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School of Engineering

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Master’s Programme in Innovative Sustainable Energy Engineering (ISEE)

Enhancing Battery Energy Storage in the Finnish FCR-N Market with Flywheel Technology

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Abstract

The integration of flywheel technology with battery energy storage systems presents a promising strategy to improve both the operational lifetime and economic viability of energy storage solutions for providing ancillary services. In this study, mixed integer linear programming optimisation modeling is employed to investigate the benefits of combining batteries with flywheels in the context of the Finnish FCR-N market. Different flywheel:battery capacity ratios are considered to investigate the optimal ratio. Furthermore, the impact of grid frequency and battery degradation is taken into account.

The results reveal that battery degradation has little impact on the optimal dispatch of a hybrid system. Highlighting the robustness of the flywheel-battery combination in mitigating battery degradation during ancillary services provision.

The findings demonstrate that integrating flywheels into battery systems can extend the operational lifetime or reduce operational cost of the battery through removing the burden of small cycles from the battery. Specifically, a hybrid system with a flywheel-to-battery capacity ratio of 0.2 is recommended, exhibiting a notable 2.7-fold extension of battery lifetime as well as being less strongly impacted by different grid frequency scenarios than higher capacity ratios. Moreover, the incorporation of flywheels unlocks diverse business opportunities, enhancing the overall economic value of the energy storage assets.

Keywords Ancillary services, BESS , Energy storage, FESS, MILP modeling

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Douwe van Alderwerelt van Rosenburgh

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Abbreviations

FESS	Flywheel Energy Storage System
BESS	Battery Energy Storage System
HESS	Hybrid Energy Storage System
TSO	Transmission System Operator
DSO	Distribution System Operator
FFR	Fast Frequency Reserve
FCR-N	Frequency Containment Reserve - Normal
FCR-D	Frequency Containment Reserve - Disturbed
aFRR	automatic Frequency Restoration Reserve
mFRR	manual Frequency Restoration Reserve
LER	Limited Energy Resource
SoC	State of Charge
DoD	Depth of Discharge
NPV	Net Present Value
LFP	Lithium Iron Phosphate
NMC	Nickel Manganese Cobalt

1 Introduction

Europe is progressively shifting towards renewable energy sources like wind and solar power. Despite their importance in reducing carbon emissions, these sources can pose challenges to grid stability due to their intermittency. The fluctuations inherent with renewable energy production can strain the grid and affect reliability [1].

Furthermore, a significant portion of Europe's power infrastructure is ageing and requires modernisation, necessitating substantial investment [2]. Ageing power plants, transmission lines, and distribution networks are susceptible to outages and failures, which can diminish the overall reliability of the power supply.

Having a reliable and secure power supply has an impact on society, as it affects nearly every aspect of modern life. Economic growth depends on it, as industries rely on a consistent power supply to operate. Additionally, UN sustainability goals are closely linked with the power system. Goal 7, "Affordable and Clean Energy," emphasises the importance of ensuring access to affordable and reliable energy [3].

There are various methods to enhance the reliability of a power system. Ancillary services, in particular, play a crucial role in addressing challenges related to the reliability and security of the power supply [4]. Services such as frequency regulation and voltage control contribute to maintaining grid stability by balancing supply and demand in real-time. Frequency regulation, for instance, helps to stabilise the grid by adjusting power output to match fluctuations in demand or supply [5], which is important with the integration of intermittent renewable energy sources. Especially since the share of these sources is predicted to increase from 15% to 46% of total energy by 2050 [6].

1.1 The role of energy storage

Energy storage assets possess robust characteristics that make them suitable for providing ancillary services and serve as a critical technology in achieving sustainability goals [7], [8]. These systems can quickly respond to changes in grid frequency. They enable load shifting, where energy is stored during off-peak hours and distributed during peak hours. Alternatively, they can store excess energy from renewable sources and release it during periods of high demand, thereby reducing power fluctuations and enhancing grid stability [9].

Various types of energy storage systems are suitable for ancillary services. Services that demand extremely rapid response times and lower energy quantities, such as the Fast Frequency Reserve (FFR) market, are suitable for Flywheel Energy Storage System (FESS) [10]. On the other hand, markets such as Frequency Containment Reserve (FCR), which require larger energy quantities and less rapid response times, are suitable for Battery Energy Storage Systems (BESS) [11].

Flywheels are distinguished by their high power output and long lifetime of 25 years or more[12]. These characteristics make them suitable for providing ancillary services, as a high power output is often desirable for such applications [10][13]. A drawback of FESS, however, is their low energy capacity, which limits their ability to support the grid during prolonged frequency fluctuations. As a result, widespread adoption of FESS as a standalone unit participating in ancillary services is hindered.

Batteries are utilised in ancillary services due to several advantages they offer. BESS exhibit decreasing investment costs, high energy capacities, and high round-trip efficiencies. This means they can store a large amount of energy and release it with minimal losses [14].

Batteries can provide a wide range of ancillary services, including frequency regulation, voltage support, peak shaving, and grid stabilisation [15]. Their versatility enables them to address multiple grid challenges simultaneously, making them valuable assets for grid operators aiming to optimise system performance and reliability. This work is specifically focused on frequency regulation.

Despite these strong benefits, BESS are not without their disadvantages. Specifically, their harmful environmental impact and relatively short lifetime [16] [17].

The sourcing and extraction methods of materials used in battery production raise concerns regarding their environmental impact. Critical minerals like cobalt and lithium are scarce and have insecure supply chains [18]. The mining of these materials leads to negative environmental and societal impacts, including deforestation, water pollution, and human rights issues [19]. Additionally, the manufacturing process is energy-intensive, often relying on non-renewable energy sources, producing one ton of lithium can emit up to 15 tons of CO_2 into the air [20].

Battery lifetime refers to the finite operational duration of batteries, which presents challenges for their economic feasibility [17]. Several factors influence battery lifetime, including the specific chemical composition of the battery, usage patterns and other factors like calendar ageing [21].

Batteries have a finite number of charge-discharge cycles before they degrade and lose their ability to store and release energy effectively [8]. Each cycle contributes to wear and tear on the battery's electrodes and electrolyte, gradually reducing its capacity and performance over time [14]. Thus high frequency charge/discharge cycles can contribute to accelerated degradation of a battery, leading to the need for earlier and more frequent replacement. Thus extending the lifetime of a battery is valuable from an environmental perspective.

Combining FESS and BESS into a Hybrid Energy Storage System (HESS) could make effective use of their respective advantages and minimise inherent disadvantages. One key benefit of a hybrid system is addressing the battery lifetime issue. The high-frequency and low-depth charge cycles that typically cause a large fraction of battery degradation are precisely the types of cycles that a flywheel excels in performing [13]. By offloading these cycles to the flywheel, the battery can engage in deeper cycles with less overall damage, thereby extending its lifetime and reducing environmental costs.

Another benefit of flywheel hybridisation of batteries is that flywheel can reduce the operational costs within the context of frequency regulation markets. Lowered costs facilitate more aggressive bidding strategies, which can emphasise the impact and profitability of energy storage assets in the short term. Flywheel-battery hybrid systems thus offer an intriguing opportunity for lifetime extension or enhancing bidding strategy within ancillary services.

1.2 Research questions

The research questions address both technical and financial aspects of integrating flywheels with batteries within the context of the Finnish FCR-N market. Specifically, the focus is solely on the FCR-N market, as detailed in Section 3.3.

1. *How and to what extent can flywheels support batteries in the FCR-N market?*
2. *What is the recommended flywheel to battery capacity ratio for providing ancillary services in the FCR-N market?*

The first research question investigates the technical potential of hybridisation using flywheels independently of financial variables associated with participating in ancillary services. This analysis aims to showcase the capabilities and benefits of integrating flywheels with batteries in terms of technical performance and degradation mitigation.

The second research questions also explore economic analysis in conjunction with technical analysis. This aspect of the study focuses on assessing the financial viability and benefits derived from hybrid systems, considering factors such as revenue generation, cost savings, and overall economic value. Culminating in a recommendation of capacity ratio, taking technical and economic factors into account.

1.2.1 Sub-questions

To delve deeper into the mechanisms and dynamics of flywheel hybridisation, several sub-questions are examined. These sub-questions aim to tackle specific aspects related to the integration of flywheels with batteries and their impact on performance and degradation.

Firstly, what are the goals of flywheel hybridisation to support batteries in the FCR-N market? Using flywheels in different ways could yield alternative results and might only be suitable under specific conditions. Goals could be more focused on short term or long term effectiveness.

Secondly, how do different capacity ratios impact the performance of hybrid systems in the FCR-N market? Where "capacity ratio" refers to the share of power that flywheels can provide compared to the battery. By exploring different capacity ratios, one can identify the most suitable configuration that maximises the benefits of flywheel hybridisation while minimising potential drawbacks.

Thirdly, how does grid frequency affect performance in the FCR-N market? Understanding how a hybrid storage asset interacts with grid frequency is crucial for assessing its performance and effectiveness. Grid frequency directly influences the operation and dispatch of storage assets, by analysing this interaction, valuable insights are gained into how hybrid system optimise their response to grid frequency fluctuations.

Finally, how does the battery degradation rate affect the performance of hybrid systems in the FCR-N market? The aim of integrating flywheels with batteries is to increase the battery's lifetime by reducing the damage caused during operation.

This damage is quantified by degradation rate. Understanding the impact of battery degradation is crucial for determining the effectiveness and suitability of flywheel hybridisation in prolonging battery life.

1.3 Limitations

Due to time and resource constraints, certain limitations are imposed which influence the results and findings of this work. This section transparently discusses these limitations. Section 3 also goes into detail about modeling specific choices made in this work.

This work only considers two different ways in which a flywheel can be used to enhance batteries in the FCR-N market. These ways are; Lifetime extension and enhancing bidding strategy. This work does not state that these two are the only options, nor the best.

This work uses a deterministic Mixed-Integer Linear Programming (MILP) model to optimise the participation of an energy storage assets in frequency regulation markets. Deterministic MILPs are commonplace in energy modeling and optimisation, providing a balance between accuracy and complexity.

Modeling is done over a time frame of 1h, as this is the Fingrid standard market time unit. This provides sufficient opportunity to realise the potential of hybrid systems, however some factors which might take place over longer time frames can go unnoticed. Over the time frame, perfect foresight is assumed, thus the results of this work suggest the potential of a hybrid system, rather than results immediately applicable to real-world scenarios.

This work focuses exclusively on modeling within the context of the Finnish FCR-N market. The decision to model only this market is driven by the need to establish a clear framework for the study without introducing unnecessary complexity. Considering a single market provides a sufficient framework to demonstrate the potential of a hybrid system. The FCR-N market is chosen as it is deemed the most appropriate single market for BESS [22]. By extension, a hybrid system is also likely to be effective in this market.

Only the Finnish market is considered as rules and regulations vary between regions, thus modeling multiple regions adds complexity. The Finnish region is chosen due to the transparent and easily accessible regulation and data provided by Fingrid. Thus the findings of this work are most applicable to the Finnish context. The Nordic nations have the same regulations, making findings more applicable to Nordic nations than any others.

The battery degradation models in this work exclusively consider cyclic degradation as it is often considered in other works and shown to be impactful ([8], [14], [23], [24]). Other degradation factors, such as calendar degradation, which are constant across different models would be cancelled out during comparison and are thus not considered.

This work only evaluates two degradation profiles, which are different yet both reasonable representations for lithium-ion batteries. No more additional degradation profiles are considered as a profile that falls between the existing two would likely offer little added value, more extreme profiles, on the other hand, are less realistic.

To investigate the impact of grid frequency, different grid frequency scenarios are considered by using 2023 Fingrid data sets. The number of scenarios is limited to 3, this allows more extreme and normal conditions to be taken into account. In the case of the two more extreme scenarios, the data is chosen such that at least 99% of the data points are within FCR-N frequency range, thus ensuring the findings are applicable to the FCR-N market. Due to time constraints, only three scenarios are used in this study. Certainly, using a larger quantity of frequency volatility scenarios would offer more comprehensive insights.

The number of flywheels is varied as discrete integer steps from 0 to 5 flywheels. While this does strongly constrain the results of this work, the results are more realistic for the flywheels in question. The maximum number of flywheels is limited to 5 for two reasons. Firstly, flywheels are proportionately more expensive than batteries and are used sparingly in real-world scenarios. While 5 flywheels might seem excessive for the 10 MWh battery in question, they are considered in this work for academic interest and comprehensive analysis.

Secondly, due to the Fingrid symmetry requirement, 5 flywheels could theoretically fulfil the peak power needs, thus adding more flywheels would be unnecessary within the context of the FCR-N market's requirements. This is discussed further in Section 3.3.

Considering economic performance indicators, there are two key limitations. When calculating Net Present Value (NPV), it is assumed that the battery does not degrade over the operational years, simplifying the analysis by maintaining a consistent performance level throughout the project duration. Secondly, when bidding strategies are considered, this strategy is simplified and has perfect foresight of market prices and procurement volumes, making them unrealistic in real-world applications.

2 Theory

This section explains background theory of relevant information on various frequency regulation markets and energy storage technologies. Information about specific frequency regulation markets is gained from Fingrid sources [25], [26], [27], [28], [29].

2.1 Ancillary services: Frequency Regulation

Ancillary Services are provided by external parties to Transmission System Operators (TSOs) and Distribution System Operators (DSOs) in order to help maintain the reliability and stability of the grid. A number of service can be considered "ancillary" such as; frequency regulation, voltage control and black start capability. This paper focuses on frequency regulation, as this is the most mature ancillary service with established markets.

Frequency regulation markets help keep the frequency of the grid to the normal value of 50 Hz, maintaining the balance between generation and consumption. Changes in either generation or consumption can lead to frequency deviations, thereby presenting a need for ancillary services to correct this problem and ensure a stable grid. When the grid frequency needs to be increased, up-regulation markets support this by boosting power production or reducing consumption, while down-regulation involves reducing power production or increasing consumption in order to decrease the frequency.

The frequency regulation markets are unbundled, that is to say, TSOs cannot own frequency regulation assets. As the services must be provided by third parties, unbundling promotes competition between service providers, stimulating providers to reduce costs and increase the efficiency of their service.

To further emphasise the element of competition the markets employ a bidding system. Financial compensation, provided by the TSO, can take the form of a capacity fee and an energy fee. The bidding system and remuneration mechanisms are discussed in Section 2.1.5 and Section 2.1.6, respectively.

Different markets aim to achieve different goals with regard to maintaining frequency, working together to cover the entire spectrum of frequency regulation. This section goes into detail about some of the markets, all within the context of energy storage being used. An overview of important aspects of the different markets is given in Section 2.1.4. The requirements described in this work are on the basis of Limited Energy Resources (LER), the categorisation that BESS and FESS fall into if not combined with a form of power generation.

2.1.1 Fast Frequency Reserve (FFR)

The FFR market has the aim of dealing with low-inertia situations. Meaning that a power system has a reduced ability to resist changes in frequency due to a low level of rotating masses. If there is enough inertia in the system, a short interruption will have little impact and FFR might not be procured. When inertia is low, FFR procurement is more likely. This is often the case with renewable energy sources, as these sources typically have little inertia.

FFR is the fastest reacting ancillary service. The speed at which reserve units are required to react varies depending on grid frequency and varies between 0.7 and 1.3 s. The minimum activation duration is 5 s and assets should be reactivatable after 15 minutes. The maximum allowable bid for the FFR market is 10 MW, the minimum bid is 1 MW.

Only capacity fees are appointed in the FFR market, not energy fees. Despite the fast reaction times and short duration of the FFR market, it is the least frequently procured market and also estimated to be the least valuable.

2.1.2 Frequency Containment Reserve (FCR)

FCR, also known as primary control, helps balance supply and demand in real time to keep the grid frequency stable. The FCR market has two subdivisions; FCR for Normal Operations (FCR-N) and FCR for Disturbances (FCR-D). Both markets are automatically controlled on the basis of frequency deviation.

FCR-N contains frequency within the standard frequency range of 49.9 Hz to 50.1 Hz. FCR-D contains frequency to within 49.5 Hz and 50.5 Hz when the frequency goes outside of FCR-N range. FCR-D is further split into up and down-regulation. Figure 1 shows the frequency ranges of FCR-N, FCR-D up and FCR-D down.

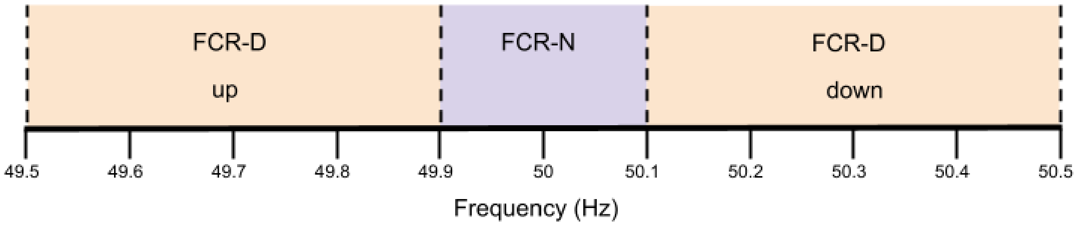

Figure 1: Operational frequency ranges for FCR-N and FCR-D markets.

The FCR-N market has no maximum bid size, the minimum bid size of 0.1 MW. The FCR-D market on the other hand has a maximum bid size of 10 MW and a minimum of 1 MW. The FCR markets have an additional requirement for LER assets. That when starting provision in the FCR-N market the asset must be at approximately 50% capacity. For the FCR-D market capacity must be close to 0 or 100% at the start of provision.

Capacity fees are appointed to both markets, but only FCR-N is appointed energy fees. All three markets are procured similarly frequently by Fingrid however have varying average prices, affecting their market value estimate.

2.1.3 Frequency Restoration Reserve (FRR)

The goal of the FRR markets is to restore frequency to 50 Hz and restore power balance, but does so over a relatively long time-frame compared to FCR. FRR has two subdivisions; aFRR and mFRR (automatic and manual, respectively). The automatic variation is centrally controlled by Fingrid, while the manual variation is ordered from the Balancing Energy Market. Due to the manual nature of mFRR, activation times are longer.

The maximum allowable bids for the FRR automatic and manuals markets are 50 MW and 200 MW, respectively.The minimum bids are 1 MW and 5 MW respectively. The large maximum bid size of mFRR allows the market to procure a large quantity of assets and have major impact on the grid, also leading to both mFRR up and down to have the highest market value estimations.

While mFRR assets must be able to provide power over the entire hour, aFRR has no specification on minimum activation duration. The aFRR market does however update requests on a 10 s basis. Both markets receive capacity and energy fees alike. Furthermore, other markets receiving energy fees do so on the basis of the mFRR hourly market price.

2.1.4 Frequency regulation market overview

The rules and regulations for each market are detailed. This section serves to highlight only sufficient information to provide a general understanding. An overview of key information is given in Table 1 below. Any form of energy storage must be able to meet the requirements set by Fingrid in order to participate.

Table 1: Overview of frequency regulation markets

Frequency regulation market	FFR [26]	FCR-N [27]	FCR-D up [27]	FCR-D down[27]	aFRR up [28]	aFRR down [28]	mFRR up [28]	mFRR down [28]
Minimum activation duration (s)	5	3600	900	900	n.a	n.a	3600	3600
Reaction time (s)	0.7	30	9	9	300	300	900	900
Symmetrical	NO	YES	NO	NO	NO	NO	NO	NO
Maximum bid (MW)	10	n/a	10	10	50	50	200	200
Minimum bid (MW)	1	0.1	1	1	1	1	5	5
Average procured volume (MW)	2	45	68	50	47	38	184	200
Average market price (€/MW)	38	47	28	17	41	29	15	17
Average market value estimate(€)	76	2,115	1,904	850	1,927	1,102	2,760	3,400

The "Minimum activation duration" is the amount of time the unit must be able to provide full power for. "Reaction time" is the amount of time before which a storage asset must be delivering full power. "Symmetrical" markets require the ability to carry out both up-regulation and down-regulation in equal quantities. Maximum and minimum bids are the largest and smallest bid sizes allowed by Fingrid. "Average procured volume" is the average amount of capacity that Fingrid chooses to buy. "Average market price" is the average price Fingrid paid for capacity in 2023. "Average market value estimate" is the multiplication of volume and price, providing an estimate of how valuable a market is.

2.1.5 Bidding system

All frequency regulation markets work on the basis of a bidding system, where ancillary service providers send bids to TSOs or DSOs. Bids may be submitted for each separate hour of the day in advance. The time unit for all the markets is one hour, meaning the day is split into 24 hourly segments in which different bids can be made. Fingrid provides forecasts to aid service providers in making appropriate bids.

Bids to specific markets contain 3 key pieces of information. Firstly, the hour in which the service provider intends to participate in. Secondly, the amount of power capacity that a service provider keeps available for the given hour. Thirdly, the price for said power. Marginal pricing is the mechanism used to price bids for all frequency regulation markets.

2.1.6 Remuneration

Fingrid offers two types of remuneration, capacity fee and energy fee. All frequency regulation markets offer capacity fees, while only some also offer energy fees.

Capacity fees are paid to service providers for their readiness to provide support for the given time-frame. Irrespective of if their assets are activated or not. These payments compensate providers for the costs associated with maintaining standby resources or infrastructure capable of delivering ancillary services when needed.

The capacity fee is calculated by multiplying the maintained reserve capacity for that hour by the hourly market price, given by Equation (1). However, TSOs may also impose sanctions on service providers if they fail to provide capacity of the bid. The sanction is calculated by multiplying the capacity not delivered, by 3 times the hourly market price, as given by Equation (2). Sanctions are either subtracted from the payment from the TSO to the service provider, or, in the case that the sanctions exceed capacity and energy fees, the TSO receives funds from the service provider.

$$F^C = C \cdot P - S \tag{1}$$

$$S = C' \cdot P \cdot 3 \tag{2}$$

F^C is the capacity fee (€), C is capacity (MWh), P is price ($€/MWh$) and S in sanctions (€). In Equation (2), C' refers to the amount of capacity not delivered by the service provider.

Energy fees are paid to service providers on the basis of the energy throughput the unit has experienced. The throughput is split into up and down regulation. The quantities of energy are then multiplied by the hourly mFRR market price, as given in Equation (3),

$$F^E = E^{u,d} \cdot P^{u,d}_{mFRR} \tag{3}$$

where F^E is the energy fee (€), $E^{u,d}$ is the up or down regulation energy and $P^{u,d}_{mFRR}$ is the up or down price of the mFRR market. Energy fees are based upon real-time data of energy provided and are not subject to any form of sanctions.

2.2 Energy storage

Energy storage can be achieved with a variety of technologies, each employing radically different techniques to do so. This section gives background knowledge of energy storage in general, as well as on BESS, FESS, and HESS. The following key definitions below are generic and applicable to most forms of energy storage.

State of Charge (SoC) is a normalised representation of how full a battery is, a measure of current capacity relative to full capacity, as given by Equation (4), expressing SoC at a given time t,

$$SoC_t = \frac{Q_t^{remaining}}{Q^{total}} \tag{4}$$

where $Q_t^{remaining}$ is the remaining charge in the battery (MWh), at a time t, Q^{total} is the total capacity of the battery when fully charged. At full charge, the SoC is said to be equal to 1. While empty, the SoC is equal to 0, thus SoC is bounded by 0 and 1.

Depth of Discharge (DoD_t) is the percentage of a battery's total capacity which is discharged relative to fully capacity at a given time t. It indicates how much of the available energy stored in the battery has been utilised during a specific discharge cycle and is given by Equation (5),

$$DoD_t = \frac{Q_t^{discharged}}{Q^{total}} = SoC_t - SoC_{t-1} \tag{5}$$

where $Q_t^{discharged}$ is the amount of charge discharged from the battery during a cycle at time t. SoC_t and SoC_{t-1} are the SoCs at time t and $t-1$ respectively, [8].

Finally, C-rate refers to the rate at which an energy storage asset is charged or discharged relative to its maximum capacity, on an hourly basis. If the battery is being charged or discharged at a rate of 0.5 C, it means using half of its capacity in one hour.

2.2.1 Battery energy storage

Batteries are a popular and mature form of energy storage. The advantages of batteries are that they typically have a high energy density, high efficiency (90%), are cost-effective and are applicable across many different sectors [30], [31].

On the other hand, batteries tend to demonstrate mediocre power density and a limited cycle life [17], [21]. Battery lifetime refers to the number of cycles a battery can effectively operate for before its capacity degrades to a certain threshold, e.g. 80%, of original capacity [32]. The lifetime of a battery is dependent on a wide range of factors, including; charging and discharging behaviour, SoC, C-rate and temperature [8],[21]. Having a clear understanding of battery degradation mechanism is essential to applying batteries effectively and has been researched by a variety of industries [33].

Battery degradation is a complex area of study. Models to approximate it are restricted to taking only a handful of factors into consideration. Some factors are dependent on the use-patterns of the battery, that is to say, how they are deployed, e.g. cyclic degradation. While other factors are independent of this and remains the same no matter the use-pattern [8], e.g. calendar degradation or external (ambient) temperature.

Many models consider cyclic and calendar degradation ([8], [34]) as key forms of degradation. However, both of these factors are non-linear [23], making them complex to model appropriately. Non-linear rainflow-counting algorithms were used by [35] and [36] to model cyclic degradation. Despite the feasibility of non-linear modeling of cyclic degradation, other works seek to avoid this due to high computational time, complex algorithms and the risk of said algorithms becoming stuck at local optima [23]. Linear rainflow-counting algorithms are thus used to model cyclic degradation, avoiding some of the issues with the non-linear equivalent, but reducing the accuracy of the result.

In order to facilitate the application of individual degradation models to multiple batteries. Tuning variables, based on experimental data, are used to approximate the degradation of the batteries [24]. Different sets of tuning variables correspond to different batteries and their specific degradation profiles.

For batteries acting in the energy system, which is most commonly done in either energy arbitrage or ancillary services [4], [22]. Lithium-Ion batteries are the most well represented [34], [24], [22]. In part due to their longer lifetime and better safety than lead acid batteries [37].

Of the Li-ion varieties, Lithium Iron Phosphate (LFP) batteries are often used because of their superior safety and economic viability compared to the historically more prevalent Nickel Manganese Cobalt (NMC) batteries [38],[39].

The lifetime of batteries is difficult to estimate, as it is dependent on how the battery is used and under which conditions. In the context of a microgrid application, the lifetime is estimated as 10 years [40]. While within frequency regulation, lifetime is estimated at 4 years [41].

2.2.2 Flywheel energy storage

Flywheels store energy by transforming electrical energy into angular kinetic energy through the acceleration of a rotor using an electric motor. To retrieve the energy, the motor can act as a generator, thereby converting kinetic energy back to electricity. The amount of energy stored is given by Equation (6),

$$KE = \frac{1}{2} I \omega^2 \tag{6}$$

where KE is kinetic energy, I is the moment of inertia and ω is the angular velocity. As the angular velocity is squared, prioritising the maximisation of angular velocity, rather than the moment of inertia, allows for comparatively more energy to be stored. This is the approach taken by Teraloop, as a light-weight carbon composite rotor is used which can withstand higher angular velocities.

Power electronics are used to control the system and are a limiting factors in terms of reaction time. Nevertheless, the extremely fast reaction speed and high power output of a flywheel is one of the main advantages to the technology, 20 ms. The another major advantage is that flywheels have a long lifetime of more than 25 years and over that lifetime have a theoretically unlimited number of cycles they can perform. The round-trip efficiency of flywheels is also high, ranging from 90-95% [12]. Finally, adding multiple flywheels to a system is easy due to their modular nature, providing the potential for the scaling up of storage systems.

Due to the negligible degradation of flywheels compared to other forms of energy storage, degradation models for flywheels are rarely made. Their degradation stems from the electronics in the system such as the motors [42].

The key disadvantage of flywheels as an energy storage technology is a small energy capacity. This prevents flywheels from taking part in many ancillary services as they cannot maintain the power requirements for a sufficient amount of time to qualify. Furthermore, in part due to the low energy capacity, the cost of flywheel per kWh is high. Flywheels also suffer from a high self-discharge rate which can vary from 5-20% per hour [43], [44], making flywheels unsuitable for the long term storage of energy.

When flywheels are used in ancillary services, they are often combined with other technologies, either other storage assets or generation assets such a wind and hydro [45], [46]. They smooth power supply through leveraging essential characteristics: fast reaction speed, high cycle life and high power output [47],

2.2.3 Hybrid energy storage

Hybrid systems join multiple technologies which complement each other by compensating the weakness of one technology with the strength of the other technology. BESS has been combined with different secondary technologies such as super capacitors and flywheels to great effect to reduce stress on the battery and extending lifetime [48], [49]. The hybrid system allows power-sharing and results in improved performance

Table 2: Comparison of BESS and FESS characteristics, showing their compatibility [31]

	BESS	FESS
Energy Density	High	Low
Power Density	Low	High
Reaction Speed	Medium	Fast
Degradation	High	Low
Maturity	High	Medium
Price	Medium	High

over both the short and the long term, in comparison to each individual technology. In those cases, the battery provides the bulk of the energy and the secondary storage satisfies the peaks. In [49] flywheel hybridisation is applied and leads to the extension of lifetime by a factor of 3.6.

Table 2 shows a comparison of BESS and FESS regarding key characteristics [31]. As the "values" are often opposite for each technology, this shows that two technologies are complementary to each other with regard to hybridisation.

3 Method

To address the research question, 3 distinct models and subsequent calculations are employed. An overview of the methodology of this work is given in Figure 2. Firstly, the battery degradation model, which determines the costs associated with battery damage resulting from usage. The battery degradation model produces two degradation profiles named; A and B. These models are then compared to gauge the impact of having different degradation profiles.

Secondly, the FCR-N dispatch models determines the use-pattern of the energy storage assets. The FCR-N dispatch models are divided into two distinct variations: Battery-only and hybrid. The FCR-N dispatch model for hybrid systems is further divided by variations in the number of flywheels.

The results from the FCR-N dispatch models can fit two different goals of hybridisation to support batteries; Lifetime extension and enhancing bidding strategy. Where lifetime extension leverages reduced battery damage to extend the time for which a battery can take part in the FCR-N market. Enhancing bidding strategy leverages reduced operational costs to facilitate a more aggressive bidding strategy. In both of these cases, the battery-only variation is used as a control with which the hybrid variations are compared to.

Finally, the performance of the hybrid systems, in the context of lifetime extension and enhancing bidding strategy, are subject to technical and economic analysis. To perform this analysis, normalised NPV calculations are done for each goal.

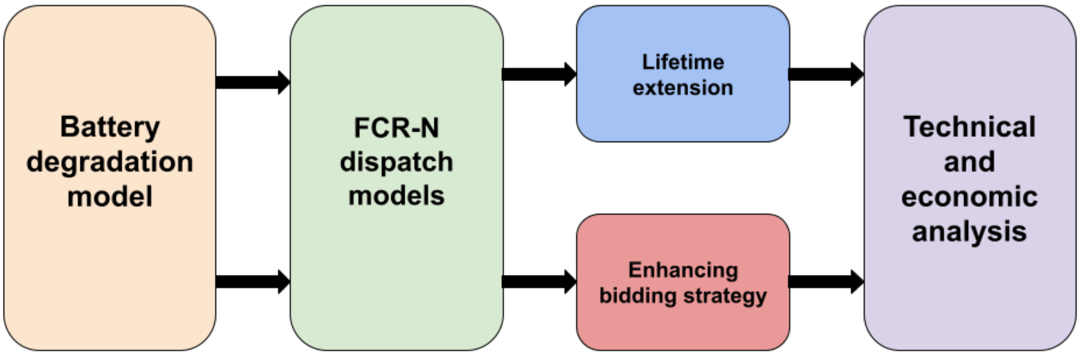

Figure 2: Methodology flow chart, containing two distinct models, two hybridisation goals and culminating in technical and economic analysis.

3.1 Battery degradation models and profiles

To assess the economic impact of battery degradation, the battery's degradation is quantified in terms of a monetary cost associated with a specific level of degradation. Different degradation profiles lead to different costs for the same discharge cycle.

This work focuses on the impact of flywheels, specifically considering cyclic degradation as it is directly affected by the addition of a flywheel. The cyclic degradation is calculated by examining the SoC at the beginning and end of each cycle, disregarding the path taken to reach the endpoint. While it is feasible to compute the impact of the path itself, the algorithm required for this is too complex given the time constraints of this work. The methodology employed here, which identifies peaks and valleys in the SoC is also used in other works [8]. Additionally, the assumption that charging and discharging have equal impacts on degradation, while potentially not entirely accurate, is a common approach in degradation models [8], [24].

Factors such as calendar degradation or external temperature remain constant between the two degradation profiles, as they are not impacted by the usage pattern of the battery. As these factors do not vary between the models being compared, their effects become redundant for the purposes of comparison. Therefore, these factors are not taken into consideration.

The two degradation profiles used in this work are named "A" and "B". Profile A is a genuine model of cyclic degradation for a lithium-ion battery [24]. Profile "B", on the other hand, is fictitious but shares identical start and end points with profile A. The key difference lies in the curvature, with profile A being a more conservative or strict degradation profile, as depicted in Figure 3. This variation in curvature is intended to illustrate the impact of different degradation characteristics on the FCR-N dispatch models and economic outcomes.

Variables other than the curvature could have been investigated, modifying linear variables within the degradation model would yield linear changes in economics, which would be less informative for the analysis. Instead, varying the curvature of the exponent provides a more meaningful comparison between the two degradation profiles.

To enable the integration of degradation profiles with the MILP dispatch models in the next section, piecewise-linearization of degradation profiles is necessary. This involves splitting the profiles into 200 linear segments, which provides a high-fidelity approximation of the profiles. Piecewise-linearizations with a greater number of linear segments are not used due to limits on computational intensity.

3.2 Grid frequency scenarios

Battery degradation is linked to the use-pattern of storage assets. Understanding how an asset is used within the FCR-N market is therefore essential to understanding how much degradation occurs. Fingrid uses grid frequency to control assets in the FCR-N market. To evaluate the extent to which use-pattern impacts degradation, three grid frequency scenarios are considered.

The scenarios are categorised based on their number of cycles and average gradient. The most rapidly and extremely changing scenario is referred to as having high frequency volatility. The least volatile scenario is referred to as having low frequency volatility, with the medium scenario being in-between the other two, and referred to as having medium frequency volatility. In the figures of this work, these scenarios are indicated according to their volatility, e.g. "Medium".

These scenarios use Fingrid frequency data from 2023, where each scenario spans 1 h as this is the standard market time unit for all Fingrid frequency regulation markets.

The data of each scenario has a time-step of 0.1 s, meaning there is a data point every 0.1 s.

3.3 Dispatch models and variations

The FCR-N dispatch models determine the usage patterns of the modelled batteries and flywheels within the FCR-N market, optimising their dispatch to minimise battery damage. In order to understand the impact of adding a flywheel to a battery, the battery-only variation is modelled to serve as a control. The hybrid variation considers the same battery as the battery-only variation, but in conjunction with a varying number of flywheels ranging from 1 to 5 flywheels. This corresponds to battery:flywheel power capacity ratios in a range from 0.1 and 0.5. The battery considered is a 10 MW/10 MWh battery. This is a reasonable size as such batteries are already in use and facilitates convenient iterations with respect to hybrid models [50].

The system is modelled and optimised over an entire hour, assuming perfect foresight of frequency. All variations of the dispatch model are iterated over the three frequency volatility scenarios. An associated assumption is that the reaction times for a given storage asset are negligible, which is reasonable in this context because time related complexities are also negligible when perfect foresight is considered.

3.4 Technical analysis

To compare the performances of the FCR-N dispatch models a number of metrics are used, these metrics are applicable to hybrid systems in general and are not specific to a goal. The metrics are; number of cycles performed by the battery, the distribution of those cycles, flywheel activation time and flywheel energy throughput.

The first performance indicator is the total number of cycles performed by the battery. In general, more cycles corresponds to more damage. Understanding which variations result in fewer total cycles provides insight into the overall damage sustained by the battery.

A derivative of the first indicator is the distribution of battery cycles. This metric provides detailed information about the distribution of cycle DoDs. It reveals the extent to which small DoD cycles or large DoD cycles are mitigated by flywheels.

To understand how flywheels perform, the metrics of "activation time" and "energy throughput" are used. "Activation time" represents the percentage of time that the flywheel is active compared to the battery. "Energy throughput" is also represented as a percentage compared to the battery-only dispatch variation, indicating the total amount of energy handled by the flywheel. Generally, a high activation time and high energy throughput suggest that the flywheel effectively supports the battery, potentially extending its lifetime. These metrics provide insights into the utilisation and effectiveness of the flywheel within the hybrid system.

Technical analysis depending on hybridisation goal is less straightforward. Relative to the battery-only variation, the performance is measured as a percentage. For the goal of lifetime extension, the percentage is an increase of lifetime. For the goal of enhancing bidding strategy, the percentage is a decrease in operational cost, which facilitates a more aggressive bidding strategy.

3.5 Economic analysis

To evaluate the economic value of flywheel hybridisation of batteries, normalised Net Present Value (NPV) is calculated. NPVs are calculated based on each hybridisation goal. More detail for each calculation if given in Section 4.3.

The first NPV calculation is based on the lifetime extension made possible by flywheels. Assuming all other factors remain constant, such as income, having a longer lifetime means that a system has more time in which it can provide ancillary services, more time to generate revenue and thus increase NPV.

The second NPV calculation is based on reducing operational to enhance bidding strategy. Such a bidding strategy involves bidding hybrid systems at a lower price, as the operational costs decrease with the number of flywheels. By bidding at a lower price, the hybrid system can secure more frequent procurement and potentially increase revenue. However, each procurement event incurs some level of damage to the battery, and more frequent procurement can accelerate battery degradation, shortening its operational lifespan.

The bidding strategy is applied across all hours of 2023, taking into account Fingrid price and procurement data. Providing an estimate for yearly revenue which is then extrapolated over each year of lifetime.

For both calculations the capital investment cost considers the additional costs incurred by flywheels. Thus, a cost-benefit analysis is conducted to compare the benefits of life extension with the monetary cost of implementing flywheels in the hybrid system. This analysis helps assess the economic viability and potential returns associated with hybridisation strategies.

4 Modeling and calculations

This section provides detail information on how modeling is carried out in this work. Section 4.1 describes the modeling of cyclic degradation to generate two degradation profile. Section 4.2 describes battery-only and hybrid variations of the FCR-N dispatch models. Section 4.3 describes calculations pertaining to technical and economic analysis.

4.1 Battery degradation models

The objective of the battery degradation model is to translate the battery's usage pattern into a quantifiable monetary cost. This cost is contingent upon the degradation profile which signifies the loss of life incurred due to usage.

To calculate the loss of life as a result of usage, this work considers cyclic degradation. Cyclic degradation is modeled in this work by the exponential function described in Equation (7), as used in [23],

$$N^T = a \cdot (DoD)^b + c \tag{7}$$

where N^T is the amount of cycles (in thousands) that can be performed at the specific DoD, where DoD is calculated using Equation (5). Exponential curves cannot be directly used in MILP models, a way of getting around this nonlinearity is by using piecewise-linearisation. Figure 3 shows the piecwise-linearisation of Equation (7) with tuning variable values given in Table 3.

Table 3: Cyclic degradation profile tuning variables

Profile	A	B
a	17390	4895974
b	-0.4052	-0.005
c	-2153	-4880737

The tuning variables of degradation profile A are calculated from experimental data [23]. The tuning variables of profile B are chosen such each profile starts and ends points are identical compared to profile A, changing only the curvature. In Figure 3, the lower line of degradation profile A is much steeper in terms of curvature, thus profile A is a more conservative degradation profile. Where for the same DoD, the number of cycles that can be performed by degradation profile A is less than that of B.

With a known, and limited, number of cycles that can be withstood for a given DoD, Equation (8) calculates a monetary cost of damage to the battery,

$$D^B = \frac{I^B}{N^T} \tag{8}$$

where D^B is the damage to the battery as a cost and I^B represent the capital investment costs of the battery. Figure 4 shows the piecewise-linearisation of Equation (8) for

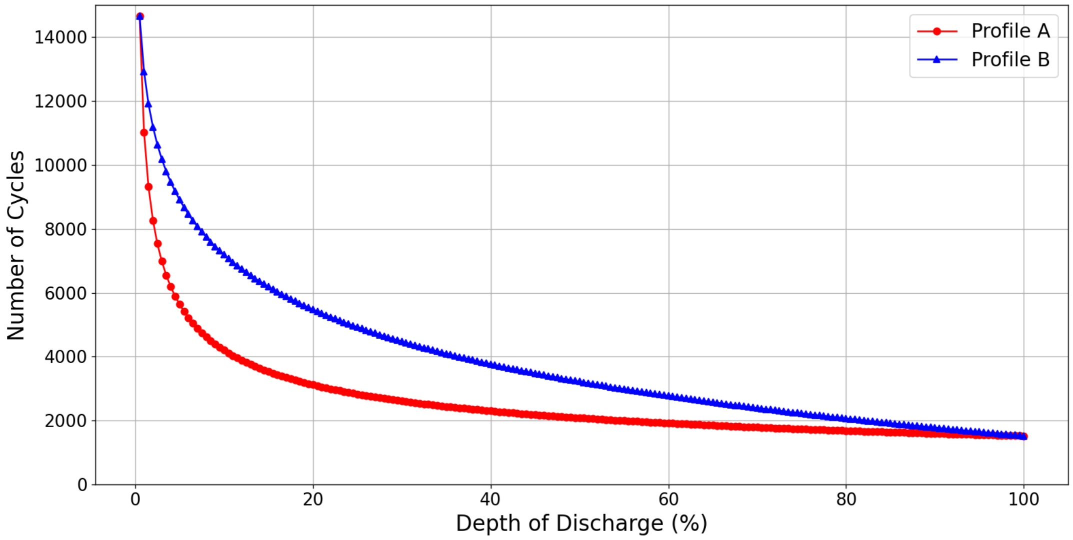

Figure 3: Piecewise-linearisation of degradation profile cycle curves A and B, showing the number of cycles that can be performed for a given DoD. Profile A is the more conservative profile, being able to perform fewer cycles than B for the same DoD.

both degradation profiles. In this figure, the idea that degradation profile A is more conservative is further exemplified. Degradation profile A is either equal to or greater than B in the entirety of the figure for the same DoD, thus a battery with degradation profile A always has a greater operational cost.

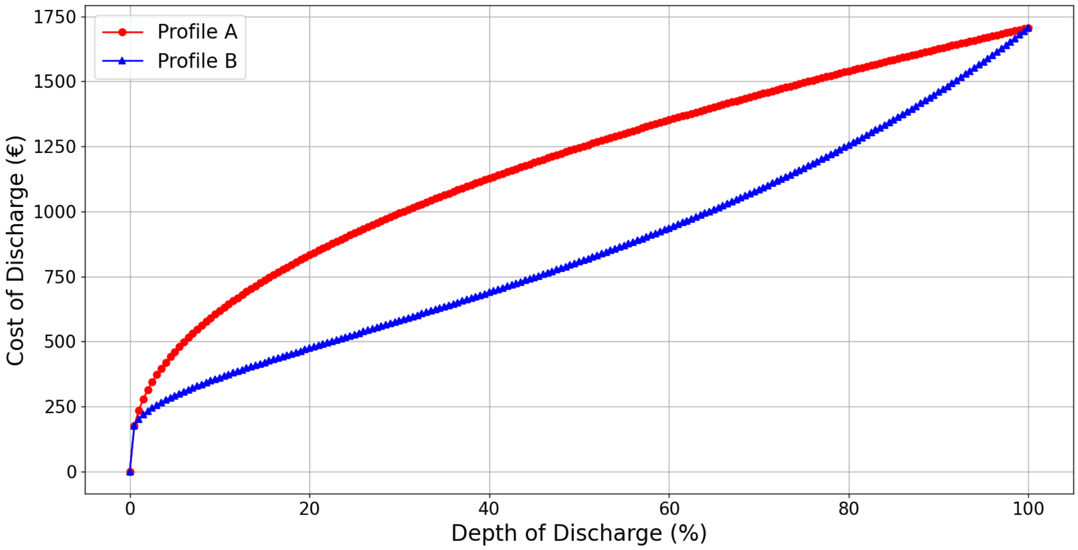

Figure 4: Piecewise-linearisation of degradation profile cost curves, showing the cost of a cycle for a given DoD. Profile A is the more conservative profile, having a higher cost of discharge than B for the same DoD.

4.2 FCR-N dispatch model

This section details the models used to optimise the dispatch strategy for both battery-only and hybrid dispatch variation, considering battery degradation and aiming to minimise damage to the battery. The battery-only and hybrid variations share numerous similarities in terms of parameters and constraints, with the hybrid variation expanding upon the battery-only variation. It can be assumed that the constraints of the battery-only variation also apply to the hybrid variation unless explicitly stated otherwise.

4.2.1 Objective function

The objective of each FCR-N dispatch model variation is the same; to minimise the cost, and thus also damage, to the battery while still adhering to all of the FCR-N rules and regulations. Thus, the objective function is given as Equation (9),

$$Objective = minimse \sum_{t}^{n} Cost_t^B(DoD_t^{B,m}) \tag{9}$$

where $Cost_t^B$ is the operational damage cost to the battery incurred by charging/discharging. The charging/discharging behaviour is taken into account by observing $DoD_t^{B,m}$, which is dependent on SoC^B as given by Equation (10),

$$DoD_t^{B,m} = DoD_t^{B,m}(SoC_t^B) \tag{10}$$

where the local maxima and minima of SoC_t^B are taken as the start and end points of each individual cycle. With Equation (5) $DoD_t^{B,m}$ is calculated for each cycle, using a degradation profile $Cost_t^B$ is calculated for each $DoD_t^{B,m}$.

4.2.2 Parameters

Table 4 presents key parameters used in the dispatch models as well as NPV calculations. The value of each parameter is defined, along with a symbol and a corresponding unit. Values have been derived from literature and methodology decisions.

4.2.3 Charging control parameters

For the dispatch models, the frequency dictates if storage assets will charge, discharge or remain constant. In order to incorporate this logic, charging control parameters are integrated into constraints in Sections 4.2.4 and 4.2.5. This section explains the logic used. An overview of the logic used to determine values of charging control parameters is given in Figure 5.

The charging control parameter δ_t^{ND} determines if Fq_t is within the allowable FCR-N frequency range of FCR-N. If this is the case, δ_t^{ND} is assigned a value of 1 signifying that charging or discharge is allowed. Conversely, if Fq_t is outside this range, δ_t^{ND} is assigned a value of 0. In this case the power output is kept at 100% of bid power.

Table 4: Overview of FCR-N dispatch model and NPV calculation parameters.

Parameter	Symbol	Value	Unit
Battery capacity	$E^{B,max}$	10	MWh
Battery power	$P^{B,max}$	10	MW
Battery efficiency	η^{B}	90 [31]	%
Battery cost	n/a	260 [4]	€/kWh
Flywheel capacity	$E^{F,max}$	0.04 [12]	MWh
Flywheel power	$P^{F,max}$	1 [12]	MW
Flywheel efficiency	η^{F}	95 [12]	%
Maximum bid size	P^{bid}	5	MW
Initial SoC	SoC_{init}	0.5	n/a
Discount rate	n/a	5.5 [51]	%
Time-step	t^{step}	$\frac{1}{36000}$	s

The charging control parameter δ_t^N determines (within the range of FCR-N) whether charging or discharging should take place. If Fq_t is greater than the normal frequency (50 Hz), the grid must decrease the amount of power in the system. In this case δ_t^N is assigned a value of 1, allowing storage assets to charge while simultaneously preventing them from discharging. The opposite is true when Fq_t is less than 50 Hz, assigning a value of 0. Allowing discharging and preventing charging, because the grid is at a power deficit. The magnitude of charging or discharging is determined by the magnitude of frequency deviations, as described in Equation (16).

The charging control parameter δ_t^{50} considers the rare case that Fq_t is equal to 50 Hz. In this case, neither charging nor discharging is allowed as the grid balanced and δ_t^{50} is assigned a value of 1. Otherwise, in the more common case, a value of 0 is assigned.

4.2.4 Battery-only constraints

Many of the constraints described in this section are valid for both the battery-only variation and hybrid variations. Section 4.2.5 explicitly states if a constraint is no longer valid for the battery-only variation.

SoC increases or decreases depending on if the battery is charging or discharging. The new SoC is calculated by considering what is charger or discharged relative to the previous SoC, as given by Equation (11),

$$SoC_t^B = SoC_{t-1}^B + [((P_t^{B,ch} \cdot \eta^B) - (\frac{P_t^{B,dch}}{\eta^B})) \cdot \frac{t^{step}}{E^{B,max}}] \quad \forall t, t \neq 1 \tag{11}$$

$$SoC_t^B = SoC_{init} + [((P_t^{B,ch} \cdot \eta^B) - (\frac{P_t^{B,dch}}{\eta^B})) \cdot \frac{t^{step}}{E^{B,max}}] \quad t = 1 \tag{12}$$

where $P_t^{B,ch}$ is the power charged by the battery at time t, $P_t^{B,dch}$ is the power discharged by the battery at time t, SoC_t^B is the "State of Charge" of the battery at time t. Where

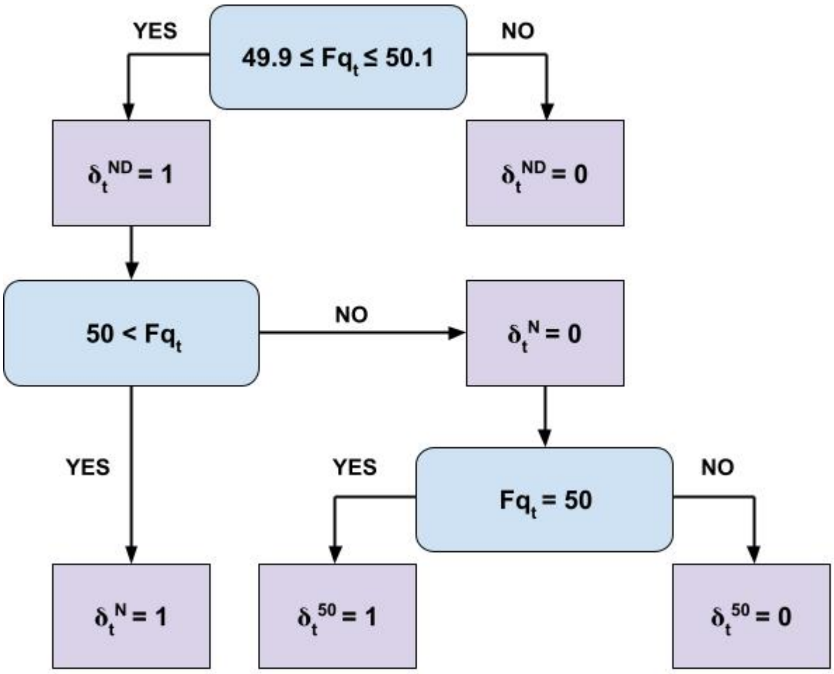

Figure 5: Logic flow chart for charging control parameters, which control charging behaviour in FCR-N dispatch models according to Fingrid requirements.

t is bounded by the frequency volatility scenario which has a range of 0 to 36,000. t^{step} and $E^{B,max}$ function to convert charging power into an SoC [15]. SoC_{init} is the initial SoC as defined by Equation (13) in accordance with Fingrid requirements,

$$SoC_{init} = 0.5 \tag{13}$$

$$0 \leq SoC_t^B \leq 1 \qquad \forall t \tag{14}$$

where SoC_{init} is purposefully left without the superscript "B" as the initial state of charge also applies to the flywheel. Equation (14) restricts the SoC in a way that the battery is prevented from charging or discharging beyond its maximum capacity.

Equation (13) ensures the battery starts in the neutral position. As discussed in Section 2.1.2 to take part in the FCR-N market, a battery must be at approximately 50% capacity at the start of support.

It is crucial to emphasise that, for the battery-only variation, the bid size is determined relative to the maximum power that the battery can deliver, considering the symmetry requirement. It is assumed that one bids the maximum capacity in order to maximise profit. This symmetry requirement is why $P^{B,max}$ is divided by 2 in Equation (15).

$$P^{Bid} = \frac{P^{B,max}}{2} \tag{15}$$

The power output of the battery is constrained on the basis of the maximum bid and the frequency of the grid at time t, as given by Equations (16) and (17). In accordance with Fingrid requirements, the power is scaled proportionally to the magnitude of frequency deviation,

$$P_t^{B,ch} = P^{Bid} \cdot \delta_t^N \cdot (\frac{|Fq_t - 50|}{0.1} \cdot (1 - \delta_t^{ND}) \cdot (1 - \delta_t^{50}) + \delta_t^{ND}) \qquad \forall t \tag{16}$$

$$P_t^{B,dch} = P^{Bid} \cdot (1 - \delta_t^N) \cdot (\frac{|Fq_t - 50|}{0.1} \cdot (1 - \delta_t^{ND}) \cdot (1 - \delta_t^{50}) + \delta_t^{ND}) \quad \forall t \tag{17}$$

where Fq_t is the frequency at time t. δ_t^N,δ_t^{ND} and δ_t^{50} ensure that SoC_t^B only changes when the frequency determines it is reasonable to do so as defined in Section 4.2.3.

4.2.5 Hybrid model constraints

The constraints in this section are only applicable to hybrid dispatch variations. Equations (18) and (19) are the flywheel equivalent to Equations (11) and (12). Determining how the SoC changes based on charging and discharging of the flywheel.

$$SoC_t^F = SoC_{t-1}^F + ((P_t^{F,ch} \cdot \eta^F) - (\frac{P_t^{F,dch}}{\eta^F})) \cdot \frac{t^{step}}{E^F} \quad \forall t, t \neq 1 \tag{18}$$

$$SoC_t^F = SoC_{init} + ((P_t^{F,ch} \cdot \eta^F) - (\frac{P_t^{F,dch}}{\eta^F})) \cdot \frac{t^{step}}{E^F} \quad t = 1 \tag{19}$$

$P_t^{F,ch}$ is the power charged by the flywheel at time t, $P_t^{F,dch}$ is the power discharged by the flywheel at time t, SoC_t^F is the "State of Charge" of the flywheel at time t. η^F is the efficiency of the flywheel. E^F is the combined energy capacity of all the flywheels, as defined by Equation (20),

$$E^F = n^F \cdot E^{F,max} \tag{20}$$

where $E^{F,max}$ is the energy capacity of a single flywheel and n^F is the number of flywheels considered. The number of flywheels considered is in a range of 1 to 5. Corresponding to capacity ratios of 0.1 to 0.5.

Equation (21) is the flywheel equivalent to Equation (14). Tackling the same concepts of SoC, but in the context of a flywheel rather than a battery.

$$0 \leq SoC_t^F \leq 1 \qquad \forall t \tag{21}$$

The self-discharge of the flywheel is also taken into account. When flywheels are idle, neither charging nor discharging. The flywheel looses energy at a rate of 20% of full capacity per hour [43], [44]. Battery self-discharge is negligible compared to flywheels and thus not considered.

In the battery-only dispatch variation, the battery is required to provide the full power of the bid. However, in the hybrid variations, both the battery and flywheel can collaborate to deliver the specified power. Therefore, Equation (15) is no longer applicable, and it is replaced by Equation (22),

$$P_t^F + P_t^B = P^{bid} \tag{22}$$

where P^F is the power (charge or discharge) of the flywheels at a given time t and P^B is the power (charge or discharge) of the battery at a given time t. This is a key aspect of the hybrid model, as the share of power taken by each storage asset can be optimised to minimise damage to the battery. The range of power output for flywheels is dependent on how many are considered, as given by Equations (23) and (24).

$$0 \le P_t^{F,ch} \le n^F \cdot P^{F,max} \qquad \forall t \tag{23}$$

$$0 \le P_t^{F,dch} \le n^F \cdot P^{F,max} \qquad \forall t \tag{24}$$

Similarly, Equations (25) and (26) fulfil the same purpose but specifically for the battery within the context of the hybrid model variation. It is important to clarify that charging and discharging are both represented as positive values in these equations; negative symbols are applied in other constraints to indicate if power is discharging.

$$0 \le P_t^{B,ch} \le P^{B,max} \qquad \forall t \tag{25}$$

$$0 \le P_t^{B,dch} \le P^{B,max} \qquad \forall t \tag{26}$$

Equations (25) and (26) are not needed in the battery-only dispatch model variation, as the power is fully constrained by Equations (15), (16) and (17). Equations (27) and (28) replace the battery-only equations (16) and (17), and determine the power output of the system depending on the magnitude of frequency deviation.

$$P_t^{B,ch} + P_t^{F,ch} = P^{Bid} \cdot \delta_t^N \cdot \left(\frac{|Fq_t - 50|}{0.1} \cdot (1 - \delta_t^{ND}) \cdot (1 - \delta_t^{50}) + \delta_t^{ND}\right) \quad \forall t \tag{27}$$

$$P_t^{B,dch} + P_t^{F,dch} = P^{Bid} \cdot (1 - \delta_t^N) \cdot \left(\frac{|Fq_t - 50|}{0.1} \cdot (1 - \delta_t^{ND}) \cdot (1 - \delta_t^{50}) + \delta_t^{ND}\right) \quad \forall t \tag{28}$$

4.3 Net Present Value calculations

This section provides a detailed explanation of how variables of NPV; income, lifetime, investment cost and discount rate, are calculated. Income and lifetime are calculated in different ways depending on what the goal of hybridisation is. For the calculation itself, the standard NPV equation is used. Battery cost and discount rate can also be found in Table 4.

Income for the goal of lifetime extension is calculated such that the battery-only dispatch variation achieves a break-even point, resulting in an NPV of zero. This income is then applied to all variations. Thus assuming that the procurement and deployment processes are identical across all variations. The NPV for each variation within a given frequency scenario is calculated. In order to normalise the NPV results, the NPV values are divided by the calculated income, as one cannot divide the NPV of the battery-only case, 0.

When flywheels are considered to reduce operational costs, income is calculated depending on a bidding strategy and is unique to each dispatch variation. The bidding strategy determines if a system is profitable given the prices for capacity, energy and sanctions. In the scenario that the system is profitable for a given hour, the system is assumed to be both procured and deployed. This is repeated for all hours of 2023, generating a yearly income.

Additionally, the maximum bid allowed by the strategy is cross-referenced with Fingrid procurement data so that the strategy does not overestimate the demand of the market. The NPVs are normalised against the NPV of the battery-only variation within the same frequency volatility scenario.

Battery lifetime when using flywheels to extend lifetime is relative to the battery-only dispatch variation. For this variation, the lifetime is assumed to be 4 years [41]. The lifetimes of hybrid variations are scaled proportionally based on the calculated life extension and the initial lifetime of the battery-only variation. This scaling ensures that the projected lifetime of each of the hybrid variations reflects the corresponding reduction in battery damage.

Battery lifetime, when using flywheels to enhance bidding strategy, is calculated depending on the damages incurred by participating in the FCR-N market. Where the bidding strategy determines when the system is procured and deployed. Each deployment incurs damage and from this damage a lifetime is calculated.

The investment cost is divided into battery and flywheel cost. A battery of cost 260 €/kWh is utilised, resulting in a battery cost of €2,600,000. The flywheel cost is linearly dependent on the number of flywheels used in each variation. The price of a single flywheel used in the calculation is based on confidential information from Teraloop.

To tailor this calculation to the Finnish context, a country-specific estimate for discount rates applicable to storage systems in electricity markets is used [51]. For Finland, the discount rate used is 5.5%. This rate is crucial for computing NPV and reflecting the economic conditions specific to Finland.

5 Results

This section is structured into four subsections. Firstly, Section 5.1 focuses on how the number of cycles performed by the battery changes with the addition of flywheels. Secondly, Section 5.2 discusses how flywheel performance evolves as the number of flywheels increases. Thirdly, Section 5.3 examines how battery lifetime is extended with the inclusion of flywheels. Section 5.4 discusses the economic implications of lifetime extension. Finally, Section 5.5 discussed the economic implication of enhancing bidding strategy.

Throughout many of the figures in this section, the X-axis is given as "Capacity Ratio", which refers to the ratio of power capacity between flywheel and battery. In this way, the figures take different numbers of flywheels into account. A capacity ratio of 0.1, in this work specifically, is equal to one flywheel and so on. A capacity ratio of 0 refer to battery-only variations.

This work solely considers discrete numbers of flywheels, however it employs line graphs in the following section for visual representation. It is important to note that linear interpolation between points is not feasible in this context, as the capacity ratio is calculated based on integer numbers of flywheels. However, the inclusion of lines in the graphs aids in enhancing the visualisation of the results.

In select figures, only a single degradation profile is shown in order to improve the legibility of results. If this is the case, degradation profile A is always shown as it is a genuine lithium-ion degradation profile as well as being the more conservative profile

5.1 Battery cycles

This section goes into detail about how the number of cycles performed by batteries changes with increasing battery ratio, considering the distribution of those cycles. Also taking degradation profiles and frequency volatility scenarios into account. Figure 6 shows the total number of cycles that are performed by the battery.

Figure 6 illustrates a trend that profile A usually experiences more cycles than profile B. Another trend is that as the number of flywheels increases, the number of cycles performed by the battery decreases. The curves plateau at close to a number of cycles of approximately 25. This plateauing indicates that flywheels struggle to mitigate the largest cycles, most likely due to their limited energy capacity.

In Figure 6, degradation profiles A and B exhibit very similar behaviour for most data points, indicating that the optimal use of the flywheel is minimally affected by the specific degradation profile of the battery. This observation is further supported by Figure 7, which provides a detailed representation of battery cycle distribution for degradation profiles A and B compared to the battery-only dispatch variation.

It is important to note that the cycle distribution in battery-only dispatch variations remains consistent regardless of the degradation profile, enabling meaningful comparisons with hybrid variations incorporating both profiles. To ensure the clarity of the histograms, the x-axis is limited to 10% DoD. While cycles with depths exceeding

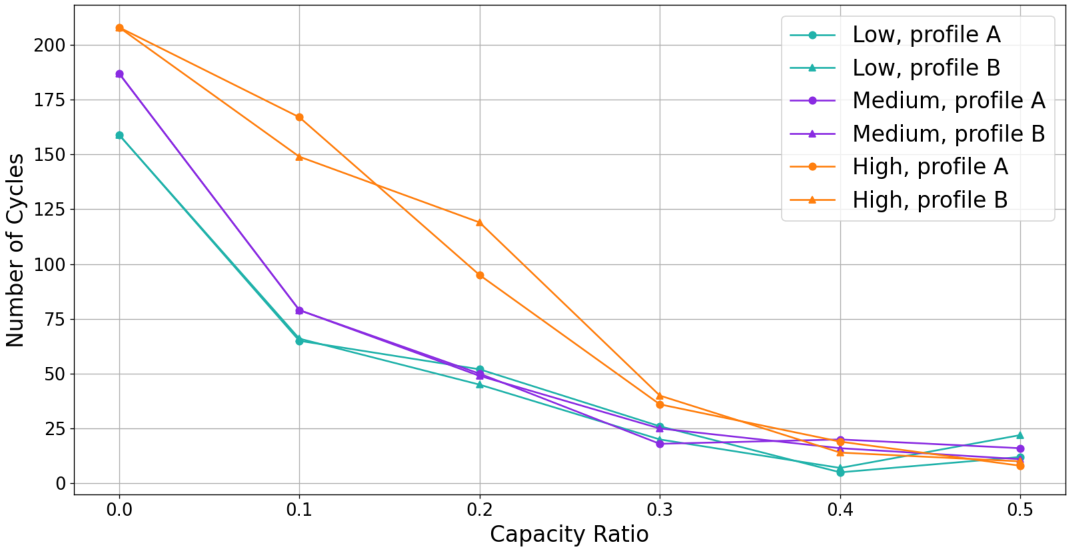

Figure 6: Number of cycles performed by the battery in an hour. Comparing different capacity ratios, degradation profiles and frequency volatility scenarios. Where results approach a similar number of cycles as capacity ratio increases.

10% DoD do occur, they remain unchanged and add no value to the findings of this work.

Figure 7 illustrates that the cycle DoD distribution for the battery-only dispatch variation is primarily characterised by small cycles ranging from 0% to 1% DoD. The frequency of instances rapidly decreases as cycle DoD increases. This trend is shared

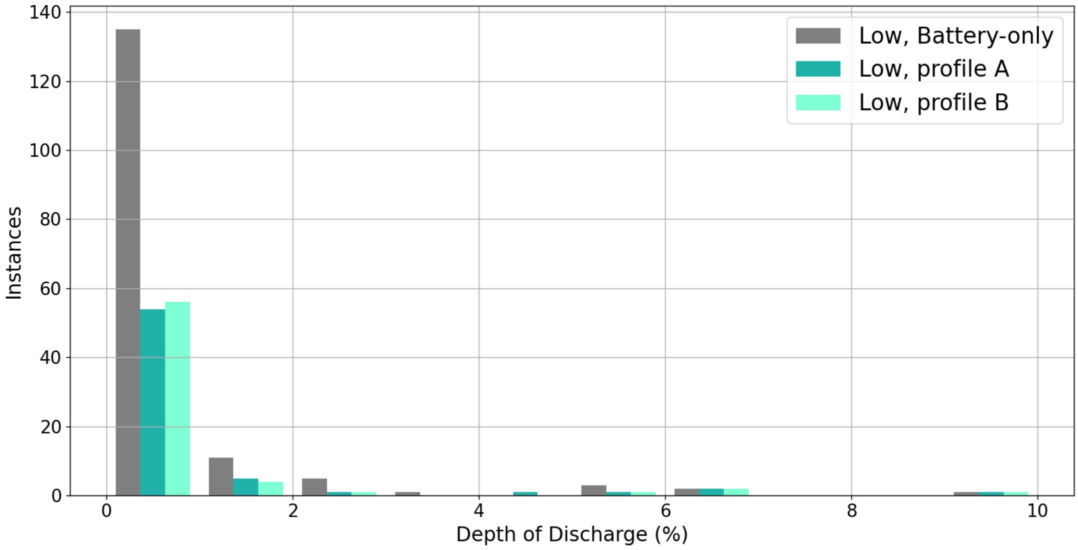

Figure 7: Comparison of cycle DoD distribution between the battery-only dispatch variation and hybrid variations of capacity ratio 0.1 with degradation profiles A and B, for the low frequency volatility scenario. Showing only small differences in cycle distribution between degradation profiles.

between all frequency volatility scenarios. This observation indicates that independent of frequency volatility scenario, the majority of cycles exhibit shallow depths, offering ample opportunities for a flywheel to provide support to the battery.

Support to the battery is shown to be focused on small cycles as flywheels are shown to remove cycle up-to approximately 6% DoD in Figure 7. It is in the first 6 groups of columns that the hybrid variations show decreased cycles compared to the battery-only variation. Cycles with deeper depths, such as 6% DoD and greater, are impacted less as the columns of battery-only and hybrid variations are similar. Across other frequency volatility scenarios, cycles up-to 3% DoD are always impacted by flywheels. Cycles greater than 10% DoD are rarely impacted.

When comparing the cycle distribution of hybrid variations with different capacity ratios, as shown in Figure 8, it is evident that the range of DoDs impacted remains largely the same across different scenarios. However, the extent to which this range is impacted becomes more pronounced. When 2 flywheels are considered, still the lowest cycles DoDs are most affected and a greater number of cycles are removed.

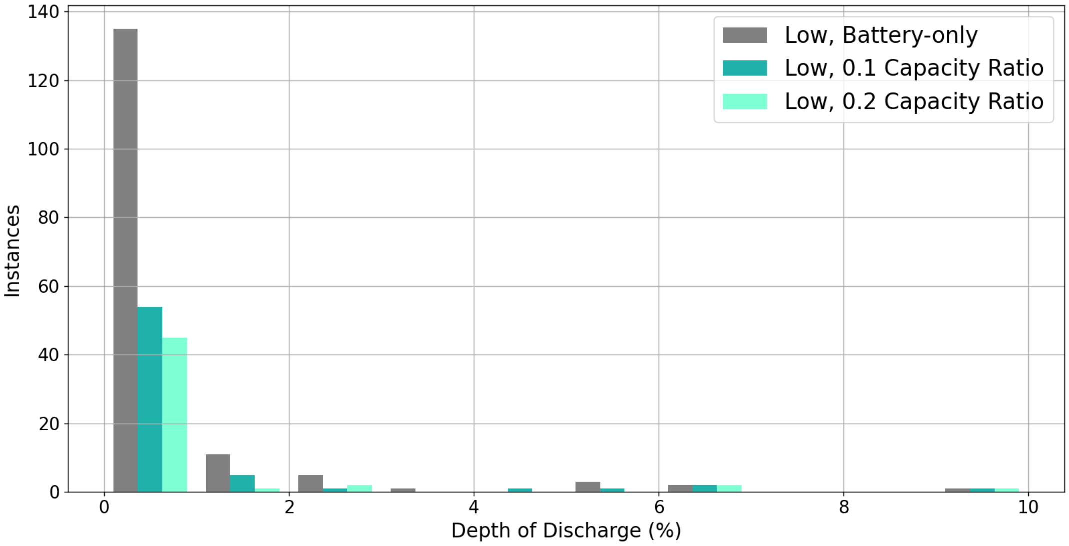

Figure 8: Comparison of cycle DoD distribution between the battery-only dispatch variation and hybrid variations of capacity ratios 0.1 and 0.2 with degradation profile A, for the low frequency volatility scenario. Showing that even at higher capacity ratios, low DoD cycles are affected the most.

Despite the number of flywheel doubling, diminishing returns can be observed in Figure 8. The number of cycles removed is greater, however the number removed is proportionally less. The deeper DoD cycles are largely unchanged by the addition of another flywheel.

In certain instances, the typical patterns observed in Figure 6 are not followed. One notable anomaly occurs in the low frequency volatility scenario, specifically between capacity ratios of 0.4 and 0.5, where the number of cycles unexpectedly increases. The mechanisms for this are explained in Section 6.2, however the impact of these anomalies is negligible with regard to subsequent results.

5.2 Flywheel performance

This section goes into detail about how flywheel performance changes as capacity ratio increases. Figure 9 displays the key performance indicators of flywheels. Only a single degradation profile is shown, as the differences in results between profiles A and B are small. Suggesting that the specific degradation profile has a negligible impact on how a flywheel operates.

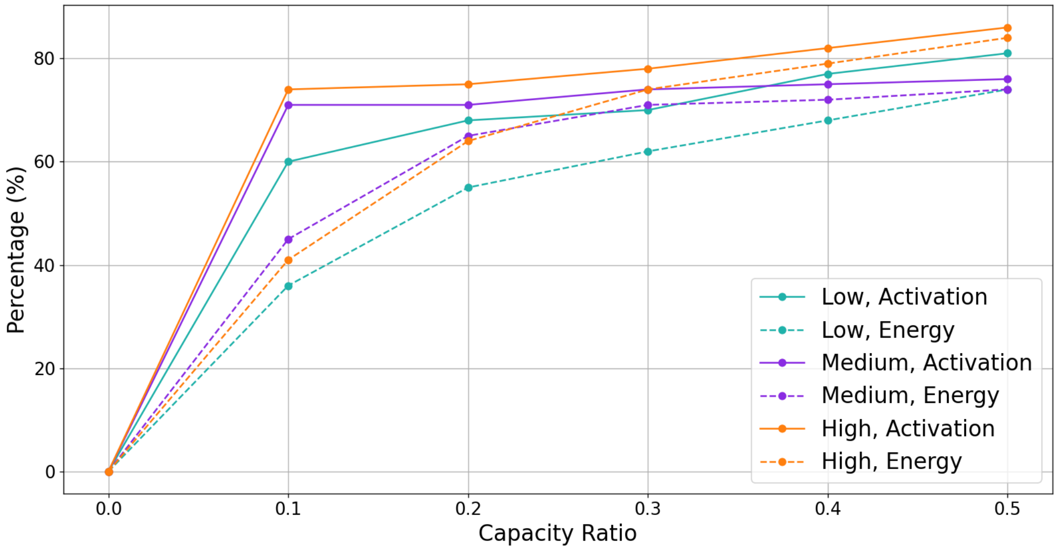

Figure 9: Activation time and energy throughput percentages of flywheels considering the 3 frequency volatility scenarios, with degradation profile A. Showing activation time gradually increasing while energy throughput plateaus with increasing capacity ratio.

The frequency volatility scenarios are arranged in descending order at low capacity ratios with regard to activation percentage, where the high frequency volatility scenario has the largest activation percentage and the low scenario has the least. This ordering is expected, as the greater number of cycles in the high scenario provides more opportunities for flywheel support, leading to a higher activation percentage.

For higher capacity ratios, the activation percentage for the low scenario exceeds that of the medium scenario. This is likely because the low scenario has sufficiently small cycles such that at a capacity ratio of 0.5, the flywheels can perform entire cycles independent of the battery. In contrast, in the medium scenario, many cycles require more power or energy than the flywheels can provide, limiting activation time. This analysis highlights how the characteristics of different frequency volatility scenarios influence the ability of flywheels to provide support based on cycle size and power requirements.

The variability in flywheel performance across different frequency volatility scenarios underscores the importance of considering specific operational conditions and cycle characteristics when analysing their effectiveness. While general trends can be identified from the data, it is essential to recognise the nuances and dependencies on specific parameters for accurate extrapolation to broader scenarios.

The number of cycles, the maximum power of those cycles, and the energy requirement of the cycles all influence how flywheels perform in different scenarios. Therefore, only the overarching trends observed in Figure 9 can be extrapolated to the general case.

The first trend observed is that activation percentage steadily increases with capacity ratio. Secondly, energy percentage increases rapidly at first, but then plateaus with increasing capacity ratio. While activation time aids in understanding flywheel performance, it is flywheel energy throughput that provides support to the battery; therefore, energy percentage is a more meaningful metric for comparison. The plateauing of the energy percentage supports the idea of diminishing returns with increasing capacity ratio, which is also highlighted in Section 5.1. The diminishing returns suggest that the cycles in the frequency volatility scenarios that can be removed by means of power, have been removed. The remaining cycles must be removed by means of energy capacity.

5.3 Hybrid system performance

Flywheels remove the burden of small DoD cycles from the battery. The ultimate goal of this is to reduce battery damage. This section goes into detail as to the extent of damage reduction, this reduction can be interpreted according to the hybridisation goals of lifetime extension and enhancing bidding strategy, where operational costs are reduced. The percentages shown in Figure 10 are applicable to both hybridisation goals. The result can be interpreted as either percentage lifetime extension or percentage cost reduction, collectively referred to as "hybrid system performance".

For low capacity ratios, all scenarios and degradation profiles exhibit very similar results. This suggests that hybrid system performance is influenced less by either grid frequency or battery degradation profiles at these lower ratios. The consistency observed in results up to capacity ratios of 0.2 indicates that such a ratio may be more suitable for real-world applications, as it offers predictability and stability compared to higher ratios.

For higher capacity ratios, the results exhibit more variability. However, at a capacity ratio of 0.3, the bottom two frequency scenarios (medium and low) still show similar hybrid system performance, while the high scenario diverges. This observation suggests hybrid system performance is dependent on the frequency volatility scenario at higher capacity ratios, as discussed in Section 5.2. Similarly, the overarching trends are evaluated, the details are likely specific to frequency volatility scenarios and difficult to apply to general cases.

The second trend observed is that the results show positive outcomes, with the top two scenarios (high and low) at higher capacity ratios increasing close to linearly. The second trend is that hybrid system performance for degradation profile B is always greater than that of profile A. This is expected, as profile A is the more conservative

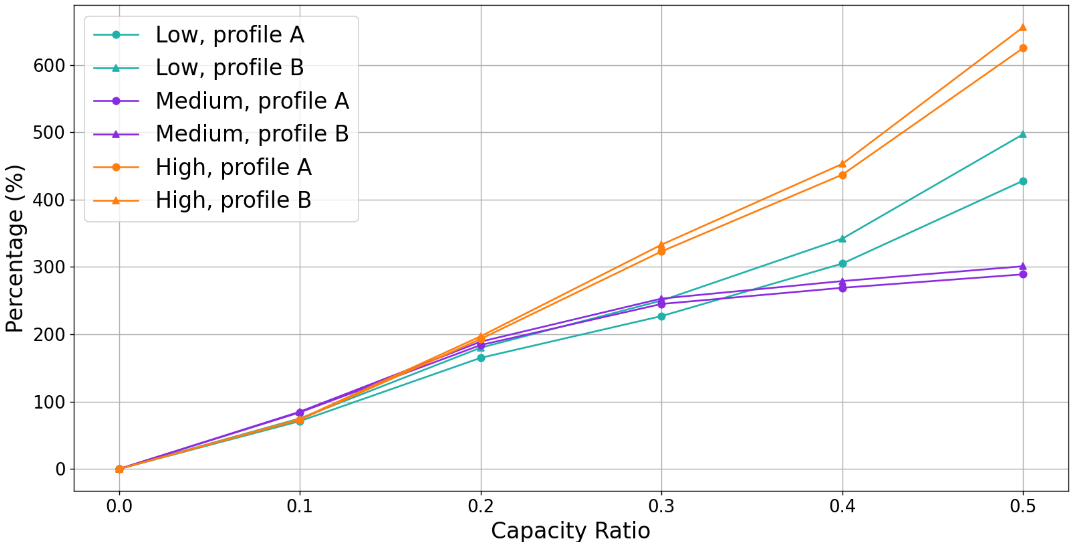

Figure 10: The performance of different frequency volatility scenarios, degradation profiles and dispatch variations represented as a percentage. Where the percentage can be interpreted as percentage lifetime extension or percentage operational cost reduction, depending on the hybridisation goal. At low capacity ratios, the results are closely distributed, while they are more widely distributed at high capacity ratios.

of the degradation profiles. The difference between the two profiles is, however, often quite small. Emphasising the minimal impact that battery degradation profile curvature has on hybrid system performance.

5.4 NPV: Lifetime extension

The NPV is calculated based on lifetime extension, with the battery-only variation assumed to have a lifetime of 4 years, as explained in Section 4.3. The average lifetimes of all hybrid variations are provided in Table 5.

Table 5: Average of battery lifetime extension and lifetime across all frequency volatility scenarios and degradation profiles for different capacity ratios.

Capacity Ratio	0	0.1	0.2	0.3	0.4	0.5
Lifetime Extension (%)	0	160	270	360	440	560
Lifetime (years)	4	6.3	10.8	14.5	17.5	22.2

Figure 11 shows the NPV of each variation calculated with their respective extended lifetimes. Each curve bares resemblance to its counterpart in Figure 10. Despite the similarities, note the low percentage increase of NPV (maximum of 9%) in comparison to the higher degree of lifetime extension (greater than 600%).

The numerical values of NPV are unrealistic due to the assumptions made in this study, this is discussed in section 6.3. Nevertheless, the trends revealed by the analysis still provide valuable insights. Similarly to Figure 10, the trend observed in Figure 11

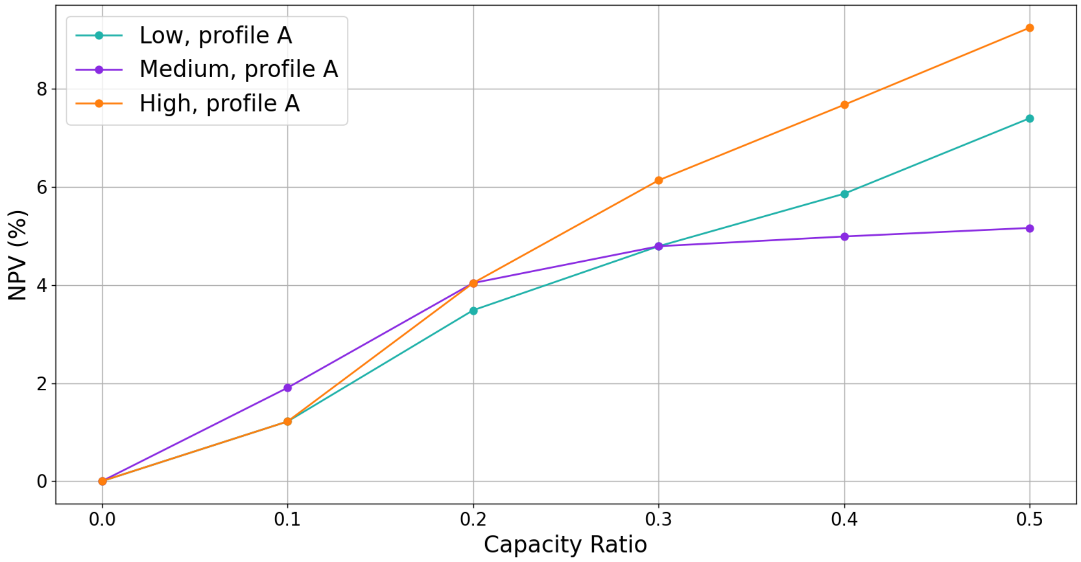

Figure 11: Normalised NPV based on lifetime extension for degradation profile A across all 3 frequency volatility scenarios. At low capacity ratios, the results are closely distributed, while they are more widely distributed at high capacity ratios.

is positive, and there is no immediate financial optimal solution evident solely based on capacity ratio. While the highest capacity ratios show the largest NPV values, it cannot be inferred that this is the optimal solution, as no greater capacity ratio are considered in this work.

The second similarity is that up to a capacity ratio of 0.2, the three scenarios are closely distributed. However, at higher capacity ratios, the results become more dispersed. The close distribution of results at low capacity ratios suggests that these outcomes are less dependent on the frequency volatility scenario used, indicating a higher degree of stability.

5.5 NPV: Enhancing bidding strategy

Figure 12 shows the normalised NPV through enhancing bidding strategy. Note, the y-axis values are not the same as Figure 11.

The results of NPV based on a bidding strategy in Figure 12 have a distribution 12 times greater compared to the NPV based on life extension in Figure 11. This is both in terms of different frequency volatility scenarios and battery degradation profiles. Figure 12 does not show the ever increasing trend present in other results. In some instances, as capacity ratio increases, NPV decreases. This is most visible in the medium scenario, where NPV decrease for 3 consecutive increases in capacity ratio. There seems to be no pattern at which an increase in capacity ratio leads to a decrease in NPV. This is behaviour is likely dependent on the specifics of each volatility scenario.

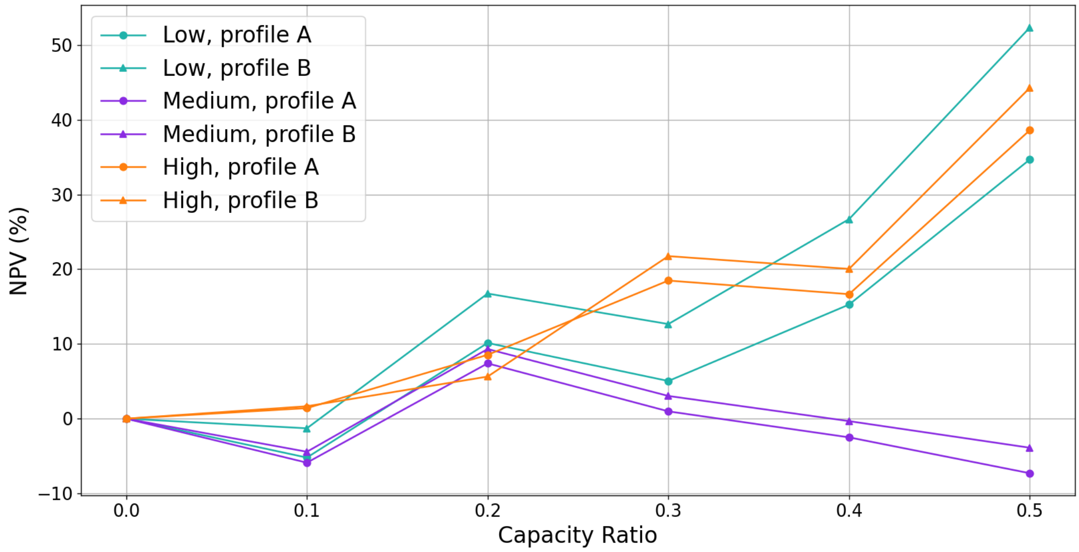

Figure 12: Normalised NPV based on enhancing bidding strategy for degradation profiles A and B across all 3 frequency volatility scenarios. Degradation profiles show greater discrepancy than usual and results are more distributed as capacity ratio increases.

The volatility can be seen again at a capacity ratio of 0.2, for the high scenario. The only instance in the work where the NPV of degradation profile A outperforms the NPV of profile B.

Despite the general increase in the volatility of results, one key trend is still present, however less pronounced. The results are more closely distributed at lower capacity ratios than they are at higher capacity ratios.

6 Discussion

This section delves into various methodological decisions, anomalous results and explores aspects of hybrid systems that extend beyond the direct results of the model. Some sections also discuss the potential for future work, which is discussed further in Section 8.

6.1 Methodology

In this work, several assumptions and modeling decisions are employed to simplify the complexities of real-world scenarios into a more manageable framework. While many of these assumptions are typical and realistic within the realm of energy storage modeling, certain aspects of the methodology are subjected to scrutiny in this section.

When calculating cyclic degradation in this study, only the start and end points of cycles are considered, neglecting the specific "path" of DoD throughout each cycle. This means that the charging or discharging C-rate, which impacts various degradation mechanisms including cyclic degradation ([52],[53]), is not accounted for.

The C-rate is exclusively controlled by grid frequency and thus varies proportionally to the frequency of the data sets. Resulting in variability across different frequency volatility scenarios. If C-rate were considered, it is likely that the high scenario would be influenced the strongest because of the relatively more volatile frequency. Taking the C-rate into account presents an opportunity for improvement of the battery degradation model and a greater understanding of how frequency affects the degradation of the battery within the context of a hybrid system.

Perhaps the most important aspect of this work which must be subject to scrutiny is regarding the frequency volatility scenarios. The frequency scenarios are not necessarily at the extremes which they seem to represent. Other hourly periods which are more extreme in their volatility could exist. Thus a short-coming of this work is not having a more structured methodology for selecting frequency volatility scenarios.

The importance of frequency volatility scenarios is underscored by their impact on hybrid system behaviour and results. Utilising a broader range of scenarios would have improved the insights of this work, enabling a more comprehensive analysis and identification of the specific factors influencing the results.

6.2 Cycle anomalies

This section discusses the anomalies that are found in Figure 6, where the typical trends are not adhered to. While it may be interesting to discuss how these anomalies occur, the impact on hybrid system performance in negligible.

One notable anomaly occurs in the low frequency volatility scenario, specifically between capacity ratios of 0.4 and 0.5, where the number of cycles unexpectedly increases. Figure 13 provides a detailed histogram of the cycle distributions. The negligible impact is emphasised by noting, despite the increase in number of cycles, the damage to the battery does in fact reduce by 23% as capacity ratio increases. This observation raises the question: How can more cycles result in less damage to the battery?

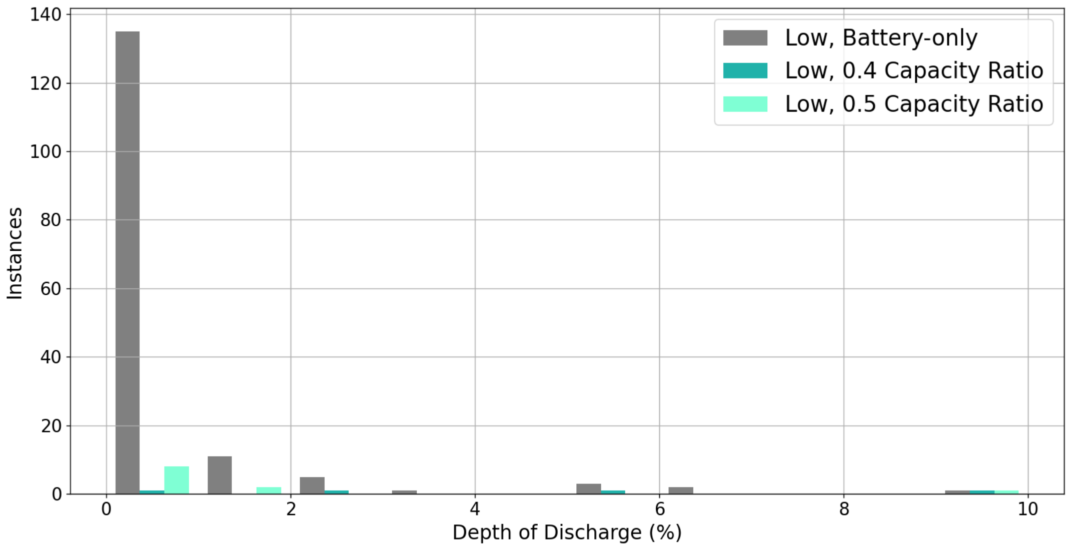

Figure 13: Comparison of cycle DoD distribution between the battery-only dispatch variation and hybrid variations of capacity ratios 0.4 and 0.5 with degradation profile A, for the low frequency volatility scenario. Showing unusual behaviour where a greater capacity ratio results in more cycles than a lower capacity ratio.

In Figure 13, there is a larger number of cycles observed for the variation with a larger capacity ratio. However, the greater number of cycles at 1% DoD causes a negligible amount of degradation, which can be misleading at first glance. Notably, cycles with greater DoD in the distribution, such as 5-6% DoD, are not present with a capacity ratio of 0.5, while they are present with a capacity ratio of 0.4. What the histogram of Figure 13 fails to highlight is that the cycles up to 1% DoD are in fact less than 0.25% DoD. This emphasises the insignificance of these cycles compared to a cycle between 5-6% DoD. Thus at a higher capacity ratio, despite having more total cycles, the damage to the battery is less.

Other similar instance are present in Figure 6. In the top two lines, the high frequency volatility scenario, at a capacity ratios of 0.2, degradation profiles A and B are no longer in the usual orientation where profile A has more cycles than B. In this instance, similarly to the previous one, the dispatch model allows multiple low DoD cycles for profile B which creates a misleading result.

If multiple frequency volatility scenarios were used for each categorisation of frequency volatility, it is unlikely that these irregularities would occur consistently at the same capacity ratios across different data sets. Using multiple scenarios would provide a broader range of scenarios and variations, which could help identify and understand the specific conditions or factors leading to irregularities in cycle behaviour at certain capacity ratios.

While these occurrences may be misleading, their impact is negligible when considering the results of the hybridisation goals and economics in Sections 5.3, 5.4

and 5.5. Furthermore, since the irregularities are distributed across the capacity ratio and frequency data sets, and no clear pattern has emerged, it suggests that there is not a significant flaw in the model.

6.3 Net Present Value

This section discusses the findings and assumptions of the NPV calculations of this work, as well as scrutinising select methodological decisions and developing ideas further. NPV on the basis of lifetime extension is considered first, followed by NPV on the basis of enhancing bidding strategy. In Section 6.4 it is discussed how the different approaches to calculating NPV can be applied to real-world application based on market price and economic risk.

While extending the lifetime of a battery to an average of 22.2 years may initially seem attractive due to the increased profit-generating potential, it is important to consider the practical limitations imposed by battery calendar degradation in real-world applications. In the case of lithium-ion batteries, where the expected calendar life is approximately 10 year, a lifetime extension of 22.2 years is not feasible. Irrespective of how the battery is used, a battery is no longer operational after 10 years. Thus the extra costs of the high capacity ratios are for nought.

Calendar degradation effectively sets an upper limit on the achievable lifetime extension. As the NPV calculation does not account for calendar degradation, the results are misleading. The maximum viable capacity ratio for a hybrid energy storage system is determined by the ability to extend the battery's lifetime up to its calendar degradation limit. Exceeding this limit would result in inefficient use of the flywheel storage assets, as the battery would degrade prematurely regardless of the presence of flywheels to mitigate cyclic degradation.

For the hybridisation goal of enhancing bidding strategy, this feasibility limit does not apply. Battery lifetime in the case of enhancing bidding strategy ranges between 1 and 4 years. With such short lifetimes, the calendar degradation does not have the same limiting effect. Thus higher capacity ratios are technically and economically feasible.

In the remained of this section, some assumptions and their repercussions are discussed which directly relate to the NPV calculations. Many of the NPV results are unrealistic due to the assumptions, despite this they do not entirely negate the insights that can be gained. Before applying these findings to practical applications, it is essential to scrutinise the insights derived from these assumptions within the context of a specific application.

It is worth noting that there are currently profitable batteries providing ancillary services [54], which suggests that a negative NPV should not be interpreted as an inherent sign of unprofitability for hybrid systems. Rather, it underscores the importance of refining assumptions and avoiding oversimplifications in economic models.

The key assumptions requiring scrutiny is the assumption that the NPV of the battery-only case is equal to 0. This assumption seems realistic at first, as profitable batteries exist and an NPV of 0 is a less strict requirement. The resulting annual profit is $700,000$ €, which is unrealistic for a system which can only bid 5MW in the FCR-N market. This high level of income is due to the high capital costs of the battery, which are assumed to be recouped in 4 years. Perhaps the combination of assuming a lifetime of 4 years and profitability is unrealistic.

A consequence of this assumption, is that normalisation is made more complex as dividing by the battery only NPV is not mathematically possible. Thus normalisation is done relative to the annual income, which skews the results. In part due to this assumption and the high cost of flywheels, the percentage NPV for lifetime extension is thus low, reaching a maximum of 9%.

NPV calculations made on the basis of enhancing bidding strategy are infeasible in real-world applications due to the assumption of perfect foresight. Even with this assumption, the simplistic bidding strategy used is insufficient to generate profitable results. The poor quality of the strategy is further emphasised by the need to increase Fingrid prices to facilitate the procurement of the battery-only variations. That is to say, the strategy does not lead to the procurement of the battery-only variations with unchanged Fingrid price data, as the operational costs are too high. The prices are increased in order to have the battery-only variations have an income, allowing the normalisation of other variations. It is only because the NPV is normalised, that flywheel potential is evident.

The simplistic assumption where; if an asset is procured, it is also deployed, is a major flaw in the strategy used in this work. This is unrealistic in real-world applications and gives a pessimistic result on economic performance.

A more effective bidding strategy would aim to be procured as frequently as possible while minimising deployments. This approach could increase profits and avoid unnecessary damage to storage assets. On the other hand, such an approach would deprive the system of energy fees, however this accounts for an average of 8.9% of total income across all variations and scenarios, thus the loss of energy related income is minor.

Bidding strategies must make a trade-off between operational frequency, revenue generation, and battery degradation, highlights the complexity of optimising bidding strategies for hybrid systems in energy markets. Balancing the benefits of increased market participation and revenue with the potential costs of accelerated battery degradation is a key consideration in designing effective and sustainable operational strategies. While this work serves to highlight the potential of flywheel hybridisation. Having appropriate and effect bidding strategies is crucial for the success of the system for real-world applications.

Finally, what both NPV calculation fail to take into account, is the residual value of flywheels once the battery's lifetime is exceeded. Even after the 10 years of maximum lithium battery life, a flywheel remains comfortably within its estimated operational lifetime. This opens up opportunities for the flywheel to be redeployed in combination with a new battery or other forms of energy storage. Essentially, the initial battery can serve to finance the high capital cost of the flywheels. Subsequently, future battery can benefit from the flywheel without incurring additional costs. If batteries are used in such a way that their lifetime is very short, e.g. enhancing bidding strategy, then many batteries can benefit from the same flywheels. Thus the NPVs calculated in this work do not fully exhaust the value of flywheels, but link the value of the flywheel to the life of a single battery.

6.4 Impact of market price

This section discusses how different hybridisation goals, lifetime extension vs enhancing bidding strategy are related to market prices. The prices of frequency regulation markets are crucial in determining if a system participating in that market can be profitable or not. Hu, Y., Armada, M., & Sanchez, M. J. noted that "Economic performance of battery systems should be considered as a derivative based on the clearing price of the local market." (p.2).

This core of this work explains how battery lifetime can be extended with a flywheel, generating long-term revenue. On the other hand, flywheels can be used to increase short-term revenue by method of a bidding strategy with decreased operational costs. This begs the questions: Under which conditions is it preferable to extend the life of the battery? Alternatively, when is it preferable to accept a shorter lifetime in favour of enhancing bidding strategy?

The decision between extending battery life and prioritising short-term profitability is fundamentally a risk assessment rather than solely a matter of market price. If there is an expectation of future market price increases, the system stands to be more profitable in the long run. In such scenarios, it may be prudent to accept the associated risks and leverage flywheels to extend the battery's lifetime, aiming to capture higher profits down the line.

On the other hand, if the risk is significant, indicating that prices are unlikely to increase or may even decrease, a HESS owner should choose to maximise their output in the short term when prices are less uncertain. This approach helps mitigate their risk by "using" the battery's lifetime during a period with potentially higher prices, optimising profitability within a more predictable market environment.

In general, high prices make it easier for ancillary service providers to recoup their operational costs, potentially attracting more parties to the frequency regulation markets and expanding a TSO's resource pool while increasing competition. As market prices rise and competition intensifies, strategies to reduce operational costs to facilitate more frequent procurement or increase profit margins become increasingly valuable. In which case using flywheels to enhance bidding strategy is preferable to extending lifetime.

6.5 Flywheel Control

This section discusses the importance of flywheel control strategies that can be used in real-world applications. This work analyses the potential of flywheels using unrealistic assumptions which are interesting from a technical standpoint, however make it difficult to apply findings to real-world cases.

Effective control of the flywheel is fundamental to the success of a hybrid energy storage system. Control strategies for flywheels can vary widely in terms of complexity, ranging from simplistic to more sophisticated approaches.

One of the simplest control strategies involves providing the requested power, provided it falls within the capabilities of the flywheel. If the requested power exceeds the flywheel's capacity, the flywheel delivers its maximum power output.

While straightforward, this basic strategy can be effective in certain applications where power demands are relatively stable and predictable. However, it may not fully leverage the potential benefits of flywheel technology, particularly in dynamic and variable grid conditions. The flywheel's SoC can rapidly reach its limit, temporarily limiting its ability to support the battery until its charging direction changes again.

More advanced control strategies can involve predictive algorithms that anticipate power demands based on historical data and real-time grid conditions. These strategies aim to optimise the operation of the hybrid system by intelligently managing the interactions between the battery and flywheel components.

For example, the "rolling average" approach, takes the average battery power requirements from the previous "x" seconds into account. Considering the difference between the required battery power and the rolling average of battery power, the flywheel can be controlled to compensate the difference. This more nuanced approach would reduce how often the flywheels become limited by SoC, thereby increasing activation time and energy throughput.

Implementing control strategies that incorporate detailed information about SoC, reaction times, and degradation characteristics of energy storage technologies could enhance system performance. However, these strategies would require sophisticated algorithms and rapid computational capabilities to make real-time decisions effectively.

The complexity of control strategies is often constrained by the speed at which calculations can be performed to control energy storage assets on the grid. Balancing the need for detailed optimisation with real-time responsiveness is a key challenge in developing advanced control approaches for hybrid systems.

6.6 Different markets

This analysis of this work exclusively considers the FCR-N market, however, in real world applications hybrid system are applicable in other markets as well, e.g. the FRR market. Hybrid systems could take part in the FRR market, however their effectiveness would be dependent on how the storage asset is registered within the Fingrid system.

One could consider the hybrid system as a single storage asset. In which case the flywheel would have little added benefit because Fingrid only allows a storage asset to participate in a single market for each hour. The result of this is that the added benefit of the flywheel is the minor increase in energy capacity. This is ill-advised, as the low energy capacity is a key short-coming of flywheel technology.

The benefit of hybrid systems registered as one storage asset is that an element of flexibility is gained. The system is able to operate in multiple markets for different hours, while also providing the benefits of lifetime extension or enhancing bidding strategy. This integration allows for more dynamic and versatile operation in the energy markets.

Alternatively, registering the two storage assets as separate units within the Fingrid system offers the advantage of allowing both assets to bid in separate markets during the same hour, thereby generating more revenue. Simultaneously, the flywheel can still offer support to the battery, enhancing the overall flexibility and revenue potential of the hybrid system. This strategy optimises the utilisation of both the battery and flywheel across different market opportunities while maintaining operational synergy between the two assets.

One approach is to bid flywheel capacity in the FFR markets and battery capacity in the FCR-N market. Given the infrequent deployment of the FFR market the flywheel is likely to be idle often, the flywheel can then support the battery in providing FCR-N, thus reducing potential damage. In the event of an FFR deployment, the flywheel can prioritise FFR support while the battery continues providing FCR-N support, accepting any damages to the battery. Typically, FFR deployments are short-lived, so the flywheels are rarely unavailable and thus any impacts on the battery are minimal.

There is a risk that the flywheel's SoC may not support the necessary power output for the FFR market, potentially resulting in sanctions. However, due to the rarity and relatively low market value of FFR deployments, any sanctions incurred would be infrequent and low-cost compared to the FCR-N market. While the revenue from the FFR market may not be substantial, this strategy offers additional income with occasional, minor impacts on battery health. This approach is characterized as low-risk with low return potential.

A more complex strategy involves combining the FCR-N market and the aFRR markets, which typically offer higher value compared to the FFR market. In this approach, a large share of flywheels is needed such that approximately 80% of energy throughput of the FCR-N bid is handled by the flywheels. With the large share of flywheel providing the majority of FCR-N support, the battery is thus free to provide aFRR support.

The issue of limited energy capacity still remains, as even numerous flywheels are not able to provide power for long enough to qualify for FCR-N. The hybrid system must be registered to Fingrid as a single unit to participate in FCR-N. The current regulations would therefore not allow this strategy, as a single asset would be participating in multiple market simultaneously. If the regulations were to change, such a strategy would be high risk high reward as the market values and procurement rates of both FCR-N and aFRR are high.

Expanding beyond frequency regulation markets, a multi-market approach can involve combining FCR-N with time-shifting in the Day Ahead Market (DAM). Under 2023 regulations, FCR-N and time-shifting can operate concurrently. In this scenario, flywheels predominantly provide the FCR-N support, while the battery handles time-shifting in the DAM. During instances of large cycles in FCR-N, the battery can either step in to provide support or accept sanctions, depending on the profitability of each option.

To mitigate the risk of sanctions, a battery control strategy can be implemented to maintain the SoC within a specified band. This involves reserving a portion of the battery's energy capacity to provide support during larger FCR-N cycles. Implementing such a strategy requires conducting a cost-benefit analysis to determine the optimal threshold for the SoC band.

Adding time-shifting capabilities to a hybrid storage system introduces complexity and risk, especially considering Fingrid's requirement for the SoC to be near 50% before starting support. If the battery is charged and waiting to discharge at a later time, its SoC will be higher than the regulation threshold. The asset may not be allowed to provide support, or accept sanctions if insufficient support can be provided.

To address this issue, one potential solution is to integrate the hybrid storage system with a renewable energy generation source such as wind or solar. By combining storage with generation, the system can avoid the more stringent requirements of the LER classification imposed by Fingrid regarding ancillary markets. This integration provides operational flexibility and opens up opportunities for maximising revenue through energy time-shifting. This approach is not universally applicable due to the availability of generation sources. On the other hand, the regulations associated with a generation source could also add complexity. Further investigation is needed in this area.

Fingrid's regulations influence the viability of different business cases and the future outlook for ancillary services. Under current regulations that prohibit multi-market approaches, each individual market must possess a sufficiently large resource pool to meet its own demands. While this approach may appear logical, although conservative, from Fingrid's standpoint, it could result in an oversized and inefficient system where assets experience unnecessary idle periods.

The objective of decentralised markets is to establish an efficient energy system. Allowing participation in multiple markets could enhance efficiency by reducing idle time but introduces more risk. Fingrid can communicate this risk through the sanction system by adjusting multiplication factors accordingly. This approach incentivises service providers to deliver the support they are contracted for.

By setting sanctions at levels that accurately reflect the risk to the grid, Fingrid can empower service providers to make decisions about participating in multiple markets based on the associated risks and rewards. If regulations are effectively adapted, the inefficiencies of an oversized system would be reduced. Furthermore, the value of hybrid systems would become greater than the sum of its parts, where each storage asset can work individually but also in harmony.

The opportunities for multi-market business cases for hybrid systems are currently limited by regulations, but there are some approaches that can be applied to leverage the benefits of combined flywheel and battery storage assets. To effectively implement these business cases, it is essential to develop appropriate bidding strategies and hybrid control systems that consider the associated risks, market regulations and the specific characteristics of each storage asset.

7 Conclusions

Due to the strong similarities in results between the two battery degradation profiles, the following conclusion can be made. When exclusively considering cyclic degradation, the specific profile has a minor impact on the optimal dispatch of the hybrid system. While occasionally differences arise due to battery degradation profile, their impact is negligible on the performance of hybrid systems.

At low capacity ratios, up to 0.2, lifetime extension and NPV are less dependent on frequency volatility scenario compared to higher ratios, with results being more closely distributed. Low capacity ratios are thus recommended as they are likely to be more stable in their results in the face of unpredictable and volatile grid frequency. A greater stability makes low capacity ratios more predictable, reducing long-term economic risk.

Flywheels can extend the lifetimes of batteries used in ancillary services to the point where cyclic degradation is no longer the primary concern, shifting the limiting factor to other factors such as calendar degradation. Alternatively, flywheels can reduce the operating costs of batteries in ancillary services, however performance is limited by the quality of bidding strategy.

The recommended capacity ratio for this work is 0.2. Such a ratio falls within the ranges defined by calendar degradation and by reducing economic risk. With a capacity ratio of 0.2, lifetime is extended by a factor of 2.7, leading to an average 3.9% increase in NPV. When flywheel enhance bidding strategy, NPV is increased by an average of 9.6%. Flywheel hybridisation of batteries has potential across a variety of business cases, where the interaction between flywheel and battery allows the value of a hybrid system to be greater than the sum of its parts. It is important to note that this work is an optimisation and serves as a suggestion. The manner in which results are interpreted and the goals of a given party can impact what one might consider "optimal".

8 Future work

To better understand flywheel-battery hybrid energy storage in ancillary markets, research can be divided into two primary directions. First, improving the understanding of the maximum potential of hybrid systems. Second, developing practical insights for applying hybrid systems in real-world applications.

One key area warranting further investigation is the impact of grid frequency on hybrid energy storage systems. The behaviour of different grid frequency scenarios cannot be simply predicted by the term "volatility," as this study's results do not yield strong conclusions. Instead, the relationship is more complex and demands greater attention. To better understand the impact of grid frequency, more specific characteristics should be investigated, such as; the peak power of cycles, the number of cycles and the average energy requirement of cycles. Examining these characteristics will provide a more detailed insight into the impact of grid frequency.

To further understand the impact of flywheels, it is essential to dedicate more attention to batteries as well. Developing a more in-depth degradation model would enhance the accuracy of the findings. For instance, considering the entire charging behaviour and additional degradation factors such as C-rate, as discussed in Section 6.1, would provide a more comprehensive analysis. Additionally, investigating different battery chemistries could reveal which types stand to gain the most from flywheel hybridisation.

Investigating hybrid systems over a longer time frame could also yield interesting results. Extending the time frame of analysis may uncover scenarios that are currently unaccounted for, potentially revealing new pitfalls or opportunities for flywheel hybridisation

Understanding how flywheel-battery hybrid systems can be applied in real-world applications is an essential area of investigation. Successful application depends on having effective control systems in place, not only for managing the interaction between the two storage technologies but also for optimising their participation in ancillary markets.

One could investigate different flywheel control strategies, as outlined in Section 6.5, to understand how to best support the battery under various conditions for the hybridisation goal of lifetime extension. Ensuring effective use and maximising the value of each storage technology.

Finally, future work on bidding strategies for hybrid systems is essential. Strategies applicable across multiple markets are likely more valuable and thus merit deeper investigation compared to those confined to a single market. The relationship between flywheel control and bidding strategies adds complexity, making their investigation challenging. Leveraging AI capabilities could potentially enhance this research. Regardless, it is crucial to explore these control strategies comprehensively to ensure the successful implementation of flywheel-battery hybrid energy storage systems in ancillary markets.

References

[1] Gross, R., Heptonstall, P., Leach, M., Anderson, D., Green, T., & Skea, J. (2007). Renewables and the grid: Understanding intermittency. Proceedings of the Institution of Civil Engineers - Energy, 160(1), 31-41.

[2] Abnett, K. (2023, September 20). Europe's power industry warns ageing grids risk green goals. Reuters. Retrieved May 4, 2024 `https://www.reuters.com/world/europe/europes-power-industry-warns-ageing-grids-risk-green-goals-2023-09-20/`

[3] United Nations. (2023). Goal 7: Ensure access to affordable, reliable, sustainable and modern energy for all. Retrieved May 4, 2024, from `https://sdgs.un.org/goals/goal7`

[4] Hu, Y., Armada, M., & Sanchez, M. J. (2022). Potential utilization of battery energy storage systems (BESS) in the major European electricity markets. Applied Energy, 322.

[5] Fingrid. (n.d.). Reserves and balancing power. Retrieved May 4, 2024, from `https://www.fingrid.fi/en/electricity-market/reserves_and_balancing/`

[6] DNV. (2023). Energy Transition Outlook. Retrieved May 4, 2024

[7] Zsiboracs, H., Baranyai, N. H., Vincze, A., Zentko, L., Birkner, Z., Mate, K., et al. (2019). Intermittent renewable energy sources: The role of energy storage in the European power system of 2040. Electronics, 8(7), 729.

[8] Liu, C., Ma, H., Zhang, H., Shi, X., & Shi, F. (2023). A MILP-Based Battery Degradation Model for Economic Scheduling of Power System. IEEE Transactions on Sustainable Energy, 14(2).

[9] Association of European Automotive and Industrial Battery Manufacturers. (2013). Battery Energy Storage for Smart Grid Applications. Brussels.

[10] Meng, L., et al. (2020). Fast Frequency Response From Energy Storage Systems—A Review of Grid Standards, Projects and Technical Issues. IEEE Transactions on Smart Grid, 11(2), 1566-1581.

[11] Hameed, Z., Træholt, C., & Hashemi, S. (2023). Investigating the participation of battery energy storage systems in the Nordic ancillary services markets from a business perspective. Journal of Energy Storage, 58, 106464.

[12] Teraloop. (n.d.). Retrieved May 4, 2024, from https://www.teraloop.org

[13] Awadallah, M. A., & Venkatesh, B. (2015). Energy Storage in Flywheels: An Overview. Canadian Journal of Electrical and Computer Engineering, 38(2), 183-193.

[14] Xu, B., Oudalov, A., Ulbig, A., Andersson, G., & Kirschen, D. S. (2018). Modeling of Lithium-Ion Battery Degradation for Cell Life Assessment. IEEE Transactions on Smart Grid, 9(2), 1131-1140.

[15] Argiolas, L., Stecca, M., Ramirez-Elizondo, L. M., Soeiro, T. B., & Bauer, P. (2022). Optimal Battery Energy Storage Dispatch in Energy and Frequency Regulation Markets While Peak Shaving an EV Fast Charging Station. IEEE Open Access Journal of Power and Energy, 9, 374-385.

[16] Peters, J. F., Baumann, M., Zimmermann, B., Braun, J., & Weil, M. (2017). The environmental impact of Li-Ion batteries and the role of key parameters – A review. Renewable and Sustainable Energy Reviews, 67,.

[17] Li, J., Gee, A. M., Zhang, M., & Yuan, W. (2015). Analysis of battery lifetime extension in a SMES-battery hybrid energy storage system using a novel battery lifetime model. Energy, 86, 175-185.

[18] European Commission. (2021). Raw Material Information System. Battery supply chain challenges.

[19] APM Research Lab. (2024). Lithium mining for EVs: How sustainable is it? Retrieved May 4, 2024, from https://www.apmresearchlab.org/10x/lithium-mining-for-evs-sustainability.

[20] MIT Climate Portal. (2022). How much CO2 is emitted by manufacturing batteries? Retrieved May 4, 2024, from https://climate.mit.edu/ask-mit/how-much-co2-emitted-manufacturingbatteries#:~:text=CO2%20emissions%20for%20manufacturing,kg%20(16%20metric%20tons).

[21] Zhang, P., Liang, J., & Zhang, F. (2017). An Overview of Different Approaches for Battery Lifetime Prediction. IOP Conference Series: Materials Science and Engineering.

[22] Astero, P., & Evens, C. (2020). Optimum operation of battery storage system in frequency containment reserves markets. IEEE Transactions on Smart Grid, 11(6), 4906-4915.

[23] Mohammad Amini, Mohammad Hassan Nazari, Seyed Hossein Hosseinian, Optimal energy management of battery with high wind energy penetration: A comprehensive linear battery degradation cost model, Sustainable Cities and Society, Volume 93, 2023, 104492, ISSN 2210-6707

[24] Oliveira, D. B. S., Glória, L. L., Kraemer, R. A. S., & Silva, A. C. (2022). Mixed-Integer Linear Programming Model to Assess Lithium-Ion Battery Degradation Cost. Energies, 15(6), 3060.

[25] Fingrid. (n.d.). Reserve market information. Fingrid. Retrieved May 4, 2024,from https://www.fingrid.fi/en/electricity-market-information/reserve-market-information/

[26] Fingrid Oyj. (2023). Terms and conditions for providers of Fast Frequency Reserves (FFR).

[27] Fingrid Oyj. (2023). Terms and conditions for providers of Frequency Containment Reserves (FCR).

[28] Fingrid Oyj. (2023). Terms and conditions for providers of manual Frequency Restoration Reserves (mFRR).

[29] Fingrid Oyj. (2019). Technical requirements and prequalification process for the Manual Frequency Restoration Reserve (mFRR).

[30] Colthorpe, A. (2023). LFP cell average falls below US$100/kWh as battery pack prices drop to record low in 2023. Energy Storage News. Retrieved May 4, 2024, from https://www.energy-storage.news/lfp-cell-average-falls-below-us100-kwh-as-battery-pack-prices-drop-to-record-low-in-2023/

[31] Choudhury S. Flywheel energy storage systems: A critical review on technologies, applications, and future prospects. Int Trans Electr Energ Syst. 2021; 31(9):e13024.

[32] Elena M. Krieger, John Cannarella, Craig B. Arnold, A comparison of lead-acid and lithium-based battery behavior and capacity fade in off-grid renewable charging applications, Energy,60, 2013,492-500,

[33] Pelletier, S., Jabali, O., Laporte, G., & Veneroni, M. (2017). Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models. Transportation Research Part B: Methodological, 103, 158-187.

[34] Stroe, D. I., Swierczynski, M., Stroe, A. I., Laerke, R., Kjaer, P. C., & Teodorescu, R. (2016). Degradation behavior of lithium-ion batteries based on lifetime models and field measured frequency regulation mission profile. IEEE Transactions on Industry Applications, 52(6), 5009–5018.

[35] Niu, Y., & Santoso, S. (2016). Sizing and coordinating fast- and slow-response energy storage systems to mitigate hourly wind power variations. IEEE Transactions on Smart Grid, 9(2), 1107–1117.

[36] Moghaddam, I. N., Chowdhury, B. H., & Mohajeryami, S. (2017). Predictive operation and optimal sizing of battery energy storage with high wind energy penetration. IEEE Transactions on Industrial Electronics, 65(8), 6686–6695.Tpll

[37] EG Solar. (n.d.). What makes it so special on using Lithium ion LFP battery for Solar Energy Storage. Retrieved May 4, 2024, from https://osmbattery.com/faq-items/what-makes-it-so-special-on-using-lithium-ion-lfp-battery-for-solar-energy-storage/

[38] Yang, Y., Ye, Y., Cheng, Z., Ruan, G., Lu, Q., Wang, X., & Zhong, H. (2023). Life cycle economic viability analysis of battery storage in electricity market. Journal of Energy Storage, 70.

[39] Murray, C. (2022). Do LFP battery systems deliver lower returns than NMC ones? Energy Storage News. Retrieved May 4, 2024, from `https://www.energy-storage.news/do-lfp-battery-systems-deliver-lower-returns-than-nmc-ones/`

[40] Esparcia, E. A., Castro, M. T., Odulio, C. M. F., & Ocon, J. D. (2022). A stochastic techno-economic comparison of generation-integrated long duration flywheel, lithium-ion battery, and lead-acid battery energy storage technologies for isolated microgrid applications. Journal of Energy Storage, 52(A), 104681.

[41] M. M., Bhaskar, D. V., Krishan, R., Krishnan, J. R., & Reddy, N. (2020). Lifetime enhancement of Li-Ion batteries used for ancillary services. In 2020 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES) (pp. 1-5). Jaipur, India.

[42] Cheng, Y., Jiang, B., Han, X., & Wang, Z. (2019). A life prediction model of flywheel systems using stochastic hybrid automaton. Electronics, 8, 1236.

[43] Luo, X., Wang, J., Dooner, M., & Clarke, J. (2015). Overview of current development in electrical energy storage technologies and the application potential in power system operation. Applied Energy, 137, 511-536.

[44] Zhang, F., Tokombayev, M., Song, Y., & Gross, G. (2014). Effective flywheel energy storage (FES) offer strategies for frequency regulation service provision. In 2014 Power Systems Computation Conference (pp. 1-7). Wroclaw, Poland.

[45] Khaterchi, M., Belhadj, J., & Elleuch, M. (2010). Participation of direct drive Wind Turbine to the grid ancillary services using a Flywheel Energy Storage System. In Proceedings of the conference (pp. 1-6).

[46] Lu, N., et al. (2010). Evaluation of the flywheel potential for providing regulation service in California. In Proceedings of the IEEE PES General Meeting (pp. 1-6). Minneapolis, MN, USA.

[47] Goris, F., & Severson, E. L. (2018). A review of flywheel energy storage systems for grid application. In Proceedings of IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society (pp. 1633-1639). Washington, DC, USA.

[48] Bahloul, M., & Khadem, S. K. (2019). Impact of power sharing method on battery life extension in HESS for grid ancillary services. IEEE Transactions on Energy Conversion, 34(3), 1317-1327.

[49] Barelli, L., Bidini, G., Bonucci, F., Castellini, L., Fratini, A., Gallorini, F., & Zuccari, A. (2019). Flywheel hybridization to improve battery life in energy storage systems coupled to RES plants. Energy, 173, 937-950.

[50] Stoker, L. (2017). New UK company Eelpower commissions first 10MWh battery on path to 'battery energy storage utility'. Energy Storage News. Retrieved May 4, 2024, from https://www.energy-storage.news/new-uk-company-eelpower-commissions-first-10mwh-battery-on-path-to-battery-energy-storage-utility/

[51] Núñez, F., Canca, D., & Arcos-Vargas, Á. (2022). An assessment of European electricity arbitrage using storage systems. Energy, 242, 122916.

[52] Wong, D. N., Wetz, D. A., Mansour, A. M., & Heinzel, J. M. (2015). The influence of high C rate pulsed discharge on lithium-ion battery cell degradation. In 2015 IEEE Pulsed Power Conference (PPC) (pp. 1-6). Austin, TX, USA.

[53] Seo, G., Ha, J., Kim, M., Park, J., Lee, J., Park, E., Bong, S., Lee, K., Kwon, S. J., Moon, S.-P., Choi, J., & Lee, J. (2022). Rapid determination of lithium-ion battery degradation: High C-rate LAM and calculated limiting LLI. Journal of Energy Chemistry, 67, 663-671

[54] Colthorpe, A. (2022). Batteries earn big in European ancillary services, but investors warned of high expectations. Energy Storage News. Retrieved May 4, 2024, from https://www.energy-storage.news/batteries-earn-big-in-european-ancillary-services-but-investors-warned-of-high-expectations/