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The Potential for Energy Arbitrage Using Battery Energy Storage Systems in Norwegian Power Markets

An Economic Viability Study through Financial Valuation

Ian Benjamin Kiil & André Risnes Nordbø

Supervisor: André Wattø Sjuve

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Abstract

Energy arbitrage, the process of storing energy when prices are low and offering it when prices are high, has, through increased electricity prices and price volatility, shown greater economic potential over the past couple of years. In light of these developments, this study analyzes the economic viability, through a financial valuation, of a 10MW/10MWh Battery Energy Storage System (BESS) performing energy arbitrage in the Norwegian power markets over a 30-year project. To account for the latest developments in electricity prices and evaluate the economic viability of the BESS, the study incorporates 2022 electricity price data. Furthermore, the analysis includes electricity price data from the period of 2016-2019 to assess the BESS's economic viability in the event of a return to historically “normal” Norwegian electricity prices. The study aims to present a comprehensive and holistic valuation of the BESS through the inclusion of all factors affecting the profits generated and the related costs of performing the energy arbitrage. The optimal energy arbitrage trading pattern is identified through a Mixed-Integer Nonlinear Programming (MINLP) model, and the resulting trading profits are valued through a Discounted Cash Flow (DCF) encompassing all relevant expenditures. The discount rate in the DCF is derived from an estimated Weighted Average Cost of Capital based on a Comparable Companies Analysis.

The results from the analysis show that a BESS performing energy arbitrage in the Norwegian power markets is not economically viable with the current BESS cost estimations and power market conditions. The results for the 2022 electricity price scenario show the greatest promise in the southern price zones of Norway due to the historically high electricity prices and price volatility. However, the Net Present Value (NPV) of the cash flows for the BESS in the best performing price zone is still significantly negative. With optimal trading profits of 39.6 MNOK, the best performing project generates a NPV of -120.4 MNOK when considering all Capital Expenditure (CAPEX), Operations and Maintenance (O&M) costs, and trading profits. When utilizing 2016-2019 electricity price data, the results worsen significantly due to the lower electricity price and price volatility in the period, resulting in a total trading profit of 2.3 MNOK and a total NPV of -157.7 MNOK for the BESS in the best performing price zone.

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1. Introduction

1.1 Introduction

Energy arbitrage, also known as electricity arbitrage or time-shifting, refers to the practice of storing energy during periods of low electricity prices and subsequently supplying energy during times of higher prices. As energy arbitrage involves leveraging the short-term fluctuations in power prices, the profitability is heavily influenced by the price levels and price volatility of the individual power markets (Hu et al., 2022).

The prices in the European power markets have in recent years increased substantially due to increased energy demand, inflated gas and coal commodity prices due to Russian import bans, and dry weather conditions (European Council, n.d.). The increase in power market prices in Europe is reflected in the Norwegian power markets, where, in addition to dry weather conditions, the markets have experienced price spillover effects due to power market integration with Europe as a result of an increased number of interconnectors[1] (Thema, 2021). In addition to higher prices, we observe a shift towards a larger share of variable renewable energy (VRE) sources in the power mix of many European countries (Rystad Energy, 2023a) which in contrast to traditional energy sources, such as oil and gas, lack flexibility in determining when energy production occurs (Zsiborács et al., 2019). Although the impact of VRE sources on electricity price volatility remains a topic of ongoing debate, Cevik and Ninomiya (2022) found indications suggesting that a higher proportion of VRE sources in the energy mix could, due to their intermittent nature, lead to increased volatility in electricity prices if appropriate measures are not taken to dampen the effects. As a result of the power market developments, the power markets have in the last couple of years shown an improved potential for the viability and profitability of energy arbitrage using energy storage solutions.

[1] A structure which enables high voltage DC electricity to flow between electrical grids.

An energy storage system is a system that converts energy from one form, usually electricity, to another form that can be reserved in a storage medium and then converted back to electricity when required (Rahman et al., 2020). Energy storage systems technologies include systems like flywheels, pumped hydro, and hydrogen fuel cells, as well as electro chemical energy solutions encompassing chemistries such as lithium-ion and lead acid (Koohi-Fayegh & Rosen, 2020). Although energy arbitrage can be accomplished using any of the aforementioned energy storage methods, Battery Energy Storage Systems (BESSs) using lithium-ion battery cells have become increasingly popular due to their high efficiency, fast response times, and high energy density (Bera et al., 2020). When utilizing a BESS for energy arbitrage activities, it is possible to engage in direct energy trading on a power grid. By treating energy trading as cash flows and considering associated costs, one can perform a valuation to assess the economic viability of energy arbitrage trading. In this paper, we apply the aforementioned rationale to perform a financial valuation of a 10MW/10MWh lithium-ion BESS trading on Norwegian power grids, through the use of trading optimization and financial modelling.

The paper is organized as follows: Section 1 provides an introduction to the paper, an overview of relevant scientific articles, and the motivation and scientific contribution of this study. Section 2 presents an overview of the European and Norwegian power markets in recent years, the selected electricity price scenarios on which the paper is based, an elaboration on the grid connection used in the project, and a description and summary of the tariffs and taxation schemes applicable when operating on the Norwegian power grids. Section 3 introduces BESS fundamentals, the choice of battery and BESS specifications and their impact on the arbitrage trading modelling, and an elaboration of the applied BESS cost structure. Section 4 provides the financial methodology employed in this paper, including the steps to select an appropriate discount rate which is used in both the arbitrage trading model and the valuation of the project. Section 5 presents the arbitrage trading model, which is based on a Mixed-Integer Nonlinear Programming (MINLP) optimization model. Section 6 provides the final valuation expression, drawing on outputs from the arbitrage trading model and the financial modelling. Section 7 summarizes and reviews the results from the valuation of the BESSs, drawing insights from the optimal trading patterns. Section 8 discusses the relevant limitations and potential alterations to the valuation modelling and presents the main conclusions of this paper.

1.2 Background

Numerous papers have been devoted to analyzing the possibilities for profitable energy arbitrage through the use of different energy storage systems. Some of the main energy storage systems studied for energy arbitrage purposes are compressed air energy storage[2], pumped hydroelectric storage[3], flywheels[4], and various types of electrochemical batteries[5]. These studies were performed applying a diverse set of models to different physical markets at different points in time, resulting in varying outcomes in terms of economic viability. This paper will concentrate on lithium-ion batteries, as this battery type has demonstrated the most promising economic performance (Terlouw et al., 2019).

There are multiple papers devoted to analyzing profit-maximizing use cases for lithium-ion batteries, covering different applications of the technology. Some common use cases are ancillary services (such as maintaining grid stability[6] and peak shaving[7]), time shifting arbitrage[8], or a combination[9]. Through Pusceddu et al. (2021), Schneider et al. (2021) and Shi et al. (2018) it was found that by using the concept of the stacked application, i.e. participating in multi-application interchangeably, one can achieve higher profits than when performing either of the individual

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[2] (Berrada et al., 2016), (Yucekaya, 2013), (Das et al., 2015), (Zakeri & Syri, 2014) and (Bradbury et al., 2014).

[3] (Jalal Kazempour et al., 2009) and (Berrada et al., 2016).

[4] (Walawalkar et al., 2007), (Zakeri & Syri, 2014) and (Bradbury et al., 2014).

[5] (Jalal Kazempour et al., 2009), (Walawalkar et al., 2007), (Zakeri & Syri, 2014) and (Bradbury et al., 2014).

[6] (Shi et al., 2018), (Pusceddu et al., 2021), (Du et al., 2022) and (Hu et al., 2022).

[7] (Shi et al., 2018) and (Schneider et al., 2021).

[8] (Núñez et al., 2022) and (Du et al., 2022).

[9] (Schneider et al., 2021), (Pusceddu et al., 2021), (Du et al., 2022) and (Hu et al., 2022).

services separately (single-application). Additionally, by building on Zhang et al. (2020), Du et al. (2022) found that profits from multi-application can be improved further by utilizing the BESS for specific services during specific stages of its lifecycle. The findings in these studies indicate that an optimal strategy for a profit maximizing lithium-ion BESS would be to apply multi-application with ancillary services, instead of single-application. Regardless, this paper will solely evaluate lithium-ion BESSs performing energy arbitrage in single-application, as the detailed nature of the analysis does not allow for a broader scope given the time constraints. Due to the limitation this restriction has on potential revenue streams, the output of our analysis is presumably a conservative valuation estimate.

In the realm of lithium-ion BESSs performing energy arbitrage in single-application, several studies have already been conducted with diverse research purposes. While some studies have been conducted on the profitability of BESSs performing energy arbitrage while attached to energy parks[10,11], the focus of this paper will be on standalone systems connected solely to a power grid. Looking at standalone systems, some authors have proposed particularly attentive analyses of single factors which can affect the profitability of the energy arbitrage trading, such as battery degradation[12], without a valuation of the BESS as the end goal. Others have added layers of financial modelling, where Núñez et al. (2022) has discounted future cash flows corresponding to a project, and Hu et al. (2022) has valued the battery system as a series of real options.

While prior studies have addressed multiple of the key aspects of economic viability, many of their models have oversimplified or disregarded input factors that are important for conducting an accurate valuation. For instance, Wankmüller et al. (2017) and Krishnamurthy et al. (2018) do not account for Operations and Maintenance (O&M) costs in their studies. For Wankmüller et al. (2017), ignoring these costs is logical as the purpose of the paper is to examine the impact of various battery degradation models on energy arbitrage profits, making O&M costs an unnecessary

[10] A separate area used for the purpose of clean energy development, like wind and solar generation facilities.

[11] (Durna et al., 2014) and (Daggett et al., 2017).

[12] (Wankmüller et al., 2017) and (Lee & Kim, 2022)

consideration. Likewise, Krishnamurthy et al. (2018) focus on maximizing arbitrage profits in the face of uncertainty (with a particular emphasis on market bidding), making O&M costs less of an important factor to consider. Núñez et al. (2022) have included O&M costs but made the simplification of adding it as a percentage of the Capital Expenditure (CAPEX), possibly due to the challenges associated with estimating BESS O&M costs as discussed in Cole et al. (2021). Lastly, Hu et al. (2022) have, in addition to ignoring the time-dependent value of money, limited the BESS to only one trade-cycle per day, ultimately limiting the number of potential profitable trades.

1.3 Motivation

While previous scientific articles have explored the potential of using BESSs to perform energy arbitrage across various countries, they have often neglected region-specific factors affecting the results. This is also true in the case of Norway, where prior studies have overlooked factors such as region-specific taxes and tariffs. Furthermore, previous studies have often oversimplified either the financial or trading modeling, resulting in inaccurate estimates of the economic viability.

By addressing limitation in existing literature, the main objective of this paper is to provide an augmented evaluation, though a financial valuation with as few simplifications as data availability allows for, of the economic viability of BESSs performing energy arbitrage in Norway. The valuation is applied to the five Norwegian price zones, while considering CAPEX and O&M cost estimates as well as local taxes and tariffs.

2. Power markets

Energy arbitrage can be defined as taking advantage of daily energy price volatility to purchase and store cheap energy at times when prices are low and sell the stored energy when prices are high (Wankmüller et al., 2017). In the context of BESSs, the profitability of energy arbitrage is in large decided by the electricity price and price volatility. Thus, understanding the power markets is important when evaluating the viability and profitability of BESSs for energy arbitrage. This section will introduce: 1) an overview of the European and Norwegian power markets, 2) an examination of the prices and price volatility pertaining to the Norwegian power market, as well as those of closely related markets, 3) the selection of the electricity price scenarios for the analysis, 4) an overview of the supply chain of the Norwegian power market, with rationales for the decisions on grid connection and the price data foundation, and 5) an overview of the relevant tariffs and taxation schemes in the Norwegian power markets affecting the cost of energy.

2.1 The European and Norwegian power markets

The European Union (EU) has long been committed to creating a single and integrated power market for all members of the European Economic Area (EEA) (Lago et al., 2018). To achieve this, the EU has passed several legislations and promoted the development of cross-border interconnectors among member countries in an attempt to connect the markets (European Commission, 2019). Through a number of these interconnectors (see overview in Appendix A – Interconnectors), Norway is integrated with a large part of the European power market. Although these interconnectors are known to converge the electricity price in the price zones they connect (Sapio & Spagnolo, 2020), large disparities in electricity prices persist between and within the power markets of different countries (Eurostat, 2023), indicating that the goal of a single European power market has not yet been achieved.

In Norway, the power market is divided into five distinct geographic regions, each with its own unique prize zone where the electricity is traded at the same spot price (Capital, 2019). These price zones are identified as NO1 to NO5. Due to there being price disparities among the individual price zones, we will in this paper perform valuations for all the zones.

2.2 Electricity prices and price volatility developments in Norway and the EEA

As energy arbitrage generates profits by purchasing energy when prices are low and offering it to the market when prices are high, the absolute price volatility[13] of the power market is a key deciding factor for the profitability of energy arbitrage. Consequently, the recent surge in electricity prices and price volatility throughout Europe (including Norway) increases the economic viability of energy arbitrage, making it a relevant topic for analysis.

According to the European Council (n.d.), the elevated electricity prices in Europe since 2021 can be attributed to multiple determinants. Firstly, following the turmoil of the Covid-19 pandemic there was a surge in energy demand which contributed to the increase in electricity prices. Secondly, the unilateral decision to suspend gas and coal imports from Russia to EU member states resulted in a substantial increase in the corresponding commodity prices. The impact of increased commodity prices on electricity prices was particularly noteworthy given that 35% of the power generation in Europe in 2022 stemmed from coal power plants and gas turbines (Rystad Energy, 2023a). Lastly, the heatwaves experienced during the summer of 2022 also played a significant role in the rise of electricity prices in Europe. High temperatures increased energy consumption for cooling appliances during the summer months, contributing to an increase in demand, while dry weather reduced the availability of water for hydropower production, further exacerbating the situation. In essence, electricity prices have in recent years been exceptionally high due to a series of factors happening simultaneously.

The Norwegian electricity prices have increased dramatically since 2020, especially in the southern price zones (NO1, NO2 and NO5). Although Norway does not have any commercial gas turbines or coal powerplants, the electricity prices are impacted by the increase in commodity prices due to the integration with Europe (Thema, 2021). The southern regions in Norway are to the largest extent connected to the EU economic area through interconnectors, which can partially

[13] Absolute volatility, in contrast to relative volatility, quantifies the overall magnitude of price fluctuations regardless of their direction or relationship to the average price, providing a comprehensive assessment of the total range of price movements.

explain how the electricity prices in recent times have been higher in the south than in the north of Norway (Thema, 2021). Moreover, southern Norway has experienced one of its driest weather patterns in the last 21 years (Metrologisk institutt, 2022), leading to a substantial decrease of 20-30 percentage points in the water levels of hydroelectric power plants' reservoirs (Fornybar Norge, 2023). Consequently, as the value of the potential energy in reservoirs of hydroelectric power plants increases with diminishing water levels, the southern Norwegian electricity prices have been affected by the experienced dry weather of 2022 (Statnett, 2021a). The substantial impact these factors have had on the electricity prices in Norway can be seen in Figure 1.

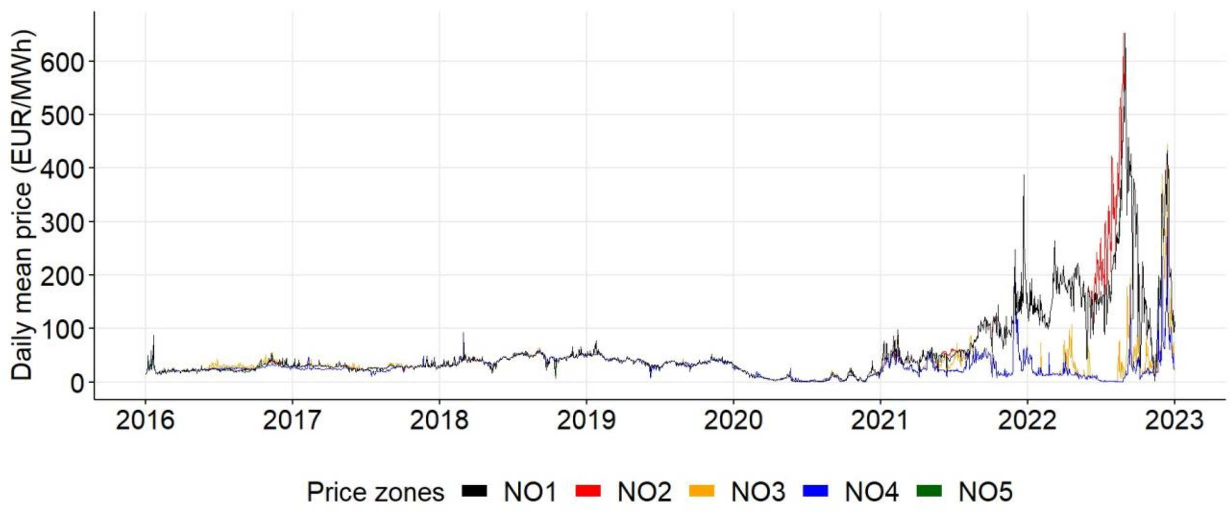

Figure 1: Daily mean electricity prices for NO1-NO5 [14]

As we can observe in Figure 1, Norwegian electricity prices show strong similarities across all the price zones until the beginning of 2021. From 2021 onwards we can see a discernible divergence between the southern and the northern price zones. Additionally, we can observe that NO2 has a systematically higher price in the summer of 2022 compared to the other southern price zones,

[14] NO5 is not visible due to price overlap with NO1.

which can be explained by low water magazine volumes (E24, 2022) and an increased price spillover effect from the number of interconnectors to Europe (Lyse, 2023).

To further contextualize the Norwegian electricity price situation in 2022, Table 1 below shows the 2022 prices and price volatility for other selected European countries. The table highlights that Norway exhibits the lowest mean electricity prices in the northern-most price zones, and relatively low mean prices in the southern price zones, compared to its European counterparts. Moreover, the Norwegian price zones display low mean intraday price differentials compared to other European countries. The systematically low price volatility in the Norwegian markets can be explained by the high flexibility in Norwegian power generation structure (Hu et al., 2022), in which hydroelectric power represents approximately 89 percent of total power production ((Statkraft, n.d.) and (Rystad Energy, 2023a)). The findings suggest that the Norwegian power market, particularly the NO3 and NO4 price zones, may be less suited for energy arbitrage operations compared to other European power markets, as the volatility of the electricity prices is relatively low.

Table 1: 2022 Day-Ahead Market (DAM) electricity prices in selected European power markets (data gathered from ENTSO-E)

Country	Hourly electricity prices (€/MWh)		Daily price differentials (€/MWh)			
	Mean price	Std. Dev.[15]	Mean gap	Max	Min	Std. Dev.
France	275.9	145.8	174.9	2720.0	20.5	160.6
Netherlands	241.9	131.5	205.1	736.2	30.9	102.6
Germany&Lux	235.4	142.8	187.0	687.5	4.4	93.0
DK1	219.0	145.4	178.5	687.5	6.3	97.7
NO2	211.3	125.8	106.3	465.7	6.1	87.2
DK2	210.2	150.2	194.2	687.5	13.7	107.1
NO1	192.5	109.7	87.0	465.7	4.3	78.2
NO5	192.1	109.3	83.3	465.7	4.3	78.0
Spain	167.5	69.4	94.4	281.5	16.9	43.8
Finland	154.0	132.4	201.2	781.1	8.1	135.7
SE4	152.1	140.4	202.4	780.3	6.4	145.4
SE3	129.2	127.9	184.9	780.3	6.4	135.2
SE2	61.9	80.2	64.6	453.3	0.8	79.0
SE1	59.1	78.8	59.0	453.3	0.8	73.5
NO3	41.9	67.4	39.9	453.3	0.1	69.6
NO4	24.5	41.1	22.1	461.3	0.1	57.7

2.3 Selected electricity price scenarios

In the examination of the profitability of energy arbitrage in the Norwegian power markets, the selection of an appropriate price scenario is a critical choice as it will impact the arbitrage trading results. As the aim of this paper is to investigate the profitability and viability of electricity price arbitrage when considering recent developments in the power markets, 2022 price data is utilized in the analysis. Additionally, the price data from the period 2016-2019 is used as it provides a reference to a period with what we could call "normal" electricity prices. This period was chosen due to the low electricity price and price volatility, and the absence of the impact recent external shocks have had on power demand. Consequently, the 2016-2019 electricity price data serves as a

[15] Standard deviation is used as a measure of market volatility.

reference to estimate the potential results of arbitrage trading if electricity prices were to return to a "stable" 2016-2019 price level.

To align the time-series with the project's estimated timespan, the data is extrapolated in a repeated sequence over the course of the project. The decision to utilize historical electricity prices as the underlying data for the arbitrage model, rather than relying on predicted or randomized data, is grounded in the objective of maintaining the realism and integrity of the time series. By utilizing actual historical data, we accurately reflect market conditions, including price levels, price volatility, taxes, and the associated time variant tariffs (covered in section 2.5.1). Avoiding the use of predicted or randomized data ensures that the analysis, and the corresponding project results, are based on real-world market dynamics.

Although there are multiple market mechanisms that can be used to reflect the electricity prices (Energifakta Norge, 2022), the clearing prices in the Day-Ahead Market (DAM) are commonly recognized as the most important reference for electricity prices (Hu et al., 2022). Given this fact, and considering the readily accessible hourly DAM prices from ENTSO-E, this paper utilizes DAM based prices for the analysis.

2.4 Grid connection

The Norwegian electricity grid is comprised of three levels: the transmission grid operated by Statnett, the regional grid, and the distribution grid (Energifakta Norge, 2019). The transmission grid serves as the nationwide connection between electricity producers and consumers, including interconnectors with other countries, where Statnett acts as the designated Transmission System Operator (TSO). The regional grid acts as a bridge between the transmission and distribution grids, while the distribution grid supplies power to smaller end users. Large electricity producers are linked to either the transmission or regional grid, while smaller producers are connected to the regional or distribution grid. Major consumers, such as power-intensive industries, are typically linked to the transmission or regional grid, while households and small-scale consumers are commonly connected to the distribution grid.

When considering grid connection for the BESS, the size of the BESS (in kW) is the determining factor as the different grids can handle different power levels (NVE, 2018). As per the guidelines from the Norwegian Water Resources and Energy Directorate (2018), entities requiring around 10 MW of power can be too power intensive for the distribution grid and thus be best suited for the regional grid. However, this study assumes a connection to the transmission grid due to the potential for upscaling the BESS, which would require larger power capacity as provided by the transmission grid, and the significant streamlining in data accessibility of tariffs, due to nationwide standardization without regional specific regulations.

2.5 Tariffs and taxation in the Norwegian power market

In Norway, the total cost of purchasing energy comprises multiple components in addition to the electricity price. These components include fixed and variable grid tariffs, electricity taxes, electricity certificates, the Enova levy, and Value Added Tax (VAT).

2.5.1 Tariffs

Grid tariffs are one of the costliest elements of power consumption and are in place to cover the costs of maintenance and operations on the electricity grid (Energifakta Norge, 2022). Statnett is the system operator for the whole of the transmission grid and structure the tariff model based on rules set by NVE-RME (Statnett, 2021b). The grid tariffs for the transmission grid are divided into a variable component and a fixed component, with both the production and consumption of energy being subject to the tariffs.

The fixed tariff for power consumption is related to the power-consumption of a company during the peak load hour of the year[16] and is given as a ratio of NOK per unit of power-consumption (in MW) (Statnett, 2021b). The tariff is based on the average consumption in the peak load hours of the past five years which is defined each year by Statnett (Statnett, 2021c). Additionally, for large

[16] The peak load hour is defined as the hour of the year when consumption is highest.

power consumers, and for energy consumers who also produce energy, there are special considerations in place to reduce the fixed tariff (see (Statnett, 2022b)). However, due to the nature of energy arbitrage business, the BESS will not consume power (charge the battery-cells) during peak load hours as a consequence of the high prices. Accordingly, the fixed tariff for energy consumption will not impact the optimal trading pattern.

For power production, the fixed tariff (listed in Statnett (2021b)) is based on the average energy delivered to the transmission grid over the past ten years and is set to a fixed cost per net production of kWh for powerplants and fixed cost per gross production of kWh for pumped hydro powerplants (Statnett, 2022b). Although Statnett does not specifically consider tariffs for BESSs, we assume the tariffs are the same for all energy storage systems such that gross production is the foundation for the fixed production tariff for BESSs, in the same manner as for pumped hydro powerplants.

The variable energy tariff (VET), impacting both the production (input) and the consumption (output) of energy, varies depending on the electricity price (E), Marginal Loss Rate (MRL) and energy flow (EF)[17] at the given substation s at time t. The tariff is defined such that the producer and consumer of energy are directly charged or discounted for the marginal energy losses on the transmission grid resulting from the respective input and output (Statnett, 2022b). As such, the tariff is mirrored for the consumption and production of energy, such that a tariff for energy consumption, leading to an additional fee, is matched by a negative tariff (discount) for energy production in the same area in the same period. Similarly, the inverse holds true, whereby a positive tariff for energy production is matched by a negative tariff (discount) for energy consumption. The tariffs can be calculated as follows:

[17] Energy flow refers to both the input of energy (production) and the output of energy (consumption).

$$VET_{st}^{C} = E_{st} * MLR_{st}^{C} * EF_{t}^{C}$$

$$VET_{st}^{P} = E_{st} * MLR_{st}^{P} * EF_{t}^{P}$$

VET_{st}^{C}: the variable energy tariff for energy consumption at substation s at time t.

VET_{st}^{P}: the variable energy tariff for energy production at substation s at time t.

E_{st}: the area spot price in the area near substation s at time t.

MLR_{st}^{C}: the marginal loss rate for consumption at substation s at time t.

MLR_{st}^{P}: the marginal loss rate for production at substation s at time t.

EF_{t}^{C}: the energy consumed (output) at time t.

EF_{t}^{P}: the energy produced (input) at time t.

The MLR represents the percentage loss of energy arising from energy transportation and is defined such that producers and consumers of energy are directly charged for the marginal losses on the transmission grid related to their respective input and output. In areas with production deficits, a producer may have a favorable position in the power grid, such that increased production reduces grid energy losses. Consequently, the percentage of losses, as well as the variable energy tariff, becomes negative, resulting in a payment to the producer for power injection (NVE-RME, 2021). The rates are set between -15 and 15 percent and are symmetrical around zero[18] for the production and consumption of energy (Statnett, 2018). Further, the rates are adjusted at certain times of the day and during the weekends.

In September of 2022, the board of Statnett decided to set the variable energy tariff to zero for both the production and consumption of energy until the end of 2023 due to earnings being above the

[18] A positive marginal loss rate at a given percent for energy consumption (leading to an additional fee) is matched by a negative marginal loss rate (leading to a discount) for energy production at the same point in the same period.

threshold set by NVE-RME (Statnett, 2022c). Building on this logic, if prices were to stay at a 2022-level, Statnett would assumably have consistent similar earnings as in 2022 and keep the variable energy tariffs at zero. Consequently, we assume variable energy tariffs of zero for the repeated 2022 time series in the model. The variable energy tariffs for consumption and production in the 2016 to 2019 price scenario are based on the hourly mean MLRs for substations in each price zone. As we have access to historical MLRs for the different substations, one could argue that it would be optimal to place the BESS near substations with the historically most beneficial MLR for each respective price zone. However, as the marginal loss rates are subject to change over time depending on the production and consumption of energy in a specific geographic area, we cannot accurately predict the future MLRs. Therefore, we instead apply the mean hourly MLRs in each price zone.

2.5.2 Taxation and other levies

In addition to the grid tariffs, electricity consumption is levied on consumers through an electricity tax, electricity certificates, the Enova levy and VAT. While the prices for electricity certificates vary according to the developments of the electricity certificate market, the electricity tax, Enova levy and VAT are fixed by political decisions (Energifakta Norge, 2022).

The electricity consumption tax varies depending on the season, year and whether the business qualifies for a reduction in tax rate (Skatteetaten, 2018). The reduced rate is a yearly fixed rate and applies to businesses who, among other uses, utilize energy "for the production or transformation of energy products". Due to the nature of the operations of a BESS performing energy arbitrage, and the wording of the provision for the eligibility of the reduced rate, we conclude that such a system would qualify for the reduced tax rate.

Electricity certificates are financial incentives for the production of renewable energy in Norway. Power producers receive one certificate per MWh of renewable electricity they generate, which is subsequently sold to power suppliers and certain electricity customers who are required by law to purchase certificates corresponding to a certain proportion of their electricity consumption (Energifakta Norge, 2023). However, a BESS undertaking energy arbitrage activities and operating on the transmission grid is seemingly not required to purchase energy certificates under

Norwegian law, as it does not fall under the categorizations stipulated in §16 of "Lov om elsertifikater" (Lovdata, 2011). Thus, we can ignore costs related to electricity certificates.

The Enova levy applies to all electricity consumption in Norway and is a fixed levy of NOK 0.01 per kWh for households and a fixed fee of NOK 800 per metering point ID per year for businesses as stated in §3 of "Forskrift om innbetaling av påslag på nettariffen til Energifondet (forskrift om Energifondet)" (Lovdata, 2001). In this paper, we assume that the project would be subject to the business cost version of the Enova levy, and subsequently disregard the associated costs of the levy due to its fixed nature and insignificant size.

The VAT applies to both the purchase and the sale of electricity for all purposes in Norway, with the exemption of household consumption in Troms og Finnmark and Nordland counties (Regjeringen, 2022). The VAT in Norway is 25 percent on top of the electricity price and the respective levies.

3. Battery Energy Storage Systems

In this study, we utilize a Battery Energy Storage System (BESS) to perform energy arbitrage. Consequently, the profitability, and thus the overall economic viability, of energy arbitrage heavily depends on the costs associated with the system. Therefore, it is important to have a comprehensive understanding of the expenses involved in acquiring and operating the system. Furthermore, the specifications of the battery of the BESS heavily impact the trading capabilities of the system, making it important to understand how these are determined. To better understand these specifications and costs, this section will introduce: 1) an overview of the fundamentals of BESSs, 2) a deep dive into battery specifications and their impact on battery performance and lifespan, 3) an overview of the implications of different BESS size and power, and 4) an elaboration of the applied BESS cost structure.

3.1 BESS fundamentals

BESSs are electrochemical energy storage systems that charge (collects energy) from a grid or powerplant and discharge it at a later time to provide electricity or grid services when needed (NREL, 2019). The systems have various use cases, with some of the most common being grid stabilization (through ancillary services), renewable energy integration, microgrid deployments, and various commercial and industrial applications such as energy arbitrage (NREL, 2019).

For all use cases, utility scale BESSs can be categorized into three main components: a storage block, a power kit, and grid integration components (Rystad Energy, 2023b). The storage block consists of packaged battery cells (that combine to form what is referred to in this paper as “the battery”), a battery management system (BMS) and a thermal management system (TMS). As the storage block of the system houses the battery, we assume in this paper that the entire component needs replacement if the battery reaches its end-of-life capacity (this mechanism will be elaborated in the proceeding section). The power kit consists of all the required equipment to convert the DC power output of the storage block to a usable AC power output, including a Power Conversion System (PCS) and Communication and Control Systems (C&C). The grid integration components consist of a transformer (substation) and cabling.

3.2 Battery specifications

Battery specifications play a critical role in determining the lifespan, efficiency, and overall performance of the BESS (Hannan et al., 2021). Consequently, the selection of battery cell technology and its utilization have direct implications on the economic results of the project. This section presents an overview of how various battery specifications affect the BESS, and establishes the groundwork for assumptions in the trading model, such as the efficiency and lifespan of the storage block.

3.2.1 Battery chemistry

Although there are multiple battery chemistries used in BESSs, in the context of energy arbitrage the lithium-ion battery cell technology is considered to be the best performing storage technology due to the high efficiency levels, energy density, and specific energy (Núñez et al., 2022). As lithium-ion batteries present the prevailing battery cell technology for BESSs, it is the employed battery chemistry in this paper. However, "lithium-ion battery" does not refer to one specific battery chemistry but rather a family of rechargeable battery types (Qiao & Wei, 2012). According to Rystad Energy (2023b) and Wood Mackenzie (2020), the most common chemistries within the lithium-ion battery family are Lithium Iron Phosphate (LFP), Lithium Nickel Manganese Cobalt Oxide (NMC) and Lithium Nickel Cobalt Aluminum Oxide (NCA). LFP batteries are the most common battery type used in BESS applications, accounting for approximately 64% of the total BESS market in 2022 (Rystad Energy, 2023b), and is expected to continue to be the dominant chemistry in the BESS industry in the coming years according to Rystad Energy (2023b) and Wood Mackenzie (2020). The growing popularity of LFP batteries can be attributed to recent scientific advancements in battery chemistry, which have led to improved lifespan, enhanced safety features, and reduced costs (Tech Brew, 2022). Partially due to these advancements, multiple large suppliers of battery cells for BESSs, such as Tesla and CATL, have switched to LFP battery cell chemistry ((Utility Dive, 2021) and (CATL, 2023)). Given the favorable properties exhibited by LFP battery chemistry and the increasing adoption of LFP battery cells in BESSs, this paper will focus on utilizing LFP battery cell chemistry for the BESS project.

3.2.2 Battery efficiency

One important factor for the economic viability of energy storage systems performing energy arbitrage is energy efficiency, as a low system efficiency implies a high loss of energy during the charge or discharge process, hamstringing profits (Hu et al., 2022). A meta-analysis by Koohi-Fayegh & Rosen (2020) finds that energy efficiency varies significantly based on energy storage type, and that lithium-ion batteries are top performers in terms of efficiency. Further, the efficiency of LFP batteries has been observed to vary somewhat across different battery cell manufacturers and studies, as summarized in Table 2.

Table 2: Reported energy efficiencies of LFP battery cells and BESSs

Batteries, BESSs and studies	**Round-trip Efficiency[19]**	**Source**
Tesla Megapack ½C	92%	(Tesla, 2021a)
Tesla Megapack ¼C	93.7%	(Tesla, 2021a)
Tesla Powerwall ½C	90%	(Tesla, 2021b)
CATL High energy pack 6C	91%	(CATL, 2022a)
Topology study of BESS	97%	(Chatzinikolaou & Rogers, 2017)
Case study of high-power grid connected BESS	91.1%	(Feehally et al., 2018)

As seen in Table 2, the cell manufacturers and studies all yield relatively similar round-trip efficiencies (RTEs), notably for both batteries and BESSs. Based on the RTE rates in Table 2, this study assumes a somewhat conservative 92% RTE rate for the BESS, divided equally between the charging and discharging of the storage block.

3.2.3 Battery life and degradation

Lithium-ion batteries have a limited lifespan primarily because of undesired side reactions that result in reduced energy capacity, often referred to as degradation (Stiaszny et al., 2014). Degradation occurs primarily through two processes: calendar aging and usage (Wankmüller et

[19] Round-trip efficiency refers to the amount of energy preserved through a charge-discharge cycle.

al., 2017). As the degree of degradation influences the performance of BESSs through a series of factors, a deeper understanding of degradation mechanisms is important. This subsection introduces the determinants of battery life and the resulting considerations applied in the analysis.

As presented in Preger et al. (2020), battery cells have a threshold capacity indicating that the battery has degraded to its end-of-life (EOL) capacity. After reaching said threshold, the battery enters a "saturation" stage, where the capacity rapidly declines (Lin et al., 2013). Although batteries can technically be used after reaching their defined EOL capacity, the threshold serves as a useful benchmark for estimating battery life as it is the reference value used by manufacturers to specify battery EOL (Preger et al., 2020).

Battery cell calendar life refers to the limited lifespan of a battery due to deterioration of the battery cells happening over time caused by passivation layers forming at the anode (often referred to as solid electrolyte interphase (SEI)) (Keil et al., 2016). As the degree of SEI increases, the capacity of the battery decreases (Edge et al., 2021). Although the dynamics behind batteries' calendar life is well understood, there is little empirical data on the calendar life of batteries utilized for large-scale grid applications (Wankmüller et al., 2017). Due to this limitation, finding an appropriate calendar life estimate for the battery in this study poses a challenge. An approach that can be used to estimate battery lifespan, as demonstrated by Wankmüller et al. (2017) and employed in this study, is to rely on the warranty periods offered by battery cell manufacturers. Among the largest manufacturers, Tesla offers a "no defect" and "energy retention" warranty of 10-years for their Powerwall and 15-year for their Megapack, with the option to purchase extended performance guarantees for up to 20 years (Tesla, 2019). Likewise, CATL offers varying warranties on their products, ranging from 5 years (CATL, 2022b) to 10 years ((CATL, 2022a) and (CATL, 2022c)). Although calendar life may exceed warranties issued by manufacturers, this paper assumes a conservative calendar life of 10 years for battery cells, and thus the storage block, based on available information.

Cycle life refers to the usage a battery can endure before degrading to its EOL capacity. To measure battery usage, we employ "Equivalent Full Cycles" (EFC), defined as the total capacity throughput divided by the nominal capacity[20] (Preger et al., 2020). Different academic papers have utilized different numbers of EFC to model the economic performance of BESSs performing energy arbitrage, with for instance Núñez et al. (2022) using 5000 cycles and Hu et al. (2022) using 3000. However, due to the rapid technological progress observed in LFP battery cell chemistry, their assumptions regarding cycle life can arguably be considered outdated. This paper employs 280 Ah LFP battery cells from CATL (2023), which are specifically designed for BESSs, as a benchmark to assume a realistic battery cycle life. As CATL is the world's largest LFP battery cell producer (Rystad Energy, 2023b), their battery cell specifications reflect the current state of LFP technology and are therefore a suitable reference point for the number of EFC a battery can endure. Since the 280 Ah battery cells can endure up to 8,000 EFC before reaching the EOL threshold capacity of 70%, we assume the same attributes for the battery deployed in this paper.

Since battery capacity is affected by degradation stemming from both calendar life and cycle life, one should consider both factors when modeling the trading pattern of BESSs. However, doing so significantly complicates the degradation modeling compared to only considering one of the factors. The approach applied in this paper is to use cycles as the primary factor for battery degradation and treat calendar life as a definitive limit for the battery's lifetime. Using this approach, the battery degradation is dependent only on the battery use, while the end of the battery life occurs either when the remaining battery capacity reaches the predefined EOL threshold or when the maximum calendar life of 10 years is reached, similar to Wankmüller et al. (2017).

3.2.4 Factors impacting cycle life degradation

In the model of this paper, as mentioned in the preceding section, reduction in battery capacity is solely influenced by degradation resulting from utilized battery cycles. As the degradation in capacity will directly impact the profitability of the project, it is useful to understand the factors that determine the rate of degradation.

[20] Nominal capacity is the capacity of the battery throughout its life, decreasing with increased degradation.

According to Wankmüller et al. (2017), battery degradation and the number of EFC are impacted by the operation and characteristics of the battery, where the most impactful factors are state of health (SoH), depth of discharge (DoD), charge/discharge rate (C-rate) and temperature. The characteristics of a battery are influenced by the choice of battery and, consequently, the battery manufacturer. This is because manufacturers offer batteries with varying specifications and characteristics, as for instance shown in Table 2 which highlights the differences in efficiency between various batteries and manufacturers.

SoH refers to the current energy capacity of the battery compared to the rated capacity[21] (Sundén, 2019). Thus, a SoH of 70% infers that the nominal maximum capacity of the battery is 70% of the rated capacity and the battery has degraded by 30%. Different battery chemistries and battery manufacturers have different SoH thresholds to indicate battery EOL. According to product sheets from CATL (2023), the benchmark battery cells can achieve 8,000 EFC before reaching their EOL capacity threshold of 70%.

DoD is defined as the percentage of a battery's total capacity that has been discharged in a cycle. The DoD of a cycle varies depending on use, where a 100% DoD is referred to as a full cycle. Although some research indicates that DoD has a non-linear relationship with battery degradation, where deeper cycles (high DoD) reduce the battery’s SoH exponentially faster than shallower DoD cycles, Preger et al. (2020) finds that the capacity of LFP battery cells is significantly less impacted by variations in DoD compared to competing battery chemistries (such as NCA and NCM). Based on this finding, we assume in this paper that the battery can perform all 8,000 EFC with a 100% DoD.

The C-rate is the charge/discharge current of a battery cell and refers to its power-to-size ratio. For instance, 1C is equal to a 1-to-1 ratio between MW and MWh (the battery charges/discharges all its energy in one hour), while a ½C is equal to a 1 to 2 ratio (the battery charges/discharges its total energy over the course of two hours). A higher C-rate is beneficial for energy arbitrage as it allows

[21] Rated capacity is the battery capacity at beginning of its life.

for faster charging to utilize low electricity prices and faster discharging to benefit from higher electricity prices. Similarly to DoD, although some research indicates that a higher C-rate is expected to increase battery degradation and reduce the total EFC of a battery cell, Preger et al. (2020) finds that the impact of higher C-rates on battery SoH is significantly lower for LFP battery cells compared to other cell chemistries. Due to the reduced impact of different C-rates on LFP battery cell degradation and the specified 8,000 EFC at a C-rate of 1C before reaching battery EOL in our benchmark battery cells (CATL, 2023), this paper does not differentiate between the impact of different C-rates on the degradation on the battery cells.

According to Li et al. (2011), temperature has a direct effect on battery degradation rate, where too high or low battery temperatures increase the degradation rate. To keep temperatures stable, thermal management systems are found in the storage block, where they consume electricity to manage the battery-cell temperature. In this paper, we assume that thermal management systems always maintain the battery cells at the ideal temperature levels, ensuring optimal battery performance. To compensate for this, we assume that the cost of electricity for the thermal management is reflected in the O&M costs (see section 3.4.2) of the project.

In summary, we base the battery characteristics on 280 Ah battery cells from CATL (2023) and perform trading operations using 100% DoD for all trades, resulting in 8,000 EFC before reaching the EOL capacity threshold of 70% independent of the C-rate. Additionally, through the integrated thermal management systems in the storage block, we ignore the effect of temperature on battery degradation, but reflect the cost of operating these systems in the O&M costs.

3.2.5 Applied degradation modelling

Although batteries tend to show a slightly accelerated rate of degradation at the start and end of the battery cycle life (Preger et al., 2020), Preger et al. (2020) shows that lithium-ion battery cells exhibited primarily linear degradation behavior. Based on this research, we allow for the utilization of a linear degradation model.

By applying a linear degradation model, we can calculate a constant degradation factor (DF), which reduces the capacity after a completed cycle based on the rated capacity, EOL threshold capacity, and number of EFC. The degradation factor can be calculated as follows:

$$\mathrm{DF} = \frac{\mathrm{BC_{max}} - \mathrm{BC_{min}}}{\mathrm{EFC}}$$

$\mathrm{BC_{max}}$: the maximum battery capacity, which is equal to the rated capacity of a new battery.

$\mathrm{BC_{min}}$: the minimum battery capacity, which corresponds to EOL threshold capacity of the battery.

EFC: the number of EFC the battery can withstand before it reaches its EOL threshold and needs replacement.

Based on the expression above, the capacity will linearly decrease with the degradation factor after a full cycle. Thus, the nominal capacity of the battery gradually decreases with usage until it reaches the threshold capacity or the calendar life limit, requiring a replacement of the storage block.

3.3 BESS size and power

When considering a BESS performing energy arbitrage, the BESS size and power are two important factors as they affect the trading profits and the costs of the system. This subsection presents: 1) an introduction to BESS size and power, 2) an overview of the implications different BESS size and power have on costs and trading profits, and 3) the chosen size and power of the BESS in this paper.

The size of the BESS refers to the maximum energy capacity of the system, measured in MWh, and serves as the basis for determining the overall costs. Further, the BESS size determines the potential energy that can be stored and released, ultimately influencing the ability to generate trading revenue. The power of the BESS represents the capacity of the power conversion system measured in MW, indicating the rate at which energy is charged to or discharged from the system

(Yoo et al., 2020). Subsequently, the power of the BESS, in combination with the size, influences how fast the BESS can react to electricity price changes and perform energy arbitrage trades.

As covered in section 3.2.4, the C-rate is a function of the charge and discharge current (power) to the energy capacity of the battery (size) and implies the time it takes for a battery to fully charge or discharge. Through the implicit C-rate, the choice of BESS size and power will directly impact the arbitrage trading pattern, as the system would require different amounts of time to fully charge or discharge its energy. Due to the utilization of hourly DAM electricity prices in this study (as covered in section 2.3), employing a BESS with a 1-to-1 size-to-power ratio (C-rate of 1C) enables the system to optimize arbitrage trading by taking advantage of the lowest and highest hourly electricity prices throughout the time series. However, a higher system power also contributes to significantly higher infrastructure costs (see section 3.4.1 for an elaboration on the CAPEX segmentation applied in the paper), due to higher grid integration and power kit costs (Rystad Energy, 2023b). Table 3 below summarizes the infrastructure CAPEX per MWh for BESSs of varying power and size, while Table 4 presents the storage block costs per MWh for different BESS power and size specifications.

Table 3: Infrastructure CAPEX per MWh (in NOK 1000) for different BESS size and power specifications (data based on Rystad Energy (2023b))

		Megawatt						
		2	**5**	**10**	**25**	**50**	**100**	**250**
C-rate	**1C**	12,613	8,408	6,274	4,445	4,017	3,708	3,571
	1/2C	6,935	4,819	3,746	2,825	2,603	2,444	2,376
	1/4C	4,103	3,025	2,477	2,009	1,892	1,808	1,774
	1/6C	3,155	2,425	2,053	1,737	1,654	1,595	1,572

Table 4: Storage block costs per MWh (in NOK 1000) for different BESS size and power specifications (data based on Rystad Energy (2023b))

		Megawatt						
		2	**5**	**10**	**25**	**50**	**100**	**250**
C-rate	**1C**	2,285	2,246	2,217	2,179	2,150	2,122	2,086
	1/2C	2,260	2,221	2,192	2,154	2,126	2,099	2,063
	1/4C	2,239	2,201	2,172	2,135	2,107	2,079	2,044
	1/6C	2,231	2,192	2,164	2,127	2,099	2,072	2,036

As we can observe from Table 3, there are significant economies of scale for the BESS infrastructure costs, indicating that a large BESS would be more economically viable as the arbitrage trading profits scale proportionally with the size of the BESS when the C-rate is held constant. Additionally, we observe that the cost per MWh decreases significantly with a lower C-rate due to the lower grid integration and power kit costs. However, since the operation policy is conditioned by the power/size ratio (a lower C-rate constricts optimal arbitrage trading), the economic implications of reducing the BESS power through a lower C-rate is uncertain without further analysis as the choice would reduce both the infrastructure costs and the arbitrage trading profits.

This study utilizes a 10MW/10MWh BESS with an implied C-rate of 1C to estimate the economic viability of the BESS project. The choice of a small-to-medium sized BESS allows for the assumption that the BESS arbitrage trading does not impact the electricity prices nor the area marginal loss rates, and the choice of a 1-to-1 size-to-power ratio allows us to estimate the maximum achievable arbitrage trading profits when utilizing hourly DAM electricity prices for different time series while also simplifying the arbitrage trading model. Nevertheless, the chosen size-to-power ratio is not necessarily optimal for maximizing project profitability, due to the associated high CAPEX. To identify the optimal BESS size and power for the distinct electricity price scenarios in this paper, further analysis is required.

3.4 BESS cost structure

The cost structure of a standalone BESS engaged in energy arbitrage can be classified into two main components: CAPEX and O&M costs. Within the CAPEX category there are two distinct cost divisions: initial CAPEX in the form of storage blocks and infrastructure, and decommissioning costs at the end of the project. All costs presented in this section are based on a 10MW/10MWh BESS specification, as discussed in section 3.3.

3.4.1 Capital Expenditure (CAPEX)

In this paper, we split CAPEX into initial CAPEX and decommissioning costs. For initial CAPEX, we adopt the methodology of Rystad Energy's Battery Solutions (2023b) and segment the BESS into four main components: storage block, power kit, grid connection, and project development. Applying this component segmentation, the segmented initial CAPEX is grouped into two categories: storage block costs and infrastructure costs (comprising power kit, grid connection, and project development). This distinction is made because the storage blocks are expected to degrade more rapidly than the project's infrastructure, due to the degradation of the battery cells, thus necessitating replacement throughout the project. Infrastructure components are on the other hand anticipated to gradually depreciate until they reach a residual value of zero at the end of the project. The decommissioning costs, which encompass the activities of recycling materials and restoring the site to its original condition, occur at the end of the project.

As the infrastructure components are expected to depreciate progressively, reaching a residual value of zero by the project's conclusion, the lifespan of the infrastructure effectively determines the project's duration. In turn, the duration of the project influences the number of storage block installations as well as the value of the discounted cash flow for the decommissioning expenses, considering the time value of money. Determining an appropriate lifespan for BESS infrastructure is a complex task due to the emerging nature of end-of-life management for energy storage systems, resulting in a scarcity of empirical evidence to depend upon (U.S. Energy Storage Association, 2020). Furthermore, the estimated lifetime of BESS infrastructure in relevant reports varies. For instance, the U.S. Energy Storage Association (2020) suggests that a typical BESS can have a lifespan exceeding 15 years. Similarly, Stantec (2023) states that the specific 99MW/396MWh BESS project mentioned in the report can last 15-20 years, with possibilities for extended project lifetime with equipment replacement or augmentation. Noteworthy, the report does not provide details on the extent to which replacing or augmenting equipment would improve the lifespan. Lastly, Convergent (2020) suggests that the 4MW/17.9MWh BESS project discussed in the report can easily be extended to 35 years due to its straightforward augmentation and upgradability. Drawing inspiration from the analyses presented above, we adopt an estimate of 30 years for the lifetime of our project in this paper.

The storage block, costing ~22.2 MNOK (Rystad Energy, 2023b), comprises the cost of battery cells, packing (including costs such as battery thermal management), and system balancing. Since the battery has a lifespan of 10 years, as discussed in section 3.2.3, the project will require at least three storage blocks. Additional storage blocks may be necessary if the battery at any point exhausts its cycles before reaching its calendar life limit, which would require replacement before the 10-year lifespan is reached. Since the storage block installations will take place at different times, we need to assess any potential price fluctuations between these installations. As per Statista's report from (2020), lithium-ion battery packs had consistently become more affordable until 2020, with a continued expected decrease over time. However, around 2020 the price of battery cells increased due to a manifold increase in raw material costs (Rystad Energy, 2023b), which complicated price predictions. While technological advancements are arguably likely to decrease battery prices, the future price of raw materials are uncertain, and, according to Rystad Energy (2023b), the raw material prices, especially of lithium, are expected to increase in the long term. As the development of battery prices is uncertain, we have assumed a constant price for the storage blocks throughout the project timeframe.

The infrastructure costs are comprised of the costs related to the power kit, grid connection, and project development. The components making up the power kit and grid integration are covered in section 3.1 and cost ~17.3 and ~29.2 MNOK, respectively. Project development costs include cost buckets such as engineering, procurement and construction, land use, labor, and licensing. While the power kit and grid connection costs are relatively fixed, the project development cost segment can, according to Rystad Energy (2023b), vary significantly depending on location and cost of labor. Given this uncertainty, we have applied Rystad Energy's cost calculator (2023b) for estimating the project development cost, totaling ~16.1 MNOK. The total infrastructure costs applied in this paper amount to ~62.7 MNOK.

When estimating decommissioning cost, there is little empirical evidence to rely on for accurate cost estimates (U.S. Energy Storage Association, 2020). Some reports attempt to conduct such estimates, yet none fully account for every contributing factor that could influence these costs. For example, EPRI (2017) neglects the cost of decommissioning grid integration equipment and site restoration, while Convergent (2020), Renewance (2020) and Stantec (2023) disregard the salvage values of recyclable materials. Furthermore, there is a substantial variation in the cost estimates across these different reports. Renewance (2020) explains that the potential differences in decommissioning cost estimations can depend on factors such as the specific site location and jurisdiction, the type and structure of the battery chemistry, and the level of expertise and sophistication of the battery recycling facility. Given the limitations of the available benchmarks, we base the decommissioning cost estimates in this paper on the report we believe is most similar to the project in this study. Specifically, we rely on the Renewance (2020) report, which focuses on LFP batteries and deploys the same BESS size as in this paper, resulting in $474,000 decommissioning costs. To align this cost estimation with the projected lifetime of the project, we also apply a forward inflation of 30 years, assuming an annual inflation rate of 2%. As the decommissioning costs from the chosen report do not include any potential salvage values from recyclable materials, due to the inherent difficulties in accurately predicting salvage values for recyclable materials over such a long timeframe, this study also excludes any salvage value considerations. Consequently, the decommissioning costs are likely somewhat high.

3.4.2 Operations and Maintenance costs (O&M)

Due to the inherent confidentiality of most BESS projects, detailed information regarding operational processes and associated costs is scarce and difficult to obtain (Wingren & Johnsson, 2018). Yet, according to a meta-analysis conducted by Cole et al. (2021), numerous studies have estimated O&M costs of BESSs, revealing considerable variation in both current and projected costs. According to the meta-analysis, all the research analyzed, except Schmidt et al. (2019), indicate that variable O&M costs are negligible. In contrast, the meta-analysis found that estimates for fixed O&M costs range widely, spanning from zero to 25 USD per kW per year. Based on this meta-analysis, we will in this paper assume variable O&M costs to be zero and fixed O&M costs to be 15 USD per kW per year (converted to NOK). The fixed O&M costs are chosen as they represent a middle ground value in the estimated cost range from the relevant literature. The costs are assumed to grow with a moderate inflation rate of 2%, as they are based on components that are likely to be affected by inflation, such as salaries. As all the O&M costs used in this paper are fixed, they are not impacted by operating strategy, making them inconsequential for the BESS trading model.

4. Financial modelling

This section provides the financial modelling applied in the valuation of the BESS. In the section we: 1) argue for the use of a traditional Net Present Value (NPV) method utilizing discounted cash flows as the valuation tool, and 2) select an appropriate discount rate for the analysis.

4.1 Financial methodology

Valuation refers to the process of determining the true value of an asset, investment, or company (Brealey et al., 2014). There are several methods of valuation, each with its own strengths and weaknesses. The most commonly used methods include:

Asset-based approach: This approach estimates the value of an asset based on its underlying assets. It is typically used to value companies that have substantial tangible assets like machinery or real estate.

Market approach: This method estimates the value of an asset by assessing the prices of recently sold similar assets in the market. The method assumes that the market is efficient and that the prices of similar assets reflect their true value.

Discounted Cash Flow (DCF) analysis: This approach estimates the NPV of an asset based on the cash flows it generates. Since cash flows occur at different points in time, the cash flows are discounted to their present values using an appropriate discount rate.

Comparable Companies Analysis (CCA): This method compares a company's financial metrics to those of its peers to estimate its value. It is commonly used in the valuation of privately traded companies.

Although a significant portion of the assets in the BESS project discussed in this paper are tangible, the majority of the assets are results of niche specifications (such as grid connection to a remote area) that are likely to be illiquid and may not be worth the initial purchasing price after installation. Therefore, the asset-based approach is not suitable for this valuation. Further, there is, to our knowledge, no transparent market for BESS projects, which makes information on sales of similar projects scarce. Consequently, a valuation through the market approach is unsuitable. However, we can accurately estimate the cash flows the BESS will generate using a trading optimization model. Consequently, a DCF approach can be used, but further requires the selection of a discount rate. In the selection of a discount rate, we apply the Weighted Average Cost of Capital (WACC) method, where a CCA is used to estimate necessary inputs for the WACC.

4.2 Selecting a discount rate

An appropriate discount rate for the cash flow analysis is achieved by employing the WACC method. The WACC formula requires specific inputs, namely the cost of debt and equity of the project, the tax rate, and the weights of each source of financing (debt and equity) in the company's capital structure (Brealey et al., 2014). The WACC formula is formulated as follows:

$$\mathrm{WACC} = \frac{\mathrm{E}}{\mathrm{E}+\mathrm{D}} * \mathrm{R_e} + \frac{\mathrm{D}}{\mathrm{E}+\mathrm{D}} * \mathrm{R_d} * (1 - \mathrm{T_c})$$

E: the market value of the firm's equity.

D: the market value of the firm's debt.

$\mathrm{R_e}$: the cost of equity.

$\mathrm{R_d}$: the cost of debt.

$\mathrm{T_c}$: the corporate income tax rate.

The corporate income tax rate is readily available, but the remining variables need to be calculated. However, obtaining accurate estimates of these variables can be challenging, especially for private companies or firms without readily available financial information like with the project in this paper. In such cases, a CCA can be a useful tool to estimate these metrics (Brealey et al., 2014).

4.2.1 Comparable Companies Analysis (CCA)

Performing a CCA involves comparing the financial metrics and performance of a target company to those of similar companies in the same industry or market (Brealey et al., 2014). By identifying comparable companies with similar business models, revenue streams, growth prospects, and risk profiles, we can estimate the target company's cost of equity and debt, as well as identify an appropriate financial structure.

The first step of the CCA is to identify comparable companies that operate in the same industry or market as the project in this paper (Brealey et al., 2014). Ideally, a set of comparable companies would be engaged in similar operations. However, there are few, if any, publicly traded companies dedicated to electricity trading, aside from traders dealing in derivatives. Yet, such trading companies generally trade in various other types of securities, rendering them unsuitable as comparable companies. Consequentially, we require the adoption of an alternative approach for identifying comparable companies. Thus, we employ companies exposed to similar business risks to the BESS project as the comparable companies in the CCA.

Among potential comparable companies, power producers face comparable business risks to the project in this paper and can thus be considered suitable proxies. These risks include fluctuations in electricity prices, volatility in power markets, and regulatory changes. Since most major Norwegian power producers are either state-owned or privately held (Largest Companies, n.d.), it is challenging to find relevant financial data for the WACC calculation. Thus, we expand the peer selection to include power producers in nearby European countries. As a consequence of this expansion, it becomes important to adapt the metrics from the companies' individual markets to align with the Norwegian market.

The selected comparable companies are:

- **Fortum Oyj** (HEL: FORTUM) - A Finnish energy company that focuses on clean energy solutions, including hydroelectric, nuclear, and solar power (Fortum, n.d.). The company operates across Europe and is exposed to risks involving electricity prices and regulatory changes in the region.
- **Ørsted A/S** (CPH: ORSTED) - A Danish multinational power company specializing in renewable energy, with a strong focus on offshore wind power generation (Ørsted, n.d.). Ørsted operates in Europe and its risks include fluctuations in electricity prices and regulatory environments.
- **PNE AG** (ETR: PNE3) - A German renewable energy company that develops, constructs, and operates wind and solar power projects (PNE, n.d.). PNE AG operates in multiple European countries and is exposed to risks such as electricity price fluctuations and regulatory changes.
- **Neoen SA** (EPA: NEOEN) - A French independent power producer specializing in renewable energy sources, including solar, wind, and energy storage (Neoen, n.d.). Neoen operates in Europe and its risk factors include electricity price volatility, and regulatory changes in the markets.

The selected companies share several commonalities that make them suitable comparable companies to estimating the WACC inputs. Primarily, these firms are engaged in the production of electricity, with a general focus on the Nordic and/or European markets. This ensures that their business operations and risk exposures are likely to be similar to a commercial BESS, thus providing a relevant basis for comparison. Furthermore, these companies are involved in diversified energy production, encompassing various energy sources such as hydro, wind, solar, and thermal. This diversity ensures a comprehensive representation of the industry's risk factors, which improves reliability when establishing the input estimations.

4.2.2 Cost of debt and financial structure

In determining the cost of debt for the project, two critical factors must be ascertained, namely the credit risk premium and the risk-free rate. For the estimation of the credit risk premium associated with the BESS project, the CCA is employed. Assuming analogous risk profiles between the BESS project and the average of the comparable companies, the outstanding bonds of the latter can be utilized to establish a credit risk premium for the former. In selecting the bonds for comparison, a long-term maturity is preferred, ideally 30 years, to align with the project's financing duration. In the absence of bonds with a 30-year maturity, the nearest available maturity is considered.

Fortum Oyj has an outstanding euro bond (ISIN: XS0939100524), rated BBB by Fitch Ratings (Fitch Ratings, 2023), issued in 2013 and maturing in 2043 (LUXSE, n.d.). The bond has, at the time of this study, a yield-to-maturity (YTM) of approximately 4.4%. The credit risk premium can be calculated by subtracting a suitable risk-free rate, which in this case is the Finnish 20-Year Government Bond Yield, yielding approximately 3.0% (World Government Bonds, 2017a). The resulting credit risk premium equals about 1.4%.

Ørsted A/S has an outstanding pound bond (ISIN: XS2531570112), rated BBB+ by Fitch Ratings (Ørsted, 2023), issued in 2022 and maturing in 2042 (Börse Frankfurt, n.d.) (Ørsted, 2023). The bond has, at the time of this study, a YTM of approximately 5.5%. As the bond is denominated in pounds, the UK 20-Year Government Bond Yield of approximately 4.0% (Investing.com, n.d.) is employed, yielding a credit risk premium of about 1.5%.

The remaining two comparable companies lacked outstanding bonds with similar years to maturity, making them unsuitable for this portion of the analysis.

By utilizing the average of the credit risk premiums of Fortum Oyj and Ørsted A/S, a credit risk premium of 1.45% can be assigned to the BESS project. The applied risk premium suggests that we assume the BESS project bears a comparable risk profile to the selected companies. Since a portion of the risk profile is derived from the financial structure of the company's assets, we adopt a financial structure for the BESS project that closely aligns with those of the comparable companies to maintain consistency in the risk assessment process. Utilizing data from Yahoo Finance, Fortum Oyj and Ørsted A/S have market value debt-to-equity (D/E) ratios of approximately 0.289 and 0.136, respectively. By utilizing the average, a D/E-ratio of 0.213 can be applied to the BESS project. In order to keep the WACC constant, the D/E-ratio is assumed to be constant over the lifespan of the project.

As the BESS project will be executed in Norway and involve payments in NOK, it is appropriate to employ the Norwegian Government Bond Yield as the risk-free rate for the project. At the time of this analysis, the Norwegian 20-Year Government Bond Yield stands at approximately 2.94% (World Governemnt Bonds, 2017b). By adding the credit risk premium of 1.45% to the risk-free rate of 2.94%, the resulting cost of debt for the BESS project equals 4.39%.

4.2.3 Cost of equity

The Capital Asset Pricing Model (CAPM) is widely used to estimate the cost of equity of a company or project (Brealey et al., 2014). Finding the cost of equity requires specific inputs, namely the risk-free interest rate, the expected market return, and the equity beta (systematic risk). The formula is expressed as:

$$\mathrm{R_e} = \mathrm{R_f} + \beta_\mathrm{e} * (\mathrm{R_m} - \mathrm{R_f})$$

$\mathrm{R_e}$: the cost of equity.

$\mathrm{R_f}$: the risk-free interest rate, assumed to be the Norwegian 20-Year Government Bond Yield of 2.94% for the project in this paper.

β_e: the equity beta coefficient, which is a measure of the volatility of a company's stock compared to the market as a whole.

$(\mathrm{R_m} - \mathrm{R_f})$: the Norwegian market risk premium, assumed to be 5.8% based on Statista (2022).

As the BESS project in this paper is not publicly traded it does not have a market price, making it difficult to estimate the equity beta coefficient (β_e). However, there are ways to estimate the equity beta for such a project by using CCA. When estimating the cost of equity using CCA, it is not appropriate to simply use the equity beta of the comparable companies as they may have different levels of financial leverage, affecting the equity beta (Brealey et al., 2014). To account for the differences in capital structure between the BESS project and the comparable companies, we follow the three-step calculation of first “unlevering” the equity betas of the comparable companies, then take the average of those unlevered betas, and finally “relever” the beta using the average of the unlevered betas and the D/E-ratio of the BESS project. Unlevering the equity beta entails removing the effects of financial leverage from a company's beta, leaving only the risk inherent in the company's operations (commonly called asset beta, β_a). Taking the average of the unlevered betas of the comparable companies provides a benchmark for the industry, as this average represents the systematic risk inherent in the industry as a whole. Finally, relevering the beta by factoring in the effects of financial leverage of the BESS project yields an estimated equity beta for the project. The three steps can be formulated mathematically as follows:

Step 1) Unlevering the betas of the comparable companies:

$$\beta_{a_{comp}} = \frac{\beta_{e_{comp}}}{1 + \left(1 - T_{c_{comp}}\right) * \frac{D_{comp}}{E_{comp}}}$$

Step 2) Averaging the unlevered betas:

$$\beta_{a_{comp.avg}} = \frac{\sum \beta_{a_{comp}}}{\#\text{ of comps}}$$

Step 3) Relevering the beta to the BESS project:

$$\beta_e = \beta_{a_{comp.avg}} * \left(1 + (1 - T_c) * \frac{D}{E}\right)$$

It is important to consider that the betas from the comparable companies may need to be adjusted to account for their respective operations belonging to different markets that hold inherently different market risks. However, it should be noted that the comparable companies included in this analysis operate in markets that are very similar to the market in which the BESS project operates. Consequently, we assume that no further adjustments need to be made to the betas in this analysis.

Utilizing data from Yahoo Finance and PwC Worldwide Tax Summaries (PwC, n.d.), Table 5 below includes all the necessary data to perform the three steps.

Table 5: Summary of comparable companies' data used for the project beta estimation

Company	Equity beta (5Y monthly)	Market value debt-to-equity ratio22	Corporate income tax rate	Unlevered beta
Fortum Oyj	0.70	0.289	20%	0.5686
Ørsted A/S	0.57	0.136	22%	0.5153
PNE AG	0.45	0.452	15.825%	0.3260
Neoen SA	0.76	0.821	25%	0.4704

By applying the CCA to estimate the equity beta for the BESS project (β_e), the beta becomes equal to 0.5480. Applying this to the CAPM formula, the estimated cost of equity for the BESS project (R_e) becomes 6.12%.

4.2.4 Project discount rate

Based on the CCA, the cost of equity (R_e), cost of debt (R_d) and the financial structure (D/E) for the BESS project are estimated to be 6.12%, 4.39% and 0.213, respectively. By applying these values and the current Norwegian corporate tax rate of 22% (PwC, n.d.) to the WACC function, we get a discount rate for the project equaling **5.65%**.

$$WACC = \left(\frac{1}{1+0.213} * 6.12\%\right) + \left(\frac{0.213}{1+0.213} * 4.39\% * (1-22\%)\right) = 5.65\%$$

It has been suggested by Núñez et al. (2022) that the BESS project should be classified as a "regulated activity", thereby necessitating a decrease in the discount rate due to reduced risk associated with regulated activities. While Núñez et al. (2022) does not provided a clear rationale for this adjustment, we contend that such an adjustment to the discount rate is unwarranted. This is because the influence regulation might have on risk is considered in the estimation of the WACC through the selection of the comparable companies in the CCA, which are subject to similar regulatory frameworks and measures as the BESS project. Therefore, the potential influence of regulation on risk is appropriately reflected in the analysis.

[22] Implied market value of debt is calculated using enterprise value less market capitalization.

5. Arbitrage trading modelling

In this section we present the details of the energy arbitrage trading model for the BESS, which is based on Mixed-Integer Linear Programming (MILP) and Mixed-Integer Nonlinear Programming (MINLP). The section is structured in the following way: 1) an introduction to a two-stage optimization methodology designed to streamline the optimization process by reducing the amount of data required, 2) a test to see whether we can omit redundant variables and constraints based on the cause for storage block replacement, and 3) an explanation for the final optimization model used to determine the optimal arbitrage trading patterns for the various price zones.

5.1 Two-stage optimization rationale

In the optimization problem, the program needs to determine the optimal trading pattern for a given number of time periods, T. Every time period holds a row of data and as T increases, the complexity of the problem grows exponentially, making it increasingly challenging for the optimization program to find an optimal solution within a reasonable timeframe. To address this issue, a two-stage methodology is implemented, which effectively reduces the number of evaluated time periods in the optimization function. This simplification allows the program to find a solution more efficiently and expedites the process.

In the first stage, we apply the hourly electricity prices for the complete evaluation period on a simplified optimization problem, aiming to maximize the arbitrage trading profit with very limited constraints. Upon solving the optimization problem in the first stage, the model outputs the optimal trading pattern, which is then stored in a DataFrame. This DataFrame is filtered to include only the time periods with trading activity to ensure that only potentially profitable trades are considered.

In the second stage, a second optimization model is run on the condensed dataset from the first stage. Since the dataset has been reduced to only include potentially profitable trades, the second stage of the model can focus on optimizing the trading pattern while considering appropriate costs and constraints without evaluating a large number of infeasible trades.

5.2 Identifying omittable variables and constraints

Although the two-stage optimization approach significantly reduces the computational burden of the problem, the sheer number of variables and constraints within the optimization function remains overwhelming for the current computational resources at our disposal. To further streamline the optimization model, we can identify and eliminate redundant variables and constraints by evaluating whether the limiting factor for battery life necessitating storage block replacement (as presented in section 3.2.3), is consistently the battery cycle life or the calendar life of the batteries in the storage block. If there is a clear pattern, wherein either battery cycle life or calendar life consistently serves as the limiting factor, the optimization formulation can be substantially simplified without compromising the integrity of the results.

By conducting a test to determine if the maximum number of potentially profitable trades that the battery can perform ever exceeds the total number of available EFC, before reaching the end of its calendar life, we can ascertain whether battery cycle life can ever be the limiting factor. Due to degradation, each trade affects the remaining capacity of the battery, reducing the storage block value, which effectively acts as a marginal cost of usage if battery cycle life was to be the limiting factor necessitating storage block replacement. By applying this rationale, we can reduce the total number of potentially profitable trades to only include trades which are still profitable when considering a marginal cost, and see whether the number of potential trades outweighs the total number of available EFC (see Appendix B – Testing battery cycle life as the limiting factor for a detailed outline of this process). We apply the test to the NO2 price dataset extrapolated over a 30-year period, as this dataset exhibits the highest average prices and greatest standard deviation (portrayed in section 2.2), and will consequently most likely utilize the highest number of EFC. From the test we observe that the maximum number of potentially profitable trades that the battery can perform never exceeds 8,000 (the total number of available EFC), before reaching the end of its 10-year calendar life. Consequently, the calendar life, rather than the battery cycle life, consistently serves as the limiting factor necessitating storage block replacement for all data inputs relevant to this study. This discovery enables a simplification of the model by omitting variables and constraints pertaining to the preservation of battery value, as these variables and constraints will never dictate the trading behavior.

5.3 Final trading optimization model

Having identified the calendar life as the deciding factor for storage block replacement, we employ the two-stage optimization approach to determine optimal trading patterns for the BESS using the different price zone data.

5.3.1 First stage of the optimization

The primary objective of the first stage of the optimization is to streamline the dataset by allowing for the model in the second stage to solely evaluate potentially profitable trades. Given that the battery life cycles are not a constraining factor, there is no need to include a marginal cost term when filtering the data (see section 5.2). Consequently, we can adapt the model outlined in Appendix B by omitting the marginal cost term (see Appendix C – Shortening the optimization input dataset for a detailed outline of this process). The resulting DataFrame comprises potentially profitable trades considering electricity prices, fixed and variable production and consumption taxes and tariffs, efficiency losses, and VAT.

5.3.2 Second stage of the optimization

The outcome of the first stage of the model is a streamlined dataset, with a large number of irrelevant time periods (t) excluded. When performing the second stage of the optimization based on this dataset, we introduce a new variable for periods, i. Importantly, the distance between i and $(i+1)$ is not necessarily equal one, as it is for t and $(t+1)$. Thus, each i variable has a corresponding t variable (notation i_t and t_i), that we use to ensure correct replacement times for the storage block and accurate discounting of all cash flows. To correctly account for storage block replacement periods, we append the data series ($i \in \{1, \ldots, \mathrm{I}\}$) with periods ($i_t$) for year 10 and 20, noted as $i_{\frac{1}{3}T}$ and $i_{\frac{2}{3}T}$, on the condition that these periods (i_t) are not already part of the data series.

In this paper, we assume that a new storage block is installed once the previous has reached its EOL, regardless of whether storage block replacement maximizes the NPV or not. This assumption is made as the purpose of the analysis is to test the lifetime economic viability of the BESS performing energy arbitrage, necessitating storage block replacement for continued operations throughout the lifespan of the project. Since the model spans 30 years, and as each storage block has a lifetime of 10 years, we use three storage blocks, each with its own objective function. For each function, we refresh the battery-related terms, such as battery capacity, while continuing from the last period in the previous function to ensure accurate cash flow discounting.

The second stage of the optimization model can be expressed as follows:

Decision variables:

$\alpha_i \in \{0,1\},\ i \in \{1,\ldots,I\}$: binary variable representing if the battery is discharging at period i.

$\beta_i \in \{0,1\},\ i \in \{1,\ldots,I\}$: binary variable representing if the battery is charging at period i.

$BS_i \in \{0,1\},\ i \in \{1,\ldots,I\}$: binary variable representing the battery state (charged/not charged) at period i.

$BC_i \in [BC_{min}, BC_{max}],\ i \in \{1,\ldots,I\}$: battery capacity at period i.

Objective functions:

$$\max_{\alpha_i,\beta_i,BS_i,BC_i,C_i} \sum_{i=1}^{i_{\frac{1}{3}T}} \left(\frac{\left(S_{pi} - P_{pi}\right) * (1-\theta)}{(1+r)^{t_i}}\right), \qquad i \in \left\{1, \ldots, i_{\frac{1}{3}T}\right\}$$

$$\max_{\alpha_i,\beta_i,BS_i,BC_i,C_i} \sum_{i=i_{\frac{1}{3}T}+1}^{i_{\frac{2}{3}T}} \left(\frac{\left(S_{pi} - P_{pi}\right) * (1-\theta)}{(1+r)^{t_i}}\right), \qquad i \in \left\{i_{\frac{1}{3}T} + 1, \ldots, i_{\frac{2}{3}T}\right\}$$

$$\max_{\alpha_i,\beta_i,BS_i,BC_i,C_i} \sum_{i=i_{\frac{2}{3}T}+1}^{I} \left(\frac{\left(S_{pi} - P_{pi}\right) * (1-\theta)}{(1+r)^{t_i}}\right), \qquad i \in \left\{i_{\frac{2}{3}T} + 1, \ldots, I\right\}$$

$$S_{pi} = \alpha_i * BC_i * (E_{pi} - \gamma_i - \Gamma_{pi}) * (1 - \varepsilon), \qquad i \in \{1, \ldots, I\}$$

$$P_{pi} = \beta_i * BC_i * \frac{(E_{pi} + \lambda_i + \Lambda_{pi})}{(1 - \varepsilon)}, \qquad i \in \{1, \ldots, I\}$$

E_{pi}, $i \in \{1, \ldots, I\}$: the electricity price in price zone p at period i.

γ_i, $i \in \{1, \ldots, I\}$: the fixed production tariff at period i. The variability is necessary as the tariff is only fixed for one year at a time.

Γ_{pi}, $i \in \{1, \ldots, I\}$: the mean variable production tariff in price zone p at period i.

λ_i, $i \in \{1, \ldots, I\}$: the fixed tax for electricity consumption at period i. The variability is necessary as the tax is only fixed for one year at a time.

Λ_{pi}, $i \in \{1, \ldots, I\}$: the mean variable tariff for electricity consumption in price zone p at period i.

t_i, $i \in \{1, \ldots, I\}$: the corresponding discount time period t for period i.

θ: the VAT applied to all trade profits.

ε: the efficiency loss with every charge and discharge. The efficiency loss is divided equally between the charging and discharging of the battery, calculated: $\varepsilon = 1 - \sqrt{RTE}$.

Constraints:

$\alpha_i + \beta_i \leq 1$, $i \in \{1, \ldots, I\}$: the BESS cannot charge and discharge simultaneously at period i.

$BS_1, BS_{i_{\frac{1}{3}T}+1}, BS_{i_{\frac{2}{3}T}+1} = 0$: the initial battery state of each objective function is set to uncharged.

$BS_i = BS_{i-1} - \alpha_i + \beta_i$, $i \in \{1, \ldots, I\}$: the battery state is affected by buying or selling at period i.

$BC_1, BC_{i_{\frac{1}{3}T}+1}, BC_{i_{\frac{2}{3}T}+1} = BC_{max}$: the initial battery capacity of each objective function is set to the max capacity.

$\mathrm{BC_i} = \mathrm{BC_{i-1}} - \mathrm{DF} * \alpha_{\mathrm{i-1}},\ \mathrm{i} \in \{1, \ldots, \mathrm{I}\}$: the battery capacity is reduced after a discharge. The degradation factor, DF, is a function of linear degradation from maximum capacity to minimum capacity.

The model outputs an optimal electricity trading pattern for the 30-year timespan the BESS is active. The trading activity is used in the valuation expression formulated in section 6.

6. Valuation expression

As discussed in section 4.1, the valuation expression for the BESS is structured as a DCF analysis. The valuation expression for a given price zone p is expressed as[23]:

$$\mathrm{NPV_p} = \sum_{t=0}^{T}\left(\frac{(\mathrm{S_{pt}} - \mathrm{P_{pt}}) * (1-\theta) - \mathrm{SB_t} - \mathrm{OM_t} - \tau_t}{(1+r)^t}\right) - \mathrm{IC_0} - \frac{\mathrm{DC_T}}{(1+r)^T}, \qquad t \in \{0, \dots, T\}$$

$$\mathrm{S_{pt}} = \alpha_t * \mathrm{BC_t} * (\mathrm{E_{pt}} - \gamma_t - \Gamma_{pt}) * (1 - \varepsilon), \qquad t \in \{1, \dots, T\}$$

$$\mathrm{P_{pt}} = \beta_t * \mathrm{BC_t} * \frac{(\mathrm{E_{pt}} + \lambda_t + \Lambda_{pt})}{(1 - \varepsilon)}, \qquad t \in \{1, \dots, T\}$$

$\mathrm{SB_t},\ t \in \{0, \dots, T\}$: the storage block costs at time t. The costs occur at $t = \{0, T/3,\ 2T/3\}$.

$\mathrm{OM_t},\ t \in \{1, \dots, T\}$: the O&M costs at time t.

$\tau_t,\ t \in \{1, \dots, T\}$: the corporate income tax costs at time t (if applicable). If the tax is negative, it will carry forward to the next tax-relevant period as a tax shield.

$\mathrm{IC_0}$: the infrastructure costs at the beginning of the project.

$\mathrm{DC_T}$: the decommissioning costs at the end of the project.

The optimal trading inputs (α_t and β_t) are taken from the results of the second stage of the trading optimization model outlined in section 5.3.2, resulting in the optimal trading profits. The electricity price data (E_{pt}) is based on hourly DAM prices taken from ENTSO-E, and is converted from euro to NOK using daily conversion rates from Norges Bank (weekend values extrapolated equal to Friday values). The fixed energy production tariffs (γ_t) and consumption taxes (λ_t) are yearly fixed rates per MWh, as explained in sections 2.5.1 and 2.5.2. The variable energy tariffs (Γ_{pt} and

[23] Note how the time periods are t, not i, as all periods are relevant in this expression.

Λ_{pt}) are based on the mean marginal loss rates for the substations in each price zone, as explained in section 2.5.1, and are calculated for all years except 2022 where the rate is set to zero in accordance with Statnett's reduction of the fee. Since the aforementioned metrics are impacted by the battery energy capacity of the BESS, the battery capacity at the relevant period (BC_t) adjusts for the effects of degradation.

The CAPEX is divided into three categories: storage block costs (referred to as SB_t in the valuation expression), infrastructure costs (encompassing the costs of the power kit, grid connection, and project development, together referred to as IC_0), and decommissioning costs (referred to as DC_T). The storage block and infrastructure costs are based on Rystad Energy's cost estimator (2023b), and the decommissioning costs are based on costs from Renewance (2020), both elaborated in section 3.4.1. While storage block costs occur at times $t = \{0,\ T/3,\ 2T/3\}$ (as it is replaced every 10 years until the project is decommissioned), the infrastructure costs take place at time $t = 0$, and the decommissioning costs occur at the end of the project at time $t = T$.

The O&M costs (referred to as OM_t) use a middle-ground value from Cole et al. (2021), as discussed in section 3.4.2.

The corporate income tax (τ_t) is calculated annually and paid at the end of the fiscal year, if applicable. Tax loss carryforwards are utilized, if applicable. For the calculation of the tax, a linear depreciation method is employed for all CAPEX, where the storage blocks and the infrastructure are assigned lifetimes of 10 and 30 years, respectively.

The discount rate applied (r) is based on the estimated WACC from the financial modelling in section 4.2, and is transformed to a per-period (hourly) compounding rate.

7. Trading results and project valuation

This section presents the trading results and the valuation of the 10MW/10MWh BESS performing energy arbitrage in the different electricity price zones in Norway. The analysis considers two distinct price scenarios, drawing from electricity prices in 2022 and the period from 2016 to 2019 (as reasoned for in section 2.3). The section is structured as follows: 1) an overview of the arbitrage trading profits and battery utilization rates for the BESS in the different electricity price zones and price scenarios, and 2) a presentation of the results from the valuations of the BESS projects.

The inputs used in the trading optimization and the valuation expression are summarized in Table 6 below.

Table 6: Inputs used for modelling purposes, all in future values.

Input	Value	Explanations	Elaboration in section
Price scenarios			
Electricity price data	Hourly electricity prices	The hourly DAM electricity prices for 2022 and 2016-2019	2.3
BESS specifications			
Battery chemistry	LFP	The chosen chemistry laying the foundation for the respective battery specifications	3.2.1
Battery power	10 MW	The maximum amount of power the BESS can deliver	3.3
Initial battery capacity	10 MWh	The initial energy storage capability of the BESS	3.3
Round-trip efficiency	92%	The amount of energy retained during the charge-discharge process	3.2.2
Calendar life	10 years	The number of years before the battery expires, and storage block replacement is required	3.2.3
EFC	8,000	The maximum number of cycles before the battery reaches EOL capacity, and storage block replacement is required	3.2.3
Battery EOL capacity	70%	The battery capacity threshold indicating battery EOL	3.2.4

Battery cycle degradation	3.75*10-4	The reduction in battery capacity per utilized EFC	3.2.4
General costs			
Storage block costs	~22.2 MNOK	The cost of the BESS component housing the battery	3.4.1
Infrastructure costs	~62.7 MNOK	All the CAPEX needed to initiate the project, except for the storage block	3.4.1
Decommissioning costs	~9.0 MNOK	The costs at the end of the project for recycling materials and restoring the site to its original condition	3.4.1
O&M costs	NOK157/kW/year, inflated 2% p.a.	The fixed costs related to the operation and maintenance of the BESS	3.4.2
Tariffs and taxation			
Fixed consumption tariff	Omitted	The fixed tariff per MW of power consumption	2.5.1
Variable consumption tariff	Time- and area dependent	The variable tariff per MWh of power consumption	2.5.1
Fixed production tariff	Time dependent	The fixed tariff per MWh of power production	2.5.1
Variable production tariff	Time- and area dependent	The variable tariff per MWh of power production	2.5.1
Consumption tax	Time dependent	The tax rate per MWh of power consumption	2.5.2
Value Added Tax (VAT)	25%	The tax levied on the added value of arbitrage trading	2.5.2
Corporate income tax	22%	The tax rate on profits	4.2.4
Financial factors			
Discount rate	5.65%	The cost of capital for the project, utilized to determine present values of future cash flows	4.2.4

7.1 Trading profits and battery cycle utilization

The arbitrage trading results are based on the optimal trading pattern produced by the second stage of the optimization model presented in section 5.3.2. The results are assessed in terms of present values and presented in Table 7 below.

Table 7: Cycles utilization and present values of energy arbitrage trading profits of the BESS (in NOK 1000), based on 2022 and 2016-19 electricity prices.

Trading results	**NO1**	**NO2**	**NO3**	**NO4**	**NO5**
2022-based trading					
Trading profits	32,231	39,644	14,120	8,843	30,821
Cycles utilized (out of 24,000)	*12,407*	*14,623*	*9,092*	*7,209*	*12,772*
2016-19-based trading					
Trading profits	2,161	1,525	2,303	1,429	1,344
Cycles utilized (out of 24,000)	*6,544*	*6,116*	*8,007*	*5,157*	*5,382*

As discussed in section 3.2.3 and 5.2, we have identified the calendar life of the battery cells as the determinant factor necessitating storage block replacement, indicating that there will be unutilized cycles in the optimal trading pattern. In Table 7 we can observe different battery cycle utilization rates for the BESS when connected to the five different price zones, for both price data scenarios. We see that all variations show a substantial number of unused cycles, indicating that the price levels and price volatility in the Norwegian markets are too low for the BESS to fully take advantage of the chosen battery specifications.

When analyzing the trading patterns based on 2022 data, we observe a distinctly higher battery cycle utilization rate in the southern price zones (NO1, NO2, and NO5) compared to the northern price zones (NO3 and NO4). The difference in the utilization rates is explained by the systematically higher electricity prices and price volatility in the southern price zones (as presented in Figure 1 and Table 1 in section 2.2), which allows for more frequent and profitable trades. Consequently, we observe higher battery cycle utilization rates and trading profits in the southern price zones compared to the northern price zones. The divergence between the southern and northern price zones, caused by the differences in electricity price and price volatility, is illustrated in Figure 2, where the trading patterns for NO2 and NO4 are compared (further see Appendix D – Optimal trading patterns for NO1-NO5 for all trading patterns). The BESS connected to NO2 using repeated 2022 electricity prices has the highest cycle utilization rate and trading profits out of the all the explored price zones, utilizing 14,623 of the 24,000 total cycles available, and achieves trading profits of 39.6 MNOK.

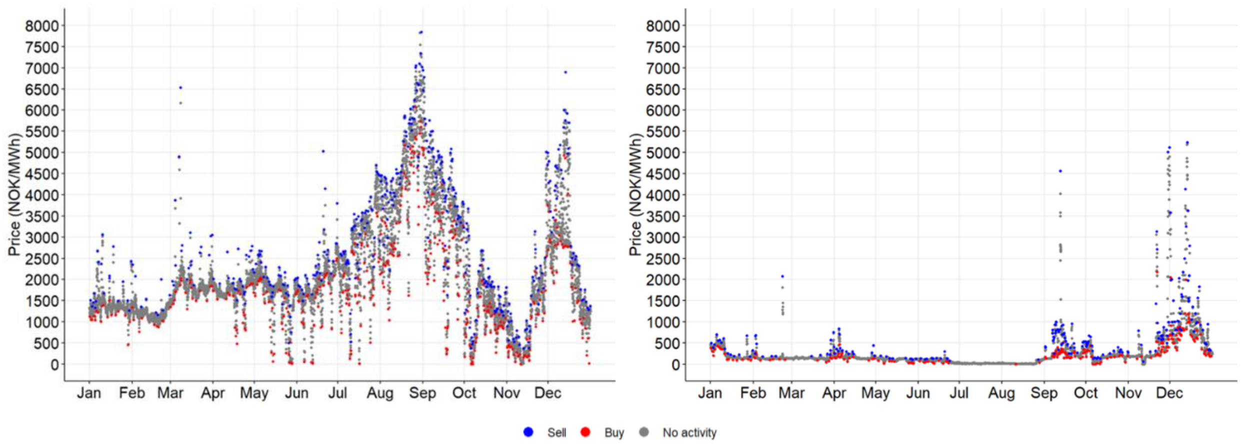

Figure 2: Optimal trading activity in NO2 (left) and NO4 (right) based on 2022 price data (first year of trading)

When examining the optimal arbitrage trading patterns based on the electricity price data from 2016 to 2019, we find that there is a higher degree of similarity between the trading patterns of the northern and the southern price zones (see Figure 3), compared to the price scenario based on 2022 electricity prices (see Appendix D – Optimal trading patterns for NO1-NO5). This is explained by the similarity in the electricity prices and the price volatility of the price zones in the period 2016 to 2019, as illustrated in Figure 1. As a result of the comparatively low electricity prices and price volatility in 2016 to 2019, we observe lower battery cycle utilization rates and lower trading profits, as there are fewer profitable trades in the period compared to the 2022 electricity price scenario.

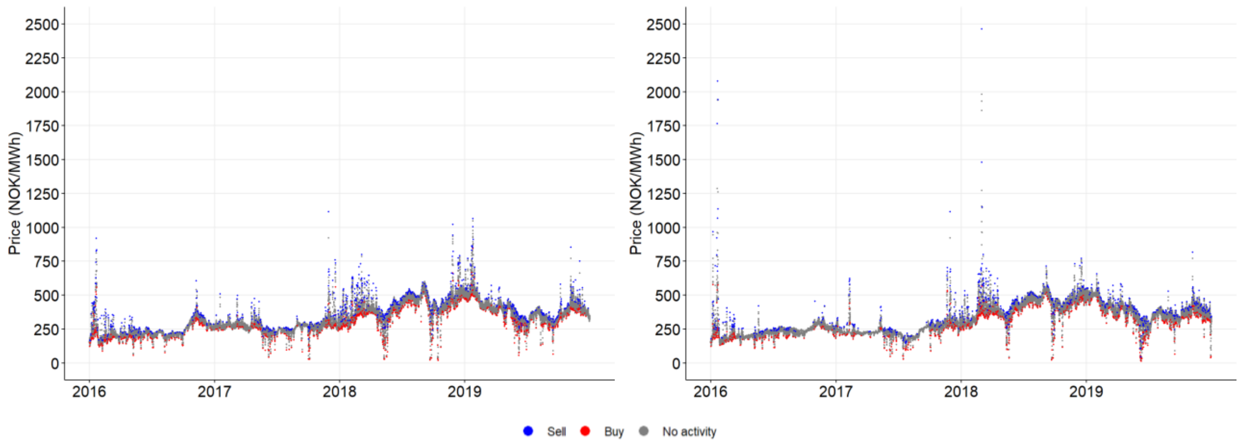

Figure 3: Optimal trading activity in NO2 (left) and NO4 (right) based on 2016-2019 price data (first four years of trading)

7.2 BESS project valuations

The valuations of the BESS project are based on the valuation expression in section 6 and are presented in Table 8 below.

Table 8: Valuations of the BESS project (in NOK 1000), based on 2022 and 2016-19 electricity prices.

Valuation components	NO1	NO2	NO3	NO4	NO5
Trading profits					
Trading profits, 2022-based	32,231	39,644	14,120	8,843	30,821
Trading profits, 2016-19-based	2,161	1,525	2,303	1,429	1,344
General costs					
CAPEX	130,971	130,971	130,971	130,971	130,971
Storage block costs	66,502	66,502	66,502	66,502	66,502
Infrastructure costs	62,744	62,744	62,744	62,744	62,744
Decommissioning cost	1,725	1,725	1,725	1,725	1,725
O&M cost	29,056	29,056	29,056	29,056	29,056
Total	160,027	160,027	160,027	160,027	160,027
Valuations					
Valuation, 2022-based	**-127,796**	**-120,383**	**-145,907**	**-151,185**	**-129,207**
Valuation, 2016-19-based	**-157,866**	**-158,502**	**-157,724**	**-158,598**	**-158,683**
Accrued tax shields					
Tax shields using, 2022-based	*12,106*	*10,475*	*16,090*	*17,251*	*12,416*
Tax shields using 2016-19-based	*18,721*	*18,861*	*18,690*	*18,882*	*18,901*

As presented in Table 8, the valuations of the BESS project based on 2022 electricity prices result in negative NPVs for all five price zones. When applying 2022 electricity prices, even the BESS project in the best performing price zone, namely NO2, yields an NPV of -120.4 MNOK. These unfavorable results are caused by a combination of low trading profits combined with high system costs, as shown in Table 8. To underscore the extent of the project's unprofitability, we note that even under the best-case scenario (NO2 using 2022 prices) the costs of the storage blocks alone exceed the profits generated from the arbitrage trading. Furthermore, the O&M costs alone exceed the trading profits in both the northern price zones (NO3 and NO4) when utilizing 2022 data, and in all of the price zones when utilizing 2016-2019 data, further emphasizing the cost issues.

The valuations for the various price zones based on 2016-2019 electricity prices produce lower NPVs proportional to the reduced trading profits in each price zone, as we keep CAPEX and O&M costs fixed and independent of trading activity. The valuation results when applying 2016-2019 prices demonstrate the negative impact that a reduction in electricity prices and price volatility would have on the overall performance and valuation of a BESS performing energy arbitrage.

8. Discussion and conclusion

The results presented in section 7 show that a lithium-ion BESS performing energy arbitrage in single-application produces significantly negative NPVs when applied to Norwegian grids, even when applying best-case scenario price data from 2022. These results indicate that such a system is not economically viable and, given the extent of the negative values, is unlikely to become viable in the near future. However, there is a set of key factors, decisions, and assumptions that, if altered, could impact the results, which warrants a discussion. This section seeks to: 1) discuss the main factors impacting the valuation and the necessary changes to the revenue and cost streams to achieve economic viability, 2) elaborate on how the choice of BESS power and size could impact the profitability of the project, 3) discuss how key model assumptions impact the results, and 4) provide a final conclusion to the paper.

8.1 Main factors impacting the results

The valuation of the project is primarily influenced by two factors: the revenue stream and the related cost. The findings in section 7 indicate that the trading revenues and/or the related costs need to be improved drastically for the project to become economically viable. However, the likelihood of improvement differs for each factor, which raises the question of where we are most likely to see improvements in the future.

As discussed in section 2.2, Norway has systematically low electricity prices and price volatility compared to European counterparts. The main reason for this is, as discussed in section 2.2, the large proportion of energy in the Norwegian power mix coming from hydroelectric power plants. Hydroelectric power is expected to stay dominant in the Norwegian power mix (Rystad Energy, 2023a), which implies that Norwegian electricity prices will likely remain less volatile than in other power markets, due to the flexibility of the technology. We have further stated in section 2.2 that the 2016-2019 price data arguably represents "normal" electricity price levels due to lack of irregular external shocks such as the ones affecting the 2022 electricity prices, meaning that we view a reduction, rather than an increase, in prices and price volatility in the coming years as being the most likely. Thus, we do not expect the income from trading to improve significantly in the future, consequently limiting the necessary improvements for economic viability to stem from cost reductions.

As presented in section 3.4, the applied costs in this paper are determined based on the most reliable and current information available at the time of this study. As such, it is challenging to argue for significant changes in system costs without applying corresponding changes to the system itself. An important question that arises in this regard is whether alterations in the power and size of the BESS can address the prevailing cost issues.

8.2 The impact of the size and power of the BESS

The choice of the size and power of the BESS are the two main factors impacting the initial CAPEX and O&M costs. While this study applies a 10MW/10MWh system (implying a C-rate of 1C), a different strategy, opting for a BESS with reduced power or increased energy capacity, is also reasonable but would impact the results in various ways.

Deploying a larger (in MWh) BESS would reduce the NOK per MWh costs of the initial CAPEX significantly. This is especially true for infrastructure CAPEX, (as seen in section 3.3) which would have a 40% relative cost reduction in terms of NOK per MWh if scaling the system to 100 MWh. However, as we increase the size of the BESS, the assumption that the energy arbitrage trading does not impact local electricity prices and tariffs becomes less realistic, making such a size increase a potential problem for the model assumptions.

Reducing the power (in MW) of the BESS will significantly reduce both CAPEX (as presented in section 3.3) and O&M costs (as presented in section 3.4.2) but will in return also reduce the energy arbitrage trading profits as a C-rate below 1C does not allow for maximized trading profits when utilizing hourly electricity prices (for a detailed explanation of this mechanic, see section 3.3). As we can observe from Table 3, a reduction of the C-rate (power-to-size ratio) decreases the initial CAPEX significantly in terms of NOK per MWh, indicating that a lower powered BESS could lead to a significant reduction in costs. Yet, as a significant portion of the CAPEX is related to the storage blocks, and the cost reduction is mainly attributed to other components than the storage block (as seen in Table 4), the effect such a reduction in power has on the total system costs is limited.

From the results in section 0 we see that the relevant costs heavily outweigh the revenues for all the different variations of the valuation. Based on what has been discussed in this section, we still argue that the nonviability of a BESS performing energy arbitrage is independent of the choice of power and size of the system due to the magnitude of the necessary cost reduction. Yet, we acknowledge that a deeper analysis of the optimal choice of power and size could yield higher NPVs due to reduced costs, even when considering the accompanying decrease in energy arbitrage trading profits.

8.3 Key model assumptions impacting the results

In addition to the main factors presented in section 8.2, the models of this study are subject to a set of assumptions that, if altered, would impact the valuation results. These assumptions include the efficiency rate, the calendar life, and the degradation modelling of the battery.

Since a lower efficiency rate effectively reduces the volatility of the electricity price data, by decreasing the maximum values (due to lower discharging revenues) and increasing the minimum values (due to more expensive charging), introducing a higher efficiency rate would enhance battery utilization and trading profits. The efficiency rate in this study relies on the efficiency rates provided by various manufacturers and previous studies, without incorporating any forecasts regarding potentially improved future efficiency rates resulting from technological advancements. As there are multiple storage block replacements, improvements in efficiency rates would subsequently improve the efficiency of the BESS through the installation of new storage blocks with higher efficiency. Thus, in the event of any improvements in battery efficiency rates during the lifetime of the project, maintaining a constant efficiency rate would limit the arbitrage trading profits, as the assumed efficiency rate would be too conservative.

In this study, battery EOL occurs either when the remaining battery capacity reaches the predefined EOL threshold or when the maximum calendar life of 10 years is reached. Since battery calendar life is the determining factor of battery life in all the price zones for both price scenarios (see section 5.2), extending the number of years in the calendar life assumption would improve the valuation results, as the system would require fewer storage blocks over the course of the project life.

Although this study bases battery EOL on both cycle life and calendar life, the degradation mechanism of the arbitrage trading modelling is solely based on battery cycles, ignoring the impact of calendar aging on the capacity. By only considering battery cycle degradation mechanisms and neglecting calendar life degradation, the battery capacity is systematically higher than if we were to account for both factors throughout the project. Consequently, basing the degradation in the model on both battery cycles and calendar aging would worsen the results.

In summary, the assumptions regarding efficiency rate, calendar life, and the battery degradation pattern have significant impacts on the valuations through various factors impacting the costs and the arbitrage trading profits. Altering these assumptions could potentially lead to higher or lower NPVs, depending on the alterations made.

8.4 Conclusion

In conclusion, the study reveals that a commercial single-application BESS engaged in energy arbitrage is currently deemed economically unviable in Norway when considering both investment and operating costs. Furthermore, the study highlights that economic viability requires a significant reduction in associated costs.

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Appendix A – Interconnectors to Norway

Table 9: Interconnectors between Norway and other countries (NVE, 2016)

Interconnector	Connects to	Capacity
Skagerrak 1-4	Denmark	1700 MW
NordLink	Germany	1400 MW
North Sea Link	Great Britain	1400 MW
NorNed	the Netherlands	700 MW
Several lines on the various borders	Sweden	3695 MW

Appendix B – Testing battery cycle life as the limiting factor

The purpose of this test is to evaluate whether battery cycle life can ever be the limiting factor necessitating storage block replacement. To do so, we determine the maximum number of trades feasible when assuming a simplified minimal marginal cost of trading. The marginal cost is simplified to be static (always the lowest possible marginal cost value) in order to keep the expression linear. Further, as we have included a marginal cost term, we exclude the effect of gradual degradation on capacity, which in turn keeps the problem linear. As this optimization model is only utilized for this particular test, omitting the effects of battery degradation on battery capacity does not pose a problem for the accuracy of the valuation of the project.

The optimization model consists of three main components:

Decision variables:

$\alpha_t \in \{0,1\}$ for $t \in \{1,\dots,T\}$: binary variable representing if the battery is discharging at time t.

$\beta_t \in \{0,1\}$ for $t \in \{1,\dots,T\}$: binary variable representing if the battery is charging at time t.

$BS_t \in \{0,1\}$ for $t \in \{1,\dots,T\}$: binary variable representing the battery state (charged/not charged) at time t.

Objective function:

$$\max_{\alpha_t,\beta_t,BS_t} \sum_{t=1}^{T} \left((S_{pt} - P_{pt}) * (1-\theta) - MC_t \right), \qquad t \in \{1,\dots,T\}$$

$$S_{pt} = \alpha_t * (E_{pt} - \gamma_t - \Gamma_{pt}) * (1-\varepsilon), \qquad t \in \{1,\dots,T\}$$

$$P_{pt} = \beta_t * \frac{(E_{pt} + \lambda_t + \Lambda_{pt})}{(1-\varepsilon)}, \qquad t \in \{1,\dots,T\}$$

$$MC_t = \alpha_t * MC_{set}, \qquad t \in \{1,\dots,T\}$$

E_{pt}, $t \in \{1, \dots, T\}$: the electricity price in price zone p at time t.

γ_t, $t \in \{1, \dots, T\}$: the fixed production tariff at time t. The time variability is necessary as the tariff is only fixed for one year at a time.

Γ_{pt}, $t \in \{1, \dots, T\}$: the mean variable production tariff in price zone p at time t.

λ_i, $t \in \{1, \dots, T\}$: the fixed tax for electricity consumption at time t. The time variability is necessary as the tax is only fixed for one year at a time.

Λ_{pt}, $t \in \{1, \dots, T\}$: the mean variable tariff for electricity consumption in price zone p at time t.

θ: the VAT applied to all trade profits.

ε: the efficiency loss with every trade. The efficiency loss is divided equally between the charging and discharging of the battery, calculated: $\varepsilon = 1 - \sqrt{RTE}$.

MC_{set}: a simplified marginal cost attached to all discharges, determined through the methodology explained below.

Constraints:

$\alpha_t + \beta_t \leq 1$, $t \in \{1, \dots, T\}$: the BESS cannot charge and discharge simultaneously at time t.

$BS_t = BS_{t-1} - \alpha_t + \beta_t$, $t \in \{1, \dots, T\}$: the battery state is affected by buying or selling at time t.

$BS_0 = 0$: the initial battery state is set to uncharged.

Output:

t for $\{t \mid \alpha_t = 1 \lor \beta_t = 1\}$: time at relevant time periods t.

In this paper, the marginal cost utilized in the optimization model is derived from the methodology employed when assessing a storage block's value. Thus, to identify a marginal cost, it is necessary to first establish a method of valuing a storage block. In this paper, this is achieved by considering the storage block's value as a linear function of the amount of energy the battery can process until it degrades to its threshold capacity. The remaining total amount of energy the battery can process until it needs replacement is in this paper referred to as the "potential energy" of the battery. Following this logic, the formula used to value a storage block at time t is:

$$\mathrm{SBV_t} = \mathrm{SBV_0} * \frac{\mathrm{PE_t}}{\mathrm{PE_0}}, \qquad \mathrm{t} \in \{0, \dots, \mathrm{T}\}$$

$\mathrm{SBV_t},\ \mathrm{t} \in \{0, \dots, \mathrm{T}\}$: the storage block value at time t.

$\mathrm{SBV_0}$: the storage block value at time $t = 0$, which is equal to the purchasing price of a new storage block. As we assume constant storage block prices (see section 3.4.1), this value is constant.

$\mathrm{PE_t},\ \mathrm{t} \in \{0, \dots, \mathrm{T}\}$: the potential energy of the battery at time t.

$\mathrm{PE_0}$: the potential energy of the battery at time $t = 0$, which is the full potential energy of a new battery.

Applying this rationale for valuing storage blocks, we can calculate the marginal cost of use (MC_t) as the difference in a storage block's value before and after a completed cycle:

$$\mathrm{MC_t} = \mathrm{SBV_{t-1}} - \mathrm{SBV_t}, \qquad \mathrm{t} \in \{1 \dots, \mathrm{T}\}$$

Although we assume a linear reduction in capacity per cycle (constant degradation factor), as explained in section 3.2.5, the degradation factor's effect on the residual value of the storage block is not constant. This is because the degradation factor affects the capacity of every remaining EFC equally, where the number of remaining EFC, which in this paper is referred to as Residual Full Cycles (RFC), differs throughout the lifespan of the storage block based on usage. As a result, the initial cycle degrades the value of the storage block the most, while the final cycle degrades the value of the storage block the least. This mechanism is explained in the following:

As the degradation effect is attached to the process of discharging (when $\alpha_t = 1$), the number of RFC in the battery at time t can be expressed:

$$\mathrm{RFC_t} = \mathrm{EFC} - \sum_{t=0}^{t} \alpha_t, \qquad t \in \{0, \dots, T\}$$

As the potential energy (PE) is defined as the amount of energy the battery can process until it degrades to its threshold capacity, it can be calculated:

$$\mathrm{PE_t} = \sum_{i=0}^{\mathrm{RFC_t}} (\mathrm{BC_t} - \mathrm{i} * \mathrm{DF}), \qquad t \in \{0, \dots, T\}$$

The potential energy of a full battery at time $t = 0$ can thus be expressed:

$$\mathrm{PE_0} = \sum_{i=0}^{\mathrm{RFC_0=EFC}} \big((\mathrm{BC_0} = \mathrm{BC_{max}}) - \mathrm{i} * \mathrm{DF}\big), \qquad t \in \{0, \dots, T\}$$

To find SBV_t using PE_t and PE_0, we get the following formula:

$$\mathrm{SBV_t} = \mathrm{SBV_0} * \frac{\mathrm{PE_t}}{\mathrm{PE_0}} = \mathrm{SBV_0} * \frac{\sum_{i=0}^{\mathrm{RFC_t}} (\mathrm{BC_t} - \mathrm{i} * \mathrm{DF})}{\sum_{i=0}^{\mathrm{EFC}} (\mathrm{BC_{max}} - \mathrm{i} * \mathrm{DF})}, \qquad t \in \{0, \dots, T\}$$

Finally, the marginal cost at time t can be expressed as[24]:

$$\mathrm{MC_t} = \mathrm{SBV_0} * \left(\frac{\sum_{i=0}^{\mathrm{RFC_{t-1}}} (\mathrm{BC_{t-1}} - \mathrm{i} * \mathrm{DF}) - \sum_{i=0}^{\mathrm{RFC_t}} (\mathrm{BC_t} - \mathrm{i} * \mathrm{DF})}{\sum_{i=0}^{\mathrm{EFC}} (\mathrm{BC_{max}} - \mathrm{i} * \mathrm{DF})}\right), \qquad t \in \{0, \dots, T\}$$

We note that the marginal cost is variable, which is due to the degradation factor's effect on the residual value of the storage block being variable, as mentioned above. Yet, the marginal cost used

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[24]Note that if there has not been a trade from time $(t-1)$ to time t, $MC_t = 0$. This is due to $RFC_t = EFC - \sum_{t=0}^{t} \alpha_t$, if $\alpha_t = 0$, then $RFC_t = RFC_{t-1}$, which makes $PE_t = PE_{t-1}$, because $\sum_{i=0}^{RFC_t} (BC_t - i * DF) = \sum_{i=0}^{RFC_{t-1}} (BC_{t-1} - i * DF)$

in the objective function, MC_{set}, is constant and equal to the smallest marginal cost the storage block will face, namely:

$$\mathrm{MC_{set}} = \mathrm{SBV_j} - \mathrm{SBV_{j-1}}$$

$\mathrm{SBV_j}$: the storage block value at the period where the battery reaches maximum cycles (called period j). Any further charge-discharge cycles require a new storage block.

$\mathrm{SBV_{j-1}}$: the storage block value one period prior to the battery reaching the maximum number of cycles.

Note that this marginal cost is a simplification, as the real marginal cost would be dynamic and higher at all times except for the last cycle of a battery's life. Yet, incorporating this specific marginal cost (MC_{set}) into the objective function allows the model to identify and focus solely on promising trades while avoiding transactions that will always result in losses if the battery cycle life was the limiting factor leading to storage block replacements.

Appendix C – Shortening the optimization input dataset

The purpose of applying this first stage of the optimization is to shorten the dataset to only contain relevant trades, which allows the second stage of the model to find an optimal solution significantly faster. The methodology's logic remains unchanged from that presented in Appendix B, except for the exclusion of the simplified marginal cost term. Note that we also exclude the effect of gradual degradation on capacity in this model in order to keep the problem linear. Thus, the first stage cannot be used in isolation for valuation purposes but will condense the dataset as intended without jeopardizing the integrity of the valuation.

The optimization model consists of three main components:

Decision variables:

$\mathrm{\alpha_t} \in \{0, 1\}$ for $\mathrm{t} \in \{1, \dots, \mathrm{T}\}$: binary variable representing if the battery is discharging at time t.

$\mathrm{\beta_t} \in \{0, 1\}$ for $\mathrm{t} \in \{1, \dots, \mathrm{T}\}$: binary variable representing if the battery is charging at time t.

$\mathrm{BS_t} \in \{0, 1\}$ for $\mathrm{t} \in \{1, \dots, \mathrm{T}\}$: binary variable representing the battery state (charged/not charged) at time t.

Objective function:

$$\max_{\alpha_t, \beta_t, BS_t} \sum_{t=1}^{T} \left((S_{pt} - P_{pt}) * (1 - \theta) \right), \qquad t \in \{1, \dots, T\}$$

$$S_{pt} = \alpha_t * (E_{pt} - \gamma_t - \Gamma_{pt}) * (1 - \varepsilon), \qquad t \in \{1, \dots, T\}$$

$$P_{pt} = \beta_t * \frac{(E_{pt} + \lambda_t + \Lambda_{pt})}{(1 - \varepsilon)}, \qquad t \in \{1, \dots, T\}$$

E_{pt}, $t \in \{1, \dots, T\}$: the electricity price in price zone p at time t.

γ_t, $t \in \{1, \dots, T\}$: the fixed production tariff at time t. The time variability is necessary as the tariff is only fixed for one year at a time.

Γ_{pt}, $t \in \{1, \dots, T\}$: the mean variable production tariff in price zone p at time t.

λ_i, $t \in \{1, \dots, T\}$: the fixed tax for electricity consumption at time t. The time variability is necessary as the tax is only fixed for one year at a time.

Λ_{pt}, $t \in \{1, \dots, T\}$: the mean variable tariff for electricity consumption in price zone p at time t.

θ: the VAT applied to all trade profits.

ε: the efficiency loss with every trade. The efficiency loss is divided equally between the charging and discharging of the battery, calculated: $\varepsilon = 1 - \sqrt{RTE}$.

Constraints:

$\alpha_t + \beta_t \leq 1$, $t \in \{1, \dots, T\}$: the BESS cannot charge and discharge simultaneously at time t.

$BS_t = BS_{t-1} - \alpha_t + \beta_t$, $t \in \{1, \dots, T\}$: the battery state is affected by buying or selling at time t.

$BS_0 = 0$: the initial battery state is set to uncharged.

Output:

E_{pt} for $\{t \mid \alpha_t = 1 \vee \beta_t = 1\}$: electricity price data in price zone p for relevant time periods t.

γ_t for $\{t \mid \alpha_t = 1 \vee \beta_t = 1\}$: the fixed production tariff for relevant time periods t.

Γ_{pt} for $\{t \mid \alpha_t = 1 \vee \beta_t = 1\}$: the mean variable production tariff in price zone p for relevant time periods t.

λ_i for $\{t \mid \alpha_t = 1 \vee \beta_t = 1\}$: the fixed tax for electricity consumption for relevant time periods t

Λ_{pt} for $\{t \mid \alpha_t = 1 \vee \beta_t = 1\}$: the mean variable tariff for electricity consumption in price zone p for relevant time periods t.

t for $\{t \mid \alpha_t = 1 \vee \beta_t = 1\}$: time at relevant time periods t.

Appendix D – Optimal trading patterns for NO1-NO5

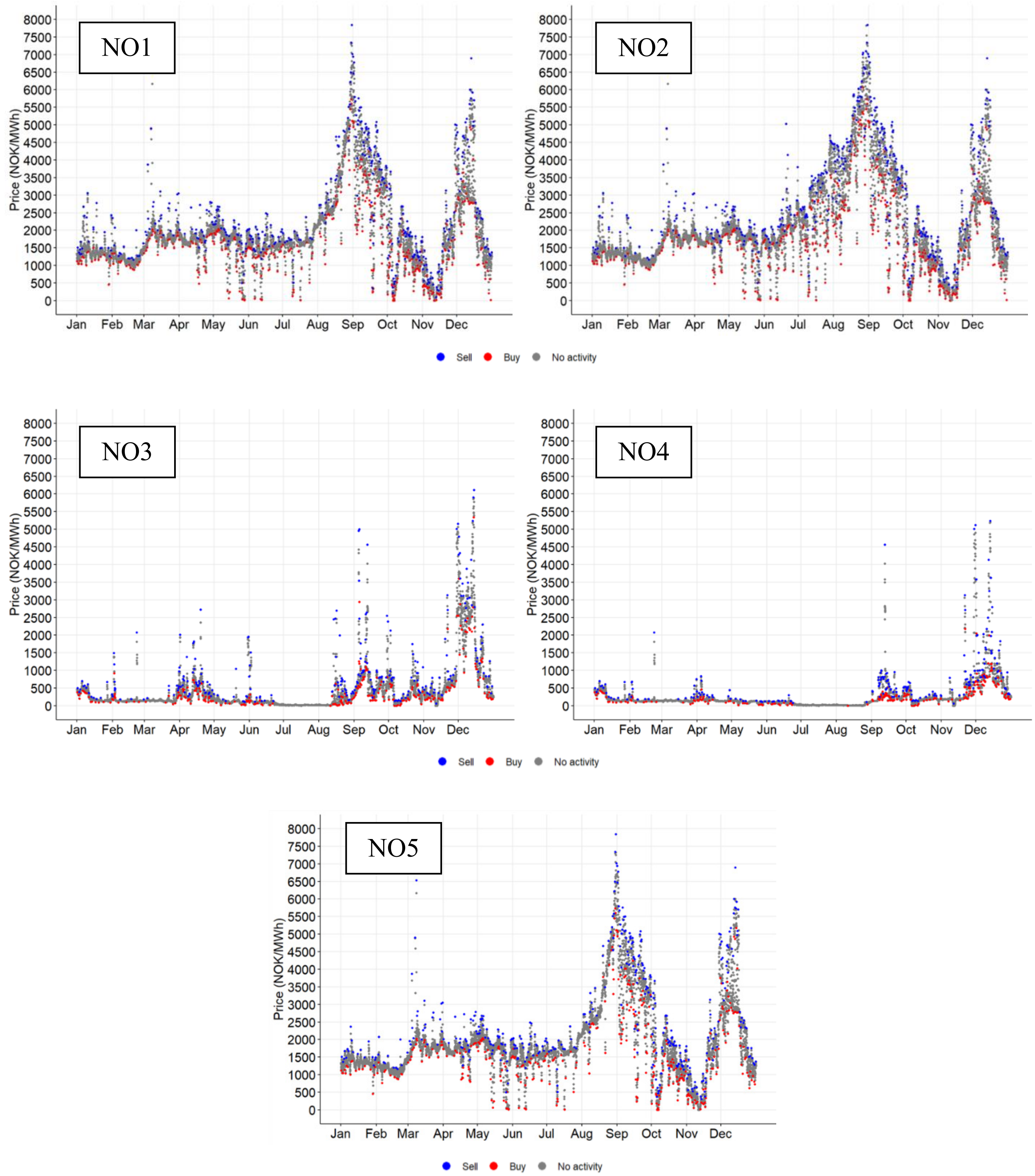

Figure 4: Optimal trading activity based on 2022 price data (first year of trading)

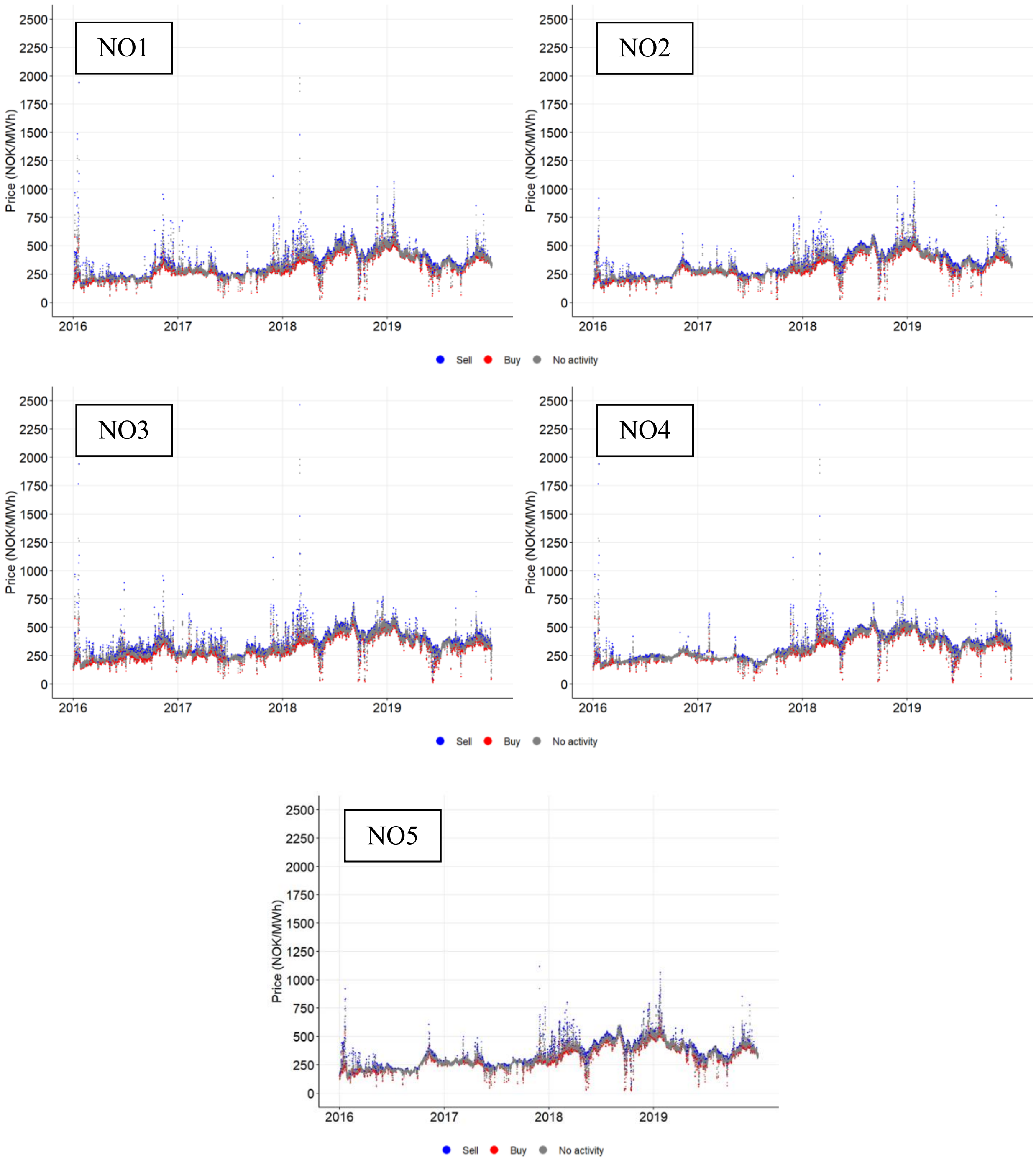

Figure 5: Optimal trading activity based on 2016-2019 price data (first four years of trading)