Battery Scheduling Optimisation in Energy and Ancillary Services Markets: Quantifying Unrealised Revenue in the Australian NEM

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ABSTRACT

Despite the high flexibility of Battery Energy Storage Systems (BESS), existing operation strategies often fail to fully utilise these assets. Additionally, the current literature on optimal BESS scheduling often relies on simplistic assumptions regarding their power efficiency and ignores the intricacies of simultaneous participation in energy and ancillary services markets. This makes these models inadequate for estimating the maximum potential revenue of existing BESSs. Thus, this paper aims to quantify their unrealised revenue in the Australian National Electricity Market (NEM). We first introduce a new methodology that systematically identifies the operational characteristics of BESSs using public data. Then, we propose a mathematical model to optimise BESS scheduling across NEM energy and ancillary services markets. By applying this model to six BESSs in the NEM, we uncover their unrealised potential revenue and show that nearly half of potential energy arbitrage revenue is forfeited due to suboptimal dispatch decisions or inaccuracies in price forecasting.

CCS CONCEPTS

• **Mathematics of computing** → **Mathematical optimization**; • **Hardware** → **Batteries**; • **General and reference** → *Estimation.*

KEYWORDS

Battery Energy Storage Systems (BESS), Battery Operational Characteristics, Battery Scheduling Optimisation, Australian National Electricity Market (NEM)

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NOMENCLATURE

Superscripts, Subscripts, and Indices

abs, typ	"Absolute" and "typical" bounds
con	Contingency FCAS
d, c	Discharging and charging
f	FCAS index
g, l	Generator and load modes of the BESS
i	Four-second interval index
min, max	Minimum and Maximum values
rc, lc	Raise and lower contingency index
reg	Regulation FCAS
rr, lr	Raise and lower regulation index
sd	Self-discharging
t	Dispatch interval index

Parameters and Variables

P^{sd}	Self-discharging power of BESS
$\bar{E}$	Total energy capacity of BESS
$\bar{F}^f$	Maximum enabled capacity of FCAS f
$\bar{P}$	Power capacity
Δi	Duration of a 4-second interval, i.e., 4 seconds
Δt	Duration of a dispatch interval, i.e., 5 minutes
Δt^f	Maximum delivery duration of FCAS f
η	Efficiency during charging or discharging
λ_t	Price of energy or FCAS at interval t
F^f	Enabled amounts of FCAS f
P^d, P^c	Discharging and charging power of BESS
soc	State of Charge (SoC)
U^{rr}, U^{lr}	Utilisation, average delivered proportion of enabled raise and lower regulation FCAS
x_t	Binary variable indicating if the BESS is discharged at the dispatch interval t

Sets

$\mathcal{LCF}$	Set of lower contingency services
$\mathcal{F}$	Set of all FCAS, including 2 regulation FCAS and 6 contingency FCAS
$\mathcal{RCF}$	Set of raise contingency services
$\mathcal{T}$	Set of all dispatch intervals in the receding horizon
Ω_η	Set of all possible BESS efficiencies
I	Set of all four-second intervals in a month

1 INTRODUCTION

As the shift to renewable energy sources is gaining momentum, Battery Energy Storage Systems (BESSs) have become a necessary component of contemporary power grids. The Australian National Electricity Market (NEM), characterised by high penetration of renewable energy generation and volatility of energy prices, presents a unique context for investigating the operational efficiency and revenue realisation of BESSs. NEM is an interconnected system that fulfils about 80% of Australia's electricity demand and operates only on a spot market basis, making it unique compared to many electricity markets around the world. Australian Energy Market Operator (AEMO) allows units to rebid (i.e., change their offer) up to a couple

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of minutes before the start of each five-minute dispatch interval [6]. Subsequently, AEMO employs a security-constrained linear optimal power flow model to co-optimise the dispatch of energy and Frequency Control Ancillary Services (FCAS), ensuring supply-demand balance and system security in the most cost-efficient way [8].

Given their rapid response and flexibility, BESSs are in a unique position, compared to other utility-scale assets, to meet various requirements of power grids in an optimal way, including the provision of inertia, frequency control, voltage support, and peak demand shaving [24]. Beyond non-market services and contractual agreements, BESSs can generate revenue by participating in nine different markets in the NEM: the energy market, two regulation FCAS (rFCAS) markets (raise and lower), and six contingency FCAS (cFCAS) markets (raise and lower for 6-second, 60-second, and 5-minute services). The rFCAS market addresses small frequency deviations within the standard operating range, whereas the cFCAS market manages larger sudden frequency deviations. Each of these markets presents an opportunity for revenue generation and value stacking of BESSs. Therefore, optimal scheduling of BESSs across these markets is essential to maximise their revenue and provide the necessary services to the grid.

Recent studies, however, have identified suboptimal operation of existing BESSs, particularly in the energy market, leading to unrealised potential revenue [23]. There are several elements that could contribute to this underperformance, including inaccurate price forecasts, operational inefficiencies, and suboptimal revenue stacking. However, no research has been done to comprehensively evaluate the maximum potential revenue that existing BESSs can generate by optimally participating in energy and FCAS markets.

Furthermore, the models proposed for the optimal scheduling of BESSs in the literature cannot be used to determine the potential revenue of actual BESSs in the NEM [16–19, 21, 23]. A major shortcoming of these models is that they do not take into account the operational characteristics and limitations of actual BESSs, making them inadequate for accurately calculating their potential revenue [16–19, 21, 23]. For example, these models often use constant charging and discharging efficiencies, overlooking the significant variance in efficiency across different BESSs, as well as the variances for an individual BESS over time. Furthermore, they do not offer methodologies to estimate these important operational parameters that can considerably affect the calculated potential revenue [16–19, 21, 23]. Second, the existing literature investigated the participation in the energy, and cFCAS or rFCAS markets, but not all three together [17–19, 23]. These studies also do not accurately model market rules related to different revenue streams, leading to incorrect revenue estimation [16, 18, 19, 21]. For example, the effects of energy exchanged with the grid while providing rFCAS, the complementary nature of different cFCAS, and the joint energy-FCAS constraints in the operation model are often overlooked. As such, these models are unable to accurately calculate the revenue of existing BESSs that participate in energy, cFCAS, and rFCAS markets simultaneously.

We aim to fill these gaps by providing a new methodology for estimating the BESS operational characteristics, as well as a new model for optimal BESS scheduling in the NEM. First, we propose a systematic method to determine the operational characteristics of the BESSs installed in the NEM. We then present a Mixed-Integer Linear Programming (MILP) model that considers these BESS operational characteristics and limitations, together with important market details to optimise BESS scheduling for maximum revenue across energy and all FCAS markets in the NEM. We use the proposed optimisation model to calculate the maximum potential revenue that existing BESSs can achieve when optimally dispatched. We finally compare this with the actual revenue they earned over a six-month period, calculated using public NEM data, to quantify their unrealised potential revenue.

The rest of this paper is organised as follows. Section 2 provides an overview of the proposed methodology. Section 3 presents the details of our systematic approach to estimating the operational characteristics of BESS. In Section 4, we describe our BESS scheduling optimisation model. In Section 5, we present the outcomes of our model when applied to six existing NEM BESSs and compare their maximum potential and actual revenue. Finally, we discuss the applications of our modelling approach and future research avenues, and conclude the paper in Section 6.

2 METHODOLOGY OVERVIEW

This study aims to determine the maximum potential revenue of BESSs in the NEM when optimally dispatched to quantify unrealised potential revenue due to their suboptimal operation. For a fair comparison, potential revenue must be calculated while considering key operational limitations and characteristics of BESS, their availability, total energy throughput, and total capacity dispatched in the FCAS markets. The operational parameters of most BESSs are not publicly available due to their commercially sensitive nature and, therefore, must be estimated.

Estimating the operational characteristics of BESSs, such as charging and discharging efficiencies, is the first step to finding their maximum potential revenue. Operational characteristics of different BESSs are not similar and change over time, caused by various factors, such as the age of the batteries, the temperature and environmental conditions, the original battery equipment manufacturer, and the usage patterns [20, 22]. As these parameters are used as the input to the BESS scheduling optimisation model, they can significantly influence the calculation of BESSs' potential revenue. Therefore, we must first estimate these operational characteristics as accurately as possible. As such, we use historical 4-second discharging and charging power of the NEM BESSs for the methodology detailed in Section 3. This data are measured by the Supervisory Control and Data Acquisition (SCADA) system and are published by AEMO on [2].

In addition to operational characteristics, there are operational limitations for the BESS operation. Due to many factors, such as contractual agreements, BESS warranty terms, and cyclic degradation management, BESS operators may be obliged to or deliberately decide not to charge or discharge at the nominal power and energy capacity. Thus, to ensure a fair comparison, we estimate their "absolute" upper and lower state-of-charge (SoC) limits, as well as their "typical" upper and lower SoC limits. The absolute limits refer to the maximum and minimum SoC reached by the BESS at any interval during the entire study period. These absolute limits may differ from the battery being completely full or empty. The typical limits

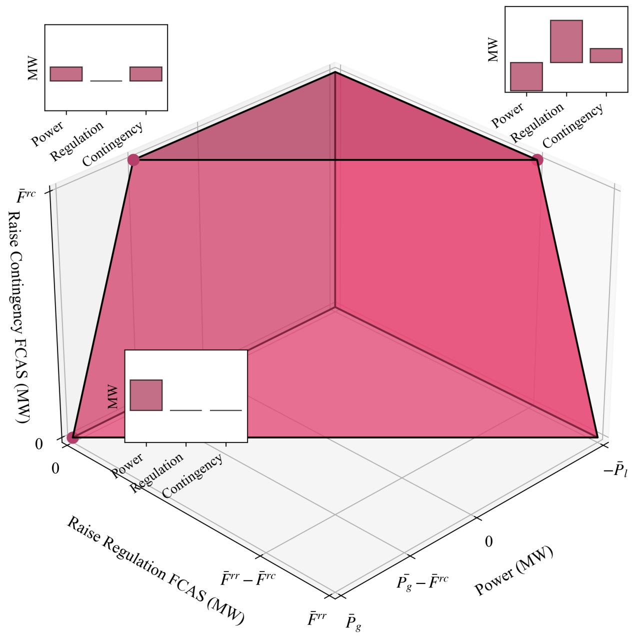

Figure 1: Energy-FCAS trapezium constraints in the NEM.

aim to show the most common range of BESS SoC over the study period, which can be significantly smaller than the nominal BESS energy capacity. These SoC limits for each BESS are estimated using historical 4-second charging and discharging data. The discharging and charging power capacity is also calculated by the lesser of the empirical energy dispatch data and the maximum SCADA-metered discharging and charging power.

Ultimately, taking into account the specified limitations, we present a BESS operation scheduling model, designed for participation in both the energy and FCAS markets, aiming to maximise revenue over a 24-hour horizon. Assuming that the BESS is a price taker, it will accept the market clearing price without attempting to alter it through its bids. Since participants are paid at the market clearing price for their dispatched energy and FCAS when their bids are accepted, a price taker participant will submit a bid at the market floor to be included in the dispatch or at the market cap to avoid being dispatched. As market participants in the NEM can rebid every 5 minutes, optimal bids are formulated based on the optimisation results obtained for the first 5-minute interval of the 24-hour horizon. Therefore, the optimisation runs on a receding horizon, advancing in 5-minute intervals, where only the optimisation results of the first interval are binding. At every 5-minute interval, the BESS can update its optimal operation based on the most recent data to determine the optimal bids for the upcoming dispatch interval.

In the NEM, a BESS can operate as both a generator and a load. As a generator, it can participate in three raise cFCAS markets, in the energy market by discharging, and in both raise and lower rFCAS. As a load, it can participate in the energy market by charging, in three types of lower cFCAS markets, and in both raise and lower rFCAS [1, 15]. To accurately capture the energy-FCAS bidding constraints of BESSs in the NEM, we have incorporated constraints on maximum dispatchable FCAS at each dispatch interval, total dispatched FCAS over the analysis period, and FCAS trapezium constraints using empirical dispatch data of the BESSs. According to the NEM regulations [1], the FCAS offer trapezium shows the capability of the plant to provide FCAS in relation to its levels of power generation, consumption, or load reduction. A sample trapezium for raise rFCAS, raise cFCAS, and power output of a BESS (for both generator and load sides of the BESS) is illustrated in Figure 1. The trapezium depicts the plant's maximum FCAS availability at various output levels, illustrating the relationship among rFCAS, cFCAS and the generation or consumption of the plant, as considered in AEMO dispatch optimisation. To align closely with the existing BESS operations in the NEM, our model integrates these essential joint energy-FCAS constraints.

3 ESTIMATING BESS OPERATIONAL CHARACTERISTICS

For every BESS in each month, we use an exhaustive search technique to estimate the monthly averages of its operational characteristics, i.e., charging efficiency, discharging efficiency, and self-discharge power[1]. One month was chosen as the analysis period, for which the characteristics are assumed constant for the following two reasons. First, a month-long interval provides sufficient data for our exhaustive search method to find the best estimates of BESS operational characteristics. Second, this timeframe is short enough to ensure that the BESS operational characteristics remain relevant, considering that battery performance can be affected by various external variables over time, e.g., seasonal temperature.

The exhaustive search tests different combinations of BESS operational characteristics within their realistic boundaries. These boundaries are discretised into finite sets to systematically explore the entire feasible operation space. For each combination, the algorithm calculates the SoC at 4-second intervals based on SCADA-metered charge and discharge data. Combinations leading to invalid SoC values, i.e., exceeding the battery's energy capacity or dropping below zero, are automatically discarded. The most precise set of parameters is determined by the tightness of the daily SoC maximums and minimums. This yields the most accurate estimate of the typical SoC range as it closely mimics how real-world BESS operates within a specific, stable SoC range on a daily basis.

Algorithm 1 outlines the pseudocode of our methodology used to find the best estimates of the BESS SoC, as well as its charging efficiency, η_c, discharging efficiency, η_d, and self-discharge power, P_{sd}. It initialises a control variable MAD_{best} to infinity, representing the baseline for the sum of Median Absolute Deviations (MAD) of daily SoC maximums and MAD of daily SoC minimums for one month. In statistics, MAD is defined as the median of deviations from the data's median. It is chosen as the variability metric of the SoC maximums and minimums as it is not affected by outliers. The best set of SoC estimates is the one with the lowest MAD_{best}.

[1]Note that self-discharge power comprises on-site energy consumption, intrinsic self-discharge of battery modules, and any other discharge that is not captured by the SCADA meter at the point of connection to the grid.

Each set of candidate operational characteristics, $(\eta_c, \eta_d, soc_0, P_{sd})$, includes the desired operational characteristics of BESS, as well as an initial SoC. For each set, the algorithm iteratively updates the SoC at each 4-second interval, i, using the candidate parameters, and the historical SCADA-metered charge and discharge data. Any set with SoC that falls outside the permissible range $[0\%, 100\%]$ is invalid and excluded from further consideration. If a set of parameters respects the SoC limits, the algorithm proceeds to calculate the daily maximum and minimum of SoC values for that candidate set, which are then used to compute their respective MADs. The sum of the MADs of the maximums and minimums is then compared to MAD_{best}. If the current parameter set results in a lower sum of MADs, the global best solution MAD_{best} will be updated and the set of associated parameters will be recorded. At the end of the loop, the set of parameters with the lowest MAD_{best} is selected as the best approximation of the operational characteristics of BESS. Finally, we use the estimated SoC values over a month to identify the absolute and typical SoC limits. The typical upper and lower limits correspond to the median of daily SoC maximums and minimums, respectively. In contrast, the absolute upper and lower limits are the overall monthly maximum and minimum SoC values. These parameters are integrated into the model discussed in the following section.

Algorithm 1 Estimating the BESS operational characteristics

Initialise $MAD_{best} \leftarrow \infty$
for $(\eta_c, \eta_d, soc_0, P_{sd})$ in $\Omega_\eta \times \Omega_\eta \times [0, 100] \times [0, P_{sd}^{max}]$ **do**
  for $i \in I$ **do**
    if $0\% < soc_i < 100\%$ **then**
      $soc_i \leftarrow soc_{i-1} + \dfrac{(P_c\eta_c - P_d/\eta_d - P_{sd})\Delta i}{\bar{E}}$
    else
      Combination $(\eta_c, \eta_d, soc_0, P_{sd})$ is invalid
    end if
  end for
  if Combination $(\eta_c, \eta_d, soc_0, P_{sd})$ is valid **then**
    Compute daily Maxes and Mins of $\{soc_i\}_{i\in I}$
    $MAD_{soc}^{max} \leftarrow$ MAD of daily SoC maximums
    $MAD_{soc}^{min} \leftarrow$ MAD of daily SoC minimums
    if $MAD_{soc}^{min} + MAD_{soc}^{max} < MAD_{best}$ **then**
      $MAD_{best} \leftarrow MAD_{soc}^{min} + MAD_{soc}^{max}$
      Estimated BESS SoC $\leftarrow \{soc_i\}_{i\in I}$
      Best estimation $\leftarrow (\eta_c, \eta_d, soc_0, P_{sd})$
    end if
  end if
end for

4 BESS OPERATION SCHEDULING OPTIMISATION

This section describes the BESS scheduling optimisation model and provides the mathematical model formulated to determine the optimal dispatch scheduling across all energy and FCAS markets. In the NEM, generators or loads earn FCAS revenue based on the enabled amount of FCAS (i.e., the reserved capacity), irrespective of whether these services are actually utilised. In the energy market, the cost or revenue is calculated based on the net energy exchanged with the grid in each dispatch interval. This can include the energy delivered due to FCAS obligations in addition to standard energy market dispatch. As cFCAS deliveries are rarely needed in the NEM [3], their impact on net energy exchange is negligible. On the contrary, enabled rFCAS is frequently used for frequency stability and has a notable impact on both energy revenue and battery throughput. As a result, our model calculates the energy exchanged due to rFCAS dispatch based on its enabled amount and the average rFCAS utilisation of BESS, U. The average utilisation is determined based on historical 4-second data of Automatic Generation Control (AGC) regulation instructions sent to BESSs (as can be found in [2]) and their empirical rFCAS dispatch data. Figure 2 provides an illustrative example, showcasing the enabled amount, the AGC regulation signal, and the utilisation of the raise rFCAS for Lake Bonney BESS during one specific hour on 1 May 2023. The utilised raise rFCAS led to 3.7 MWh discharge of the BESS at that hour. This is a significant amount of energy with an impact on energy revenue and BESS throughput and, therefore, is considered in our model.

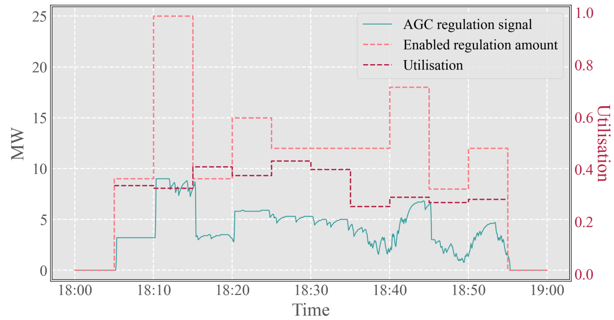

Figure 2: Raise rFCAS utilisation for Lake Bonney BESS.

We solve the optimisation model, formulated in (1), to maximise the BESS revenue for each receding horizon, subject to the market rules, BESS power and energy constraints, and other operational limitations.

$$\text{maximise} \quad \sum_{t=0}^{|\mathcal{T}|-1} \mathcal{R}_t \tag{1a}$$

subject to:

$$E_t = E_{t-1} + \Big(\eta_c\Big(P_t^c + F_t^{l,lr}U^{lr} - F_t^{l,rr}U^{rr}\Big) - P^{sd}$$
$$- \frac{1}{\eta_d}\Big(P_t^d + F_t^{g,rr}U^{rr} - F_t^{g,lr}U^{lr}\Big)\Big)\Delta t; \forall t \in \mathcal{T}/\{0\}, \tag{1b}$$

$$E_t + \sum\nolimits_{f\in\mathcal{RF}}(F_t^f \Delta t^f) \le soc_{abs}^{max}\bar{E}; \forall t \in \mathcal{T}, \tag{1c}$$

$$E_t - \sum\nolimits_{f\in\mathcal{LF}}(F_t^f \Delta t^f) \ge soc_{abs}^{min}\bar{E}; \forall t \in \mathcal{T}, \tag{1d}$$

$$E_t \le soc_{typ}^{max}\bar{E}; \forall t \in \mathcal{T}, \tag{1e}$$

$$E_t \ge soc_{typ}^{min}\bar{E}; \forall t \in \mathcal{T}, \tag{1f}$$

$$P_t^d \le \bar{P}_g x_t;\ \forall t \in \mathcal{T}, \tag{1g}$$

$$P_t^c \le \bar{P}_l(1 - x_t);\ \forall t \in \mathcal{T}, \tag{1h}$$

$$F_t^f \leq \bar{F}^f;\ \forall t \in \mathcal{T}, f \in \mathcal{F}, \tag{1i}$$

$$P_t^d + F_t^{g,rr} \leq \bar{P}_{g,reg};\ \forall t \in \mathcal{T}, \tag{1j}$$

$$0 \leq P_t^d - F_t^{g,lr};\ \forall t \in \mathcal{T}, \tag{1k}$$

$$P_t^c + F_t^{l,lr} \leq \bar{P}_{l,reg};\ \forall t \in \mathcal{T}, \tag{1l}$$

$$0 \leq P_t^c - F_t^{l,rr};\ \forall t \in \mathcal{T}, \tag{1m}$$

$$P_t^d + F_t^{g,rr} + F_t^{rc} \leq \bar{P}_{g,reg,con}; \forall t \in \mathcal{T}, rc \in \mathcal{RCF}, \tag{1n}$$

$$P_t^c + F_t^{l,lr} + F_t^{lc} \leq \bar{P}_{l,reg,con}; \forall t \in \mathcal{T}, lc \in \mathcal{LCF}, \tag{1o}$$

$$\sum\nolimits_{t \in \mathcal{T}} (P_t^c + P_t^d + F_t^{ll} U^{lr} + F_t^{rr} U^{rr}) \leq \bar{P}^{total}, \tag{1p}$$

$$\sum\nolimits_{t \in \mathcal{T}} (F_t^f) \leq \bar{F}_f^{total};\ \forall f \in \mathcal{F}, \tag{1q}$$

$$P_t^c,\ P_t^d,\ F_t^f,\ E_t \geq 0;\ \forall t \in \mathcal{T},\ f \in \mathcal{F}, \tag{1r}$$

$$x_t \in \{0, 1\};\ \forall t \in \mathcal{T}. \tag{1s}$$

The revenue of BESS at dispatch interval t is also calculated as follows:

$$\begin{aligned}\mathcal{R}_t = \Big[&\lambda_t^d (P_t^d + F_t^{g,rr} U^{rr} - F_t^{g,lr} U^{lr}) - \lambda_t^c (P_t^c \\ &+ F_t^{l,lr} U^{lr} - F_t^{l,rr} U^{rr})\Big] \Delta t + \sum_{f \in \mathcal{F}} (\lambda_t^f F_t^f) \Delta t; \forall t \in \mathcal{T}.\end{aligned} \tag{2}$$

The first term in (2) represents the energy cost or revenue of BESS, calculated using the energy price and the net energy exchange, which includes the energy and the rFCAS dispatches. The second term indicates the revenue of FCAS markets. It is worth noting that charging and discharging prices, λ_t^c and λ_t^d, are not the same due to different Marginal Loss Factors (MLFs) of the generator and load sides of the BESS [5].

The energy level (E_t) of the BESS considering its energy dispatch (charge or discharge) and enabled rFCAS volumes is formulated in (1b), while (1c)–(1f) apply the energy level constraints of the BESS. Specifically, (1c) and (1d) ensure that the BESS SoC remains within the absolute upper and lower limits, even when it is required to provide all enabled FCAS. Equations (1e) and (1f) further constrain the BESS SoC to the typical upper and lower limits, as discussed in the previous section. This ensures that the BESS operates in a way that is either similar to or more conservative than the actual case.

The constraints limiting the charging and discharging power, together with the enabled amount of rFCAS or cFCAS, are presented in (1g)–(1o). Constraints (1g) and (1h) limit the charging and discharging power to respect the battery power capacity, while (1i) restricts the enabled FCAS for each dispatch interval to the BESS's FCAS capacity. Modelling the FCAS trapezium constraints [1], (1j)–(1m) are added as joint rFACS-energy limits, while (1n) and (1o) are joint capacity constraints. These limitations ensure that the BESS maintains adequate power capacity to deliver frequency control services when enabled in the raise and lower FCAS markets.

Constraint (1p) ensures that the BESS energy throughput is below its total daily limit, which is the daily average of historical BESS throughput, determined using its 4-second telemetered data. Similarly, (1q) limits the total amount enabled for each FCAS to its total daily limit, which is equal to the daily average FCAS enablement of the BESS, calculated using its empirical dispatch data. The total daily limits of BESS throughput and FCAS enabled amount are updated at each receding horizon to reflect the changes caused by the dispatched energy and FCAS in the past five-minute dispatch interval. This ensures that, over the simulation period, both total BESS throughput and dispatched FCAS capacity are lower than their respective empirical values for the BESS.

5 CASE STUDIES

In this section, we present a comparison between the actual earnings of six BESS in the NEM and the maximum potential revenue that could have been obtained through optimal dispatch decisions under perfect information. We studied Hornsdale Power Reserve and Lake Bonney BESS in South Australia (SA), Queanbeyan and Wallgrove BESS in New South Wales (NSW), Wandoan BESS in Queensland (QLD), and Ballart BESS in Victoria (VIC).

We initially validate the proposed methodology in Section 3 by determining the operational characteristics and limitations of these BESSs. Second, we calculate the monthly revenue of each BESS for two cases,

(1) **Perfect Information Revenue**: Calculated using the battery operation optimisation model, detailed in Section 4, and assuming perfect information of market prices in the next 24 hours. It sets an upper benchmark for BESS's realisable revenue, representing the maximum potential revenue achievable under perfect market information.
(2) **Actual Revenue**: Calculated using empirical dispatch data, market prices, and telemetered charge/discharge data of the BESSs, obtained from [2, 7]. This case reflects the genuine earnings of BESSs in the NEM based on their actual operations.

Finally, a comparative assessment is carried out between the Perfect Information Revenue and the Actual Revenue for each BESS, assessing their market performance within the NEM. Perfect Information Revenue shows the potential revenue achievable under ideal conditions, but attaining this theoretical maximum in reality may be impossible due to the complexities inherent in practical operations, such as inaccuracies in electricity price prediction. This analysis highlights the potential for BESS revenue enhancement by juxtaposing the maximum potential revenue of BESSs with their actual earnings in the NEM.

The granularity of our simulation studies is 5 minutes, aligning with the NEM's 5-minute spot market structure. In each optimisation, we consider one day ahead of data, translating to 288 dispatch intervals, to determine the optimal operation of the BESS. The optimisation operates on a receding horizon, advancing in 5-minute increments, where only the optimisation results of the first interval are binding. This is because, at every 5-minute interval, the BESS can update its optimal operation based on the most recent data to determine the optimal bids for the upcoming dispatch interval. Thus, to determine the potential revenue of a BESS in each month, the optimisation is performed at least 8064 times (adjusting for the specific number of days in the month) to find optimal decisions at each interval.

Gurobi Optimiser 10.0.1 was used to solve the MILP optimisation with an optimality gap of 0% as stopping criterion. The optimisation was run on a desktop PC with an Intel i7-10700 CPU @ 2.90GHz processor and 32 GB of RAM. The average run time of the MILP

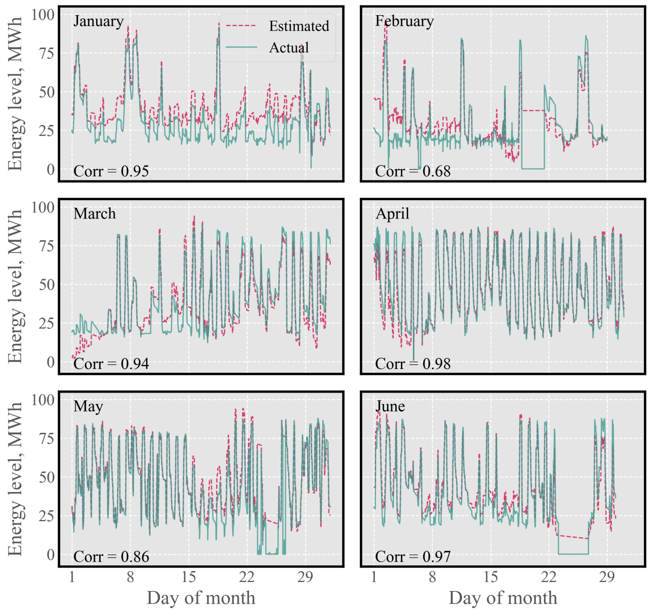

Figure 3: Comparing the actual and estimated SoC of Wallgrove BESS.

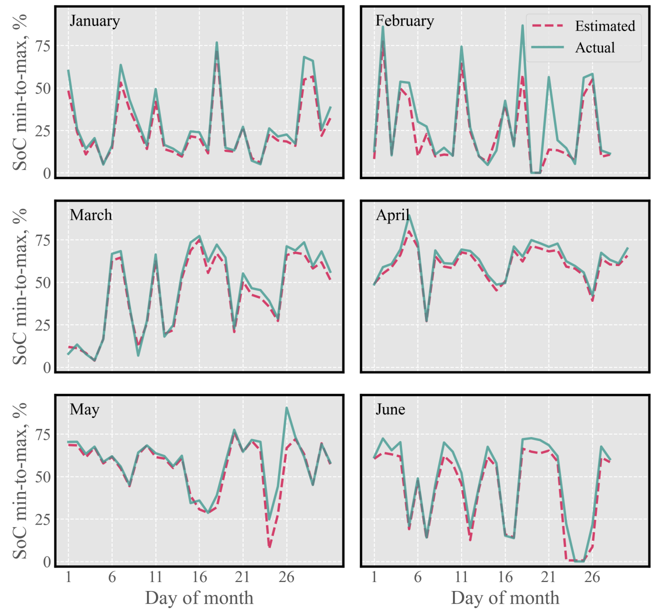

Figure 4: Daily SoC min-to-max of Wallgrove BESS.

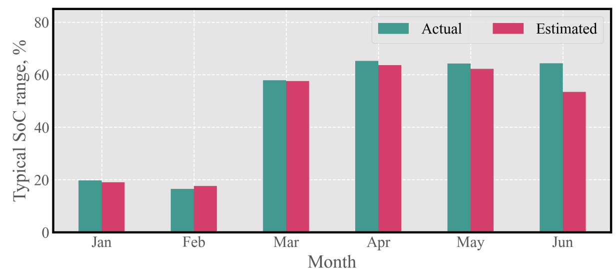

Figure 5: Actual and estimated typical SoC range of Wallgrove BESS.

optimisation was 0.16 seconds. While the addition of more markets only marginally increases the computational burden of our MILP model, its scalability can be significantly influenced by the number of BESS units and timesteps (i.e., dispatch intervals) in the optimisation. This is due to their direct effect on the number of binary variables in the optimisation. Nonetheless, the model is scalable for the applications discussed in this paper as they do not lead to a large number of binary variables, confirmed by our simulations.

Finally, it should be noted that all input data used for our simulations are publicly available. Interested readers can find 4-second SCADA data for BESSs in [2], market clearing price data in [11], predispatch price data in [9, 10], and historical unit dispatch data in [7]. Also, the power and energy capacity of the BESSs within the NEM are available at [14].

5.1 Accuracy of BESS Characteristic Estimation

To validate the exhaustive search method described in Section 3, we compare the estimated SoC of Wallgrove BESS, located in NSW, with publicly available SoC data for this battery [12]. Figure 3 visualises this comparison during the first six months of 2023, confirming a strong correlation between the estimated values and the actual data. In February, the Pearson correlation drops, attributable to the BESS being largely inactive or minimally used. This can be seen in the SoC changes of the battery in Figure 3. Although there are periods with notable discrepancies between estimated and actual energy levels, the high correlation level confirms the alignment in SoC changes between the two sets. Importantly, what affects the calculation of perfect information revenue is the range of SoC, not its absolute magnitude. As such, it is imperative that our estimated SoC range closely aligns with that of the actual BESS data. This would warrant that the perfect information revenue is determined fairly when taking into account the BESS operational limitations. Figure 4 shows the daily SoC min-to-max range for actual and estimated cases for six months. The figure confirms that our estimated SoC range closely approximates the actual values on most days, while being lower on some days.

Expanding our analysis, Figure 5 contrasts the typical SoC ranges, defined as the range between the typical minimum and maximum SoC, estimated by our model and those calculated based on actual historical data from Wallgrove BESS over the six-month period. As a reminder, typical SoC limits are calculated based on the median of daily SoC maximums and minimums, as discussed in Section 3. The figure shows that our estimates align with or are more conservative than the actual data, with our model's estimated SoC range being, on average, 3% lower than the actual data.

Overall, these comparisons confirm that the operational characteristics estimated using our methodology are aligned closely or even more conservative than those of the actual BESSs. This allows us to conduct a fair comparison between their actual and perfect

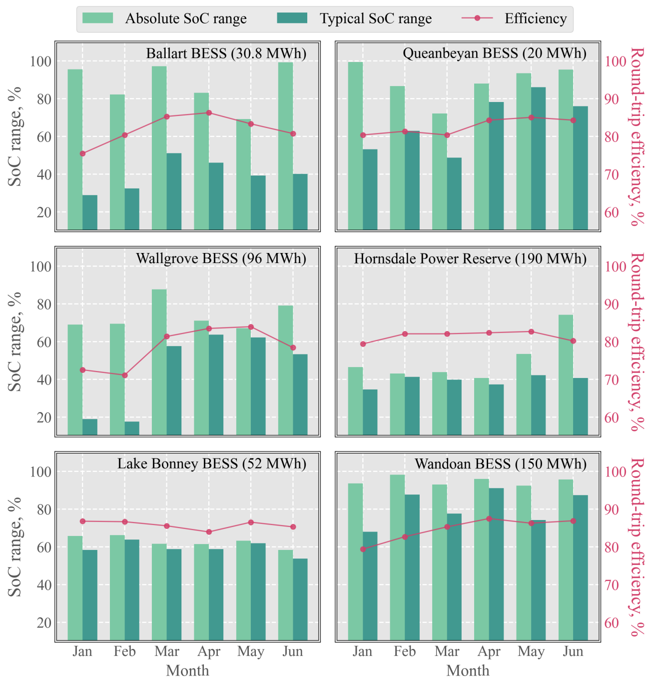

Figure 6: Absolute and typical SoC ranges of six BESSs in the NEM.

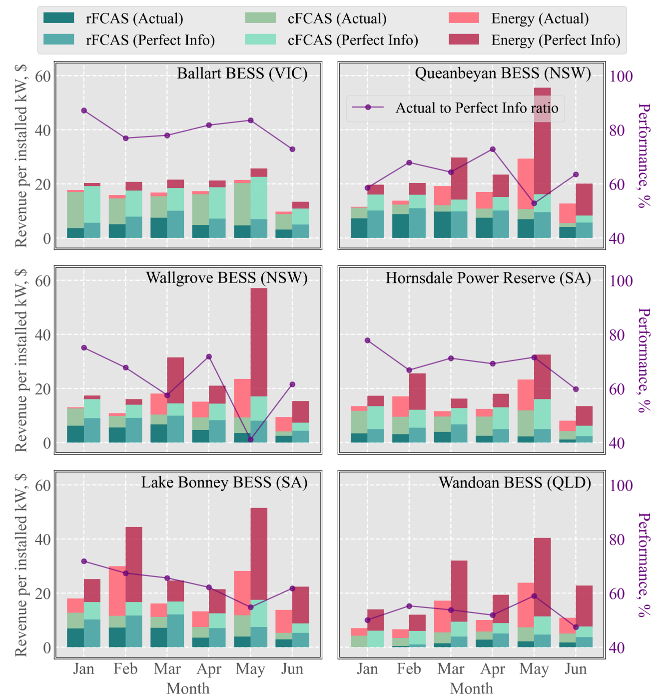

Figure 7: Comparing monthly actual and perfect information revenue of BESSs.

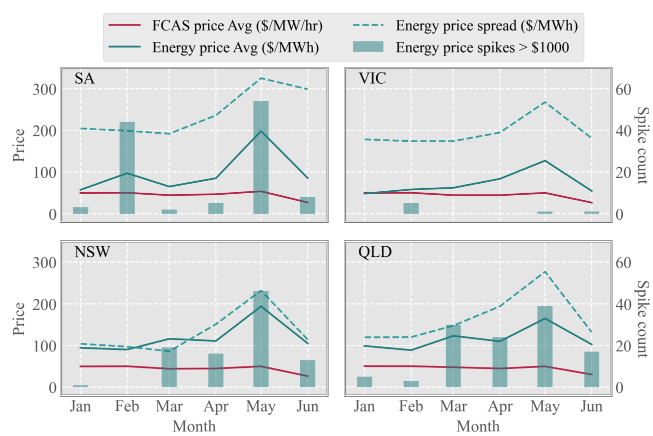

Figure 8: Average energy and FCAS prices, and energy price spread and spikes.

information revenue calculated through the optimisation model presented in Section IV.

Finally, Figure 6 shows the estimated typical and absolute SoC ranges, as well as the estimated round-trip efficiency, over six months for the six BESSs studied in this paper. Significant monthly fluctuations in SoC ranges across different BESSs further prove the necessity of having precise operational characteristics to accurately estimate maximum potential revenue. Also, an interesting observation is the significantly lower SoC range of older BESS in the NEM, such as Hornsdale and Lake Bonney, compared to recently commissioned ones, i.e., Queanbeyan and Wandoan. We use charging and discharging efficiencies, self-discharge power, and SoC limits obtained in this subsection as optimisation input parameters.

5.2 BESS Revenue Potential in the NEM

Using historical energy and FCAS prices, empirical dispatch data, and telemetered power data of the six NEM BESSs [2, 7], we first calculate their actual monthly revenue in the rFCAS, cFCAS, and energy markets for the first half of 2023. Then, we apply our BESS scheduling optimisation over 24-hour rolling windows for each BESS to determine their monthly perfect information revenue. Figure 7 shows a comparison between the actual revenue and the perfect information revenue of the BESSs in the NEM for the six months. We also show the actual revenue as a percentage of its perfect information revenue each month to make the comparison simpler, which is used as a metric to measure the BESS's performance. The figure shows that there is a significant variation in the performance of different BESSs over the six months, ranging from 40% to 80%. Additionally, while the revenue of each BESS from FCAS markets is generally consistent over different months, the perfect information revenue, as well as the actual revenue from the energy market, varies significantly. This variation can be attributed to the notably volatile energy prices compared to the more consistent FCAS prices over the six-month period analysed. This is illustrated in Figure 8, which shows the monthly average prices of energy and FCAS, the spread of the energy prices (determined based on the difference between the 10th and 90th quantiles), and

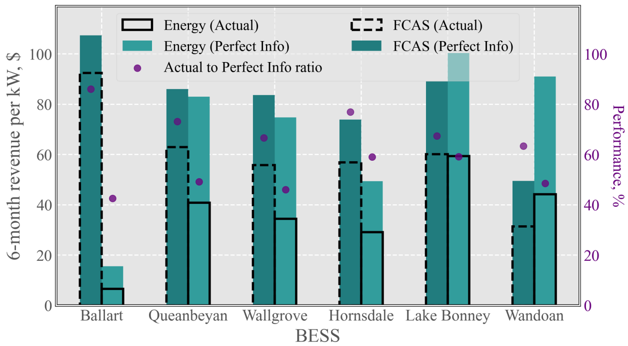

Figure 9: Comparing overall performance of the BESSs in the NEM.

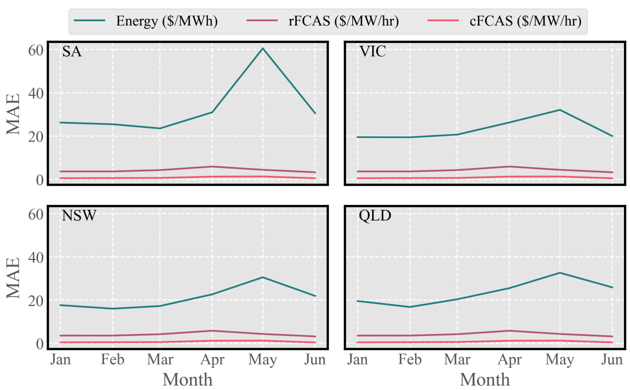

Figure 10: MAE of predispatch prices compared to actual dispatch prices.

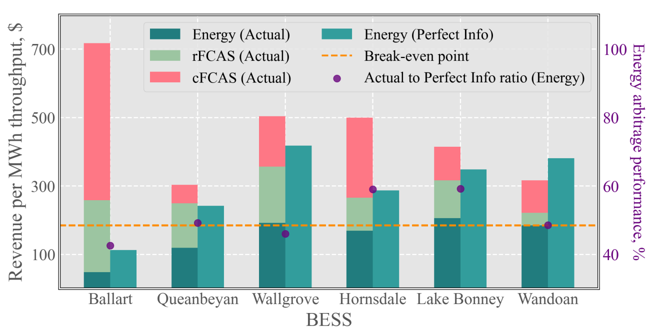

Figure 11: Energy arbitrage revenue and performance of the BESSs.

the number of spikes in energy prices greater than $1,000 for four regions of the NEM. While both the actual and the perfect information energy arbitrage revenues of each BESS are higher in the months when the energy price spread or the number of price spikes is high, the performance of BESSs often drops as they cannot realise a significant amount of the potential energy arbitrage revenue.

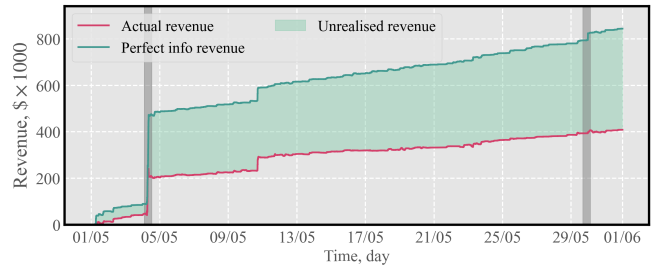

Figure 12: Revenue of Lake Bonney BESS over May 2023.

Figure 9 shows the performance of each BESS over six months in both the energy and FCAS markets. As expected, all BESSs perform better in the FCAS market compared to energy. This is mainly due to the unpredictable nature of the energy prices compared to the FCAS, as evidenced by the larger Median Absolute Errors (MAEs) in the AEMO's predispatch energy prices compared to rFCAS and cFCAS [13], shown in Figure 10. These predispatch prices influence asset operation optimisation in the NEM, either directly or indirectly. Thus, larger errors in the energy predispatch prices complicate realising the potential energy arbitrage revenue of BESSs. Additionally, Figure 9 reveals that BESSs' performance in the energy market fluctuates between 40% and 60%, averaging around 50%. This indicates that nearly half of the potential revenue from energy arbitrage goes unrealised due to suboptimal operation.

Assuming a 10-year lifetime and a cost per MWh of $673 (as given in [4] for a 2-hour BESS), a 1MWh/0.5MW BESS would require $185 per MWh throughput to break even, since it is limited to one full charge-discharge cycle per day. Figure 11 shows the monthly revenue of BESSs per MWh throughput in energy, rFCAS, and cFCAS, as well as their perfect information energy revenue and energy arbitrage performance. Due to the substantial revenue from FCAS markets, which typically require minimal energy throughput, all BESSs generate revenue well above the break-even point. However, with the likely saturation of FCAS markets in the next few years due to committed BESS projects in the NEM, FCAS revenue could significantly drop. This is alarming because four out of six BESSs have generated energy market revenue below the break-even point. While Ballart BESS appears to deliberately prioritise revenue from FCAS markets, the poor performance of the other BESSs seems largely due to suboptimal energy arbitrage strategies. Although BESS operators may have limited control over certain factors that lead to loss of potential revenue, such as temporary unavailability, temperature-imposed limitations, and system constraints, there are opportunities for improvement, particularly in the accuracy of energy price forecasting and battery operation optimisation.

5.3 Instances of Unrealised Energy Arbitrage Revenue

To show examples of significant unrealised revenue, we compare the actual cumulative five-minute revenue of Lake Bonney BESS in May 2023 with the revenue that it could generate through optimal dispatch decisions under perfect information. This case was chosen because the BESS performs well in the energy market compared to

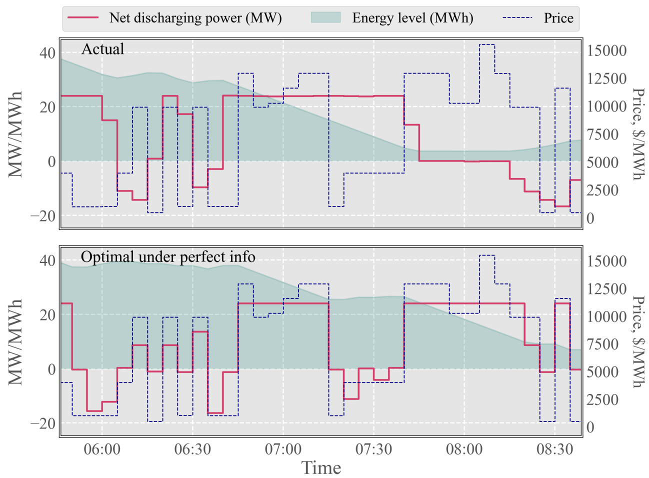

Figure 13: Comparison of empirical and optimal dispatch decisions on 4 May.

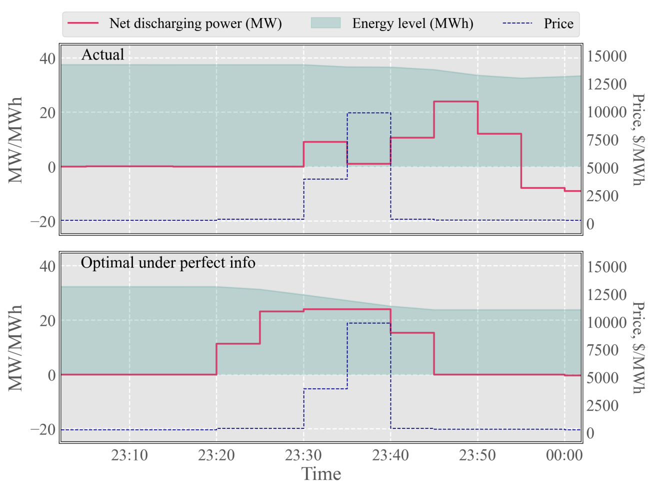

Figure 14: Comparison of empirical and optimal dispatch decisions on 29 May.

other BESSs, yet its energy arbitrage performance dropped in May. Figure 12 shows the cumulative five-minute revenue of the BESS for the two cases. While the figure shows a slow, but consistent, increase in unrealised revenue as the month progresses, the main reason for the poor performance is due to two major events on 4 May and 29 May, which are highlighted in the figure.

Figures 13 and 14 show the net-discharging power and energy level of the BESS based on the empirical data compared to the optimal dispatch decisions under perfect information. On 4 May, suboptimal decisions led to more than $200,000 in missed revenue during a 3-hour window. Figure 13 reveals several dispatch decisions made by the BESS operator on 4 May that led to this financial loss. First, the BESS charges at four dispatch intervals when price spikes occurred, including one spike between 6:30 and 7:00 and three more between 8:00 and 8:35. This could be attributed to the poor BESS operation and bidding decisions in those instances. Second, the BESS discharges all its remaining energy between 7:15 and 7:40, when the price is around or less than $4000/MWh and loses the discharging opportunities at prices above $10000/MWh, occurring later between 7:40 and 8:25. This means that the BESS captured less than one-third of the available revenue due to myopic dispatch decisions or significant price prediction errors that missed the larger price spikes. Figure 14 shows the other instance, which happened on 29 May, when the BESS could not capitalise on the two price spikes between 23:30 and 23:40. This poor performance occurred despite having sufficient energy, suggesting that the shortfall can be attributed to inefficient BESS operation and bidding strategies.

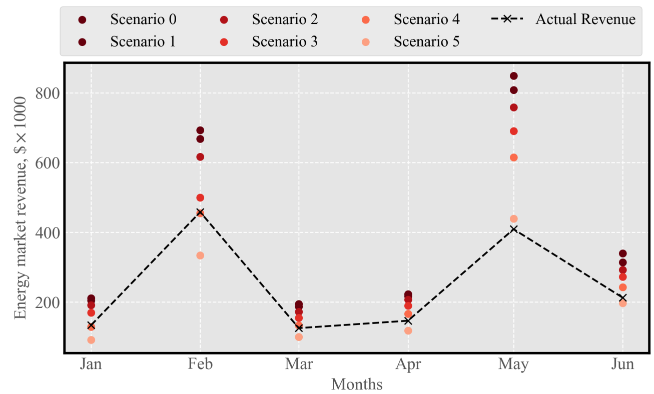

Figure 15: Sensitivity Analysis of the optimal revenue for Lake Bonney BESS under various price forecasting scenarios.

5.4 Sensitivity Analysis of BESS Revenue Based on Price Forecasting Scenarios

As mentioned earlier, Perfect Information Revenue represents the maximum revenue a BESS could achieve under perfect market information, which is realistically unattainable. Thus, this section is dedicated to examining the impact of price forecast accuracy on BESS revenue. A sensitivity analysis is conducted for the Lake Bonney BESS across six scenarios. These scenarios range from relying only on predispatch energy price forecasts, provided by AEMO, to utilising actual energy prices exclusively, with intermediate scenarios, which are generated using weighted averages of both. For example, in Scenario 1, the BESS operation optimisation model detailed in Section 4 is applied using input prices composed of 80% actual market prices and 20% predispatch prices to calculate revenue. On the contrary, Scenario 2 uses a mix of 60% actual market prices and 40% predispatch prices for revenue calculation. Therefore, as we progress from Scenario 0 to Scenario 5, the proportion of actual energy prices decreases while the reliance on predispatch prices increases, leading to a gradual decrease in the accuracy of price predictions used in the optimisation.

Figure 15 illustrates the energy market revenues for Lake Bonney BESS over six months in six different pricing scenarios, compared to actual revenue. As illustrated in this figure, the difference between revenues obtained from predispatch prices (Scenario 5) and actual prices (Scenario 0) fluctuates substantially over different months. For example, in February and May, the gap between Scenario 0 and Scenario 5 revenues is more significant than in the months of January and March, showing the importance of better price forecast accuracy in these months. In January and February, the actual revenue exceeds that of Scenario 4, which is indicative of a battery operation that effectively capitalised on market conditions. However, in other months, the actual revenue aligns more closely with that of Scenario 5, which suggests that the battery's market performance was near the level expected from predispatch price signals. In particular, May is the only month that actual revenue fell slightly below the revenue of Scenario 5. This could be due to various factors, including the higher accuracy of predispatch prices compared to the BESS operator's forecasts during important periods, suboptimal decisions by the battery operator, or network constraints.

This analysis demonstrates the important link between price forecast accuracy and BESS revenue outcomes. The Perfect Information Revenue stands as a benchmark for BESSs, as discussed in previous sections; nevertheless, it is expected that actual revenues will fall short of this mark. Additionally, the financial performance of BESS can vary substantially over time. For example, when forecasting becomes particularly complex at times, the BESS's performance may descend below its typical value.

6 CONCLUSION

In this paper, we provided a BESS scheduling optimisation model to participate in the energy and FCAS markets, aiming to uncover the unrealised revenue by BESSs in the NEM. To do so, we first presented a systematic method for estimating operational characteristics of real-world BESSs in order to use them as input parameters to the optimisation model. Second, we provided a MILP optimisation model for BESS scheduling across both energy and all FCAS markets. By combining these two methods, we could determine the maximum potential revenue of existing BESSs in the NEM. This is a significant improvement over the approaches proposed in the literature, which often rely on oversimplified operational assumptions or concentrate solely on individual markets.

We first validated our estimation method for BESS operational characteristics by testing it on Wallgrove BESS and comparing the results with the actual historical values. We then applied our BESS scheduling optimisation model to six existing BESSs in the NEM over a 6-month period and compared the results with their actual revenue over the same period. Our simulation results indicate a significant revenue gap between the current operation of BESSs in the NEM and their maximum potential. Specifically, the results show that existing BESSs are unable to capture nearly half of this potential revenue from energy arbitrage. With the anticipated saturation of FCAS markets, this inefficiency poses a risk to BESS profitability and could impede merchant BESSs from achieving their break-even points. This inefficiency also raises concerns about BESSs' availability to be dispatched when the grid needs them the most, reflected in spot market price spikes.

Our findings highlight the necessity for better price prediction and bidding algorithms to enhance BESS dispatch decision-making in the NEM, especially given the increasing volatility of spot market prices as the share of renewable generation rises in the system. The model proposed in this paper enables BESS asset managers and operators to identify unrealised potential and suboptimal dispatch decisions across all markets in the NEM, suggesting operational adjustments to maximise revenue. These potential improvements are also beneficial for the power grid as they help the process of ancillary services and energy procurement when the grid faces dire needs. The proposed model can also be used to quantify the maximum potential revenue of existing BESSs in the NEM and provide relevant insights to different stakeholders in the energy industry. However, it is important to acknowledge that this potential revenue is a theoretical benchmark that may not be fully achievable under real-world market conditions.

Additionally, it should be noted that this model cannot accurately determine the maximum potential revenue of price-maker BESSs in the NEM. Future work will include estimating the efficiency of BESSs over shorter periods by utilising additional operational data, thus improving the revenue potential assessment. Future research can also explore models that consider the unpredictable nature of spot market prices, thereby providing a clearer insight into the potential revenue that can be captured by BESSs.

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