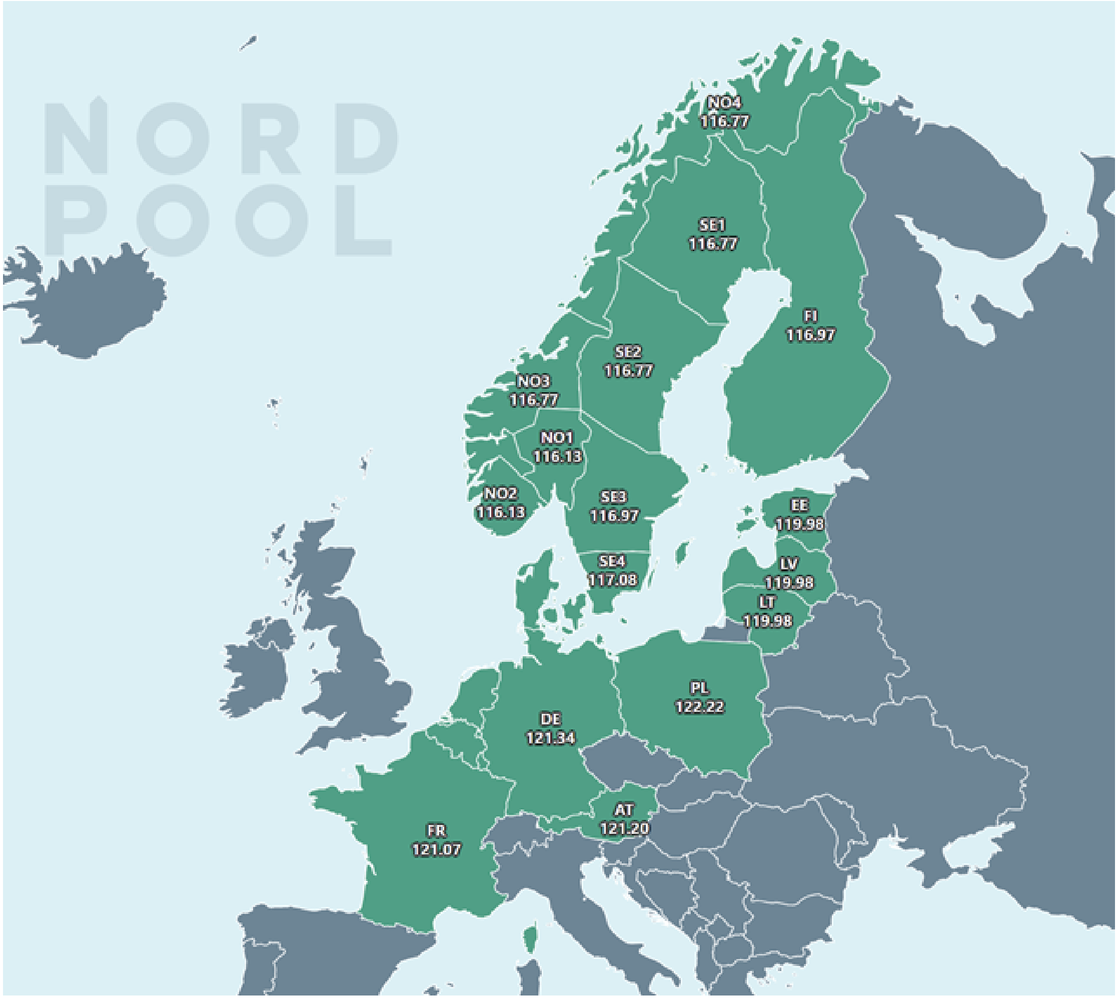


Figure 4. Nord Pool market zones with the average day-ahead (DA) price of 17.04 marked on them. These are the states for whom the NP is the market maker [18].

minutes in Denmark[21]. The participating parties cannot make any bids or offers with a shorter length in this market. Therefore in Estonia, it is not possible to, for example, make a bid of 10MWh delivered in 30 minutes.

The offers must also follow a certain structure. Assets that produce electricity (e.g. a single solar park) can be put together to form a portfolio of assets. Although there is no specified lower or upper limit to how large a portfolio needs to be, it is common to have one portfolio per enterprise. For example there can be separate portfolios for Estonia's largest electricity producing state-owned company Enefit's subsidiaries Enefit Green and Enefit Power. These portfolios comprise of multiple electricity producing assets - in the former case, of multiple WP and SP, and of multiple coal-fired power plants in the latter. Per portfolio there is one offer, in which the offering party specifies the different amounts of energy that they are willing to sell at different prices from that portfolio. The seller can specify the amounts that they would sell in as many price ranges as they want. However, they must specify the amount that they would be selling at in at least two prices - the minimum allowed price and the maximum allowed price. The minimum and maximum are set by NP. Currently the minimum price is -500 euros per MWh and the maximum is 4000 euros per MWh [21]. A simplified example of a bid can be seen at (Fig 5). As we can see, the minimum price is below zero. This can happen when the production of electricity cannot be curtailed (i.e. lowered or restricted) and the supply is higher than the demand. This can often happen because of the lack of control over the production of WP or SP. Another possible reason why prices go below zero is that states subsidize certain production methods. This can allow the supplier to offer energy to the market at a price which can be below zero, and still make profit because the government pays an additional fee for producing energy using that specific production method.[3] If such offers then cover the demand, then the price of the market can be zero or even negative. In this case, the providers have to pay for producing energy.[4]

As NP states, then for the DA market prices they use what in the political debate is called marginal price setting [23]. The price is set by the cost of producing one kWh of power from the most expensive source that is needed to employ to balance the demand and supply on the DA market. In essence what this means is that every seller in the market will be paid based on the price of the highest accepted offer. An example of how NP arrives at the price for one single bidding period using the offers to sell electricity and bids to buy electricity that they received can be seen in Fig 6.

The DA market operates according to a strict schedule. Every day at 10:00 CET, the information on available capacities in the grid and in the connections between different grids, also known as interconnectors, is published. All the offers from all the market zones for the next day must be sent to NP by 12:00 CET [23]. Usually around 13:45 CET the market results are released for all the operating hours in the next day. The price for electricity in different market areas is calculated by merging the demand and supply curve of the market for every bidding period. That is, the curve that aggregates all different prices and how large the demand for electricity is at those prices is merged with the curve that aggregates all of the different prices and how large the supply for electricity is at those prices. The resulting DA price for each period is found according to the intersection point of these curves (Fig 6). The results sent to the market participants

[3]For example subsidies have been paid in Estonia for renewable energy [22]

[4]The energy providers who also gain subsidies from the state can still make a profit, as their profit is not only reliant on the prices on the market, but also on the amount of subsidy that they receive.

		Price range						Price result
		-500 (euros per MWh)	**0**	**50**	**250**	**1000**	**4000**	
	00:00 -01:00	0 (MWh)	0	20	25	110	200	**10 (euros per MWh)**
	01:00 - 02:00	0	10	15	100	110	200	**55**
Hour	**02:00- 03:00**	0	15	20	25	110	200	**250**

Figure 5. Simplified example of a bid to NP. The Price at which the offer is made is in the upper row, whereas the time for which the bid is made is in the left side column. The values in the grid signify the energy which is offered at these prices. With the given resulting prices the quantity sold by the bidder would then be 0 MWh in the first hour (The quantity sold at prices less than 10 is 0). In the second hour the bidder would sell 15MWh (the highest quantity at a price less than the result price) at a price of 55 euros per MWh. The quantity sold in the last hour is 25MWh at a price of 250 euros per MWh.

contain the quantity sold by the producers and the quantity bought by larger consumers. NP uses forecasts for the consumption that is not announced beforehand (e.g. the cumulative electricity consumption of households in a market area),[5] which together with the uncertainty of renewable energy sources leaves room for imbalance in the system. In other words, since predictions almost always contain some error, then some market participants might produce less than they predicted they would, and some consumers might consume less. To alleviate those issues there are other markets. As is claimed by NP, then typically the results of the DA market are used as a baseline for the operations of the market participants. [24].

2.2 Balancing markets

In many market areas there are several markets for system balancing products - products that are aimed at correcting the errors in predictions under which the DA market offers and bids were made. In other words, the balancing market aims at alleviating the imbalance in the grid so as to restore balance. Imbalance itself is the difference between the energy that is supplied to the grid and the energy that is consumed from the grid. As such there are two types of imbalances from the perspective of the grid - positive imbalance whereby the supply is larger than consumption and negative imbalance whereby consumption is larger than supply [25]. Balancing markets operate on a continual basis. This means that offers and bids can be sent at any time between the market opening and the market closing. The gate closure, or the time at which the

[5] In Estonia these forecasts are sent by the grid operator Elering.

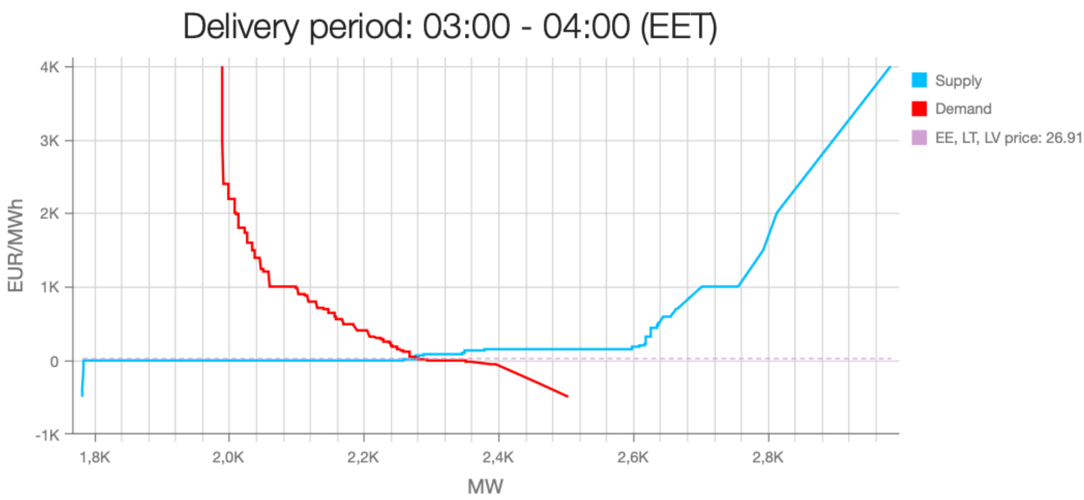


Figure 6. The aggregated bidding curve calculated by NP for 18.04 between 15:00 and 16:00. The price is determined by the intersection of the curves.

last offers must be submitted, differs from market to market. The typical products in the balancing markets are frequency containment reserve (FCR), automatic frequency restoration reserve (aFRR) and manual frequency restoration reserve (mFRR). Whereas the first is aimed at alleviating instantaneous frequency deviation from the norm that is set by the grid operator (the market agent responsible for the grid), the latter two are aimed at larger and longer deviations. As such, whereas FCR needs to respond to the deviations in a matter of 30 seconds [26], then aFRR is expected to respond in 5 minutes [27] and mFRR in 12.5 minutes [28]. The timing of when these products have to be able to supply energy into the grid from their activation can be seen in Fig 7.

The offers for these products are sent to the transmission system operator (TSO) - essentially the operator of the grid who is responsible for the functioning of the grid. The TSO is also the one that decides whether to activate the balancing energy market products or not. In Estonia, the TSO is Elering.[6] Since imbalance can be positive (too much production/too little consumption) or negative (too little production/too much consumption) [25], then there are also separate products for alleviating both. This means that there are two parallel products on the mFRR and aFRR market - upwards (increasing production/decreasing consumption) and downwards (decreasing production/increasing consumption) mFRR and aFRR. When there is negative imbalance, then upward mFRR and/or aFRR is activated (i.e. bought by the TSO) and when there is positive imbalance in the grid, then downward mFRR and/or aFRR is required. However, the gate closure for offers is such, that by the time when the TSO starts to accept these offers, then there

[6] Elering's website: `https://elering.ee`

is no longer any possibility to make the offers - these offers need to be made in advance. The market participants that make offers on the FCR market are expected to be ready to make both upward and downward adjustments.

In Estonia and other Baltic states there is currently only market for one balancing product - the manual frequency restoration reserve (mFRR) [29].[7] Therefore in the current analysis we will also be focusing solely on the mFRR market out of these different balancing markets. The mFRR, just as the name states, is a balancing reserve that historically has been activated manually [28]. In reality what this means is that it just has a longer time between the TSO announcing that the reserve needs to be activated and the time when it needs to supply energy to the grid. As was stated, it has to be able to produce the required amount of energy within 12.5 minutes from the offer being accepted.

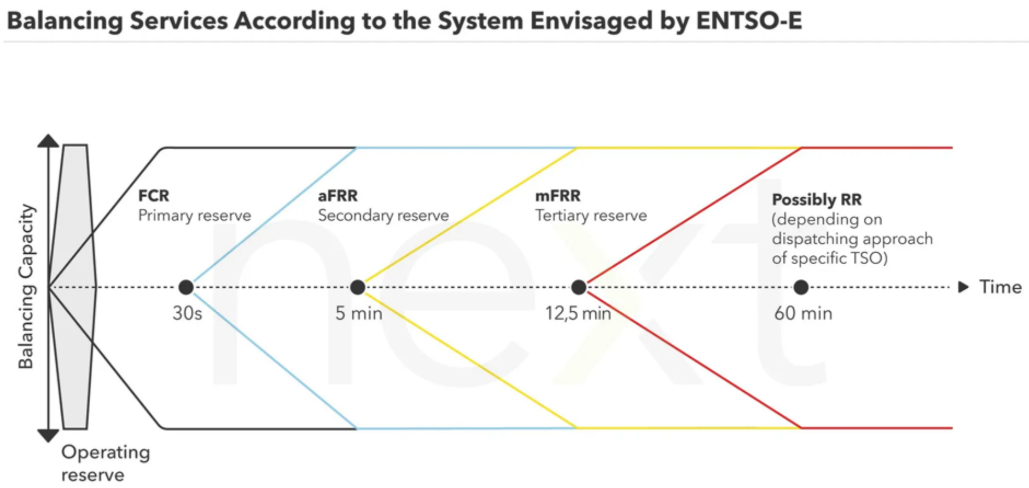


Figure 7. The onset of the products in the balancing market [28]. The times shown on the graph reflect the maximum amount of time allowed for these products to be activated after the TSO announces that they need to be activated.

The offers for mFRR are similar to DA offers in that they require the market participant to state the quantity and their price for that quantity for the hour for which they are offering their product. There is no minimum price in Estonia, but the maximum price is set at 5000 eur/MWh [29]. These offers are not sent to NP as the DA offers are, but to the TSO (in Estonia Elering) [32]. The gate closure for offers in Estonia is 45 minutes

[7] There are plans to introduce aFRR and FCR markets in Estonia as well. [30] [31].

before the delivery period begins [33]. This means that for the hour between 13:00 and 14:00 the offers must be in by 12:15. The offers are not accepted in advance, and the supplier who made the offer must ensure the capability to activate the reserves during the hour for which they have sent the offer. The resulting price of this market is also revealed after the trading period for which the offers were made. That is because it is the last accepted offer that determines the price for all accepted offers. However, we can know only at the end of the hour which offer was the last one accepted. Of course, TSO starts accepting offers from the lowest possible fee, meaning that the last accepted offer is also the priciest. There is no fee paid for offers that were not activated.

2.3 Intraday market

Intraday (ID) market is operated by the NP and it functions essentially as a marketplace between energy suppliers and large scale consumers [34]. There is no third-party that determines the price here. Subsequently, the pricing is not the same as for mFRR or DA market. You pay exactly as the bid you accept states. The market is continuous, meaning that orders and bids can be published at any time. The gate closure is an hour before the delivery period - after that the market for the given delivery period is closed. This means that for example the last possibility to make an offer or to accept an offer that is to be delivered between 13:00 and 14:00 is at 11:59. The ID market in Estonia is highly volatile, as there are few producers and large consumers, meaning that it is extremely difficult to predict this market. There is also no public data on the results of this market. Therefore this thesis will not be looking at the ID market opportunities.

2.4 Imbalance price

Imbalance price refers to the price that the TSO sets for settlements of imbalances [35]. This means that if an energy supplier supplies more energy to the grid than what it has sold on the energy markets, then they sell the excess energy with a price set by TSO to the TSO. Conversely, if the supplier supplies less energy to the grid than they have sold, then they buy the difference from the TSO with the price once again set by the TSO. The prices for both - buying from TSO and selling to the TSO are the same in Estonia. Since the only balancing market that exists in the Baltics is mFRR market, then the imbalance price is set with reference to the last accepted mFRR price, as well as to the direction of the balancing and the neutrality component [3]. Direction of the balancing just means that if there has been up regulation (i.e. TSO has accepted upward mFRR offers) then the price will reflect the upward mFRR prices. If they have acepted mFRR down offers, then the imbalance price will reflect the price of those offers. The neutrality component is an additional fee that is calculated based on the difference between the costs incurred by the TSO in purchasing or selling the electricity used to manage the imbalances. It is designed so that the TSO would not be making any profits or any losses on maintaining the balancing market.

However, strategic imbalance is in the gray area by law and is not allowed by the typical contract that the Estonian TSO, Elering, makes with the market participants. The Electricity Market Act (2024), Chapter 4, Paragraph 43, "Balance Responsibility," Part 1, states: "the market participant must ensure that the amount of electricity supplied to the network and/or purchased by the market participant in each trading period is equal to the amount of electricity acquired from the networks and/or sold by the market participant" [36]. Furthermore, it is stipulated in Elering's draft contract for electricity balance agreement with the supplier, that the electricity balance manager is not allowed to systematically buy or sell the balancing energy (i.e. the imbalance settlement) [37]. The participants are therefore not allowed to strategically deviate with their production from the quantity that they have sold on the market. This means that the market participant has the obligation to ensure that according to their predictions, it is able to fulfill the offers and bids that it puts on the market. As strategic deviation is not allowed, then we will also not be looking at the imbalance as a way to optimise our profits as the supplier, but only as a measure to fix our errors.

3 Optimisation task

In this section we will look at the formulation of our optimisation. We will look at how we calculate the profits and will go more in depth with how we calculate profits at a single time point t on the DA and mFRR markets as well as on the imbalance settlements. We will also express our cost calculations and the variables and parameters of each step. As such we set ourselves up for the optimiser, which we will express in the last section.

3.1 Problem formulation

The general formula for profit in our markets that we will be using is a modified formulation based on by Pelzer et. al. [13], and can be stated as follows:

$$\Pi = \sum_{t=1}^{T}(profit_t^{DA} + profit_t^{mFRR} + profit_t^{imb} - cost_t^{deg}) \tag{1}$$

Where Π stands for profit in euros, the first part, $profit_t^{DA}$, refers to the profit on the DA market, the second part $profit_t^{mFRR}$, refers to the mFRR market, the third, $profit_t^{imb}$ to the imbalance and the last, $cost_t^{deg}$, to the cost that degradation imposes. However, this is not our optimisation task yet, as even though it expresses the way we calculate profits, then we need to take into account the limitations of the market, and the constraints of how our BESS can behave on the market. Let us look at each part in this profit formulation in turn to understand how they contribute. We will be using the notation used by Dumas et. al. [38] for DA market profit, that we will modify using the approach by Nitsch et. al. [39] to fit the mFRR market into our optimisation. For degradation, we will use the notation and approach from Zhang et. al. [40]. We will be looking at a period of one year or 365 days. Since the granularity of the market is 1 hour, then our T will be one year in hours, meaning that $T = 8760$.

3.2 Constraints

Before we move onto the markets in our optimisation, we have to express the constraints of our battery that we have to take into account before any activity is allowed to take place. For this we have to first consider the limits on the state of charge that we allow for ourself. It is generally stated that the BESS should not reach its technical maximum capacity - the level that the battery can physically be charged to, nor the minimum - zero charge. As do Li et. al. [41] state, then if we want to operate a BESS continuously, then we need to have a range wherein we operate our BESS so as to avoid a forced shut-down because of overcharging or over-discharging. Therefore we restrict the maximum energy and minimum energy that our BESS can hold as follows:

$$s^{min} \leq s_t \leq s^{max} \tag{2}$$

where s_t stands for state of charge at time t. State of charge here refers to the amount of energy in the battery, and the unit for it is MWh. The s^{max} and s^{min} refer to the maximum and minimum amount of energy we allow our battery to contain. In our case we will limit the minimum at 5% and the maximum at 95% of the technical maximum that the BESS can technically hold.

The s_t itself is defined as follows:

$$s_t = s_{t-1} + e_t^{throughput} \cdot \eta + e_t^{imb} \tag{3}$$

in which η is defined as:

$$\eta = \begin{cases} \eta^{ch} & \text{if } e_t^{throughput} > 0 \\ 0 & \text{if } e_t^{throughput} < 0 \end{cases} \tag{4}$$

where s_{t-1} is the state of charge in the end of the last period, and $e_t^{throughput}$ is the amount of energy that we are either obliged to charge (positive) or discharge (negative) at time t. We allow it to be either positive (when we are charging) or negative (when we are discharging). The e_t^{imb} is the imbalance settlement quantity, or the quantity that we need to buy from or sell to the transmission system operator to settle our imbalance - to settle the amount of energy that we have bought but cannot fit into the battery, or the amount of energy that we have sold, but cannot deliver. It is positive, when we need to essentially buy extra energy from the TSO to cover our obligations and negative when we need to sell excess energy that otherwise would not fit into the battery. We will come back to this in Section 3.5. Parameter η^{ch} is the efficiency of charging which has to be between 0 and 1, and which in our case we assume to be 0.95. Efficiency refers to the coefficient of energy that we actually charge our battery by, or that we can deliver into the grid after loss of energy due to internal resistance. In our thesis we assume efficiency to be symmetrical for both charging and discharging, meaning that η^{ch} = η^{dis}. However, this does not mean that efficiency affects the amount of energy that contributes to the state of charge symmetrically. That is, if we are discharging our battery, then we still lose the total amount that we discharge by, although some of that will be lost because of the inefficiency. However, when we are charging the battery, then we also lose some of the energy because of the inefficiency, meaning that the amount by which our state of charge increases is affected by it. As an example, if we discharge by 20 MWh, and our and η^{dis} is 0.95, then even if $0.95 \cdot 20$MWh makes it to the grid, we are still lowering the charge in the battery by 20MWh, as $(1-0.95) \cdot 20$MWh is lost because of the inefficiency. However, if we charge the battery by 20MWh, and we assume η^{ch} to be 0.95 as well, then only $0.95 * 20$MWh makes it to the battery.

Further we have a technical restriction on our battery regarding the maximum amount it can charge or discharge by as well. This restriction on charging and discharging is as follows:

$$e^{min} \leq e_t^{throughput} \leq e^{max} \tag{5}$$

where e_{min} and e_{max} are the minimum and maximum amount that our BESS can charge or discharge in a single period. In other words, it is the maximum that we can buy from the market or discharge by in any given hour. Thus these two parameters set the limits on our maximum offers and bids on the market. In addition, we assume that the absolute value of our maximum discharging and charging sizes are the same, meaning that $|e_{min}|$ = $|e_{max}|$.

Our variable $e_t^{throughput}$ itself is the amount of energy that we are charging or discharging from our battery. depends on several markets and is therefore defined as:

$$e_t^{throughput} = e_t^{DA} + e_t^{mFRR,down} + e_t^{mFRR,up} \tag{6}$$

Here e_t^{DA} is the total amount that we are either charging or discharging by on the day-ahead market (it is negative when we are selling and positive when buying), $e_t^{mFRR,down}$ is the amount of energy that we are charging by on the mFRR down market and $e_t^{mFRR,up}$ is the amount that we are discharging by on the mFRR up market (since it is a discharging action, $e_t^{mFRR,up}$ will always be either zero or negative). That is, whereas mFRR up refers to a product that is aimed at increasing the electricity supply in the grid, then mFRR down aims at increasing the demand in the grid. This means that we will treat mFRR down as a charging activity and mFRR up as a discharging activity. The imbalance settlements are not accounted for here, since this energy never goes through our battery - it is settled on the market.

3.3 Day-Ahead profit

The DA market profit at time t can be expressed as follows:

$$profit_t^{DA} = (-\pi_t^{DA}) \cdot e_t^{DA} \cdot \eta \tag{7}$$

in which η is defined as:

$$\eta = \begin{cases} \eta^{dis} & \text{if } e_t^{DA} < 0 \\ 0 & \text{if } e_t^{DA} > 0 \end{cases} \tag{8}$$

where π_t^{DA} stands for the DA price of electricity at hour t. We are reversing the sign on the DA price since it depicts the price for buying 1MWh of energy. Reversing the sign means that we will observe selling as a profitable action, and buying as essentially a cost. That is because we have introduced e in Equation 6 as negative when we are discharging, and positive when charging. The e_t^{DA} stands for the amount of energy that we are either charging, or discharging based on the results of the DA market in MWh. Since we are operating a battery, which can buy or sell electricity, then we will allow the e_t^{DA} to be either positive (when we are buying) or negative (when we are selling). That means that we will represent the buying and selling activity with the same variable. This also creates a clear formulation in the possible activity in the DA market - we cannot charge (buy electricity) and discharge (sell electricity) at the same time. This is not only a technical restriction that we are setting, but also expresses that such activity would be of no benefit since the price for buying and selling is the same for every $t \in T$ on the DA market. This is also why in this market we are drawing no distinction between the price of selling and buying electricity. The η is accounts for the efficiency of charging/discharging. However, this does not affect our profits symmetrically either. That is, we will still be paying for the total amount that we buy from the market, whereas this only increases the state of charge in our battery by $\eta^{ch} \cdot e_t^{DA}$. However, when we are selling energy, then the state of charge in our battery diminishes by e_t^{DA}, but we will be earning only from $\eta^{dis} \cdot e_t^{DA}$ as that is the amount that we can sell after our losses. In other words if we are buying the electricity on the DA market, then we must pay for the amount that we bought, even if the charging efficiency means that we will not be able to increase our state of charge by the full amount that we bought. However, when we are selling energy, then we can only sell by the amount that we can get out of our battery, after discounting the losses that we incur because of our efficiency. We consider η therefore only when we are discharging to acount for this assymetry.

3.4 mFRR profit

For the mFRR market we will be extending the same notation. We will use an equation similar to what Nitsch et. al. [39] propose for the aFRR market since the aFRR and mFRR market operate in the same manner. The profit from the mFRR market can thus be expressed as:

$$profit_t^{mFRR} = (-\pi_t^{mFRR,up} \cdot \eta^{dis} \cdot e_t^{mFRR,up}) + (-\pi_t^{mFRR,down} \cdot e_t^{mFRR,down}) \quad (9)$$

whereby the mFRR up and down respective quantities $e_t^{mFRR,up}$ and $e_t^{mFRR,down}$ at time t follow the same logic as with our DA equations, whereby they are negative if we are discharging, and positive is we are charging. Since we also know that in the case of mFRR up we are discharging and in the case of mFRR down we are charging, then $e_t^{mFRR,up}$ will always be non-positive and $e_t^{mFRR,down}$ will always be non-negative. We also need to reverse the sign on the prices $\pi_t^{mFRR,up}$ and $\pi_t^{mFRR,down}$. This is because for mFRR up the price signifies the amount that the TSO pays per MWh supplied to the grid and since for the mFRR up the price signify the amount that we pay to the TSO for every MWh that we charge the battery by. As we have configured our quantities $e_t^{mFRR,up}$ and $e_t^{mFRR,down}$ from our perspective (positive when charging, negative when discharging) then we need to reverse the sign on the prices to account for this. Here η is again the efficiency of discharging the battery. However, since there are two different mFRR products, then we do not need the boolean - we know that discharging is associated with mFRR up and charging with mFRR down. Knowing that efficiency only affects profits that are earned from discharging, then we only need to discount the revenue earned from mFRR up. It must be noted that the way to make profit with downward mFRR, is that occasionally the price in the mFRR market for down product, $\pi_t^{mFRR,down}$, are negative, meaning that we will essentially be paid for charging our battery. The specific frequency of the prices in the mFRR down market over the course of 2023 can be seen in Fig 8.

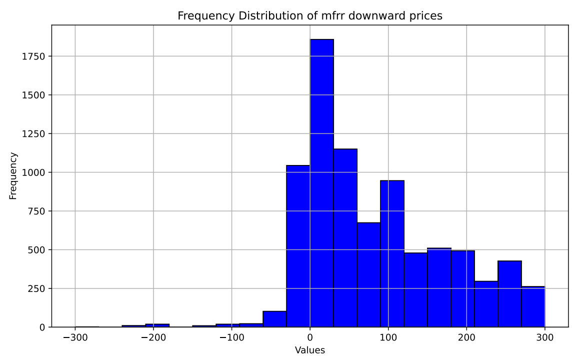


Figure 8. The frequency of mFRR prices in the Baltic region in 2023 based on the data from [42]. We can see that although most of the final prices for downwards regulation are positive, then there is still a considerable portion of instances, where the price ends up being negative, allowing for us to be paid for charging our BESS. More specifically, in our data, 13% of all prices are below 0.

3.5 Imbalance

The next factor that we need to account for in our optimisation is the imbalance. As stated in Section 2.4, it is not allowed to strategically deviate from expected consumption/supply to maximise profit from the system imbalance. As such, in our optimisation we will impose heavy penalty on any imbalance. By doing so we will ensure that we will run into imbalance only if no other action is possible. However, we will come back to this implementation in section 5.4. For now, we need to look at how imbalance can affect the profit that we are making. First, let us define what the state of charge would be without imbalance settlement at time t as:

$$\hat{s}_t = s_{t-1} + (e_t^{mFRR,down} \cdot \eta^{ch} + e_t^{mFRR,up} + e_t^{DA} \cdot \eta) \tag{10}$$

where

$$\eta = \begin{cases} \eta^{ch} & \text{if } e_t^{DA} > 0 \\ 0 & \text{if } e_t^{DA} < 0 \end{cases} \tag{11}$$

Here we are expressing what our state of charge would be without imbalance settlement at time t as $\hat{s}_t$. As we see it consists of the charging and discharging quantities from the DA and mFRR market. Using $\hat{s}_t$ we can then define the quantity by which we are in imbalance as follows:

$$e_t^{imb} = \begin{cases} (s^{max} - \hat{s}_t) & \text{if } s^{max} < \hat{s}_t, \\ (s^{min} - \hat{s}_t) & \text{if } s^{min} > \hat{s}_t, \\ 0 & \text{if } s^{min} < \hat{s}_t < s^{max} \end{cases} \tag{12}$$

In our imbalance quantity equation, $\hat{s}_t$ stands for what the BESS state of charge would be in the end of period t if we fulfilled our DA and mFRR market obligations in that period, s_{t-1} is the actual state of charge in the end of period $t-1$, s^{max} is the maximum amount of capacity that we allow our battery to be charged to and s^{min} is the lowest amount of charge that we allow our battery to fall to. This means that we cannot allow our BESS to have a lower charge than s^{min} or a higher charge than s^{max}. We simply will not go below or above those limits respectively. Therefore, the missing energy, or the excess energy will be our imbalance quantity. The way imbalance is settled is that the TSO will either buy the excess energy from us with the imbalance price, or we need to pay to the TSO for supplying more energy to the grid if we are lacking energy to fulfill our obligations. Therefore it is technically possible to make a profit on the imbalance, although as stated in Section 2.4, it is not allowed to strategically be in imbalance. Nevertheless, the profit from the imbalance settlement can be calculate as follows:

$$profit_t^{imb} = -\pi_t^{imb} \cdot e_t^{imb} \tag{13}$$

where π_t^{imb} is the price that the TSO pays for positive imbalance of 1 MWh. In other words, if we are supposed to charge by 1MWh more at time t, but our BESS is full, then we will be paid π_t^{imb} by the TSO. This does not instantly mean that we can earn more when we are in positive imbalance, as imbalance prices can also be negative. There is no efficiency coefficient here, as e_t^{imb} will never actually make it to the battery, nor will be discharged from the battery. It is simply the amount of energy that is our imbalance and will be settled completely on the market. We express e_t^{imb} as negative for electricity that we are selling to the TSO, and positive, for what we are buying from the TSO.

Furthermore, Equation 12 sets us clear instructions on when we will be using the imbalance settlements. We will only allow ourselves to use the imbalance settlement if we would otherwise go beyond our capacity threshold, or below the limit that we set. In other words, if further charging, or discharging of the battery is not viable anymore. As in our optimisation we will also be introducing heavy penalty on any imbalance, then adding this measure makes sure that we will not be strategically imbalanced, but that we will only use the imbalance settlement when in need.

3.6 Degradation cost

For the degradation cost we will be using the cost function proposed by Zhang et. al [40]. We will follow their assumption, that degradation cost can fully be counted for looking at discharge only. Based on their article the degradation in our scenario can be expressed as follows:

$$cost_t^{deg} = Q_{\text{cycle}}(h_t) \cdot (-e_t^{throughput}) \quad \text{where } e_t < 0 \tag{14}$$

Where $Q_{\text{cycle}}(h_t)$ is the capacity degradation for one cycle of size h at time t, which can be further expressed as:

$$Q_{\text{cycle}}(h_t) = A \cdot \exp\left(\frac{-E_a}{R \cdot \text{Temp}}\right) \cdot (h_t \cdot E^{\text{rate}})^z, \quad \text{where } h_t > 0 \tag{15}$$

In this equation A stands for Arrhenius equation's pre-exponential constant, E_a is the activation energy, R is the universal gas constant and $Temp$ is the absolute temperature.

Since we have no way to make sure what the internal temperature of the battery is, and since there seems to be no available data for a similar battery, then we will make the assumption that the battery always operates on the room temperature - on 300 Kelvins. The E^{rate} is the total capacity of our batter - the maximum amount that it can technically be charged to. In the equation h_t is the depth of discharge at time t. We express this further in Equation 16. We restrict h_t to only observations where we are discharging (where $h_t > 0$). That is, we are holding the assumption that the degradation can be captured by only looking at discharge. We can express our depth of discharge, h_t, here as:

$$h_t = \frac{(-e_t^{throughput})}{E^{rate}} \tag{16}$$

Where E^{rate} is again the total capacity of the battery. Essentially depth of discharge is the ratio of the discharge from the maximum possible discharge given the maximum capacity of our battery. Therefore the depth of discharge is dependent on the quantity we are discharging our battery by, and on the total capacity. Whether we allow this depth of discharge to be negative is not important, as this does not influence our calculations since we are looking at only cases where h_t is positive as was expressed in Equation 15. However, by reversing the sign on $e_t^{throughput}$ we do specify that we need to look at discharge as a non-negative number here since we are calculating the depth of discharge as a fraction of the total technical limit of the battery.

3.7 Optimisation steps

In our optimisation we will first maximise our profits on the DA market, as that is the primary market for most market participants according to NP [23]. In the DA optimisation we will be using a sliding window approach, whereby we will optimise our market behaviour for the following 168 hours which is also the time horizon proposed by Grimaldi et al. [14]. The time resolution, or the minimum amount of time for which offers and bids can be placed, is determined by the market and is 1 hour in all of the Baltic markets (Fig 9). Our stride, or the amount by which we move forward in time after every optimisation, is 24 hours, or 1 day. That is because of how the DA market operates - the offers and bids are made for the next day only. Our optimisation window is larger than 24 hours so that our optimiser can incorporate the possibility of there being better options further ahead in time. Therefore, for every single optimisation window, our optimisation task on the DA market becomes:

$$\text{maximize} \sum_{t=n}^{n+168} (profit_t^{DA} - cost_t^{deg}) \tag{17}$$

where n is the starting hour of our optimisation window. The $profit_t^{DA}$ is defined as was in Equations 7 and 11. We will not consider imbalance in this step, as according to our assumption, that we will explain in Section 5.3, we cannot fall into imbalance when trading on the DA market alone. In addition, as was already stated, we use window size 168 only for our optimiser to be able to check if there might be better possibilities further ahead. We will not be using the entirety of this optimisation window for actual offers and bids on the market, but rather only up to $t = n + 24$. That is because we will be using the optimisation for the next day only. As there will be more information regarding the future of DA market prices the next day, then we will optimise again over the following 168 hours from the beginning of the new optimisation window.

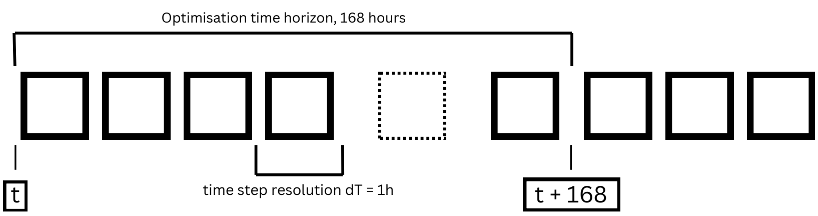


Figure 9. The DA optimisation window contains the first 168 periods. The time step resolution is 1 hour and the sliding window is 24 hours. Graph is inspired by Grimaldi et. al. [14].

On top of this optimisation, we will then have another optimisation that is done using the results of the DA market optimisation as the basis. This optimisation step revolves around making profit from the mFRR market, while maintaining the obligations that the offers and bids that we made on the DA market set on us. By the time we start optimising on the mFRR market, we already know the results of the DA market. Therefore, the DA market cannot be further optimised in this step. In this second optimisation we will be using a sliding window approach as well. Our window size is 8, and our stride is 1, since we can trade on the mFRR market continuously, as was explained in Section 2.2. As in this optimisation step we can find ourselves in imbalance (we will explain this dynamic in Section 5.4), then another aspect we need to consider here, is that we are not allowed to strategically use imbalance settlements as a way to make profit as was explained in Section 2.4. Therefore in our optimisation we will set a penalty on any imbalance that we would attain. Each window in this optimisation step can be expressed as follows:

$$\text{maximize} \sum_{t=m}^{m+8} (profit_t^{mFRR} - |e_t^{imb}| \cdot imb\_penalty - cost_t^{deg}) \tag{18}$$

where $|e_t^{imb}|$ is the amount by which we are in imbalance in either direction and $imb\_penalty$ is an arbitrarily large number that penalises our optimisation if we fall into imbalance. However, having imbalance in our optimisation in necessary as it allows us to function in situations where the only solution is to fall into imbalance. The reason why this is the only solution in those cases is further explained in Section 5.4. In this optimisation step we will include 8 periods in our optimisation as incorporating a longer time window than the window that we intend to use for trading gives the optimiser a way to find better solutions. In reality we will only be using 1 period for making trades here. Based on the trades that we make in this 1 period, and based on the underlying DA market trades in that same time window, we will calculate the state of charge expressed in Equation 3. This state of charge will be then fed into the following window of mFRR optimisation as the initial state of charge. By the end of 24 hours, i.e. after we have optimised 24 sliding windows, the resulting state of charge of the last window will be fed into the DA market optimisation as the initial SOC - this is the starting point of our new DA market optimisation. In addition, in both steps we need to maintain our constraints expressed in Equations 2 and 5.

This means that our optimisation will essentially operate as a loop, whereby the results of the DA market optimisation are fed into the mFRR market optimisation and vice versa. We will look at the implementation of this in Section 5. However, for our analysis we will also be referring to total profit, DA profit, mFRR profit and the resulting imbalance settlement profit, which will be calculated as we have expressed in this section.

4 Data preparation

4.1 Collected Data

For our practical application of optimisation we will be using public DA price data publicised by Elering [43] and balancing energy price data from the Baltic transparency dashboard (BTD) [42]. The data we are querying is from the 1st of January 2023 00:00 until and including 31st of December 2023 23:00. We are then merging this data, leaving us with the following columns with the granularity of one observation per hour per column:

- Balancing energy prices upward/downward (BTD)
- Imbalance price (BTD)
- DA prices (Elering)

whereby balancing energy prices are mFRR prices.

In practice, the main obstacle for a successful market optimisation besides the technical systems of asset operations and the asset optimisations, are the predictions of the market prices. These predictions are used by market participants that can allow their consumption or production to be flexible to decide the hours for which to make offers and bids. Since our BESS is a flexible asset, meaning that we do not have certain hours when we need to charge and when we need to discharge, then our decisions should also have to be based on market price predictions.

In this thesis we will not be making our own price predictions for the markets. Instead, we will create mock price predictions that we use to make the decisions on when to sell and when to buy energy from the market. To create these mock predictions we will be using historical price data of these markets which we will then add noise to so as to create our mock price predictions. Our aim with mock price predictions is to achieve an accuracy that has been achieved with real predictions on similar markets elsewhere. For this end we will be using the DA price forecast precision achieved on the German market [44] and the mFRR price forecast precision in the Hungarian market [45]. Thus we assume that the market predictions that can be made for the markets available in Estonia would be as precise as the precision of predictions in the aforementioned articles. Employing this asumption we will create mock predictions for the markets that we will be optimising on. That is, we will use the errors in the literature to create price predictions that would be as precise compared to our real data as the predictions in the literature to the data that they were compared to. We will then use these mock predictions as the basis of our optimisation.

4.2 mFRR mock price predictions

First, let us take a look at how we create the mFRR mock price predictions that we can use in our optimisation to decide when to participate on the market. We will model these predictions based on the actual mFRR price data that we have on the mFRR market available in Estonia. To form these mock price prediction, we will use the prediction accuracy that has previously been achieved on mFRR price predictions in a smilar market. We will use the prediction accuracy that has been achieved in the Hungarian balancing market by Balazs et. al. [45].

Table 1. Balazs et al. mean absolute error (MAE) values with ARDL [45]. The values that Balazs et. al. achieve on the mFRR market price predictions.

Step	MAE (ARDL)
Step 0	28
Step 1	40
Step 2	49
Step 3	55
Step 4	63
Step 5	69
Step 6	73
Step 7	76

Their research demonstrates that the mean absolute error (MAE) of these predictions varies greatly depending on how far ahead we are predicting these values (Table 1). Namely, if we were to predict the price in the next period, then the lowest error that the authors achieve is of mean absolute error (MAE) 28, but the one after that is already considerably less accurate, achieving a MAE value of 40. From there on, the accuracy of the predictions diminishes for every following prediction period.

For every hour, we will model the price predictions of the mFRR market for the next 8 hours so that our mock prediction error would be as close to the MAE (Table 1) values that Balazs et. al. achieved using autoregressive distributed lag (ARDL).[8] That is, we are aiming to have mock predictions which will reflect the accuracy that their research has previously achived. We will then use the resulting price values as mock predictions in our optimisation. Since their mFRR prediction research focused on the following 8 hours and since we know that the prediction accuracy will fall, then we will make the assumption that the predictions that would be made beyond that horizon would be too inaccurate to use them in our optimisation. In addition, since it is a continuous market, meaning that offers can be submitted at any time before the gate closure, then we do not need to make the offers on the mFRR market that far ahead - it is a more sensible strategy to make the offers as late as possible, as our price predictions will be more precise.

[8]We will not be delving into the methods that the authors used to achieve that results, but will merely use their results.

After having optimised over the next 8 hours, we shift the window of optimisation by 1 hour. This means that for example, we will begin optimising at hour 0 and will then optimise our behaviour for hours 1-9. After that we move to hour 1, where we will be optimising for hours 2-10 etc. We will of course keep the optimisation results for hour 1 (i.e. the hour which we currently are in by the beginning of our following optimisation window, but for which the offering window has already closed). We can thence better optimise again for the upcoming hours. For calculating market results we will then replace these mock prices with our real prices again. This allows us to create a setting that is similar to the real market setting. The specific steps of how we obtain our mock predictions can be seen in Fig 10. An example of how our next 8 hour predictions compare to the real values can be seen in Fig 11.

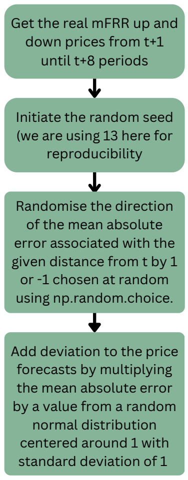


Figure 10. The steps we have taken to get the mock price predictions in the mFRR market. For the MAE values we used the values specified in Table 1

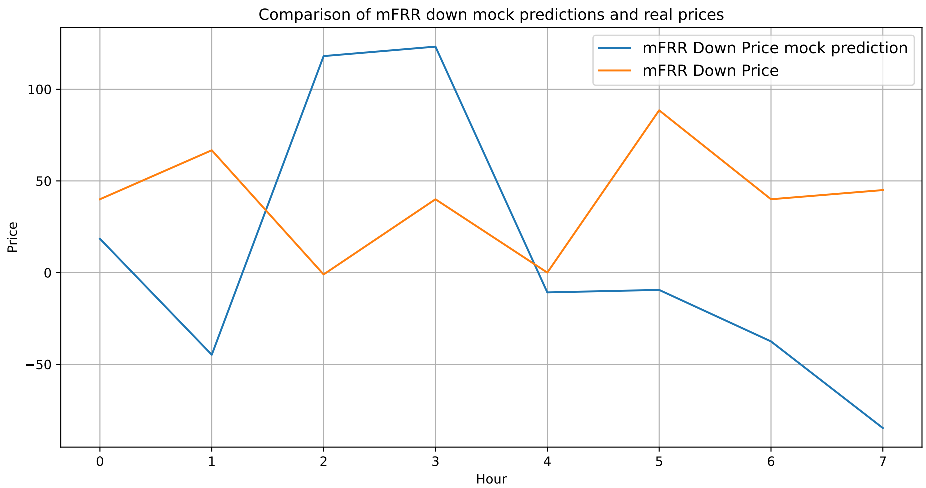


Figure 11. example of the mock predictions for mFRR up compared to the estimated values. All else kept the same, the expected error for mock prediction values grows as we get further from the current time. However, the error also depends on the size of the real values - the larger the value, the larger the expected error. The direction of the error is randomised.

4.3 DA mock price predictions

For DA prices, we will also be modelling our own mock predictions. We will use a similar approach to the one we used for mFRR mock predictions, but this time we will be using the prediction precision that Lehna et. al. (2021) achieved on German DA market [44]. We will model the data so that we will attain mock predictions whose precision matches the prediction accuracy of the aforementioned article as closely as possible. More specifically, we will model a set of DA price mock predictions with the errors close to (but not less than) MAE of 5.444 and root mean squared error (RMSE) of 7.152 that the authors achieve on an ensemble model consisting of neural network ensemble models.[9] The authors achieved these results on hourly week-ahead predictions, meaning that this precision refers to the hourly prices of the DA market for each hour one week ahead. In our optimisation we will be using this prediction precision, as it allows us to plan ahead for longer than one day, for which most predictions in the literature are made for [46] [15] [47]. Although Lehna et. al. do not specify directly how the forecast precision changes the further we go from the present time, then they do provide forecast precisions for one day ahead and for one month ahead as well. The precision accuracies in those cases do not deviate as much from the week ahead forecast errors that we are using (MAE of 5.173 and RMSE of 6.409 for one day ahead and MAE of 5.919 and RMSE of 7.917 for thirty day ahead) [44]. Because the prediction error does not deviate between the different time horizons, then we will simply model our mock predictions for the entire year in one go. This simplifies our optimisation problem, as we do not need to compute the mock predictions separately in every moving window as instead we have a dataset of DA mock price predictions that we can always refer to in our optimisation. Of course, for the results of our optimisation, we will then refer back to the actual prices again.

The way in which we approach the mock predictions in the DA market is a bit different than in the mFRR market, as we need to do it for the whole dataset and as we are also looking at RMSE in addition to MAE. We will try to find the mock dataset that compared to the original prices yields us the errors most similar to the errors specified in the work of Lehna et. al. [44]. For this end we employ a three step noise adding set up that includes noise factor, noise, and scale that can also be seen in Fig 12. However, let us take a closer look at how DA price mock predictions are calculated.

The first step is the **noise factor**. This is calculated as follows:

$$\textbf{noise\_factor} = |\pi_{\mathrm{DA}}| \cdot \text{proportionality\_factor} \tag{19}$$

where $|\pi_{\mathrm{DA}}|$ is the list of all absolute values of DA prices and proportionality factor is

[9] Once again we will not focus on their method, but are merely using their results for our mock price predictions.

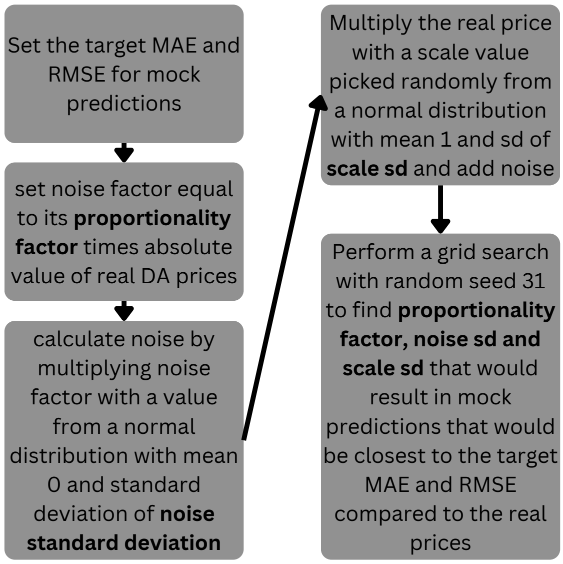


Figure 12. mock DA prices retrieval procedure. We first define how we find the parameters and then perform a grid search over them. This way we find the optimal parameters for proportionality factor, noise standard deviation and scale standard deviation.

a variable for which we are performing a grid search between 0 and 0.1 with a step of 0.001. Therefore it results in a list of noise factors, that can be used for scaling the noise based on the size of the DA values. The assumption here, is that the prediction error is larger, the larger the DA prices are. In other words we ensure that the absolute percentage error (MAPE) is similar between the higher percentiles of the prices and the lower percentiles of the prices in the data. We call this an assumption as the literature we are using to obtain this data does not calculate MAPE itself.

We then use the resulting noise factor to obtain **noise** as follows:

$$\textbf{noise} = (X_1 \cdot s_1, X_2 \cdot s_2, \ldots, X_n \cdot s_n) \tag{20}$$

where $X_i \sim N(0, \text{noise\_sd}^2)$ for $i = 1, 2, \ldots, n$, and each s_i is the corresponding element of the **noise_factor** array. Each X_i represents a random noise component scaled individually by s_i, aligning with the structure of the array of the DA prices over the year that we are looking at, and the length of which defines our n For **noise_sd** we will perform a grid search once again for values between 0 and 0.2. In that manner we have a noise for every single element in our DA prices array. We will get to how we use it shortly.

For the **scale**, we will again draw values from the normal distribution. This time centered around 1:

$$\textbf{scale} = (S_1, S_2, \ldots, S_n) \tag{21}$$

where each $S_i \sim N(1, \text{scale\_sd}^2)$ for $i = 1, 2, \ldots, n$. Here again, n is the number of elements in the array of the DA prices over the year, and each S_i represents a random coefficient generated from a normal distribution with mean 1 and standard deviation **scale sd** for which we will perform the third and last step of the grid search. Here we will use the grid search to find values between 0 and 0.1.

The resulting mock predictions will then have the form:

$$\textbf{mock\_DA\_predictions} = \pi_{\text{DA}} \cdot \text{scale} + \text{noise} \tag{22}$$

For the grid search of proportionality factor, noise standard deviation and scale standard deviation we used a random seed of 32. When we compare the resulting mock predictions with the real DA prices from 2023, then we have achieved a MAE of **5.4493** and RMSE of **7.81**, which are slightly higher than the results achieved by Lehna et. al. [44], but nevertheless reflect their results. The resulting proportionality factor is 0.007, the noise sd is 0.037 and the scale sd is 0.075. An example of mock prices compared to the real DA prices for one week can be seen in Fig 13.

4.4 Imbalance prices

As was stated in section 2.4, then even if being strategically positioned in relation to the system imbalance is not necessarily illegal, then it definitely remains in the gray area. Furthermore, as was also discussed beforehand, in the typical contract with Estonian TSO Elering, it is specifically brought out that such strategical positioning is not allowed. Since in our optimisation imbalance will therefore be the last restort option, then we will not create mock imbalance prices. We will include the possibility of the imbalance into our optimisation, but our optimiser must decide to be in imbalance if and only if there is no other choice. We will specify how we ensure that in section 5.4.

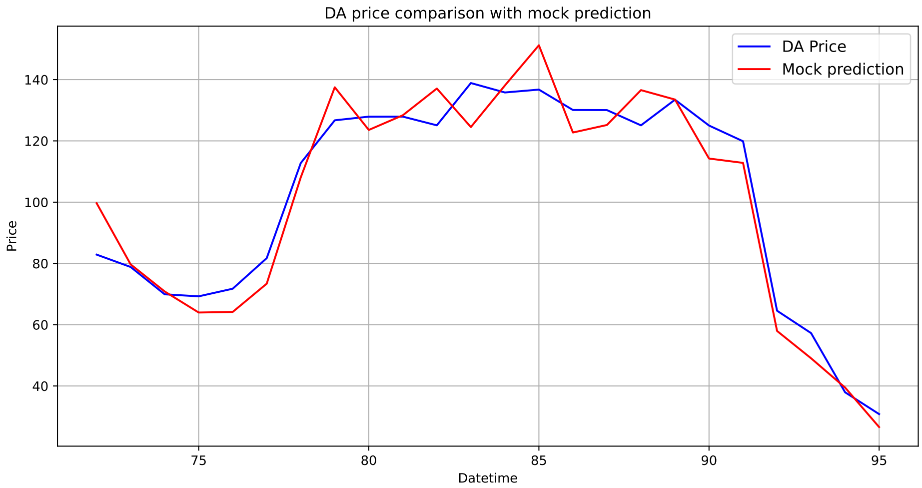


Figure 13. example of mock DA mock price predictions compared to the real prices on the 4th of January 2023. As with the mFRR predictions, the direction of the error is randomised and scaled based on the size of the real value - the larger the original DA price, the larger the expected error of the mock prediction.

5 Experiments and results

In this section we will first go over the setup of our BESS, and the scenarios of our optimisation. We then will look at cost bracket calculations from where we will move on to the DA market optimisation. In the latter we will first optimise only on the DA market, disregarding the mFRR market completely. We will then include the mFRR market in the following section and will look at different scenarios in the mFRR market, whereby we will be restricting the amount that we allow ourselves to trade on that market. We will then also put our results into perspective.

5.1 Setup

We will take the specifications of the BESS that we are optimising from the battery that Eesti Energia is currently building [48]. The battery capacity will therefore be 53.1 MWh and its maximum power will be 26.5 MW (meaning that it can at maximum charge by, or output 26.5MWh). The cost of the battery is, as is the cost of the BESS currently built by Eesti Energia, 19,600,000 euros [48]. Based on the literature we will treat this BESS as a $LiFePO_4$[10] battery, as was the battery under consideration in the article by Zhang et.al. [40] battery as there are no such specifications publicly available in any Eesti Energia published articles. We will be using data of DA and mFRR prices between 1st of January 2023 at 00:00 and 31st of December 2023 at 23:00. We restricted the minimum amount of charge allowed in the battery to 5% of the maximum technical capacity, and the maximum allowed amount to 95% of the maximum technical capacity. We assume that our efficiency is 95% both ways, meaning that we will lose 5% of energy that we charge and discharge. We started our optimisation at the minimum amount of capacity that we allowed.

We will not be optimising over the entire dataset at once. Instead we will be doing it by using a sliding window approach. This means that we take a certain stride, or step size, in which each stride consists of a specified number of observations. We will then optimise over a pre-specifed window, from which only the relevant part will be fed into the optimisation of the following stride. The relevant information in our case is the state of charge in the beginning of the following optimisation window. This helps us model the way the real market works, as we will be getting more precise information about the future as we move along in time and as the market results become available. The stride and the number of observations used in each market was discussed in Section 3.7.

The optimisation itself is composed of two connected optimisation tasks. As is laid out by Nord Pool, then the base operation of most market participants is the DA market [23].

[10] stands for lithium-iron-phosphate.

We will try to emulate such behaviour in our optimisation as well. Therefore the way that our optimisation is set up is that after we have optimised our BESS for the DA market, and have submitted our bids for the DA market, we will receive the results of that market for the next day - i.e. we will know what our obligations are on the DA market. That is, we will know when we are expected to be consuming energy (charging) and when we will be expected to be supplying energy (discharging). Once we then get to the day when we have to start fulfilling these obligations that we have gathered from the DA market, we begin the part of our mFRR optimisation. In other words, when we will be trading on the mFRR market, we will already know the results of the DA market. Before we start making decisions on the mFRR market, we will then already have a battery schedule that we need to fulfill based on the DA market. We can then trade only within these obligations set by the DA schedule. If we fail to fulfill those obligations, then we will use imbalance settlement to settle the difference.

5.2 Cost calculations

Any sort of profit calculation also has to include the costs. We have already outlined the way in which the costs are calculated in our optimisation. We are using the model of battery degradation cost proposed by Zhang. et. al [40] to calculate the battery degradation cost at different discharge depths. As they proposed, we will first calculate degradation brackets based on the discharge depth. Thus we will calculate 100 different values of degradation that we will use as a point of reference for battery discharges of different depth. We do this instead of using a continuous function to describe the degradation as the influence of this approach is not considerably different compared to creating brackets [40]. This means that to calculate our degradation cost we will first calculate the amount (in MWh) by which we discharge. Subsequently, we identify from the set of previously computed 100 degradation cost values the reference point that most accurately corresponds to the cost incurred by this specific discharge.

In order for us to be able to calculate these cost brackets, we will have to first obtain some technical details about the battery. Since we assume our battery to be a $LiFePO_4$ battery, then we will use the constants presented by Zhang et. al [40] in our calculations. These constants can be found in Table 2. We will use these constants in our cost calculation that was expressed in Equation 15.

Table 2. Arrhenius constant, E_a, R and z values that we use in our cost calculations.

Type	$Arrhenius$	E_a(J/mol)	R(J/(mol·K))	z
LiFePO4	330,330	-31,500	8.314	0.552

Using those values we arrive at the values for the cost of using the battery per MWh as laid out in Fig 14.

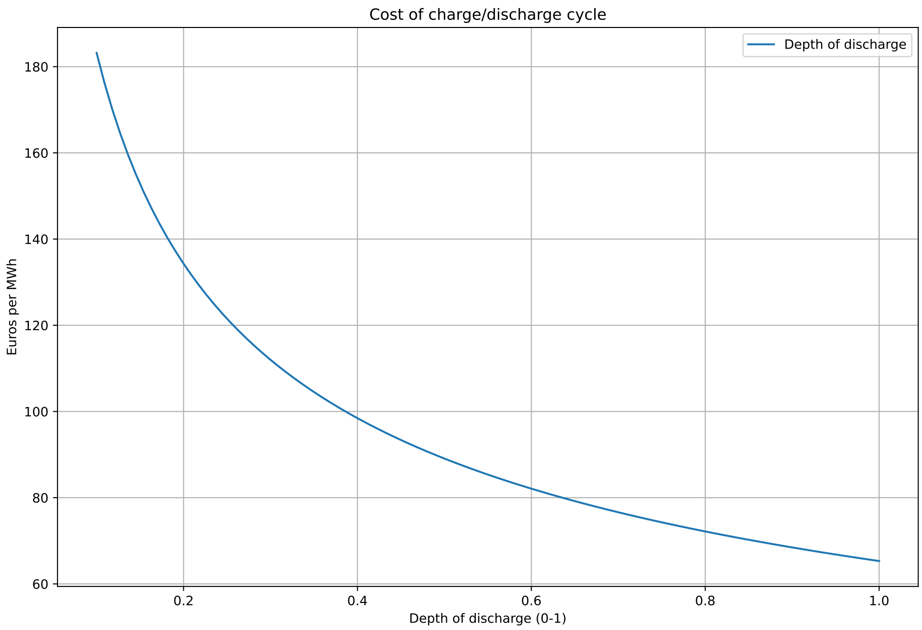


Figure 14. The cost of discharging per MWh for a given depth of discharge.

In our following optimisations we will call on those values whenever we are discharging our BESS based on the depth of the discharge. That is, if our BESS discharge falls within a certain bracket, then we retrieve the cost of discharging associated with that discharging cost bracket, and will discount it from revenue to calculate the profit for the given action.

5.3 DA market

The scenario we are setting up on the DA market, is that instead of focusing on bids, we will be using our mock DA predictions to trade. That is, we do not set a minimum value for what we would be selling for and we do not set a maximum value at which we would be buying at - instead our bids are always the same at all prices, including at the maximum price for buying (4000 euros/MWh) and at the minimum for selling (-500 euros/MWh). Although in reality such a strategy would be extremely risky, as it relies heavily on forecast precision, then it is not in the scope of our thesis to investigate how to best price the offers and bids, but rather to investigate the profitability of the battery when we operate under certain assumptions. The accuracy of our forecasts is one of those assumptions. In addition, this approach helps us to steer clear of imbalance when operating on the DA market alone, as we ensure that all of our bids are accepted, since the offers at minimum price and the bids at maximum price will always be accepted. There is still a way to find ourselves in imbalance when we include the mFRR market. However, the reason for why this happens are explained in Section 5.4.

In the DA market we will be using a sliding window approach, as was discussed in Section 3.7. As was explained, then in the DA market we will be using stride 24, meaning that we will optimise for the next 168 hours after every 24 hours. We will then be saving the state of charge in the end of those 24 hours of this optimisation that we feed into the next window as the initial state of charge. This reflects how the market operates, as we will be submitting new offers to the market for each day. That is, although our optimiser will optimise for 168 hours, then we will only be using the first 24 hours to make offers on the market. The maximisation task for each window has been expressed in Equation 17. The constraints of this optimisation are expressed in Equations 2 and 5.

Let us see how our optimisation works on the DA market before we include mFRR market in our optimisation. To set the baseline, we will first optimise our battery with perfect knowledge of the market prices. This means, that we will not be using the mock predictions, but instead will use the actual prices in our baseline optimisation. This should give us the perfect scenario whereby we will see what is the ceiling that we can reach with our optimisation. We will use exactly the same window size, stride and constraints that were explained beforehand, but will just use the actual data on DA prices to form our charging and discharging decisions. When we are discharging, then we are also considering the cost brackets that were explained in the previous section and established in Equations 14 - 16. We will also be using an optimisation window of 168 with stride 24. We will make the assumption that we are not influencing the market prices.

We are then also optimising for the same market using the mock DA price predictions. We will still be using an optimisation window of 168 and stride 24. In that run we will first use the mock prices to make our optimisation, and will then switch these mock prices for real prices when making our calculations for the profit that we as the supplier (battery owner) would attain on the DA market. Here again, we make the assumption that our battery is not large enough to influence market prices.

The comparison of profits when using precise DA prices compared to the mock prices can be seen in Fig 15. What we see from the results of only optimising for the DA market is that there is plenty of room for arbitrage on the DA market alone. Over the time span of one year we see that the profits exceed 500,000 for both of our scenarios. According to

Lamp et. al. [49] the average annual revenue per kWh is between -8.34 and 32.25 euros[11] per installed kWH for energy arbitrage in California. In our case, since we are using a 53.1 MWh battery, then our profit is around 9.75 euros per installed kWh. This means that our profit falls well in the middle of what they have shown as the possible results for a battery optimisation on the Californian DA market. However, it must be noted that the two markets are vastly different, as there are more products traded on the Californian electricity markets than in Estonia [50]. Nevertheless this similarity in the scale of profits indicates that we are in the right direction. Of course, an important assumption that we are making here is that we can manage to achieve the level of predictions that has been achieved in the work of Lehna et. al. [44] also on the Estonian market and that that our battery will not undergo any technical errors. Maintaining these assumptions, we have thus shown that according to our analysis using data from 2023, our BESS can be profitable in the Estonian market, even if we use it for DA market arbitrage only.

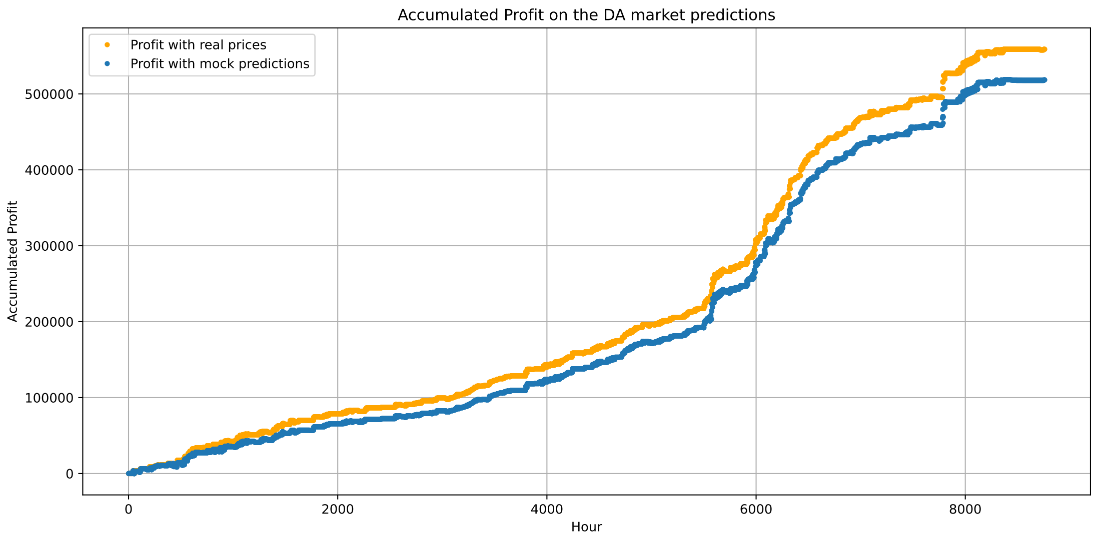


Figure 15. Accumulated profit from energy arbitrage on the DA market.

Further comparison on trades made on the DA market is in Table 3. What we see is that when we optimised on mock prices, then our battery actually traded more energy on the market than when we optimised on the actual prices. In addition, the count of deals on the market was also higher. That can be the result of the optimiser seeing opportunities, where there would not have been any, if we would have had access to the real price data. As is therefore also expected, then the average price differentials between when

[11]These numbers depend on the conversion rate from dollars to euros as the authors used dollars. This means that their expressed averages were between -9 and 34.8 dollars.

the battery decided to buy and when to sell are smaller. Using mock prices the average price at which we ended up buying was 39.57 euros per MWh and 178.87 when selling, whereas we see that if we would have perfect information on prices, then the mean buying price is lower and selling price higher.

Table 3. Summary of DA market optimisations using real and mock price data

Prices Used	Total Profit (€)	Total Sold on the DA Market (MWh)	Total Bought from the DA Market (MWh)	Mean Price for Charging (€/MWh)	Mean Price for Discharging (€/MWh)
Real	558,847.43	11,419	12,020	36.72	181.14
Mock	518,503.33	11,949	12,578	39.57	178.87

We will now build on top of these results to acquire potential extra profit from the mFRR market.

5.4 mFRR market

An important aspect that we need to consider in our optimisation, is that the volumes in the mFRR market are fairly small in Estonia (Fig 16 and 17). This means that although this market operates with the same type of pricing as the DA market (paying everyone based on the last accepted bid), then in reality we cannot ensure that our offers would not influence the price. However, single offers are not publicly available for that market, meaning that we also cannot infer what the price would become once we participate in that market. What we could state, is that if our offers are lower than the lowest offer for upward mFRR and higher than the highest offer for downward mFRR, then it will guarantee that our offer would be accepted if there is demand. However, that is not a good approach, as the lowest offer made on the market can also be aimed at probing the market [51], by which the participants offer small quantities of energy to the balancing market to understand the direction of the system imbalance. In other words, the participants of the market can make small offers on the market that may not be by themselves profitable, but are made to gain insight into what is going on in the market. This strategy is viable since there can be a lag in the publicised data - the mFRR prices and balancing direction are only publicised after the hour in which the mFRR offers are accepted, whereas if the offer is accepted, then the market participant whose offer it was instantly gets the signal that it needs to activate the reserve. This gives information to the market participant whose offer was accepted whereas the other participants do not possess this data.

Therefore, since we cannot know how our BESS influences the balancing market prices based on public data, and since such an analysis demands further research and analysis on its own, then we are going to run multiple simulations with different limitations to our offers on the mFRR market. That is, we will have multiple scenarios, in which we state the

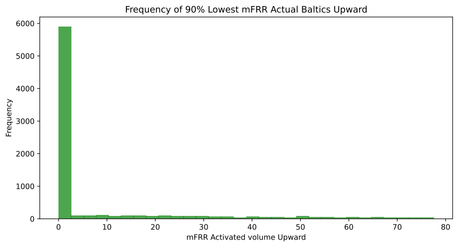


Figure 16. The frequency of accepted volumes on the Baltic Upward mFRR market. 0 to 90th percentile of quantities.

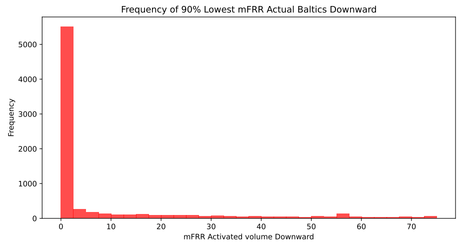


Figure 17. The frequency of accepted volumes on the Baltic Downward mFRR market. 0 to 90th percentile of quantities.

maximum amount of the size of offers we allow ourselves to make on the mFRR market in MWh. In those simulations we will assume that we are not influencing the market price. However, it needs to be noted that the higher we allow the offer to be, the lower the chance of it being a realistic market result, as the assumption on the size of the market share we can hold grows stronger. In our optimisation we will still use mock price predictions, that we discused in Section 4.2, to decide when to make offers on the market, and when not to.

For mFRR optimisation we will use the constraints expressed in Equations 2 and 5. The optimisation here follows the explanations and equations given in Section 3.7. Our mFRR optimisation takes place after our optimisation on the DA market. We will once again take the approach of making offers low enough that we expect them to be accepted if there is any demand on the market - i.e. we will offer our services at the highest price of 5000 euros per MWh. Furthermore, mFRR introduces another important concept into our optimisation - the imbalance settlements.

Since we already have optimised on the DA market by the time we will be making trades on the mFRR market, then the DA market optimisation will set us obligations - certain hours when we need to be ready to dispatch energy, or when we need to be ready to charge. That in turn means that if we fail to cover those obligations, then we are forced to accept the imbalance prices for our over production, or pay the imbalance price to cover our under production, as was discussed in Section 2.4. Therefore, if our optimisation for the mFRR market results in us not being able to dispatch the energy that we have already sold on the DA market or we cannot charge by the amount that we have bought on the DA market, then we are in imbalance. However, falling into imbalance does not necessarily mean a failure on the market - we are still able to sell/buy the missing energy with the imbalance price as was explained in Section 3.5. In our optimisation it is probable that we will be forced to be in imbalance at times.

The pretext for why we fall into imbalance is that we are not participating in the intraday (ID) market as was outlined in section 2.3 for the reasons mentioned in the same section -

there simply is no historical data that is publicly available. This means that there is no way to model the prices on that market and therefore no way to include it in our optimisation. In reality, however, ID market is an important market for the agents participating in the energy markets. ID market plays an important role in allowing the participants to correct for the errors in the offers on other markets - the errors that have become apparent as more information has become available. This data gives them knowledge on the errors that could lead to imbalances on other markets because of the obligations that they already have attained on those markets.[12] The market on which it is possible to correct these errors is the ID market. Therefore, since we are not including ID market in our optimisation, our only other option is to settle the errors by falling into imbalance and settling it with the TSO at their given price.[13]

This becomes relevant, because participating on two markets means that we will inevitably make errors. These errors stem from the difference between the horizon of our mFRR optimisation and the DA plan that we receive from optimising on the DA market. Whereas we get a plan for 24 hours for the DA market, then in the mFRR market we only look at 8 hours at a time. This means that our optimisation cannot know what happens beyond those 8 hours in the mFRR market. This means that the optimiser will make profitable trades within those 8 hours, but it is possible that as we move onwards in time, we discover that we are unable to discharge/charge the required amount back from the market to fulfill DA obligations. This is because the mFRR market does not guarantee activity - it is a need based market, which also means that if there is no imbalance, then there is no market activity. If the market offers incentives for ID trading over imbalance settlements as it is expected to [52], then instead of allowing ourselves to go into imbalance, it should be less costly to sell/buy the difference from the ID market. In short - since our mFRR prediction horizon is shorter than the DA plan that sets us obligations, then there might be situations in which we find ourselves in a dead-end street, unable to charge/discharge enough on the mFRR market to fulfill our obligations. Since we do not include the ID market, then the only way out of that situation is to fall into imbalance. This means that we have to buy/sell energy at the forced imbalance price. Nevertheless we will of course aim to minimise the imbalance that we find ourselves in.

However, our aim to minimise imbalance is not a strict constraint - it is an allowed but not a desirable outcome. This means that we set high penalties in our optimisation for whenever the model decides to go into imbalance. This penalty is a set so that it is

[12] In the Baltics that only means the DA and mFRR market, whereas in other areas there are also other markets that we discussed in section 3.

[13] As we stated in section 2.4, then it is not allowed to have a strategically positioned imbalance. In our situation, us being in imbalance is not a strategic choice, but an inability to settle our errors on other markets.

large enough to outweigh it ever becoming a strategic decision to be in imbalance.[14] Our strict limits, however, are defined by Equations 2 and 5.

Let us once again start by looking at how the results would be, if instead of using mock prices to decide when to charge and discharge, we would assume to have perfect knowledge of prices in our optimisation window. This means that we have perfect knowledge of prices for the following 8 hours on the mFRR market and 168 hours on the DA market.[15] In addition, let us assume that we can fill the mFRR market, as long as we have enough energy in the battery ready to be dispatched or we have enough space and as long as this action would not exceed our maximum charge or discharge amount. This means that we will not have an imposed limit to how much of the mFRR market share we can hold. Instead, we are only limited by the quantity of the offers that the TSO had to activate to balance the grid and the technical aspects of the battery. In other words, this would be the perfect scenario in the market, where we can get the entirety of the market share, if our other constraints so allow, and we have full knowledge of the prices within our optimisation window. This will once again give us an anchor to which we can compare our results to so as to understand how well our optimisation works using the mock prices and how much our limits on the quantity that we allow ourselves to offer on the mFRR market will have an impact on our profits. Our cumulative profit in this scenario can be seen in Fig 18.

First of all, what we see is that our total profit grows exponentially compared to only participating on the DA market (Table 4). This is expected as new market introduces new possibilities and as we currently have perfect knowledge of the market prices in that new market. What we see, is that although the total profit has increased, then the profit from the DA market has decreased. That is because the energy that could have been sold in the DA market in the next day is sold off on the mFRR market instead as our optimiser saw profit making opportunities in that market. Furthermore what we notice, is that our optimisation often finds itself in imbalance, as it has traded itself into a position on the mFRR market from where it cannot get out of. This is not a strategic disposition, but an inevitable result of our approach to the market. Nevertheless, the impact of imbalance on the total profit is not heavily felt, as it is only a small fraction of what we earn from our two markets.

Further let us see, how these results would be affected if we used mock prices instead.

[14] In our case we set the penalty at 1 million euros per each MWh we are in imbalance. This is not to say that this is the amount we use to calculate our imbalance profit, but it is a number that without doubt deters the optimiser from choosing imbalance, if there are any other options available.

[15] Since in this scenario we do not have perfect knowledge of the future, just perfect knowledge on the prices in our optimisation window, then once again we can find ourselves being in imbalance at times. In other words, being in imbalance has nothing to do with the knowledge of the prices, but with the horizon of that knowledge.

Table 4. Summary of optimising on the DA and mFRR market assuming perfect price information in previously specified horizons. In the Total profit, the profit from Imbalance is also included, which we see to be negative here. The total amount we offer on the mFRR market is limited by the technical aspects of the battery (26.5MWh). Negative imbalance signifies situations where we do not have enough energy to fulfill our day-ahead obligations and Positive imbalance is a situation whereby we have bought too much energy and cannot therefore charge further to fulfill our obligations. That is to say that here we are treating the imbalance from our perspective.

Total Profit	DA Profit	mFRR Profit	Imbalance Profit	Upward mFRR (MWh)	Downward mFRR (MWh)	DA Bought (MWh)	DA Sold (MWh)	Negative Imbalance (MWh)	Positive Imbalance (MWh)
2,692,032	452,172	2,263,286	-23,426	17,325	17,642	12,783	11,684	282	177

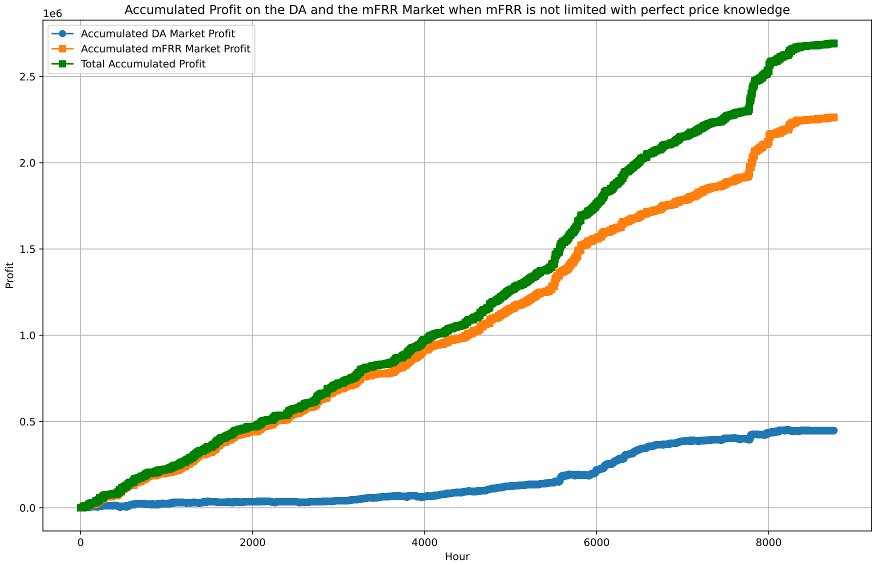


Figure 18. Total accumulated profit, DA market profit and mFRR market profit with perfect information on the market prices on both markets. In this case we are, however, still using an optimisation window for both markets, instead of optimising over the entier dataset at once.

We still will not be limiting the amount of market share that we can hold. The results of such a scenario can be seen in Fig 19 and the cumulative results in Table 5 under mFRR limit of 26.5MWh, which is the technical limit of our BESS. This table depcits our results with different limits to how much we are allowed to offer every hour on the mFRR market. We will look into some of them in more detail as well. What we see is that cumulative profit is indeed smaller when using mock predictions by almost 20%. Further we see that imbalance has fallen as well as the mFRR trades that have been made. Therefore our optimiser is less likely to find the most profitable trades on the market because of the inaccuracies of our mock predictions compared to the real market prices. Instead it might not trade at all on the mFRR market. Subsequently, this means that with mock prices our optimiser is less likely to trade in a manner that it would find itself in a situation that it cannot get out of - in imbalance.

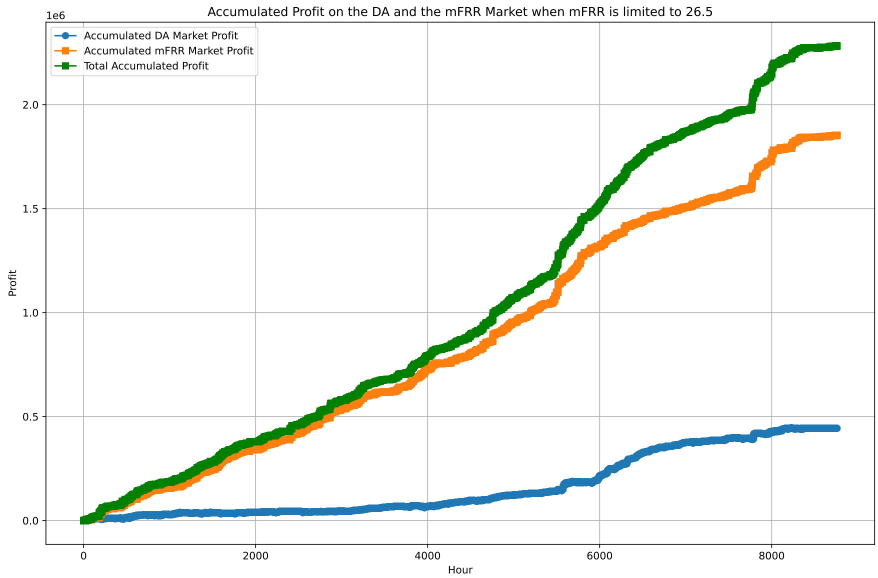


Figure 19. Total accumulated profit, DA market profit and mFRR market profit perfect information on the market prices.

For a more realistic scenario, however, we should lower the limit that we allow ourselves to hold of the mFRR market. What we see from Table 5 is that our total profit on the two markets does indeed increase considerably if we increase the mFRR limit. This increase is almost linear in nature, reaching up to 2.28 million euros in profit. However, we also see that the increase in profit between scenarios whereby the mFRR limit per hour is 24 and 25 is not as large as the difference in profit between hours 7 and 8. In other words, we see a slight diminishing of returns as we increase our mFRR limit, as can also be seen in Fig 20. As was already shown in Fig 16 and Fig 17, then in most of the hours the activity on the mFRR market is fairly low, meaning that the hours where we can make an extra profit from the additional limit allowance are limited when we reach the higher limits. This translates into slightly diminishing returns on increasing this limit.

We also see that adding mFRR to our optimisation lowers the profit that we are making on the DA market (Table 5). As was explained earlier, this is the result of our optimiser finding more profitable trades on the mFRR market. In addition, as we optimise on the mFRR market, we are at times using up the energy that could have sold on the DA market the next day. In other words, our activity on the mFRR market can have negative influence on the DA market results. However, what we are concerned with is the total

Table 5. Summary of optimising on the DA and mFRR market assuming imperfect price information in previously specified horizons. In the Total profit, the profit from Imbalance is also included, which we see to be negative here. The mFRR limit per hour depicts the maximum offer size for both mFRR up and mFRR down market. Negative imbalance signifies situations where we do not have enough energy to fulfill our day-ahead obligations and Positive imbalance is a situation whereby we have bought too much energy and cannot therefore charge enough to fulfill our obligations.

mFRR Limit Per Hour (MWh)	Total Profit	DA Profit	mFRR Profit	Imbalance Profit	Upward mFRR (MWh)	Downward mFRR (MWh)	DA Bought (MWh)	DA Sold (MWh)	Total negative imbalance	Total positive imbalance
1.0	558,887	500,050	73,915	-15,077	776	1,331	12,336	12,057	54	206
2.0	624,282	487,842	160,464	-24,024	1,593	2,487	12,199	12,118	118	359
3.0	704,759	476,726	260,399	-32,366	2,512	3,539	12,180	12,140	190	472
4.0	781,653	469,645	348,029	-36,021	3,285	4,438	12,189	12,208	214	516
5.0	856,197	449,549	443,928	-37,280	4,401	5,400	12,420	12,255	231	505
6.0	942,750	445,578	533,331	-36,159	5,195	6,237	12,476	12,302	222	503
7.0	1,035,577	441,394	630,353	-36,170	5,970	7,059	12,506	12,342	211	485
8.0	1,134,656	440,544	728,398	-34,285	6,668	7,789	12,524	12,366	206	469
9.0	1,213,627	440,524	806,045	-32,942	7,324	8,464	12,538	12,380	196	444
10.0	1,301,769	440,788	892,027	-31,045	7,974	9,114	12,572	12,412	185	401
11.0	1,397,694	439,386	986,826	-28,519	8,694	9,780	12,633	12,409	180	370
12.0	1,491,024	438,391	1,079,358	-26,726	9,339	10,428	12,673	12,429	164	342
13.0	1,562,735	440,879	1,147,220	-25,364	9,869	10,993	12,675	12,447	154	321
14.0	1,633,512	441,634	1,214,945	-23,067	10,395	11,538	12,686	12,458	139	297
15.0	1,705,584	443,356	1,283,113	-20,886	10,853	12,049	12,656	12,465	122	274
16.0	1,792,513	441,148	1,370,256	-18,892	11,455	12,621	12,700	12,461	112	251
17.0	1,856,111	443,367	1,431,683	-18,939	11,860	13,081	12,660	12,474	113	232
18.0	1,906,651	445,242	1,480,800	-19,390	12,190	13,426	12,643	12,473	116	219
19.0	1,967,902	445,583	1,541,217	-18,899	12,613	13,799	12,654	12,447	134	204
20.0	2,020,445	446,493	1,592,051	-18,100	12,895	14,088	12,653	12,449	133	193
21.0	2,072,962	447,381	1,642,948	-17,367	13,198	14,375	12,656	12,443	135	173
22.0	2,124,949	443,852	1,698,543	-17,446	13,716	14,699	12,778	12,391	167	163
23.0	2,173,292	445,172	1,744,953	-16,833	13,947	14,924	12,781	12,389	172	156
24.0	2,216,721	445,402	1,787,452	-16,133	14,201	15,174	12,786	12,387	176	150
25.0	2,247,675	446,482	1,817,646	-16,454	14,427	15,395	12,795	12,382	178	149
26.0	2,271,074	446,487	1,841,355	-16,768	14,582	15,550	12,797	12,382	180	145
26.5	2,282,513	446,636	1,852,751	-16,874	14,652	15,629	12,793	12,382	181	147

profit, rather than our profit from only one of these markets, and that profit, as we see, rises in all of our scenarios compared to when we only optimise on the DA market (Table 3).

Another thing we notice from Table 5, is that among the lower limits our total negative imbalance and total positive imbalance are increasing as we increase the limit on the mFRR market. This is because our optimiser increases the quantities of its offers, which also means that the scenarios where it has no other choice but to go to imbalance are heavier. In other words, it still makes largely the same trades, but the penalty for its inability to see further ahead is heavier. However, once our limit hits 5MWh, they both start decreasing. This is because we need less hours where the mFRR volumes are high are enough to cover our obligations. In other words, if our optimisation set-up finds

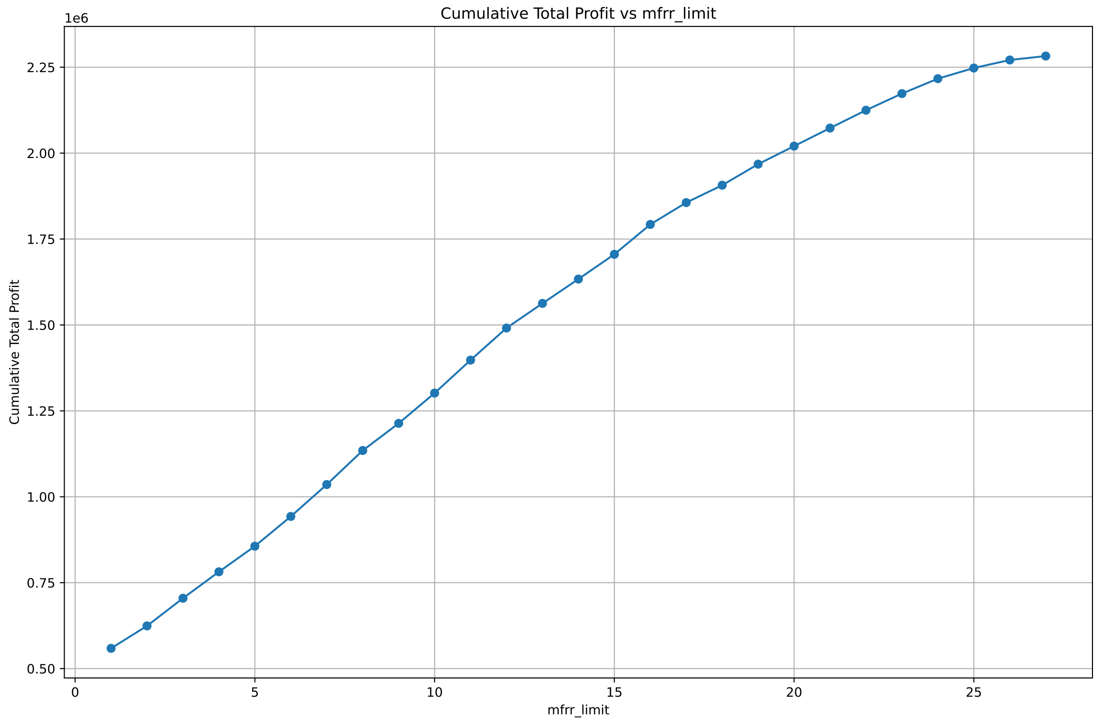


Figure 20. Total accumulated profit with different mFRR offer size limits.

profitable trades, then it needs to cover for these same hours in the later stages if our DA optimisation results need. However, if our limit is restrictive, then we are unable to fulfill this need in time - our optimiser cannot charge by 26.5MWh on the mFRR market in 5 hours, if our limit is 5MWh per hour. In the less restrictive scenarios we are much less likely to actually have to settle the imbalance with the TSO, as we can cover it on the market as we are supposed to. This is because if there is activity in the direction of mFRR that is favourable for us, then we need less amount of time to get us back on track for fulfilling obligations we took on the DA market, assuming there is enough activity on the mFRR market. Nevertheless, there are still situations in the less restrictive scenarios where the quantities on the market are not high enough to cover our needs. Conversely, if our limit is more restrictive (e.g. 2MWh per hour), then this limits us so much that we simply cannot make enough trades to fall more into imbalance.

However, what we generally see, is that the results between only optimising for the DA market and optimising for the mFRR and DA market are also vastly different. This means that most of the impact is coming from the mFRR market. Therefore, the actual result of a battery that would be optimised on the Estonian electricity markets greatly depends on the mFRR market share that it can in reality obtain. This also means that mFRR market presents good opportunities for a BESS and should not be excluded from its optimisation. In addition, this reflects what we would have expected, as the strongest aspect of a BESS is its flexibility and its ability to shift the supply or demand from one hour to another on the market.

However, let us also compare these results with what the largest energy company in Estonia, Eesti Energia, has supplied to the market and how much they have made from mFRR. In total, Eesti Energia distributed (i.e. supplied) 6475GWh of energy in 2023 [53]. In our scenarios where we were operating on the mFRR and DA market alike, our BESS distributed up to 27GWH of energy, which would form 0.4% of what Eesti Energia supplied. The total electricity sales revenue of Eesti Energia totaled 1.9 billion euros in 2023, which means that our revenue even in the case of least restrictive scenario would make up around 0.01% of that. However, just because our revenue makes up less of Eesti Energia's revenue than our distributed energy makes up of their distributed energy does not mean that we are less profitable. That is because in our case we are not producing any energy, but only doing energy arbitrage. In other words, since the BESS is our only asset, and since it cannot produce electricity as do Eesti Energia's power plants for example, then our only source of income comes from us being able to buy electricity at a cheaper price and selling it at a more expensive price. In addition, Eesti Energia has not publicised its production costs, which we would also need to take into account for a more accurate comparison.

According to Eesti Energia's annual financial report of 2023, their profit from the mFRR market is 5 million euros [53]. How this compares to our results largely depends on which mFRR limitation scenario we choose to follow. However, even in our most restrictive scenario whereby we limit our mFRR market participation to only 1MWh for each trading period, our profit makes up around 1.5% of their earnings, whereas at the least restrictive scenario, whereby our mFRR limit is 26.5 MWh, this share rises to around 44%. Compared to the sheer amount of assets that Eesti Energia possesses, this is most definitely a considerable amount. Our BESS can reach this level because of two reasons. First of all, just as most electricity producers, then Eesti Energia is most probably focused on the DA market profits, meaning that mFRR profit is secondary. That is mainly because of this market making up only a small fraction of electricity traded in Estonia. Second, Eesti Energia does not have any large assets as flexible as a BESS in Estonia - they are currently building it. This means that in order to make mFRR offers, their power plants need to either be prepared to lower or increase production. This in turn means that mFRR down does not contribute to future trades in the markets, as it does not create any future opportunities for them. In our case, mFRR down can contribute to higher quantities sold later as well. As such, the lack of flexibility and the subsequent inability to fully take advantage of the mFRR market makes it more difficult for Eesti

Energia to profit from it.

5.5 Implementation details

For the optimisation we used the gurobi[16] optimizer as was used by Grimaldi et. al. [14]. The version of gurobi that we used was 11.0.0. and we also attained the student license that Gurobi provides [54]. Additionally, the versions of the main libraries we used are as follows: NumPy version 1.23.5, Pandas version 1.5.3, and Matplotlib version 3.7.2. The computational environment for the task ran on a macOS-10.16 platform with Darwin Kernel Version 23.0.0, powered by an i386 processor operating at 2400 MHz with 8 physical cores. The machine was configured with 8.0 GB of RAM. The code for our optimisation can be found here.

[16] Gurobi's website. `https://www.gurobi.com`

6 Conclusion

We optimised a Battery Energy Storage System for battery owner's profit on the Estonian market using data from 1st of January 2023 - 31st of Decmber 2023. For our optimisation we used two markets that are currently active in Estonia - manual frequency restoration reserve and the day-ahead market. We also accounted for battery degradation and used imbalance settlements when needed. We used mock predictions for DA prices and for mFRR prices to emulate a market scenario whereby we do not have full knowledge of the upcoming market prices. For those mock predictions we used the results of previously developed DA price prediction model by Lehna et. al [44] and mFRR price prediction model results by Balazs et. al. [45]. We first optimised on the DA market over the period of 168 hours with stride of 24 hours as was expressed in Equation 17. Next, we extracted the first 24 hours from the optimisation, which emulated our DA obligations. We then optimised our mFRR market behaviour on the basis of those 24 hour schedules according to Equation 18. For the mFRR market optimisation we used a stride of 1 hour as the market is continuous, meaning that it is possible to trade in the given market at any time before the gate closure.

In our analysis we also made a number of assumptions that made it possible to carry it out on public data. The assumptions we held were following:

- The market prices will not be affected by our actions
- We can make DA price predictions as precise as Lehna et. al. [44] on the Estonian market.
- We can make mFRR price predictions as precise as Balazs et. al. [45] on the Estonian market.
- Our battery operates at 300 degrees Kelvin.
- Charging and discharging efficiencies are symmetrical.
- The absolute value of our maximum discharging and charging quantities are the same.
- Discharging degradation of the battery can sufficiently capture the full degradation.

If we accept these assumptions, then the results show us that a BESS can be profitable on the Estonian energy markets. In addition, we showed that in any scenario we examined, it is beneficial to also include the mFRR market in the optimisation. We have therefore managed to demonstrate that even without participating on the ID market, and without aFRR and FCR markets, which currently do not exist in Estonia, operating a grid-scale battery is profitable. As we argued beforehand, then such batteries will become more and more necessary as the share of renewable energy grows on the market. With our analysis we have here shown, that there is currently an economic incentive to invest in such technology. In other words, assuming that not much has changed since the beginning of the year 2024, then the market conditions for such investments are favourable without subsidies.

Further research in this domain should aim to analyse the assumptions that we have here made - whether they hold or if they do not, then how that would impact the given analysis. Especially, there should be research into forecasts of the Estonian markets, as the assumption on our ability to replicate prediction results from other markets is the strongest assumption that we are making here. Furthermore, since there will be more markets opening in Estonia over the coming years, then it should be analysed how these can affect the profitability of BESS systems in Estonia and how to optimise a BESS when these markets are available. With more markets the complexity of the task will inevitably grow, but so would the opportunities. However, since such tasks are data driven, their analysis pose difficulties before arrival of these new markets to Estonia as their impact and relevance would currently be inhibited by lack of data.

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