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The implications of battery integration for variable renewables in the Australian national electricity market

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Abstract

Renewable projects in Australia have depended on Power Purchase Agreements (PPAs) or Contracts-for-Differences (CFDs) to manage merchant risk and to guarantee revenue certainty. This study investigates to what extent lithium-ion batteries can be a substitute to CFDs and PPAs for a developer of a merchant wind farm portfolio in Australia's National Electricity Market (NEM). By developing technical and financial models, the study explores the optimal performance of the integrated portfolio in the energy, derivatives (hedge), and Frequency Control Ancillary Services (FCAS) markets. Additionally, it evaluates how battery power and energy capacities impact the cash flow of a hypothetical wind farm portfolio across diverse scenarios encompassing two battery power capacity alternatives: 25 MW and 50 MW, each with two different storage durations: 2 and 4 hours. The results show that a merchant wind farm portfolio suffers from a missing money problem, but the combined portfolio can offset this issue and under scenarios with 50MW power capacity, lead to positive net present values (NPV) over the adjusted free cash flow of the portfolio. Thus, batteries can be a viable alternative to PPAs and CFDs.

Key words: Merchant Renewables, Revenue Certainty, Lithium-ion Battery, Optimal Performance

JEL codes: C61, L22, P28, Q40

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1. Introduction

Decarbonisation targets and radical reductions in renewable generation cost have contributed to an increasing amount of intermittent renewable electricity generation (e.g. Gohdes et al., 2022). In Australia, the dominating way to handle the merchant risk involved in renewable projects has been for electricity retailers and governments to offer Power Purchase Agreements (PPAs) and Contracts-for-Differences (CFDs).[2] From 2016 to 2022, investors committed to 149 variable renewable energy (VRE) projects worth approximately $37.7 billion,[3] totalling 19,275 MW of generation capacity (Simshauser, 2020; Simshauser and Gilmore, 2022; Gohdes et al., 2023). About 80% of new VRE projects were underwritten by a PPA, with the remaining 20% almost completely 'merchant' (ibid).[4]

Corporate energy users use PPAs as a mechanism to achieve their sustainability goals while maintaining price security and visibility of their future energy expenses. However, the rapid expansion of renewable energy has led to illiquidity and intense competition in that market (Simshauser, 2020). Currently, a strong uptake in government-initiated CFDs has been observed and that has created new problems, such as unintended impacts on power systems' financial markets and economic inefficiency more generally (Simshauser, 2019; Antweiler, 2021). Simshauser (2019) examines an energy-only gross pool modelled with rising levels of off-market government-initiated CFDs, with a specific focus on spot and forward contract market outcomes. Model results show that as VRE plant enters and coal plant exit in-market firm hedge contracts are progressively replaced by off-market CFDs. This can lead to shortages of "primary issuance" hedge contracts in the forward market. This suggests that a broad program of government CFDs may not be compatible with an energy-only market design. Antweiler (2021) indicates that when intermittent power producers receive fixed feed-in-tariffs (FIT), they will continue to bid into the market just above the negative value of the FIT and still make a profit. This mechanism can lead to negative market prices that are economically inefficient. Thus, given these developments, an important question in Australia is whether the decarbonisation journey can continue at required speed without relying on government-initiated CFDs or PPAs.

A key challenge faced by developers of merchant renewable projects is raising capital at a favourable rate. Like other investments, the capital cost hinges significantly on future revenue certainty. With reduced availability of PPAs it is necessary to find alternative long-term solutions to enhance revenue certainty of these projects. To evaluate the impact of firming capacity, Simshauser (2020) examined a merchant gas turbine, merchant wind plant, and an integrated portfolio comprising both plants employed in the NEM's South Australian region. The modelling sequence shows that stand-alone gas turbine valuation metrics suffer from modest levels of missing money, that merchant wind farm can commit to some level of forward (fixed volume) swap contracts in-spite of intermittent production, but the combined portfolio improves overall valuation metrics (present value of future revenues) significantly.

[2] In line with obligations under Australia's large-scale Renewable Energy Target (RET),[2] government-initiated Power Purchase Agreements (PPAs) and Contract for Differences (CfDs) have been driving Australia's energy transition towards increasing penetration of renewable generations (Gohdes et al., 2023).
[3] In this study all dollar amounts refer to Australian dollars (AUD).
[4] Gohdes et al. (2023) examine how and why the semi-merchant investment model has arisen along with the minimum contracted coverage for bankable project financing. Results reveal that, for investors with a target of 60–65% debt within the capital structure, a revenue mix comprising 73–78% PPA coverage (and 22–27% merchant plant exposure) is viable and a tractable project financing.

Recently, grid-scale battery storage has emerged as a potential solution for stabilising intermittent renewable energy generations.[5] Flottmann et al. (2022) compare an open-cycle gas turbine (OCGT) and a battery as firming options for a hypothetical wind farm in the South Australian region of the NEM by using historic market data from 2010–2020. It suggests that if only one generator could be chosen for firming, the OCGT represents the optimal choice.[6] The authors (ibid.) also note that the speed and flexibility of batteries are distinct advantages, but they do not quantify those advantages. For FCAS revenue, they assume the battery could achieve 60% of the total target revenues from participating in the FCAS market but no specific modelling of the FCAS market was implemented.

Naemi et al. (2022) examine the optimal performance of a wind farm and an integrated battery storage system in Victoria (part of the NEM). They determine the optimal values of the battery's technical parameters for the wind farm-battery system with battery operating in the energy market only, by maximising the Net Present Value (NPV). The result suggests that the optimal battery has a capacity of 5–10 MWh and 5–8 MW. The model then assumes that the battery is limited to providing only FCAS services under varying capital costs and FCAS price scenarios. The model is based on data up to 2017 and does not consider the hedging contracts and co-optimisation across different battery revenue streams.

To analyse the impact of a battery on the financial performance of an integrated portfolio, it is necessary to maximise the battery's profit over its entire lifetime, using realistic operating conditions. In this study we evaluate wind-battery combinations across all the associated markets in the NEM including energy, derivatives (hedge), and FCAS markets.

More specifically, this study compares the performance of two different portfolios. The first is a merchant wind farm portfolio that utilises futures contracts as a hedge tool, and the second portfolio adds batteries to the mix. Four different battery configurations are considered, each with varying amounts of power and energy capacity. Modigliani and Miller's (1958) theorem is applied to isolate the operational aspects from financing decisions. By calculating the adjusted free cash flow, we are able to compare the two portfolios. An optimisation model is employed to determine the battery's behaviour under the arbitrage strategy and in the provision of frequency services, optimising ten decision variables related to battery performance in both the energy and FCAS markets, while accounting for various technical and financial constraints. The wind farm performance and optimisation model are implemented using the MATLAB software and the optimisation is a Mixed Integer Linear Programming (MILP) approach. The model assumes perfect foresight of day-ahead prices, with the wind farm and battery acting as price-takers in both the energy and eight FCAS markets, all within the context of a project located in South Australia operating under a 5-minute market settlement. The novel aspect of this modelling is the ability to simultaneously evaluate the portfolio 's performance across all relevant markets within the NEM (i.e. Energy, Derivatives and FCAS).

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[5] According to Malhotra et al. (2016), the reasons for the popularity of batteries are their (i) rapid response capabilities, (ii) sustained power delivery, (iii) geographical independence, (iv) fast deployment timeline, and (v) a decreasing trend in technology costs.

[6] The authors indicate that in October 2021, after the completion of the research, the NEM has moved from a 30-minute settlement to a 5-minute settlement. Given this change, the use of 30-minute settlement data may mean the outputs will be different from the future cases under 5-minute settlement.

Building on the existing literature, particularly the studies conducted within the Australian context by Simshauser (2020), Flottmann et al. (2022), and Naemi et al. (2022), this research not only extends their findings but also contributes by addressing gaps in the literature through several innovative methodological approaches. First, this study substitutes conventional gas turbines with Lithium-ion batteries as firming capacity for a merchant wind farm within the NEM. To achieve this, a comprehensive model is developed that encompasses both the technical and financial aspects of grid-scale batteries in energy and frequency services markets. Second, it targets gaps identified in Flottmann et al. (2022) and Naemi et al. (2022), this research evaluates the cashflow of an integrated portfolio of renewable and batteries, as well as the optimal performance of batteries across multiple associated markets—Energy, Derivatives, and Frequency Control Ancillary Services (FCAS)—simultaneously. This approach can provide a holistic view of the feasibility of these integrated portfolios. Third, the updated 5-minute price settlement intervals implemented in the NEM in October 2021, replaces the 30-minute intervals used in the previous literature. The data used in this study is the same as that used for actual financial settlements, ensuring that the analysis accurately reflects real market dynamics and makes the results more relevant. Forth, a new dimension is introduced in this research by examining the impact of battery power and energy capacity—two critical factors—on the costs and benefits of a VRE portfolio. This analysis is particularly valuable for developers of renewable and battery projects, offering insights that support informed decision-making regarding the integration of batteries into their portfolios.

The results indicate that the portfolio without battery experiences a 'missing money' problem due to its high capital costs, intermittent generation, and merit order effects. Although futures contracts can enhance revenue certainty, they may also cause periods of intense negative pricing during certain months, underscoring the need for a dynamic strategy to manage these contracts effectively and the application of firming capacity. Integrating a battery into the portfolio significantly mitigates the missing money issue across all scenarios. However, this integration does not necessarily result in a positive net present value (NPV) over the adjusted free cash flow, highlighting the critical importance of making informed decisions when selecting the appropriate battery configuration for VRE projects. Notably, by considering four different scenarios that encompass two battery power capacity alternatives: 25 MW and 50 MW, each with two different storage durations: 2 and 4 hours (energy capacity), it is observed that scenarios with higher power capacity can fully address the missing money problem, and lead to a positive NPV. Additionally, this paper finds that battery integration enables the wind farm to increase its exposure to futures contracts, which can be beneficial in enhancing liquidity in this market. We recommend that renewable project developers implement an operational model for battery integration before making any decisions. This approach will help them select the optimal battery configuration by considering market dynamics, regulatory factors, the full potential revenue streams of the entire portfolio, costs, risks, and any other constraints that may impact their project.

The article is structured as follows. Section 2 describes the existing literature in more detail and the institutional setting, focusing on Australia. Section 3 outlines the modelling framework. Section 4 presents the optimisation model. Section 5 analyses the results of the modelling and Section 6 provides a discussion of conclusions and policy implications.

2. Background

2.1. Firming renewables: insights from the Australian National Electricity Market (NEM)

Electricity generated in eastern and southern Australia is traded through the NEM, covering Queensland, New South Wales (including the ACT), Victoria, South Australia, and Tasmania. Alongside physical electricity trade, derivative markets for futures and options provide participants with tools to hedge against price fluctuations and make strategic decisions in the dynamic electricity market. The FCAS market is also crucial for maintaining system stability and reliability.

The reduced availability of PPAs, coupled with declining renewable plant costs and high spot market prices in the NEM, has driven many VRE projects to enter the market on a merchant or semi-merchant basis. Merchant plants sell their output into the spot market and hedge price risk using forward markets (Simshauser, 2020), but derivative contracts like forward swaps or futures pose significant risks as they are cash-settled at fixed volumes, unlike PPAs (Flottmann et al., 2022). Developers of these projects face market price volatility and intermittent production, impacting revenue predictability. However, effective management of these risks can lead to potential premiums and higher profitability during price spikes. Flottmann et al. (2022) notes that while some level of hedging is necessary, merchant intermittent generators in an energy-only market with high price caps also need firming capacity to manage spot price exposures.

The rise in wind and solar generation is increasing volatility in supply and demand, leading to dynamic spot market price fluctuations (AER, 2021). Volatile market conditions provide opportunities for storage. South Australia's Hornsdale battery, commissioned in 2017 and upgraded in 2020 (to 150 MW), was the first large scale battery in the NEM. In Australia, batteries are increasingly paired with wind and solar farms to smooth the contribution from these plants and respond to price opportunities (AER, 2021). Battery costs are projected to fall significantly by 2040 as global capacity for battery manufacturing rises to meet the demand for stationary storage and Electric Vehicles (CSIRO, 2020; AER, 2021).

McConnell et al. (2015) estimated the value of electricity storage under an arbitrage-only strategy by analysing historical market data in South Australia's market for a range of storage capacity scenarios from 0.5 to 10 h of storage. The results demonstrate that there was little value in having more than six hours of storage capacity in the NEM. They mention that variability in revenue and exposure to extreme prices could be reduced using common hedging strategies, such as those currently used by peak generators.

In March 2023, Australia's Commonwealth Scientific and Industrial Research Organisation (CSIRO), published the Renewable Energy Storage Roadmap, based on Levelized Cost of Storage. Given Australia's target for net zero emissions by 2050, the report shows that the demand for renewable energy storage is projected to be significant and larger investments in short- (less than 4 hours) and medium-duration (between 4 and 12 hours) electricity storage are expected to be required to provide reliable electricity supply (CSIRO, 2023).

2.2. Firming renewables: insights from other electricity markets

Several studies have explored the value of energy storage in diverse electricity markets, however, the structural differences between these markets and the Australian Electricity Market might restrict the direct applicability of their findings to the NEM. Nonetheless, these studies provide valuable perspectives.

Karhinena and Huuki (2019) assessed the long-term profitability of pumped hydro energy storage (PHES) as firming capacity in Finland's electricity market. They quantified the private and social benefits of storage after increasing wind power in the system. Their findings show that PHES reduces balancing costs following wind power penetration. From an investor's perspective, smaller power units with large storage capacities offer the best profitability, partly due to the PHES operator acting as a price-maker in the balancing market and the cannibalisation effect. Chyong and Newbery (2022) used a calibrated unit commitment dispatch model of the Great Britain (GB) electricity market, aiming to minimise total system costs, to conduct an economic analysis of the four existing hydro-pumped storage (PHES) stations. Their results show that revenues from price arbitrage, balancing, and ancillary services make the existing stations profitable. However, these revenues are insufficient to cover the capital and operating expenses of a new station without opportunities to participate in the balancing and ancillary services markets. Braff et al. (2016) investigated the potential for energy storage to increase the value of solar and wind energy in several US locations—in Massachusetts, Texas, and California—with varying electricity price dynamics and solar and wind capacity factors. This study is focused on how the energy and power costs of storage affect the value added to wind and solar energy. The results show that storage is more valuable for wind than solar in two out of the three locations studied (Texas and Massachusetts), but across all locations, the benefit from storage is roughly similar across the two energy resources in terms of the percentage increase in value due to the incorporation of optimally sized storage.

Different storage technology options in terms of applications and viability have been investigated in many studies (see Obi et al., 2017; Jülch, 2016). One of the most comprehensive is a study conducted by Schmidt et al. (2019) in the UK. This study determines the levelised cost of storage (LCOS) for nine different technologies in 12 power system applications from 2015 to 2050 based on projected investment cost reductions and current performance parameters. The results show that lithium-ion batteries are most competitive in the majority of applications from 2030 and pumped hydro, compressed air, and hydrogen are best for long discharge applications.

In deploying battery energy storage systems for firming capacity, a key challenge is determining the optimal battery size, balancing technical benefits and revenue against incremental costs. Antweiler (2023) explores grid-storage applications theoretically and uses empirical data from the Ontario electricity market to parameterise his model. He evaluates three types of grid-scale storage: energy arbitrage, supply-side storage, and demand-side storage. The results indicate that, for arbitrage, optimal battery capacity increases with charging speed and price volatility but decreases with decay rate, based on Ontario zonal prices. The study also highlights the significant economic value of price forecasting for electricity storage systems.

The United States, particularly California, has emerged as a pioneer in adopting large-scale battery storage. California's ambitious renewable energy objectives and its dedication to enhancing grid reliability has led to substantial investments in battery storage projects. Battery storage capacity grew from about 500 MW in 2020 to 5,000 MW in May 2023. Batteries currently provide over half of CAISO's up and down regulatory requirements. Net market revenue for batteries increased from about

\$73/kW-yr in 2021 to \$103/kW-yr in 2022 and this increase was driven largely by higher peak energy prices (CAISO, 2023).

3. Modelling framework

To assess the impact of integrating battery on the financial performance of a renewable project a combination of lithium-ion battery and a wind farm has been chosen. The schematic diagram in Figure 1 illustrates the configuration that will be evaluated in this study, depicting the interconnection between the battery, the wind farm, and the grid. P_w presents the wind farm power generations to the grid and P_{ch} and P_d refer to battery charging and discharging to and from the energy market or wind farm, respectively. This setup facilitates dual charging capabilities for the battery, allowing it to receive power from either the grid or the wind farm. Additionally, the wind farm can either directly dispatch power to the grid or charge the battery.

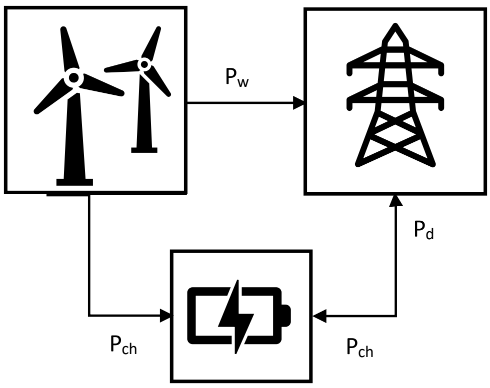

Figure 1. Schematic diagram of the integrated project.

The Australian Wind Energy Forecasting System (AWEFS) forecasts wind generation for all semi-scheduled wind units in the NEM (AEMO, 2022), and the Australian Energy Market Operator (AEMO) dispatches wind farms based on their maximum availability. Merchant wind farms sell all available power to the spot market but also rely on forward derivatives, such as futures, for managing cash flow (Simshauser, 2020). Futures contracts, trading fixed volumes at fixed prices, pose risks for VRE generators, particularly when weather conditions prevent them from fulfilling the obligations of their futures contracts, and prices are high in the electricity market. Batteries can provide physical firming capacity for the wind farm through arbitrage or time-shift applications. Thus, we explicitly test if the arbitrage strategy can offset the shortfall of the wind-futures portfolio or mitigate intermittency risk. Storage can also perform a similar role by storing excess renewable energy that would otherwise be curtailed. The functional operation of the storage system is similar in both cases (Akhil et al., 2016).

In addition, FCAS markets serve as ancillary services ideally suited for storage capacity. Therefore, within this portfolio, the integrated battery has the opportunity to generate revenue by offering frequency adjustment services. FCAS markets operate based on enablement, allowing participants to earn revenue according to the services they are enabled to provide, regardless of whether they are actively called upon to perform those services. If they are called, the battery needs to be charged or discharged in the energy market due to its associated FCAS provision.

To assess the influence of integrating a battery into the merchant wind farm portfolio, this study utilises a comparative analysis of two specific portfolios outlined as follows.[7]

1. Merchant Wind Farm + Futures Contracts.
2. Merchant Wind Farm + Futures Contracts + Battery (storage) Capacity.

South Australia is chosen for this study due to its high reliance on renewable energy, generating over 70% of its electricity from wind and solar. The state is a pioneer in large-scale battery storage, with projects like the Hornsdale Power Reserve, one of the world's largest lithium-ion batteries.

3.1 Assumptions and Input Data

To meet the research objectives and avoid unnecessary computational complexity, we assume that the wind farm and Battery Energy Storage System (BESS) are price-takers in the energy and eight FCAS markets, using historical prices as input data. Given the NEM's transition from 30-minute to 5-minute settlements in October 2021, the study focuses on the year 2023[8] to align with this change. Historical energy and FCAS market prices are sourced from AEMO (www.aemo.com.au), while the ASX (Australian Securities Exchange) archives provide data on historical futures contract prices (www.asx.com.au).

This study investigates a hypothetical 250 MW wind farm as a renewable energy source within both portfolios. Various factors, such as wind speed, grid availability, and site conditions, can influence the wind farm's capacity factor. To account for these impacts, we use the average monthly capacity factor of a real South Australian wind farm in 2023 as a benchmark, which has an annual capacity factor of approximately 30%,[9] with volatile capacity factors in different months, resulting in an average annual output of around 75 MW.

Given that NEM wind generation output tends to be at its highest during off-peak times, its average dispatch-weighted price is typically below the average time-weighted spot price, particularly as wind market share grows (Simshauser, 2020). Simshauser (2020) found that the dispatch-weighted price for a 250 MW merchant wind farm in South Australia averaged 84% of the time-weighted spot price, based on 2012–2019 data. This study adopts a similar approach, using an average of 83% for the benchmark wind farm.

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[7] This approach is similar to methodologies applied in research conducted by Simshauser (2020) and Flottmann et al. (2022).

[8] We selected 2023 as the base year because it reflects a more stable energy system compared to 2022, with wholesale electricity and gas prices declining from record highs. Additionally, 2023 marks significant shifts in the NEM, including the closure of Liddell Power Station, highlighting the ongoing energy transition and the urgent need for investments in renewable and storage projects. This feature is expected to influence the market dynamics for at least the next decade.

[9] In line with previous work, the average yearly capacity factors for wind farms in South Australia over the past 10 years have typically ranged between 28% and 35% (See AEMO, 2017; Simshauser, 2020; AEMO, 2023b). Therefore, an average capacity factor of 30% is a conservative assumption.

3.2 Methods and Conditions

Free Cash Flow (FCF) is typically determined as operating cash flow minus capital expenditures required to maintain the project's productive capacity:

$$\text{FCF} = \text{Operating Cashflow} - \text{Capital Expenditures} \tag{1}$$

For the wind farm, operating cash flow is generated by calculating the revenue from the energy market ($\text{Revenue}_{\text{W, Energy}}$). To this, the Difference Payment from base load futures contracts ($\text{DP}_{\text{Futures}}$) is added, which can be positive or negative depending on the contractual terms and spot market prices.[10] Finally, the operational expenditure of the wind farm (OPEX_{W}), representing the total variable and fixed operating costs, is subtracted. This relationship is formulated as:

$$\text{Operating Cashflow} = \text{Revenue}_{\text{W,Energy}} + \text{DP}_{\text{Futures}} - \text{OPEX}_{W} \tag{2}$$

To assess the impact of Capital Expenditures, particularly the overnight capital cost of the wind farm, the Debt Repayment Factor (DRF) will be applied to calculate the scheduled Debt Repayments (DR) associated with this expenditure for each time period. This approach allows a direct comparison of cash flows between portfolios by accounting for financial obligations. Adjusting debt repayments in the cash flow analysis also provides insights into how the investment's financial structure influences cash flow or revenue stability over the portfolios' economic life. The free cash flow for the first portfolio is calculated by using eq. (3). This approach is similar to what was used by Flottmann et al. (2022).

$$\text{FCF}_{\text{Adjusted}} = \text{Revenue}_{\text{W,Energy}} + \text{DP}_{\text{Futures}} - \text{OPEX}_{W} - \text{DR}_{W} \tag{3}$$

and:

$$DR = DRF * \text{Capital Expenditures} \tag{4}$$

where $DRF = \frac{r(1+r)^n}{(1+r)^n - 1}$; r is the interest rate; and n is the total number of payment periods.

Revenue uncertainty for renewable generation, like wind farms, arises from weather-dependent variations in wind speed, impacting wind farm generation and the ability to meet cash settlement requirements for derivatives contracts. To analyse this, we calculate the monthly adjusted cash flow for the portfolios, based on monthly periods as outlined in eq. (4). The 2023 monthly adjusted Free Cash Flow (FCF) for the first portfolio will be calculated using assumptions outlined in Table 1, derived from Aurecon (2022, 2023).

Table 1. Wind Farm Technical and Financial Assumptions

Plant size (MW)	250	Overnight Capital Cost ($/KW)	2500

[10] Since these contracts are settled financially, the payment differences must be calculated for each interval in the spot market.

Equivalent Forced outage	2.50%	Fixed O&M Cost ($/MW)	26500
Auxiliary Power Cons and Losses	3%	Variable O&M Cost	0
Marginal Loss Factor (MLF)	95%	Interest Rate (yearly)	6%
Economic Life (years)	25	Cost of Land	2.5% of CAPEX

In the model, the wind farm generates revenue only when the energy market price is positive. If the price becomes negative, the wind farm halts production, resulting in zero revenue for that interval. However, the wind farm still benefits from difference payments due to futures contracts. To calculate future contract prices, we assumed base load futures contracts were progressively accumulated over three years.[11] For 2023, quarterly strike prices were averaged using historical data from the preceding three years. For example, the Q_1 2023 strike price is based on the average of all prices from the first day of 2020 to the end of Q_4 2022. Similarly, the strike price in Q_2 2023, is calculated as the average of prices from the first day of Q_2 2020 to the last day of Q_1 2023, and so on for the following quarters. The calculated prices for each quarter are shown in Table 2.

Table2. Three Years Accumulated Prices for Yearly Futures Leading up to Each Quarter of 2023

Q1	January, February, March	$78.33
Q2	April, May, June	$80.83
Q3	July, August, September	$85.51
Q4	October, November, December	$88.67

Evaluating the impact of the battery on the portfolio involves considering two key aspects. Firstly, it needs to assess the incremental costs that the battery will impose on the portfolio. Secondly, it examines the potential incremental profitability and enhanced revenue certainty that the battery may introduce to the portfolio. Indeed, determining the power capacity ($P_{B,Max}$) and energy capacity (E_B) of the battery is crucial, as these factors significantly influence the battery's cost-effectiveness, operational behaviour, and overall performance within the portfolio

To offer the wind farm developers a new perspective in this domain, we employ a deterministic methodology that encompass two battery power capacity alternatives: 25 MW, 50 MW, each with two distinct storage durations of 2 and 4 hours (energy capacity). We will calculate the $FCF_{Adjusted}$ for all the following scenarios derived from the combinations above to explore the influence of various power and energy storage capacities on the integrated portfolio:

A. Wind-Futures Portfolio + 25 MW Battery Power Capacity with 2 hours duration (50 MWh Energy Capacity)
B. Wind-Futures Portfolio + 25 MW Battery Power Capacity with 4 hours duration (100 MWh Energy Capacity)
C. Wind-Futures Portfolio + 50 MW Battery Power Capacity with 2 hours duration (100 MWh Energy Capacity)

[11] Historical futures contract prices from the Australian Securities Exchange (ASX) are used as input data.

D. Wind-Futures Portfolio + 50 MW Battery Power Capacity with 4 hours duration (200 MWh Energy Capacity)

The National Renewable Energy Laboratory (NREL) published a set of cost projections for utility-scale lithium-ion batteries in 2016 (Cole et al., 2016), and that report was updated in 2023 (Cole and Karmakar, 2023). The new information confirms that lithium-ion battery prices are expected to decrease in the short to medium term. We use this information, along with Aurecon (2023), as references for determining the cost of battery. Table 3 shows how power and energy costs can be used to specify the total capital costs of batteries for different power ratings and storage durations. Additionally, it outlines other parameters beyond capital costs, such as the range of fixed operations and maintenance (FOM) cost, lifetime, and round-trip efficiency assumptions.

Table 3. BESS Technical and Financial Assumptions

Item	Unit	2 hours	4 hours
CAPEX - (with dedicated grid connection)			
Relative cost - Power component	\$/KW	497	525
Relative cost - Energy component	\$/KWh	450	441
Cost of land and development	\$	10,000,000	
OPEX			
Fixed O&M Cost	\$/KW-yr	2.5% of Capacity Cost	
Variable O&M Cost		-	
Annual Performance			
Annual number of cycles		365	
Economic life (design life)	Yr	20	
Annual energy storage degradation over design life	%	1.8	
Technical Parameters			
Charge efficiency	%	92	92.5
Discharge efficiency	%	92	92.5

Modelling the revenue generated by the BESS requires evaluating both its technical performance, including efficiency and adaptability to grid demands, and its financial performance, encompassing revenue from arbitrage and ancillary services. This combined assessment provides a comprehensive understanding of the battery's contribution to portfolio returns and it informs about optimal utilisation strategies. Based on this, the adjusted free cash flow for the second portfolio can be calculated as:

$$\mathrm{FCF}_{\mathrm{Adjusted}} = \mathrm{Revenue}_{\mathrm{W,Energy}} + \mathrm{DP}_{\mathrm{Futures}} + \mathrm{Revenue}_{\mathrm{B,Energy}} + \mathrm{Revenue}_{\mathrm{B,FCAS}} - \mathrm{OPEX}_{W} - \mathrm{OPEX}_{B} - \mathrm{DR}_{W\&B}, \quad (5)$$

where $\mathrm{FCF}_{\mathrm{Adjusted}}$ is the adjusted free cash flow for the second portfolio; $\mathrm{Revenue}_{\mathrm{w,\ Energy}}$ is the revenue generated by the wind farm from energy sales; $\mathrm{DP}_{\mathrm{Futures}}$ is the Difference Payment from futures contracts; $\mathrm{Revenue}_{\mathrm{B,Energy}}$ is the revenue generated by the battery from arbitrage strategy; $\mathrm{Revenue}_{\mathrm{B,FCAS}}$ is the revenue generated by the battery from FCAS markets; $\mathrm{OPEX}_{\mathrm{W}}$ and $\mathrm{OPEX}_{\mathrm{B}}$ are the total operating expenses, variable and fixed, of the wind farm and the battery, respectively; and $\mathrm{DR}_{\mathrm{W\&B}}$ is the scheduled debt repayments associated with both the wind farm and the battery capital cost.

Eq. (5) calculates the adjusted free cash flow for the second portfolio by factoring in multiple revenue sources (wind energy sales, futures contracts, battery energy sales, and ancillary services), operational costs, and debt repayments. It provides a clear view of the portfolio's cash flow dynamics and financial performance. $OPEX_B$ includes both variable and fixed operations and maintenance costs for the battery. The cost of electricity used to charge the battery is considered in $Revenue_{B,Energy}$, which represents net revenue from the wholesale spot market, as detailed in eq. (7). To calculate the cost of the battery, including fixed and variable costs, as well as debt repayments, the same methodology as previously outlined for the wind farm is applied.

The wind farm within this portfolio typically participates in the energy market by utilising all its available power. The associated revenue generated by the wind farm can be calculated by analysing some historical data. Consequently, the central focus within this portfolio is to optimise the integrated battery's performance across two key markets: the energy market ($Revenue_{B,Energy}$) and the FCAS market ($Revenue_{B,FCAS}$) by implementing a suitable optimisation algorithm tailored to these objectives. The optimisation algorithm is formulated and developed in detail in the next section.

4. Optimisation Model

4.1 Optimisation Objective

The objective function for the BESS, considering arbitrage and frequency provision, can be formulated as:

$$F = Maximise\ \{\mathrm{Revenue}_{\mathrm{B,Energy}} + \mathrm{Revenue}_{\mathrm{B,FCAS}} - \mathrm{Costs}_{\mathrm{Battery}}\}, \tag{6}$$

where $Revenue_{B,Energy}$ is the net revenue generated by the battery from energy sales; $Revenue_{B,FCAS}$ is the revenue generated by the battery from FCAS market; and $Costs_{Battery}$ is the costs associated with the degradation of the battery.

This objective function aims to maximise the overall profitability of the battery within the portfolio by combining the revenue gained from both applications while accounting for the costs associated with the battery's integration. The variables that need to be optimised are battery charge and discharge behaviour in the energy market and battery enablement amounts in eight FCAS markets as detailed in Table 4.

Table 4. Variables to be Optimised.

P_{ch} (t), P_d (t)	Battery Charging/Discharging Power in Energy Market
P_{RReg} (t), P_{LReg} (t)	Battery Enabled Power (Raise / Lower) in FCAS Regulation Market
P_{RCont6} (t), P_{LCont6} (t)	Battery Enabled Power (Raise / Lower) in 6-sec FCAS Contingency Market
$P_{RCont60}$ (t), $P_{LCont60}$ (t)	Battery Enabled Power (Raise / Lower) in 60-sec FCAS Contingency Market
P_{RCont5} (t), P_{LCont5} (t)	Battery Enabled Power (Raise / Lower) in 5-min FCAS Contingency Market

The net revenue from the energy market is formulated in eq. (7). It considers the dispatch of the battery in the energy market due to arbitrage strategy as well as the energy dispatched due to FCAS provision.

$$\text{Revenue}_{\text{B,Energy}} = \Delta t \sum_{t=1}^{T} (P_d(t) - P_{ch}(t)) * rsp(t) + \Delta t \sum_{t=1}^{T} (\alpha\, P_{RReg}(t) - \beta\, P_{LReg}(t)) * rsp(t), \quad (7)$$

where $P_d(t)$ and $P_{ch}(t)$ are discharging and charging battery power, respectively, in the energy market at time t; rsp(t) is the Regional Settlement Prices in the energy market at time t; $P_{RReg}(t)$ and $P_{LReg}(t)$ are battery raise and lower regulation bids in FCAS market, respectively; Δt is the length of dispatch interval which is equal to 5-minutes in NEM; t is dispatch interval and range from 1 to 105,120 for a full year of 5-minute dispatch intervals. The α and β coefficients indicate probabilities in which the enabled FCAS services are used to take action in the energy market. Those probabilities can be identified by analysing related reports and data available on the AEMO website. We use the monthly average raise and lower regulation usage as percentages of the enablement amount in the NEM, as proxies for α and β. Since the probability of contingency events occurring within the NEM is very low (AEMO, 2023c), the charging or discharging of the battery in response to an enabled contingency bid is likely to have minimal impact on revenue derived from the energy market. Consequently, we disregard such events.

As previously highlighted, the integrated battery stands to gain substantial advantages by engaging in the FCAS markets. The revenue in this market is formulated as:[12]

$$\text{Revenue}_{\text{B,FCAS}} = \text{Revenue}_{\text{B,Regulation}} + \text{Revenue}_{\text{B,Contingency}} \quad (8)$$

$$\text{Revenue}_{\text{B,Regulation}} = \Delta t \sum_{t=1}^{T} P_{RReg}(t) * rsp_{RReg}(t) + P_{LReg}(t) * rsp_{LReg}(t) \quad (9)$$

$$\text{Revenue}_{\text{B,Contingency}} = \Delta t \sum_{t=1}^{T} P_{Rcont6}(t) * rsp_{Rcont6}(t) + P_{Lcont6}(t) * rsp_{Lcont6}(t) + \Delta t \sum_{t=1}^{T} P_{Rcont60}(t) * rsp_{Rcont60}(t) + P_{Lcont60}(t) * rsp_{Lcont60}(t) + \Delta t \sum_{t=1}^{T} P_{Rcont5}(t) * rsp_{Rcont5}(t) + P_{Lcont5}(t) * rsp_{Lcont5}(t) \quad (10)$$

$P_{RReg}(t)$ and $P_{LReg}(t)$ are battery raise and lower regulation bids enabled in FCAS market, respectively; $P_{Rcont6}(t)$, $P_{Rcont60}(t)$, $P_{Rcont5}(t)$ are battery bids enabled for 6 second, 60 second and 5-minute raise contingency services, respectively; $P_{Lcont6}(t)$, $P_{Lcont60}(t)$, $P_{Lcont5}(t)$ are battery bids enabled for 6 second, 60 second and 5-minute lower contingency services, respectively; $rsp_{Rcontx}(t)$ and $rsp_{Lcontx}(t)$ are the FCAS settlement prices for the same different services; Δt is the length of dispatch interval which is equal to 5-minutes in the NEM; and t is dispatch interval and ranges from 1 to 105,120 for a full year of 5-minute dispatch intervals.

[12] When the BESS provides a regulatory response, the energy that is either discharged (for a raise response) or charged (for a lower response), is accounted for when calculating the metered energy response of the unit. The likelihood of the BESS being required to provide regulatory FCAS when enabled is incorporated using α and β in eq. (7). Contingency services are controlled for locally and are triggered by the frequency deviation that follows a contingency event (AEMO, 2021). There are six types of Contingency FCAS, including Fast Raise (6-second Raise), Fast Lower (6-second Lower), Slow Raise (60-second Raise), Slow Lower (60-second Lower), Delayed Raise (five-minute Raise), and Delayed Lower (five-minute Lower). Since October 9th, 2023, there are two additional Contingency FCASs: Very Fast Raise and Very Fast Lower.

Assuming price-taker status, bids in both markets are accepted without influencing market settlement prices. To ensure a robust and competitive analysis, battery participation is limited to 10% of the total enablement amount in each FCAS market, given the smaller size of the FCAS market. Future changes in the FCAS market structure could potentially accommodate more batteries without affecting prices.

Regarding the cost of the battery, it should be noted that only the degradation cost of the BESS in the regulation market will be implemented in the optimisation algorithm and will be calculated as:

$$\text{Cost}_{\text{Battery}} = \Delta t \ \sum_{t=1}^{T} \text{Energy Throughput in the Regulation Market} * \text{Degradation Coefficient} \quad (11)$$

Other battery-related costs, including purchase, installation, maintenance, and any incurred operational expenses, are estimated as fixed costs.

4.2 Arbitrage Strategy

To calculate the revenue from the arbitrage application, historical energy market prices from the AEMO website for each 5-minute interval have been used in conjunction with an optimisation model to construct daily plans that maximise the expected revenue of the BESS from the energy market. These plans adhere to constraints related to battery power rating, stored energy levels, battery efficiency, number of cycles per day, and battery performance in the FCAS market. All these constraints are discussed in detail in this section.

The model uses perfect foresight of day-ahead prices, allowing the battery to strategically manage its performance to maximise revenue during high-price periods. This approach ensures optimal charging and discharging by accurately predicting the timing and duration of these periods. Day-ahead foresight is preferred over monthly or yearly predictions because it better reflects real conditions, and AEMO's pre-dispatch prices, available about a day in advance, support this practical approach. McConnell et al. (2015) compare battery arbitrage using perfect foresight with a more realistic scenario based on pre-dispatch prices from AEMO. For FY 2012–13, they found that using pre-dispatch prices captures 85% of the potential value compared to perfect foresight, with six hours of storage.

The revenue potential of BESS in the energy market hinges on arbitrage opportunities. Table 5 delineates various factors indicative of such opportunities for storage capacities for all the months in 2023. These factors encompass the average daily differentials between the highest and lowest settlement energy prices, alongside the averages of the 10th and 90th percentiles of settlement prices on a per-day basis, calculated within a 5-minute interval.

Table 5. Market Indicators for Arbitrage Opportunity

Months	Monthly Average of 10th Percentile Per-day	Monthly Average of 90th Percentile Per-day	Monthly Average of Max/Min Difference Per-day
Jan-23	-26.94	145.38	756.85
Feb-23	-36.25	185.91	2569.0
Mar-23	-21.24	140.02	426.8
Apr-23	-14.46	177.53	885.26
May-23	44.0	308.03	2065.0

Jun-23	-10.15	166.66	1095.2
Jul-23	-8.13	176.62	718.67
Aug-23	-20.89	455.48	2561.3
Sep-23	-54.93	137.43	1390.2
Oct-23	-53.9	77.77	419.14
Nov-23	-42.66	109.67	1519.0
Dec-23	-52.44	95.73	962.78

In all months, the average difference significantly exceeds the gap between the 10th and 90th percentiles, indicating that average price disparity is driven by a few high-value arbitrage opportunities. This suggests that substantial revenue potential can be captured with limited BESS cycles, emphasising the importance of price forecasting. Higher differences between the 10th and 90th percentiles, like in August, indicate greater arbitrage potential. Factors such as storage duration also impact opportunities; for instance, a 2-hour battery cycle performed once daily can capture up to 4 hours of price variations. Additionally, co-optimising the battery for both energy and FCAS markets may cause it to miss certain energy arbitrage opportunities, potentially trading energy market earnings for higher FCAS revenue. Section 5.2 will analyse the battery's performance in co-optimised operations across both markets.

4.2.1 Frequency Services Provision

Maximising revenue from the FCAS market is a priority for the portfolio owner. Therefore, it needs to develop an optimisation algorithm that encompasses both arbitrage and frequency services provision applications to determine the optimal performance of BESS in the energy and FCAS markets. To estimate FCAS revenue, quarterly average FCAS enablement amounts and quarterly average FCAS prices for each service in South Australia are used as input data, as shown in Tables 6 and 7.

Table 6. Quarterly Average FCAS Enablement Amount in South Australia (MW) for 2023

Quarter	LOWERREG	LOWER5MIN	LOWER60SEC	LOWER6SEC	RAISEREG	RAISE5MIN	RAISE60SEC	RAISE6SEC
Q1	38	58	119	91	36	109	133	136
Q2	23	51	60	56	26	112	127	136
Q3	18	45	56	51	22	102	120	123
Q4	23	52	76	61	25	101	120	117

Source: AER, AEMO

Notes: Columns display average enablement amount for both raise and lower regulation services (LOWERREG and RAISEREG) and raise and lower contingency services for delayed 5 minute, slow 60 second and fast 6 second (LOWER5MIN, LOWER60SEC, LOWER6SEC, RAISE5MIN, RAISE60SEC and RAISE6SEC).

Table 7. Quarterly Average FCAS Prices in South Australia in $/MW for 2023

Quarter	LOWERREG	LOWER5MIN	LOWER60SEC	LOWER6SEC	RAISEREG	RAISE5MIN	RAISE60SEC	RAISE6SEC
Q1	4	0	0	0	93	1	26	78
Q2	18	10	37	11	0	0	0	0
Q3	0	0	37	0	0	0	0	0

Q4	11	2	53	8	0	0	0	0

Source: AER, AEMO

Note: Columns display average FCAS prices for both raise and lower regulation services and raise and lower contingency services for delayed 5 minute, slow 60 second and fast 6 second.

Table 6 highlights the relatively small size of the FCAS markets compared to the energy market. In 2023, FCAS market payments (including regulation and contingency services) in the NEM amounted to approximately $130 million, whereas the spot market payments totalled around $27 billion (AEMC, 2024; AER, 2023). This aligns with the concept of 'fast markets,' in the NEM where shorter dispatch intervals (5-minutes) incentivize dispatchable, flexible capacity, reducing reliance on regulation reserves (McConnell et al., 2015).

Table 7 shows that the most significant price fluctuations occurred in the first quarter (summer in South Australia) for the Regulation Raise and Fast Raise (6-second Raise) services. This heightened variability can be attributed to the stochastic production effects of VREs. The combination of 'VRE plant off' events and increased demand leads to more frequent adjustments in the form of fast frequency raise activations.

4.2.2 Optimisation Constraints

The optimisation algorithm imposes multiple constraints to ensure the BESS reliably delivers services in the energy and eight FCAS markets. These constraints prevent penalties, reduce degradation, and avoid technical damage, and ensure consistent performance of the BESS. Meticulous attention to these constraints is essential for the evaluation.

Initially, ensuring that the battery fulfils its duty cycles without enduring excessive degradation or damage necessitates adhering to a charging and discharging rate that is equal to or less than the battery's maximum power rating ($P_{B, Max}$), i.e.:

$$0 \leq P_{ch}(t) \leq P_{B,Max} \tag{12}$$
$$0 \leq P_{d}(t) \leq P_{B,Max} \tag{13}$$

The operational dynamics of storage capacity for delivering energy and frequency control services differ markedly from those of generation capacity. Storage can provide both raise and lower services in the FCAS markets beyond its power rating. For instance, 1 MW of efficient storage dispatched as a generator can deliver up to 2 MW of lower frequency services by alternately discharging and charging—1 MW by stopping discharge and another 1 MW by starting charge.[13] However, dispatch in energy, regulating, and contingency markets may be constrained by the unit's response capabilities and managed by the National Electricity Market Dispatch Engine (NEMDE) to prevent infeasible outcomes (AEMO, 2023a). This will be discussed in more detail later in this section.

It should be noted that the three-raise contingency and three-lower contingency services do not refer to multiple model time horizons, but rather refer to different categories of contingency ancillary

[13] Discharging and charging cannot occur simultaneously. For example, when the battery is charging in the FCAS market, it cannot be dispatched in the energy market at the same time.

services, which are complementary and can each be offered into the market simultaneously. These constraints are reflected in the battery's features through the following equations (Naemi et al., 2022):

$$P_d(t) + P_{RReg}(t) + P_{Rcont}(t) - P_{ch}(t) \leq P_{B,Max} \quad (14)$$
$$P_{ch}(t) + P_{LReg}(t) + P_{Lcont}(t) - P_d(t) \leq P_{B,Max} \quad (15)$$
$$P_{Rcont}(t) = \max \{P_{Rcont6}(t), P_{Rcont60}(t), P_{Rcont5}(t)\} \quad (16)$$
$$P_{Lcont}(t) = \max \{P_{Lcont6}(t), P_{Lcont60}(t), P_{Lcont5}(t)\} \quad (17)$$

Another key characteristic of a BESS in a power system is its state of energy, measured in megawatt hours, which represents the maximum available energy at any given time and can be calculated using eq. (18). By measuring and incorporating the state of energy as a variable in the constraints, the system ensures that the BESS operates within its physical limits, accurately reflecting its charging and discharging behaviour over time.

$$S_B(t) = S_B(t-1) + \left(\mu_c\, P_{ch}^{net} - \mu_d^{-1}\, P_d^{net}(t)\right) \Delta t \quad (18)$$

$S_B(t)$ represents the state of charge (or energy) available at the end of time period t. It is calculated as the state of charge at the end of the previous time period, plus the net sum of charging and discharging during the current time period. $P_{ch}^{net}(t)$ and $P_d^{net}(t)$ are the net charging and discharging power in the current interval, respectively, and refer to the sum of charging and discharging of the battery in the energy market due to any arbitrage strategy and in response to an FCAS service when called upon. The battery charging and discharging efficiencies, denoted as μ_c and μ_d respectively, are set in accordance with the assumptions in Table 3.

Another important constraint to consider involves ensuring that the battery can effectively fulfil all its energy and FCAS market obligations without facing penalties. Davies et al. (2019) addressed this concern in their research by incorporating the internal state of charge (SOC). They highlighted that utilising the 20–80% SOC range provides the widest margin to ensure the safe completion of all battery duty cycles within the California Independent System Operator (CAISO). Imposing limits on the State of Charge (SOC) and daily cycles can extend battery lifespan, reduce degradation, and enhance efficiency. In this study, an SOC range of 10% to 90% of the battery's energy capacity (E_B, which varies by scenarios) is used to ensure the battery meets both energy and FCAS requirements while minimising degradation. The following constraints are applied:

$$S_B(t-1) + \mu_c \Delta t \left[P_{ch}(t) + P_{LReg}(t) + P_{Lcont6}(t) + P_{Lcont60}(t) + P_{Lcont5}(t)\right] \leq 90\%\, E_B \quad (19)$$
$$S_B(t-1) - \mu_d^{-1} \Delta t \left[P_d(t) + P_{RReg}(t) + P_{Rcont6}(t) + P_{Rcont60}(t) + P_{Rcont5}(t)\right] \geq 10\%\, E_B \quad (20)$$

Regarding the number of cycles, a typical utility-scale battery with a technical life of 15-20 years usually undergoes one cycle per day (Akhil et al., 2016; Naemi et al., 2022). This daily cycle is assumed to coincide with a zero or near-zero variable operations and maintenance (VOM) cost over the battery's calendar lifetime, with all operating costs at the one-cycle-per-day level allocated to fixed operations and maintenance (FOM) costs (Cole and Karmakar, 2023). This study constrains the battery's arbitrage application to one cycle per day, allowing for at most one transition between charging and discharging within a 24-hour period. It assumes zero variable cost for the arbitrage application. To address degradation from the one-cycle-per-day usage and ensure that the system meets all cost requirements to operate at its rated capacity throughout its lifetime, a fixed operating and maintenance (FOM) cost set at 2.5% of the $/kW capacity cost is adopted. This approach is consistent with that outlined in Cole and Karmakar (2023).

To manage battery cycles in the Regulation FCAS market, the model allows participation without a one-cycle-per-day limit. Revenue from this market is compared against the degradation cost of additional cycling. Thus, degradation costs are subtracted from total revenue, ensuring that net profit accounts for both the immediate revenues from regulation services and the costs of battery wear and tear. To account for degradation costs, we use a coefficient that defines the battery degradation cost per $/kWh of energy throughput in the regulation market. Aurecon (2023) reports a 1.8% annual degradation rate for lithium-ion batteries with one cycle per day. Degradation is influenced by factors like energy throughput, cycle count, charge/discharge depth, and environmental conditions. Our model calculates the degradation coefficient based on the battery's capital cost and annual energy throughput, similar to the model used by Bera et al. (2020). The degradation cost coefficient ($/MWh) is calculated as:

$$\text{Degradation Cost Coefficient (\$/MWh)} = \frac{\text{Battery replacement capital cost per year}}{\text{Energy throughput of the battery per year}} \tag{21}$$

where

Battery Replacement Capital Cost per Year = Annual Energy Storage Degradation Rate * Battery Capital Cost ($/MW), and

Energy Throughput of the Battery per Year = Number of Cycles * Energy Capacity of the Battery.

Applying this formula to 25 MW and 50 MW batteries with a two-hour storage duration result in an estimated degradation cost coefficient of $33.2/MWh. For the same batteries with a four-hour storage duration, the degradation cost coefficient is reduced to $27.6/MWh. Moreover, since the probability of the battery needing to respond to a contingency event is very low, it is assumed these responses do not have any impact on battery degradation.

Offers and bids for FCAS services follow the generic FCAS trapezium, defined by enablement limits and breakpoints. This trapezium shows the maximum FCAS that can be provided for specific MW output levels of a generating unit, MW load reduction for a wholesale demand response unit, or MW consumption for a scheduled load. In each trading interval, NEMDE must enable sufficient FCAS from the submitted bids to meet the required MW enablement amounts (AEMO, 2021). This study assumes the battery is registered as a generator in the Regulation Raise, Regulation Lower, and all Raise Contingency FCAS markets, and as a load in the Regulation Raise, Regulation Lower, and all Lower Contingency FCAS markets, as specified in Table 8, which represents the battery's trapezium.

Table 8. Battery Trapezium in FCAS Markets

Battery Status	Bid Type	Max Availability (MW)	Min Enablement Level (MW)	Max Enablement Level (MW)	Lower Angle	Upper Angle

Generator	LowerReg	$P_{B,Max}$	0	$P_{B,Max}$	45	90
Generator	RaiseReg	$P_{B,Max}$	0	$P_{B,Max}$	90	45
Generator	Raise5min	$P_{B,Max}/2$	0	$P_{B,Max}$	90	45
Generator	Raise60sec	$P_{B,Max}/2$	0	$P_{B,Max}$	90	45
Generator	Raise6sec	$P_{B,Max}/2$	0	$P_{B,Max}$	90	45
Load	Lower5min	$P_{B,Max}/2$	0	$P_{B,Max}$	90	45
Load	Lower60sec	$P_{B,Max}/2$	0	$P_{B,Max}$	90	45
Load	Lower6sec	$P_{B,Max}/2$	0	$P_{B,Max}$	90	45
Load	LowerReg	$P_{B,Max}$	0	$P_{B,Max}$	90	45
Load	RaiseReg	$P_{B,Max}$	0	$P_{B,Max}$	45	90

AEMO described how the technical limits on FCAS provision are modelled within the NEMDE software (AEMO, 2023a). To ensure that combined energy dispatch and FCAS enablement stay within a unit's technical capabilities, NEMDE simultaneously applies intrinsic constraints for "joint ramping", "joint capacity", and "energy and regulating FCAS capacity" during the optimisation process. It then identifies the optimal solution that satisfies all these constraints concurrently. By considering the energy and regulating FCAS capacity constraints and joint capacity constraints outlined by AEMO, and incorporating the features of the battery in this study: 1. Maximum enablement of $P_{B,Max}$; 2. Minimum enablement of 0 MW; 3. Maximum FCAS availability equal to $P_{B,Max}$ in regulation markets and $P_{B,Max/2}$ in contingency markets; and 4. Setting both the upper and lower slope coefficients to one, it can be concluded that the NEMDE constraints for FCAS markets will align with the constraints in eq. (12) to eq. (17). For the Raise Contingency and Lower Contingency in all six markets, the only additional constraint needed is the maximum FCAS availability for these two services, which is half of $P_{B,Max}$:

$$P_{\mathrm{Rcont6}};\ P_{\mathrm{Rcont60}};\ P_{\mathrm{Rcont5}} \leq P_{\mathrm{B,Max}}/2 \tag{22}$$
$$P_{\mathrm{Lcont6}};\ P_{\mathrm{Lcont60}};\ P_{\mathrm{Lcont5}} \leq P_{\mathrm{B,Max}}/2 \tag{23}$$

In the NEM, batteries typically allocate half of their power capacity to the contingency market. Contingency events are infrequent but require a sustained response, and using only half of their capacity ensures enough energy is available to maintain this response until the system stabilises. The AEMO sets specific guidelines for battery energy storage systems in FCAS, requiring reserve capacity for effective participation in contingency events (AEMO, 2024). This study does not consider joint ramping constraints for regulation services and assumes that there is no difference between the real-time AGC (automatic generation control) ramp rates telemetered from the unit and the registered amounts in this model.

Finally, another essential constraint to prevent simultaneous charging and discharging of the battery can be formulated using binary variables and an inequality constraint. This constraint ensures that either the charging or discharging decision variable is active at any given time interval, but not both. The formulation of this constraint can be outlined as:

$$Charge(t) + Discharge(t) \leq 1 \qquad \text{for all intervals} \tag{24}$$

where Charge(t) is the decision variable for the charging action at interval t, and Discharge(t) represents the decision variable for the discharging action at interval t.

4.3 Model Implementation

The wind farm performance and optimisation model are implemented using MATLAB software and applied over the year 2023. This process utilises historical energy market prices from the AEMO website for each 5-minute interval and incorporates quarterly average FCAS prices from the Australian Energy Regulator (AER). The optimisation process employs a Mixed Integer Linear Programming (MILP) approach. The model uses a 5-minute resolution to determine 10 decision variables (as detailed in Table 4) and an additional 6 variables, including $P_{Lcont}(t)$, $P_{Rcont}(t)$, $S_B(t)$, Charging and Discharging status (binary variables), and the Transition between charging and discharging (binary variable), which are used in the optimisation constraints.

The program ran for each month to account for the impact of seasonal weather conditions on the output results. In total, there are 105,120 dispatch intervals, each with 10 associated decision variables used to estimate portfolio performance over 2023 for each scenario. The MATLAB program takes approximately 30 minutes per month to run on a computer equipped with a 12th Gen Intel(R) Core (TM) i5 Processor and 16GB RAM.

5. Analyses and Results

5.1. Merchant Wind Farm Portfolio

The adjusted free cash flow for the first portfolio, consisting of a 250MW wind farm and a 75MW futures contract, is depicted in Figure 2. This graph also illustrates the wind farm's revenue in the energy market and the differential payments for futures contracts separately over the 12 months of 2023. The data indicates that during periods of low energy revenue, particularly in the last four months of the year, futures contracts significantly contribute to increasing total revenue by generating positive income differential payments. As shown in Table 5, these results align with the price dynamics observed in 2023. The lowest average 90th and 10th percentiles per day during these four months suggest that derivatives can play an important role in enhancing revenue during times of reduced energy income. Conversely, in months like May and August, when electricity prices more frequently spike and wind farm generation falls short of fulfilling futures contracts, the portfolio can suffer significant negative revenue.

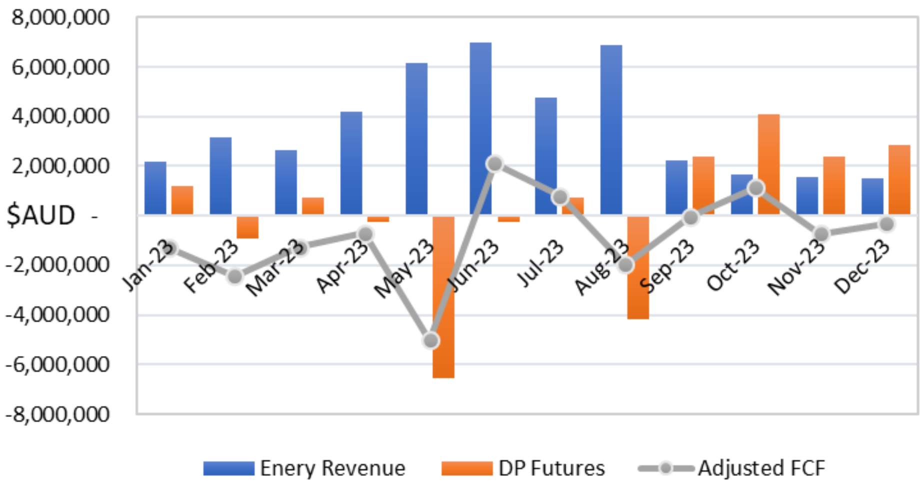

Figure 2. First Portfolio $FCF_{Adjusted}$, Wind Farm Energy Revenue and Futures Difference Payments

Over 12 months, maintaining 75 MW of futures contracts for the wind farm boosts annual revenue by approximately $2.1 million, driven by positive returns in seven months despite minor to extremely negative returns in others. The adjusted free cash flow, shown in Figure 2, includes not only energy and contract revenues, but also all capital and operating costs detailed in Section 3 and calculated using the data in Table 1. In this study, when calculating the Net Present Value (NPV) of the adjusted free cash flow ($FCF_{Adjusted}$) for the different portfolios over their economic life, we base our analysis on the 2023 results. This calculation also assumes a discount rate of 6% and excludes inflation (Simshauser, 2020), allowing for a clearer assessment of the portfolio's potential profitability over the investment horizon while facilitating easier comparison between various portfolios, aligning with the article's objective.

For the first portfolio, the NPV is approximately -$127 million. The initial capital investment, given the overnight capital cost for a 250 MW wind farm, calculated using data from Table 1, is around $625 million. This results in a shortfall of approximately 20%. Therefore, under the assumptions of this study, a merchant wind farm investment, as represented by the first portfolio, is an infeasible investment in South Australia. This finding supports the idea that wind farm developers in the NEM should apply PPAs to provide revenue certainty and feasibility for their projects.

To compare our wind farm modelling results with those of Simshauser (2020), we first address key differences in methodology and data assumptions. Simshauser uses a stochastic discounted cash flow model, incorporating market price uncertainty through Monte Carlo simulations under half-hour market settlement. After adjusting for these differences, Simshauser reports an average annual cash flow of $34.1 million for an incumbent 250 MW wind farm with 75 MW swap (or futures) contracts. To ensure comparability with the incumbent, our model, after excluding debt repayment, calculates an adjusted cash flow of $38.6 million for the same portfolio in 2023. Despite the differences in modelling techniques, both studies arrive at similar outcomes, with cash flows falling within a comparable range. Both studies exclude side-market revenues like Large-scale Generation Certificates (LGCs). In this study, the exclusion of LGC is due to uncertainties surrounding their future within the NEM, which depends on Australian government policies. If the Renewable Energy Target (RET) is deemed fulfilled, the LGC scheme could be phased out, ending LGC generation and trading. Simshauser (2020) suggests that including such revenues could increase wind farm valuations by $100-$150 million. In our study, potential LGC revenue would have been around $31 million in 2023.[14]

5.2. BESS Performance

The revenue generated by each BESS options in the energy and FCAS markets is shown based on battery power and energy capacity in Figure 3. These graphs illustrate revenue distribution, which aligns with expectations derived from energy price volatility (Table 5) and FCAS input data (Tables 6 and 7) for each month. Notably, increased price volatility in May and August led to higher arbitrage revenue, while elevated FCAS revenue during the first quarter (summer) resulted from improved FCAS enablement and higher prices in South Australia.

Analysing the impact of storage duration, we find that for a 25 MW battery, extending storage from 2 to 4 hours boosts arbitrage revenue by between 29% to 63%, depending on months, with an average annual increase of 42% without any significant change in FCAS revenue. When the battery capacity increases to 50 MW, arbitrage revenue almost doubles compared to the 25 MW battery. However, FCAS revenue only sees a modest 4-5% increase due to limited opportunities in the FCAS market relative to the larger energy market. For the 50 MW BESS, extending storage duration to 4 hours yields an average annual arbitrage revenue increase of 44%, with no significant change in FCAS revenue. Therefore, the main impact of increasing either battery capacity and/or storage duration is to increase revenue from energy arbitrage.

It is essential to consider the rising capital and operational costs alongside revenue gains for each BESS option. By applying data from Table 3, extending storage duration from 2 to 4 hours increases BESS capital costs by approximately 50% for a 25MW battery, while improving power capacity from 25MW to 50MW results in a 40% capital cost increase. The subsequent section will assess how these revenue improvements and increased capital and operational costs impact the adjusted free cash flow of the second portfolio.

[14] Considering this revenue over the next five years of wind farm operation could boost the adjusted free cash flow by approximately $130 million, which aligns with the range of results reported by Simshauser (2020).

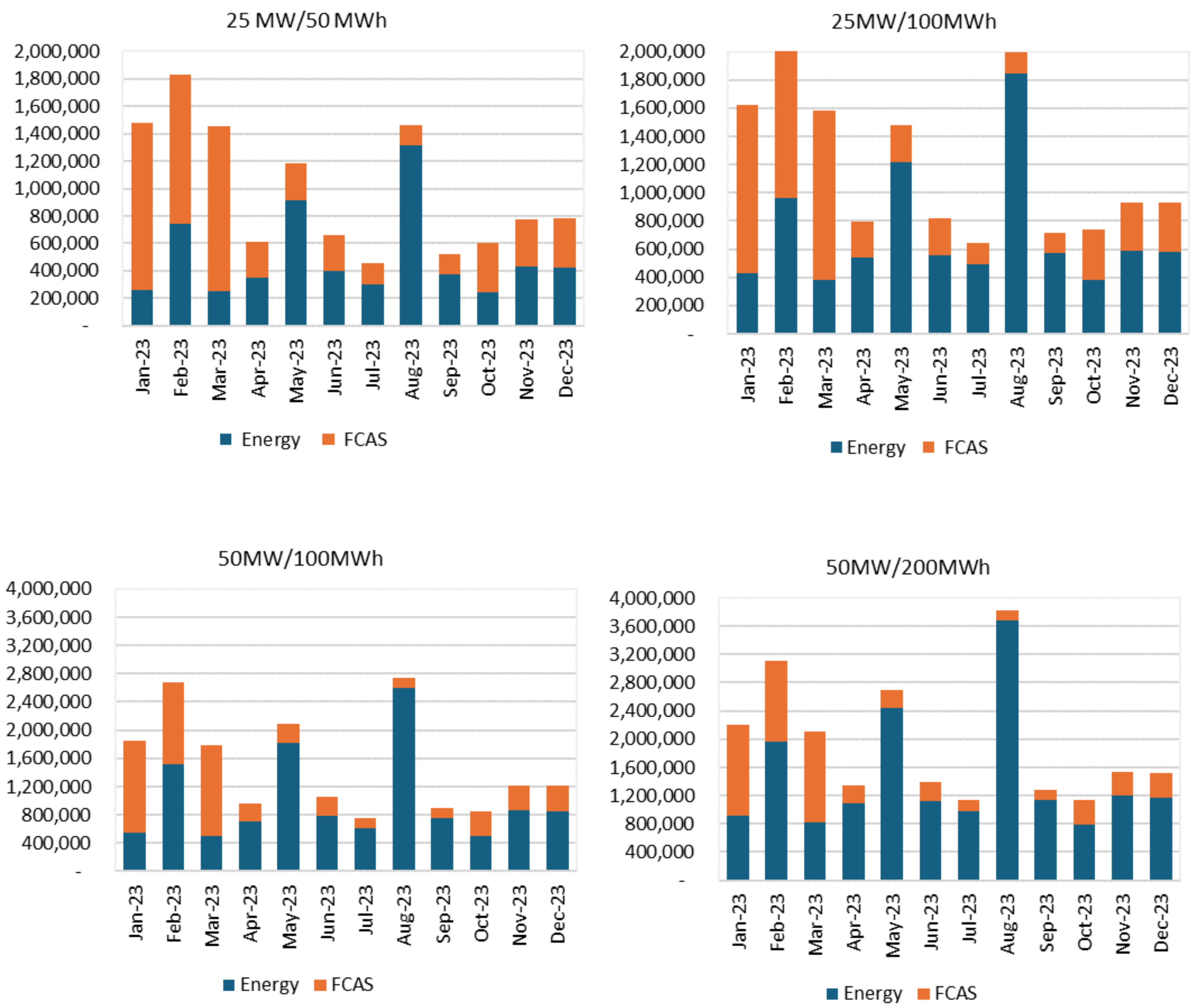

Figure 3. Revenue ($) of Various BESS Options in Energy and FCAS Markets for 2023

To evaluate the feasibility of a stand-alone BESS participating in the NEM on a 2023 cash basis, we aim to determine whether it can generate sufficient revenue to cover operational and fixed costs, as well as CAPEX debt repayments. Similar to the approach detailed in Section 3, the adjusted free cash flow for the stand-alone BESS can be calculated as follows:

$$FCF_{\text{Adjusted}} = \text{Revenue}_{B,Energy} + \text{Revenue}_{B,FCAS} - \text{OPEX}_B - \text{DR}_B \quad (25)$$

Figure 4 compares the total revenue of the battery (the sum of the first two elements in eq. (25)) with the total operating and capital costs (the sum of the third and fourth elements in eq. (25)) for the calendar year 2023. Under optimal operation and with perfect day-ahead electricity price foresight in

South Australia, the revenue generated by the following BESS options is sufficient to cover their associated costs, making them viable investments.

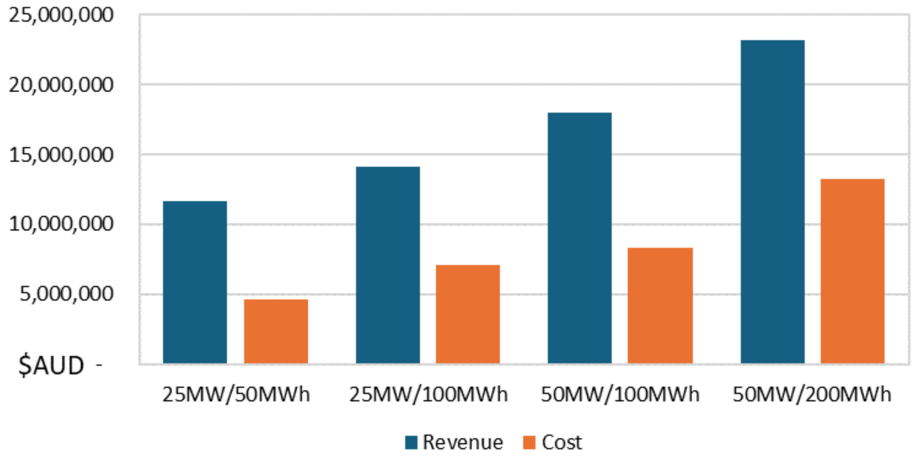

Figure 4. Comparison of Yearly Revenue and Costs for Various BESS Options in 2023

Figure 5 shows the average hourly optimal charging and discharging behaviour of the 25 MW/50 MWh battery modelled across all quarters of 2023, compared with average hourly energy prices in South Australia during the same period. The data clearly indicates that charging is more common during the middle of the day in all quarters, particularly in Quarters 1 and 4 (Q_1 and Q_4). This trend aligns with the suppressed energy prices observed during daytime hours in South Australia, which are influenced by distributed solar generations in summer and spring that reduces electricity demand in the region.

In contrast, the discharge profile of the BESS remains relatively consistent with the price trends in all quarters, with the majority of discharges occurring during the evening peak period. There is minimal to no response to peak prices at the beginning of the day, due to the battery's restriction to one cycle per day under the arbitrage strategy. The low level of charging rate at the beginning of the day, despite the observed high electricity prices, is because the BESS needs to be ready for enablement in the FCAS markets, thereby benefiting from revenue opportunities during imbalances in the energy market.

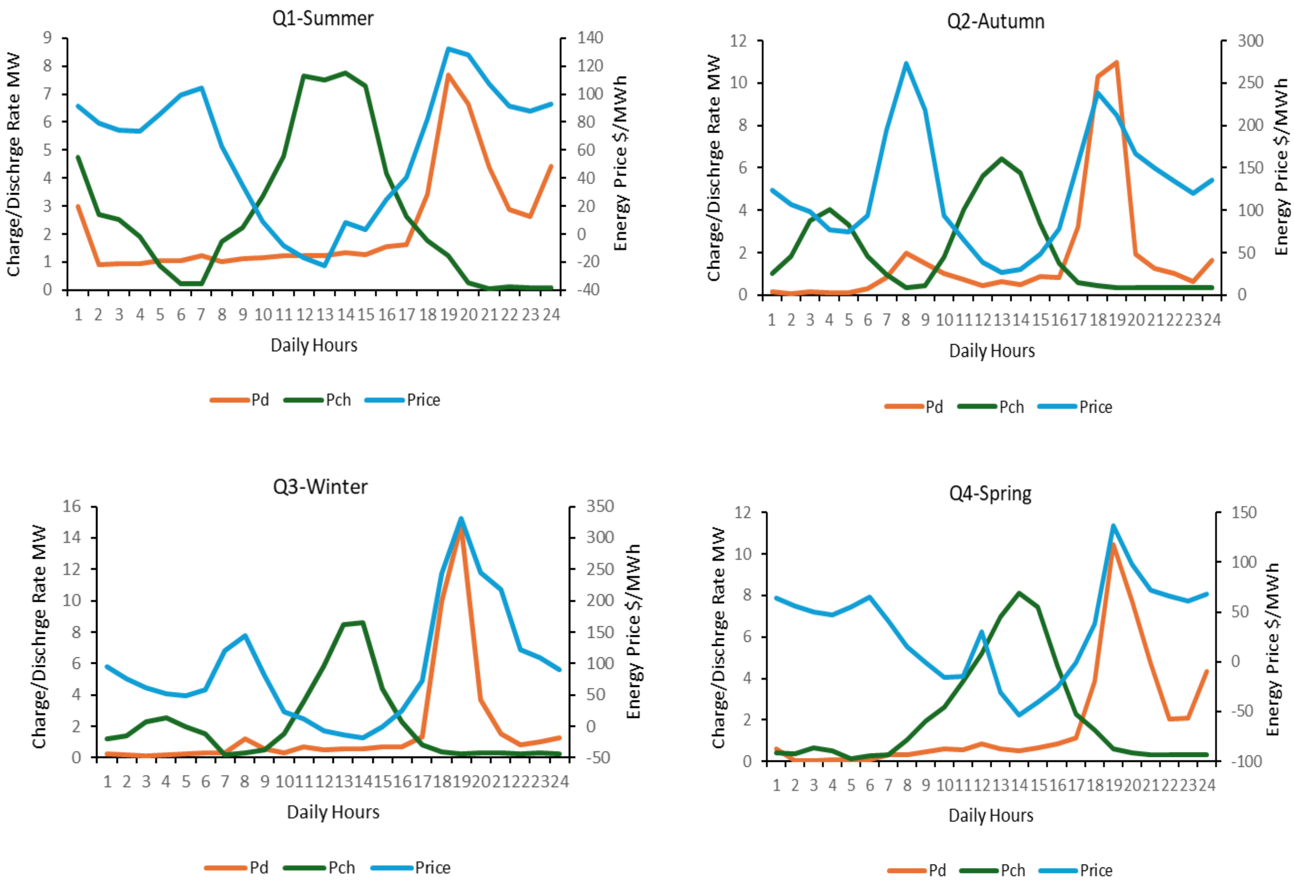

Figure 5. Average Hourly Charging and Discharging of the 25 MW/50 MWh Battery and Energy Prices by Quarter in 2023

5.3. Integrated Portfolio

Recognising that batteries mitigate the intermittency risk of wind farms; the proposal is to increase the number of base load futures contracts in the portfolio by 15 MW for every 25 MW of battery power capacity. This adjustment aims to enhance revenue certainty. Therefore, the scenarios that will be evaluated are as follows (as indicated in section 3):

A. 250 MW Wind Farm + 90 MW Futures Contract + 25 MW/50 MWh Battery
B. 250 MW Wind Farm + 90 MW Futures Contract + 25 MW/100 MWh Battery
C. 250 MW Wind Farm + 105 MW Futures Contract + 50 MW/100 MWh Battery
D. 250 MW Wind Farm + 105 MW Futures Contract + 50 MW/200 MWh Battery

Building on the results for the 250 MW wind farm with a 75 MW futures contract, we will adjust the new elements for each scenario. Using the methodology described in Section 3, we will compare the adjusted cash flows across scenarios. Figures 6 and 7 below illustrate the monthly adjusted cash flows for two of the scenarios in 2023. We will then calculate the adjusted annual future cash flows for each scenario, assess their NPV, and evaluate the feasibility of each scenario. It is important to note that this cash flow analysis excludes factors such as taxes, dividends, and changes in working capital, and therefore does not provide a precise portfolio valuation.

For Scenario A, Figure 6 illustrates the cash flow of the BESS, accounting for battery adjusted cash flow, wind farm and futures contracts adjusted cash flow, along with the adjusted free cash flow for the whole portfolio, which is the sum of these two cash flows. We observe that the BESS enhances the cash flow stream in all months, particularly during the first quarter through its FCAS revenue, and in May and August through the arbitrage strategy (as shown in Figure 5). As discussed earlier, maintaining futures contracts boosted the wind farm's total annual revenue by enhancing income in seven months. However, in May and August, the portfolio faced significant negative revenue due to futures contract obligations, frequent electricity price spikes, and the wind farm's non-dispatch during these periods.[15] The 25 MW/50 MWh battery can mitigate some negative revenues in August, but it's less effective in May. As shown in Table 5, both May and August have higher monthly averages for the Max/Min difference and 90th percentile of daily price values compared to other months. However, May uniquely features a high positive 10th percentile monthly average, indicating that minimum prices are predominantly positive and high. This impacts futures contract difference payments, leading to greater losses in May than in August. The high minimum prices in May also limit the battery's ability to effectively offset losses through arbitrage. This situation suggests a critical insight: derivatives contracts for renewable projects need more precise instigation, and a uniform strategy may not be effective for different months or varying seasonal weather conditions. This issue will be discussed in more detail in section 6.

Scenario B[16] yields nearly identical results to Scenario A. While extending battery storage from 2 to 4 hours can boost the portfolio's annual arbitrage revenue by about 42% (see Figure 3), the increased capital and operational costs offset these gains, resulting in similar final cash flows.

For both scenarios, the total adjusted cash flow over the year 2023 is negative, about -$2.2 million. When using this year as the base year to calculate the NPV of adjusted free cash flow for the second portfolio over its economic life, we obtain an NPV of -$18 million, representing a shortfall of about 2.5%–2.6% compared to the initial investment. Therefore, while the 25MW/50MWh and 25MW/100MWh battery configurations can enhance revenue certainty and increase the overall valuation of the wind farm portfolio (improving from -$127 million to -$18 million in this scenario), they remain insufficient to ensure the financial viability of integrating a 250MW merchant wind farm and storage capacity portfolio, based on the assumptions made in this study.

[15] Table 5 highlights the highest average Max/Min differences in electricity prices for February, May, and August. When the average Max/Min difference exceeds the 90th percentile, it suggests that price spikes are concentrated in a limited number of intervals. This phenomenon is more pronounced in February than in August and even more so when comparing February to May. This may explain the less negative cash flow observed in February relative to May and August. May, however, is notable for having a positive 10th percentile, which reduces the number of intervals where futures contracts can generate positive revenue for the portfolio, contributing to higher negative revenue in this month. Additionally, the benchmark wind farm capacity factors for these months are 23.5% for February, 21.8% for May, and 29% for August. We can see the lower capacity factor in May.

[16] For detailed results of the simulations, see Figure A.1 in Appendix A

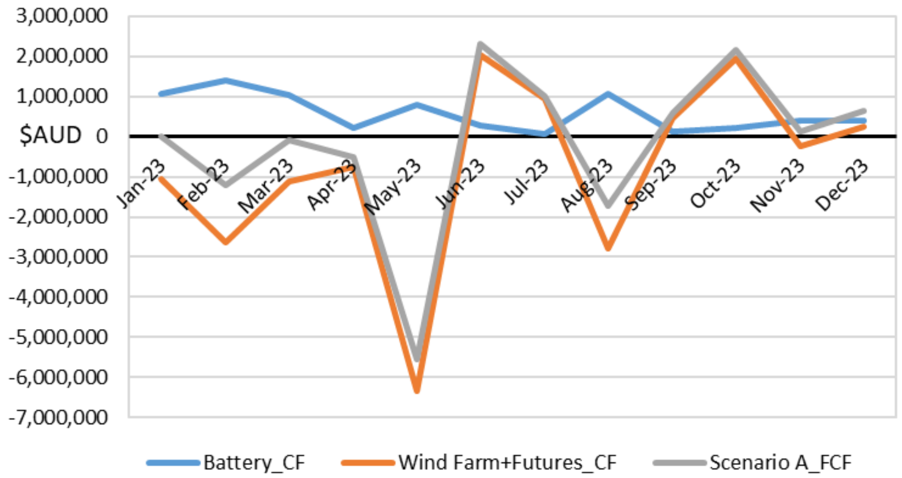

Figure 6. Scenario A: Adjusted Free Cash Flow Including a 250 MW Wind Farm, 90 MW Futures Contracts, and a 25 MW/50 MWh Battery

In Scenario C, increasing the battery power capacity to 50 MW raises BESS costs compared to the 25 MW/50 MWh battery in Scenario A but also boosts portfolio revenue. As shown in Figure 7, this higher capacity improves monthly cash flow in 10 months, with the most significant gains occurring in May and August, consistent with the data in Table 5. However, battery cash flow in October and July remains low due to limited arbitrage opportunities, and Scenario C experiences even lower cash flows in these months due to higher costs. The addition of 15 MW in futures contracts enhances annual cash flow, although the impact varies across months. For instance, it results in a 38% revenue increase in October, where arbitrage opportunities are minimal, but also a 23% increase in negative revenue in May, despite high arbitrage potential. Overall, the increase in battery capacity and futures contracts offset the higher costs, mitigate the wind farm's intermittency risk, and reduce revenue volatility compared to Scenario A. This leads to a positive annual adjusted free cash flow of approximately $0.7 million in 2023, with a net present value (NPV) of $16.3 million over the portfolio's economic life.

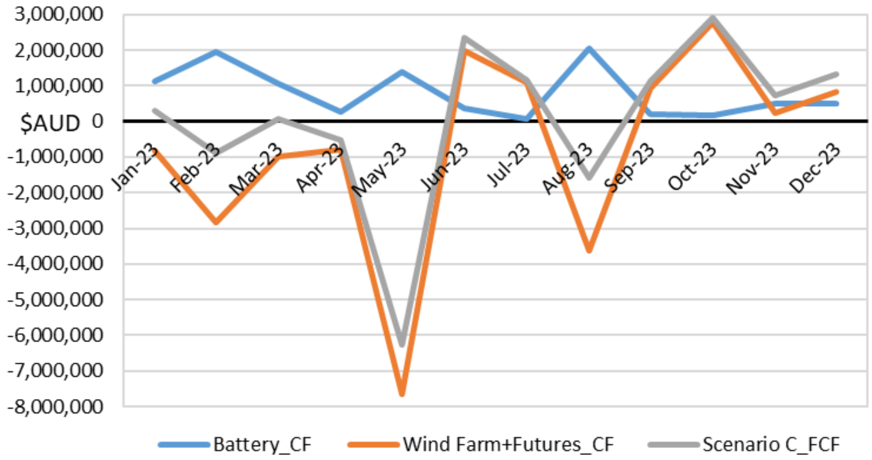

Figure 7. Scenario C: Adjusted Free Cash Flow Including a 250 MW Wind Farm, 105 MW Futures Contracts, and a 50 MW/100 MWh Battery

In Scenario D[17], increasing the battery storage duration leads to a notable rise in battery revenue through the arbitrage strategy. While this comes with higher capital and operational expenses, it enhances the overall portfolio's adjusted free cash flow to approximately $1 million in 2023. Given this scenario, the NPV for the adjusted free cash flow of the second portfolio is projected to be a positive $19.6 million, marking it as the most optimal scenario.

The findings suggest that integrating a lithium-ion battery with a capacity of 50 MW/100 MWh or 50 MW/200 MWh can greatly enhance revenue certainty and improve the viability of a 250 MW wind farm in South Australia. This integration can be considered a bankable project, likely leading to a reduced cost of capital, based on the assumptions made in this study. The increased storage capacity allows for more efficient management of energy supply and demand, stabilising cash flows and improving the overall financial attractiveness of the intermittent renewable portfolio. The battery integration also facilitates increased exposure of the wind farm to futures contracts, for example, with an increase from 75 MW to 105 MW under Scenarios C and D.

6. Conclusions and Suggestions for Future Research

In this study, we explored the integration of lithium-ion batteries into a 250 MW merchant wind farm portfolio that includes a 75 MW futures contract. The analysis is conducted under different scenarios, each varying in battery power and energy capacity, to assess the impact of these two important factors on the portfolio's viability and revenue streams. The results indicate that the optimal configuration for maximising the portfolio's performance, among those considered in this study, is a battery with a power capacity of 50 MW and a storage duration of 4 hours. This set up offers the best balance between capital and operational costs and revenue optimisation across all associated markets, underscoring the potential for the batteries to significantly enhance the financial stability and viability

[17] For detailed results of the simulations, see Figure A.2 in Appendix A

of wind farm portfolios in the evolving energy landscape toward net-zero emissions. Battery integration allowed the wind farm increased exposure to futures contracts (i.e., from 75 MW to 105 MW) and offered a potential policy benefit of increasing liquidity in the derivatives market.

Governments, instead of relying solely on PPAs, which could adversely impact market efficiency, could implement other incentives to support investment in integrated renewable energy and battery projects. These incentives could include tax credits, grants, or favourable regulatory frameworks that encourage the development of these projects. By doing so, governments can facilitate the growth of sustainable energy infrastructure while maintaining the efficiency of the electricity market.

The model developed in this paper can be applied to various combinations of wind farms and batteries and adapted for use in any region within the NEM, providing a versatile tool for evaluating and enhancing the financial feasibility of renewable energy projects. As future research, the valuation of this combination can be investigated in different regions within the NEM characterised by varying levels of renewable energy penetration, as well as varying electricity price dynamics and solar and wind capacity factors. The occurrence of intense negative prices over the two months highlights the need to evaluate the application of alternative derivatives contracts within the integrated portfolio, or the utilisation of more dynamic strategies for managing contracts, such as selling quarterly or monthly derivatives products, could help capture or mitigate risks associated with seasonal weather variability. Investigating the impact of different financial instruments and hedging strategies could provide deeper insights into optimising revenue streams and mitigating risks associated with price volatility. Additionally, considering some level of price uncertainty in the electricity market (instead of perfect foresight) would provide a more realistic assessment. These areas of future research could greatly improve the practical implementation and resilience of integrated renewable energy and battery portfolios within the energy sector, supporting the transition toward net-zero emissions.

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Appendix A: Supplementary Figures

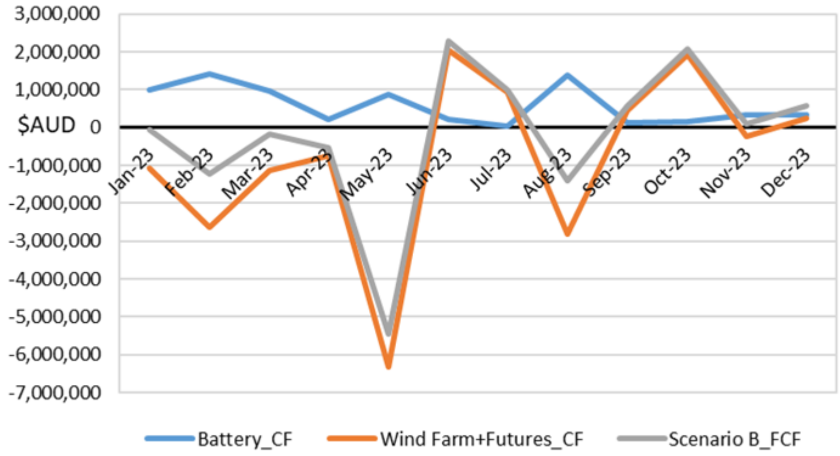

Figure A.1. Scenario B: Adjusted Free Cash Flow Including a 250 MW Wind Farm, 90 MW Futures Contracts, and a 25 MW/100 MWh Battery

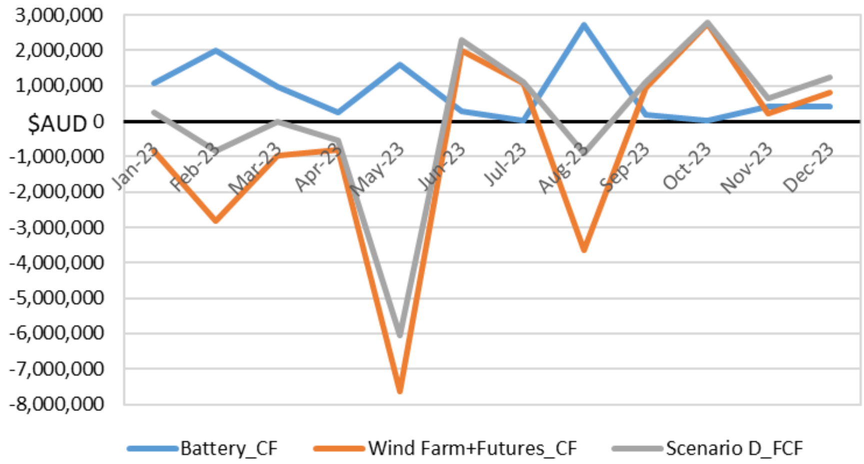

Figure A.2. Scenario D: Adjusted Free Cash Flow Including a 250 MW Wind Farm, 105 MW Futures Contracts, and a 50 MW/200 MWh Battery