Impact of Market Design on Battery Trading Strategies: A UK Case Study

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***Abstract*—The integration of large-scale battery energy storage systems in power grids is expected to increase in the coming years to compensate for the growing variability of production and consumption. In this context, the market design must provide the correct incentives for these storage systems to participate. In this paper, we analyze the impact of the UK market design and its recent reforms on the trading strategy of a battery. A mixed-binary linear program to compute the optimal hindsight trading strategy was developed to quantify inefficiencies in the market design. The multi-market model considers the available markets, including wholesale, frequency response and balancing markets. Of particular relevance to battery trading in a multi-market setting is the cost of battery degradation, which was also directly incorporated into the model. We perform a case study using real market and system data for 2023. The results reveal that the balancing market was not sufficiently attractive for batteries due to low dispatch rates. As a consequence, trading strategies were employed that harmed both the system and the battery. Based on these results, we highlight the importance of accounting for degradation in trading models and introducing an availability payment for the balancing market.**

***Index Terms*—Storage trading, Electricity market design, Balancing market, Battery degradation**

I. Introduction

Utility-scale battery energy storage systems (BESS) play a key role in the energy transition by helping integrate renewable energy sources into the grid. Reflecting their growing importance, Bloomberg predicts a remarkable 15-fold growth in global BESS capacity by 2030 [1]. The appeal of investing in BESS lies in the diverse revenue streams they offer, including:

(i) arbitrage trading in wholesale day-ahead and intraday markets,
(ii) addressing short-term imbalances in the balance market, and
(iii) providing frequency response services to the Transmission System Operator (TSO).

This study explores how market design influences the revenue streams of BESS. To achieve this, we simulate the trading behaviour of a representative BESS in the UK market over the period from January to October 2023 using real market data from the platform ModoEnergy [2]. The UK is chosen for the case study because of its highly integrated energy market and significant penetration of BESS [3]. For the simulation, we model the battery's profit maximisation as a mixed-integer program, while using the assumption of perfect hindsight information about uniform prices in the wholesale, balancing, and frequency response markets. This approach enables us to gain insight into the following three topics.

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First, the analysis identifies the markets in which the BESS *should* have been traded. While multimarket trading models often employ stochastic programming formulations to estimate realistic profits [4], [5], these methods do not always provide the most accurate insights into where the BESS capacity was most critically needed. By adopting a perfect information assumption, we can better understand the market's allocation signals, reflected in the prices revealed through wholesale, balancing, and frequency response auctions [6].

Second, it sheds light on a trading strategy called *Net Imbalance Volume (NIV) chasing*, where asset owners predict net imbalances (positive or negative) and adjust positions to profit from imbalance payments. The system-wide benefits of this practice are debated, and European TSOs have not yet reached a consensus [7], [8]. The UK market provides valuable insights due to its unique balancing auction. Sixty minutes before real-time, the TSO forecasts the NIV and conducts an auction to procure the cheapest bids or offers to offset the imbalance, effectively engaging in NIV chasing itself. However, unlike asset owners, the TSO considers system security, such as asset location and risk of unavailability, alongside price. As a result, profitable bids, often from BESS, are frequently rejected, frustrating asset owners who cannot capitalise on opportunities to mitigate imbalances [9].

The third dimension of our study examines the role of capacity payments. Interestingly, the recently introduced frequency response services in the UK - Dynamic Containment (DC), Dynamic Moderation (DM) and Dynamic Regulation (DR) — operate exclusively on capacity payments [10], unlike other reserve auctions in Europe that also include energy payments [11]. In contrast, the balancing auction, which serves a similar purpose to frequency response services but operates ahead of real-time rather than reacting in real-time, relies solely on energy payments, with no capacity payment component [12]. Our simulation indicates that incorporating a capacity payment into the balancing market could help mitigate some of the negative effects associated with the previously discussed NIV chasing strategy.

This paper is organised as follows: In Section II, we introduce our multi-market trading model, formulated as a mixed-binary linear program based on a perfect hindsight assumption. In Section III, we present simulation results, and in Section IV, we draw conclusions and provide recommendations for market design and trading strategies. Table III in Appendix summarises our battery and market models used for the case study.

II. Methodology

To analyse the perfect information revenue streams of a BESS in the 2023 UK market, we develop a comprehensive optimisation model which takes into account (i) a detailed modelling of UK wholesale, balancing and frequency response market and (ii) a detailed modelling of battery characteristics including degradation.

The complete model is given in an online appendix[1]. Simplified, it can be described as

$$\max_{x} \quad R(x) - D(x) \tag{1}$$

$$\text{s.t.} \quad x \in \mathcal{M} \tag{2}$$

$$x \in \mathcal{B}. \tag{3}$$

Here, $x \in \mathbf{R}^n$ is the batteries schedule consisting of charging and discharging operations over a certain time horizon discretised in n steps. This schedule needs to be feasible according to the battery's operating constraints modelled by $x \in \mathcal{B}$. The BESS operator tries to find a schedule that maximises revenue $R(x)$ in all markets minus the degradation costs $D(x)$ of this schedule.

The complexity of the market models requires the inclusion of additional constraints $x \in \mathcal{M}$ on the battery schedule, which allows us to accurately represent the wholesale, balancing, and frequency response markets.

In the following subsections, we first examine the battery model, focussing on the degradation function $D(x)$ and the constraints $x \in \mathcal{B}$. Subsequently, we discuss the detailed market model, including the function $R(x)$ and the constraints $x \in \mathcal{M}$.

It is important to note that in all market scenarios, we assume the BESS operates as a *price-taker*, meaning it has no influence on market prices. Moreover, we assume perfect knowledge of these prices, which are, in reality, only revealed ex-post through the auction process.

A. Battery Model

We model a large BESS with 100 MWh capacity and 50 MW discharge and charge power restriction. We assume a charging and discharging efficiency of 93. 8 %. Moreover, we take degradation cost into account by a throughput model.

[1] https://sites.google.com/view/appendix-uk-bess-case-study/startseite

A simplified version of the constraint $x \in \mathcal{B}$ can be modelled as follows. The buy and sell volume in time-step t is the difference between charging g_t and discharging d_t

$$x_t = g_t - d_t \qquad \forall t \in \mathcal{T}. \tag{4}$$

Charging and discharging are bounded by the charging respectively discharging limits $\overline{g}$ and $\overline{d}$:

$$0 \leq g_t \leq \overline{g} \cdot \delta_t \qquad \forall t \in \mathcal{T} \tag{5}$$

$$0 \leq d_t \leq \overline{d} \cdot (1 - \delta_t) \qquad \forall t \in \mathcal{T}. \tag{6}$$

The binary variable $\delta_t \in \{0, 1\}$ indicates whether the storage system is charging ($\delta_t = 1$) or discharging ($\delta_t = 0$). Including this variable is essential because, during periods of negative prices, the storage system can take advantage of its efficiency less than 100% by simultaneously charging and discharging, effectively destroying energy and profiting from negative prices.

The state-of-charge e_t is given by the balance equations:

$$e_t = e_{t-1} + n^g \cdot g_t - \frac{d_t}{n^d} \qquad \forall t \in \mathcal{T}, \tag{7}$$

where n^g is the charging, and n^d is the discharging efficiency. The state-of-charge must be kept between its lower $\underline{\mathrm{E}}$ and upper $\overline{E}$ capacity limits:

$$-\underline{\mathrm{E}} \leq e_t \leq \overline{E} \qquad \forall t \in \mathcal{T}. \tag{8}$$

For degradation cost, we multiple the energy throughput $\sum_{t \in \mathcal{T}} x_t$ with a cost factor C:

$$D(x) = \sum_{t \in \mathcal{T}} C \cdot x_t. \tag{9}$$

This cost factor C is calculated as follows: An energy throughput limit for the entire battery lifetime is assumed. After this, the battery needs to be replaced. Using this energy throughput limit and the *capital expenditure* (CapEx), i.e. the cost of buying a new battery, we can calculate the degradation cost of each MW. We assume a CapEx of $165 £/kWh$. Assuming a throughput limit of $10,050 GWh$, we arrive at $C = 18.5 £/MWh$.

B. Wholesale Markets

We model both the day-ahead auction and the continuous intraday market, assuming perfect hindsight in both cases.

In the day-ahead auction, bids to purchase energy and offers to sell energy are submitted for each hour of the following day. The auction outputs a uniform price, which we assume is known in advance. With this perfect knowledge, the battery can perform optimal arbitrage trading between hours in this market [13]. The simplified arbitrage problem can be written as

$$\max_{x \in \mathcal{B}} \quad \sum_{h=1}^{24} \lambda_h \cdot x_h \tag{10}$$

where λ_h is the hourly uniform day-ahead price.

In the continuous intraday market, bids and orders are placed and matched on an ongoing basis [14]. Unlike the day-ahead auction, transactions in this market can cover durations of 0.5 hours, 1 hour, 2 hours, or 4 hours, rather than being restricted to 1-hour intervals. We assume that the BESS has perfect hindsight of the entire order book, enabling it to select the bids and orders that maximise its revenue potential. The simplified arbitrage problem on the intra-day market can be written as

$$\max_{x \in \mathcal{B}} \quad \sum_{o=1}^{O} \lambda_o \cdot y_o \tag{11}$$

$$\text{s.t.} \quad x = \sum_{b=1}^{B} q_o \cdot y_o \tag{12}$$

$$y_o \in [0,1] \qquad \forall o = 1, \dots, O, \tag{13}$$

where $o = 1, \dots, B$ are the B bids and orders in the orderbook and q_o are their quantity and λ_b their price. The variables y_b decide on the level at which a bid or order is accepted.

C. Balancing Market

In the balancing market, bids and offers can be placed for 0.5-hour periods. The Transmission System Operator (TSO) predicts the Net Imbalance Volume (NIV) and accepts buy bids or sell offers based on the direction of the NIV. The selection process is not solely cost-driven (i.e., the cheapest bids are not always accepted), but also considers system security requirements. A uniform price is then established based on the accepted bids or offers according to a merit order.

The likelihood of a bid or offer being accepted while being below the uniform price is called *dispatch rate*. Some analysis suggests that the dispatch rate for BESS is relatively low, approximately 9% [9]. This low rate creates a “black-box” effect from the perspective of a BESS operator. Even with perfect knowledge of the uniform price and the direction of the NIV, it remains impossible to predict with certainty whether a bid or offer will be accepted.

To model the balancing market, we assume that the BESS has perfect information regarding the direction of the NIV, that is, whether buy bids or sell offers will be accepted and the uniform price at which they would have been cleared. The dispatch rate is incorporated using a random number generator based on a Bernoulli distribution, with a 9% probability of acceptance [9].

The simplified revenue maximisation on the balancing auction can be written as

$$\max_{x \in \mathcal{B}} \quad \sum_{t \in \mathcal{T}} \lambda_t \cdot x_t \tag{14}$$

$$\text{s.t.} \quad x_t \geq 0 \qquad \forall t \in \mathcal{T}^1 \tag{15}$$

$$x_t \leq 0 \qquad \forall t \in \mathcal{T}^2 \tag{16}$$

$$x_t = 0 \qquad \forall t \in \mathcal{T}^3, \tag{17}$$

where λ_t is the balancing auction’s uniform price, the set $\mathcal{T}^3$ contains all time steps where the battery cannot be dispatched according to our Bernoulli random generator, $\mathcal{T}^2$ are all the time steps where the NIV is negative and the BESS can thus charge to help the TSO counteract the negative NIV, and similarly $\mathcal{T}^1$ are all the time steps where the NIV is positive and the BESS can thus discharge to help the TSO counteract the positive NIV.

D. Frequency Response Markets

This category includes three distinct daily auctions for different products: Dynamic Containment (DC), Dynamic Moderation (DM), and Dynamic Regulation (DR). If a BESS participates in these auctions by placing a buy bid or sell offer, it must be able to provide or consume energy continuously for a 4-hour period if called upon by the TSO.

A key feature of these markets is the allowance for *asymmetric bidding*. This means that a BESS offering to provide energy for DC, DM or DR does not also need to be capable of consuming energy in the same scenario. This means that a buy bid does not always need to be accompanied by a sell offer.

The TSO remunerates each accepted bid or offer based on a uniform availability price determined by the classic merit order process. Unlike in some other countries, there are no energy payments in the UK for these services: only availability payments are made.

We model the three frequency response markets: DC, DM, and DR, under the assumption of perfect hindsight regarding the uniform price. However, similar to our balancing market model, we do not assume perfect information about activation. Assuming perfect information on activation would allow the BESS to always avoid being activated while still collecting availability payments, which would unrealistically overestimate potential revenue. To address this, we incorporate an average activation factor for each market derived from historical activation data.

Additionally, we model a fourth frequency response market: the *Monthly Firm Frequency Response Service* (MFFR). Although this service has been phased out in 2024 and replaced by DC, DM, and DR, we include it in the model because it was still operational in 2023. The MFFR auction occurs once per month but also requires 4-hour energy commitments, similar to the other three services. Except for its monthly auction frequency, it functions quite similarly to DC, DM, and DR. As with the other markets, we assume perfect knowledge of the uniform price and use average activation factors instead of perfect information on activation.

The revenue maximisation problem on each of these markets separately, can be described in a simplified way by:

$$\max_{x \in \mathcal{B}} \quad \sum_{t \in \mathcal{T}} \lambda_t \cdot y_t \tag{18}$$

$$\text{s.t.} \quad x_t = a_t \cdot y_t \qquad \forall t \in \mathcal{T}, \tag{19}$$

where λ_t represents the uniform price awarded in the auction, and y_t denotes the capacity provided by the BESS at time step t. The parameter a_t, which corresponds to the average activation factor discussed earlier, converts the promised capacity

y_t into the actual delivered or consumed energy x_t. Note that the objective function remunerates only capacity, not energy.

E. Asset-Backed Trading

Since day-ahead, intraday, and balancing markets close before real-time operations, they can be classified as *forward* markets. This opens the door to *financial arbitrage*, also known as *virtual trading*. In these trading strategies, market participants are not required to own physical assets capable of producing or consuming energy. Instead, they can engage in speculative trading by e.g. purchasing energy in the day-ahead market to resell in the intraday or balancing auction. This practice is controversial and, at least in Europe, is not explicitly permitted [15], [16].

In contrast, *asset-backed trading* ensures that all transactions are grounded in physical capability, a principle that we strictly enforce in our model. This approach is reflected in the simplified revenue maximisation problems outlined above for different markets, where we consistently imposed the physical constraint $x \in \mathcal{B}$. This constraint ensures that the model cannot buy or sell energy beyond what is physically feasible for the battery. To prevent financial arbitrage across markets, such as buying energy in the day-ahead market and reselling it on the intraday or balancing markets, we impose an additional restriction. Specifically, the BESS is allowed to either buy or sell in the given markets (day-ahead, intraday, or balancing) but not perform both simultaneously. A simplified version of these constraints can be expressed as follows:

$$M \cdot \delta_t \geq b^D + b^I + b^B \qquad \forall t \in \mathcal{T} \tag{20}$$
$$M \cdot (1 - \delta_t) \geq s^D + s^I + s^B \qquad \forall t \in \mathcal{T} \tag{21}$$
$$x_t = b^D + b^I + b^B - \left(s^D + s^I + s^B\right) \qquad \forall t \in \mathcal{T} \tag{22}$$
$$\delta_t \in \{0, 1\} \qquad \forall t \in \mathcal{T}. \tag{23}$$

The binary variables δ_t represent whether the BESS is engaged in buying or selling in the forward markets. The variables s^D, s^I, s^B denote sales in the day-ahead, intraday and balancing markets, while b^D, b^I, b^B denote buying. The above constraints ensure that simultaneous buying and selling is prohibited. The big M parameter M is set to 50 MW, reflecting the capacity of our battery system.

However, note that it remains permissible for the BESS to buy energy in the day-ahead or intraday markets and subsequently resell it in the frequency response markets. Specifically, the BESS may conclude the balancing auction with a sell position and then offer services to the TSO in the frequency response markets to reduce this sell position as needed.

III. Results

Using the above trading model, we simulated the trading behaviour of a BESS for the period from January to October 2023. The case study setup, including the modelling of the battery system and the market interactions, is summarised in Table III in Appendix.

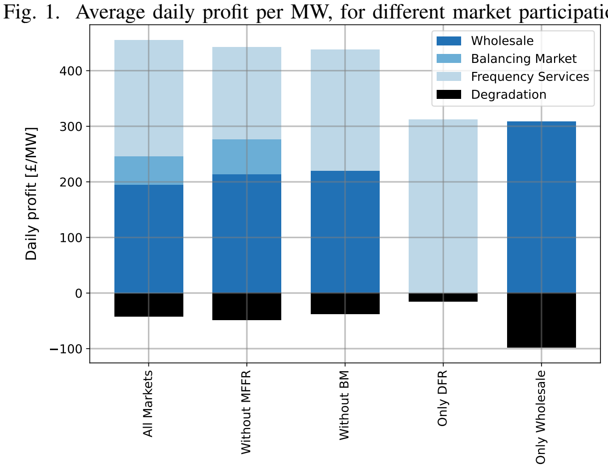
To ensure computational feasibility, we solved the model on a monthly basis and subsequently aggregated the results. The model was implemented in Python and solved using Gurobi, with market data sourced from ModoEnergy [2].

In Section III-A, we assess the profit allocation across different markets to identify where the BESS *should* have traded and where its services are most in demand. Next, in Section III-B, we examine the impact of degradation on this profit distribution. Finally, in Section III-C, we investigate how the dispatch rate employed in the balancing auction influences the allocation of profits.

A. Profit Allocation across Markets

Figure 1 illustrates the average daily profit per megawatt (MW) across different market participation strategies. It shows that comprehensive participation in all markets yields the highest profitability, while excluding markets like the Monthly Firm Frequency Response (MFFR) or Balancing Market (BM) reduces earnings slightly, and relying solely on frequency services or wholesale trading leads to significant losses.

Fig. 1. Average daily profit per MW, for different market participation.



The low profitability of the balancing market is attributed to low dispatch rates, highlighting the need for market reforms to enhance its appeal. Additionally, the figure underscores the impact of battery degradation costs on overall profitability, emphasizing the importance of integrating degradation considerations into trading strategies.

B. The Impact of Degradation

Figure 2 and Table I explore how capital expenditure (CapEx) affects profit distribution across markets. Higher CapEx increases degradation costs per unit of energy throughput, reducing profitability in energy-intensive markets.

Figure 2 shows that as CapEx rises, profits from energy-focused markets, such as the balancing market, decline, while frequency services gain importance due to availability payments. Table I provides a detailed breakdown of daily profits per MW, confirming this trend.

These results highlight the need for degradation-aware strategies, showing how higher CapEx shifts economic advantages toward low-throughput markets like frequency services.

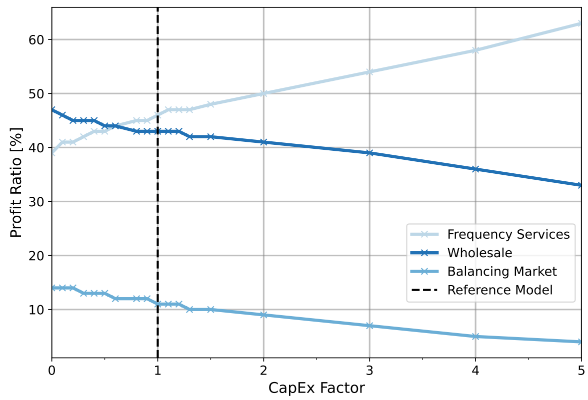


Fig. 2. The profit ratios by market group depending on the CapEx.

TABLE I
DAILY PROFIT [£/MW] FOR DIFFERENT CAPEX FACTORS.

Capex Factor	**0.0**	**0.2**	**0.4**	**0.6**	**0.8**	**1.0**	**1.2**
DayAhead	179	169	156	149	140	135	132
Intraday 0.5h	-53	-44	-33	-27	-22	-18	-15
Intraday 1h	79	76	73	68	69	64	63
Intraday 2h	5	3	3	4	4	4	4
Intraday 4h	10	9	9	10	9	10	8
Balancing	65	63	60	56	56	51	48
MFFR	70	73	79	81	82	87	87
DFR	114	117	117	121	122	122	124
Battery degradation	0	-12	-22	-30	-37	-42	-47

C. Dispatch Rate in the Balancing Market

Table II and Figure 3 examine the impact of varying balancing market dispatch rates on profitability and profit per energy throughput. Table II provides a breakdown of daily profits across different markets, showing that higher dispatch rates significantly increase overall profitability, particularly for the balancing market, but also lead to higher degradation costs.

Figure 3 highlights the trade-off by illustrating that while total profits rise with dispatch rates, the profit per energy throughput declines, which is a critical metric for battery longevity.

TABLE II
DAILY PROFIT [£/MW] FOR DIFFERENT BALANCING MARKET DISPATCH RATES.

Dispatch Rate	**BM**	**Wholesale**	**DFR**	**Sum**	**Degradation**
5	27	210	211	448	-40
9	51	194	210	455	-42
10	55	192	210	457	-42
15	90	172	201	463	-45
20	120	161	197	478	-49
25	158	142	189	489	-52
30	195	123	182	500	-55
40	263	89	174	526	-61
50	323	60	164	547	-68
60	374	37	156	567	-73
70	421	14	152	587	-78
80	473	-7	143	609	-85
90	520	-27	138	631	-90
100	565	-39	129	655	-97

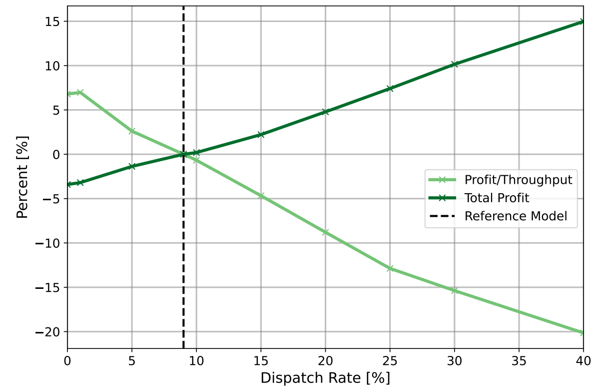


Fig. 3. Total profit and profit per throughput for different balancing market dispatch rates.

Together, these results underscore the importance of balancing higher dispatch rates with strategies to manage battery degradation, while also highlighting the need for market design reforms, such as availability payments, to incentivize optimal BESS participation.

IV. CONCLUSIONS

This study demonstrates that the UK balancing market's low dispatch rates and absence of capacity payments hinder the participation of BESS, despite their potential to address real-time imbalances. The findings suggest that structural reforms, such as introducing capacity payments and locational pricing, could make the balancing market more attractive by compensating for degradation costs and reducing congestion inefficiencies.

Frequency response services, which already rely on capacity payments, have achieved higher participation rates, highlighting the importance of aligning market incentives with operator priorities. Addressing these issues would reduce the reliance on problematic strategies like NIV chasing, enhancing BESS contributions to grid stability.

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APPENDIX

TABLE III
SUMMARY OF CASE STUDY (SIMULATION PERIOD JANUARY TO OCTOBER 2023).

Battery Model	
Parameters	BESS with 100 MWh capacity and 50 MW discharge and charge power restriction. Charging and discharging efficiency of 93.8 %.
Degradation	Degradation cost of $18.5\pounds$ per throughput (MW).
Trading	No impact on prices and activations (price-taker) and no financial arbitrage (asset-backed trading).
Wholesale Market	
Day-Ahead Auction	Perfect information about the uniform prices. Arbitrage between 24 hours constrained by capacity and charge/discharge limits of battery.
Continuous Intraday Market	Perfect information about the complete order book. BESS can accept bids and orders out of the order book up to its capacity and charge/discharge limits.
Balancing Market	
Balancing Auction	Perfect information about the uniform price and direction of the NIV. However, whether the BESS can sell or buy depends on a Bernoulli random variable modlleing a 9% dispatch rate. No availability payment, only energy payment.
Frequency Response Market	
Dynamic Containment Auction (DC) Dynamic Moderation Auction (DM) Dynamic Regulation Auction (DR)	Perfect information about the uniform price. However, no perfect information about activation; instead, average activation values, determined from historical data, are used. Only availability payment, no energy payment.
Monthly Firm Frequency Response Auction (FFR)	The same as DC, DM, and DR, but with a monthly auction instead of a daily one.