Article:

Biggins, F.A.V., Homan, S., Ejeh, J.O. et al. (1 more author) (2022) To trade or not to trade: Simultaneously optimising battery storage for arbitrage and ancillary services. Journal of Energy Storage, 50. 104234. ISSN 2352-152X

https://doi.org/10.1016/j.est.2022.104234

To Trade or Not to Trade: Simultaneously optimising battery storage for arbitrage and ancillary services

F. A. V. Biggins, S. Homan, J. O. Ejeh, S. Brown*

Department of Chemical and Biological Engineering, The University of Sheffield, Sheffield S10 2TN

Abstract

This work presents a novel methodology for determining the value a battery storage system provides while participating in a competitive frequency response market, considering uncertainties. Battery storage systems are an attractive choice for power services in low-carbon electricity grids and their optimal operation are a commonly studied matter. However, the non-deterministic nature of competitive electricity markets is often overlooked. Here, we consider these market uncertainties for a storage device providing Great Britain's Firm Frequency Response (FFR) and arbitrage services. We use a machine learning classifier to determine the set of all possible FFR market outcomes and their associated probabilities. These are then propagated through a linear optimisation model to generate a set of possible scenarios, from which the most likely can be ascertained. Several different classifiers and bidding strategies are compared, the most suitable classifier and bidding strategies which maximise revenue whilst minimising the probability of the worse-case scenario are identified. It is found that the mean expected income is overestimated by $\sim$28% when uncertainties in FFR market outcomes are not considered. Providing arbitrage over a tight band can still provide significant income and does not impede on the storage's ability to provide FFR services in real time.

Keywords: Battery Storage, Ancillary Services, Classifier, Arbitrage, Auction Modelling, Machine Learning

1. Introduction

1.1. Motivation and Previous Work

The decarbonisation of electricity systems is imperative to attaining climate goals and mitigating against global heating. This means moving away from traditional forms of power generation, which involve combustion of fossil fuels, and towards renewable alternatives. However, the intermittency of renewable generation may be problematic for power grids, as it can decrease their stability and reliability [1]. Hence, energy storage presents itself as an attractive solution to this problem, due to its fast response and ability to control power input and output. Indeed, much

*Corresponding author
Email address: `s.f.brown@sheffield.ac.uk` (S. Brown)

work suggests that renewable intermittency can be abated with the use of energy storage; [2] finds energy storage to increase the value of electricity generation, [3] finds it to reduce operational costs of a micro-grid, and [4] discusses how different types of storage may be suitable for various applications with renewable generation.

Due to their fast response and high ramp-rate, battery storage systems have been identified as an attractive choice to provide frequency control for power grids. In [5] and [6] the authors assess the profitability of energy storage providing frequency control, the latter suggests that even if frequency control is not its main purpose it may still be profitable to reserve a portion of the storage for this. Several studies have demonstrated the effectiveness of energy storage for frequency control, showing its potential to improve power quality and stability in power grids. For example, [7] finds energy storage can provide inertial response and frequency regulation similar to that of conventional power plants, and [8] shows that it can effectively provide short-term frequency control. In [9] the authors find that it can smooth power fluctuations due to wind generation and consumer load, and [10] propose a model for energy storage to enhance smoothing of frequency fluctuations in power grids. Finally, [11] presents a method for using energy storage to simultaneously provide two different power services: frequency response and reserve power. These studies have highlighted the capability of energy storage for power services; however they have mostly considered things from the point of view of a grid operator, rather than a storage device owner. In [12], the authors showed that both of these parties can be mutually satisfied even when storage owners operate their devices for personal profit maximisation; they developed a Nash-Cournot equilibrium model which finds that the strategic operation of storage devices still provides the flexibility services required for decarbonised power grids.

The optimal operation of energy storage to generate revenue in ancillary service markets (markets through which power system support is acquired) is studied in, for example, [13]–[21]. Whilst these studies present detailed methodologies for optimising the value of energy storage for ancillary service markets, they ignore one key consideration which may significantly affect its value: they assume market participation is granted. This is not always the case in competitive markets and such assumptions may result in the value being over-estimated. The authors of [13] and [14], optimised the usage of electric vehicles (EVs) and stationary batteries, respectively, to generate revenue in electricity and ancillary service markets. Both do so by formulating a MILP (Mixed Integer Linear Programming) problem, with linear terms representing profits from different revenue streams. In [15], the authors explore the strategy of an aggregator with access to storage and flexible loads who can both perform arbitrage and bid in the capacity market, determining the optimal allocation between these revenue streams. They also use a MILP optimisation which involves a penalty term for being unable to provide the required regulation capacity. In [16], the authors take a similar approach in order to optimise the self-scheduling of an energy storage facility in Alberta which is able to perform arbitrage as well as a number of different ancillary services. The authors of [17] use a stochastic process, to model market prices under uncertainty, then present an optimisation model for energy storage scheduling.

The authors of [18] take a different approach to this, using backward induction to determine a storage operator's optimum strategy in electricity and ancillary markets. In both [19] and [20], the authors present algorithms for strategic scheduling in these markets for EVs and distributed energy resources, respectively, with elements of stochasticity introduced to address uncertainties in market prices. In [21] a control strategy is presented which allows a technology neutral energy storage device to perform a frequency response service and arbitrage at the same time, in order to improve its economic feasibility. The authors find that arbitrage can be a profitable option to support frequency response provision. However only a narrow arbitrage band is considered, so it is unclear if the profits due to increasing this would be negated by frequency response unavailability penalties.

In all of the above studies the route to ancillary service market participation is not considered; this may be due to regional differences in market structures. Ancillary services are often acquired through competitive markets; in such cases, these markets need to be examined in more detail than in the previous studies to determine an appropriate bidding strategy and the uncertainties associated with participation. Furthermore, most of the studies in the literature do not include a penalty term for being unable to provide ancillary services. In [15] and [21] the authors do include this, however, they do not explore the consequences of changing its weighting according to differing levels of risk-aversion. Such an analysis is lacking in the literature and is particularly interesting when exploring the stacking of ancillary services with arbitrage, to determine if there are benefits to a riskier bidding strategy.

Additionally, recent battery storage optimisation literature has examined battery degradation issues. In [22] and [23] the authors show that including battery degradation in storage operation models, concerning off-grid storage and electric vehicle charging points respectively, can affect its value. The authors of [24] and [25] study the profitability of energy storage performing arbitrage whilst considering the impact of battery degradation; both find that degradation has a strong impact on lifetime profitability but by explicitly considering degradation, profitability can be increased. Finally, [26] considers how degradation affects the lifetime profitability of lithium ion and lead acid batteries providing frequency response services under different operational strategies. It is found that for lithium ion batteries the degradation from performing these services does not reduce their expected lifetime, of ≈ 10 years, when they are appropriately balanced in real-time. Whilst these studies highlight that it is important to consider battery degradation in the long-term, it is less relevant when optimising usage in the short-term. Therefore, degradation will not currently be considered for the short-term model presented here.

1.2. Ancillary Services

A number of studies, for example, [27], [28] and [29], have considered the design of ancillary service markets. Whilst these markets can vary regionally, they generally share one important design aspect: there exists a system operator, who is responsible for procuring and using ancillary services to balance an electricity grid. Examples of these types of services are voltage support, black start capability and reserves with differing response times. There are several methods through which they are procured, including compulsory provision, bilateral contracts, tendering and spot markets. Furthermore, the optimal design of ancillary service markets, to increase economic efficiency, is discussed in [30]. They examine different ancillary service markets across North America, and advise that integrating electricity and ancillary service markets whilst incorporating scarcity pricing improves efficiency. This is echoed in [31] in which the author advocates better scarcity pricing for ancillary services, such as in the Texas (ERCOT) market, to improve system efficiency and reliability. Whilst this is of note, here we are more interested in participating in ancillary service markets than optimising their design.

Surveys conducted by ENTSO-E (European Network of Transmission System Operators for Electricity) show that manual frequency reserve (the service considered here) is procured via competitive markets in most of the countries surveyed, including Great Britain (GB), Germany, France and Nordic countries [32]. This paper will consider the frequency reserve market in GB, namely Firm Frequency Response (FFR), which exemplifies this type of competitive, frequency reserve market. FFR is overseen by the electricity system operator (ESO) of GB, National Grid ESO (NGESO). FFR is a grid frequency balancing service which responds to frequency deviations (from 50 Hz) on a second-by-second basis. The structure of this market is very similar to those in other regions, and therefore the model developed here may be applied to many other ancillary service markets around the world.

1.3. Definition of Terms

Some of the terms used in this paper assume prior knowledge of GB's FFR and wholesale markets. For the sake of clarity and accessibility, these are explained below.

NGESO are responsible for balancing the electricity grid i.e. maintaining grid frequency at 50 Hz $\pm 1\%$, on a second-by-second basis, and they do this using balancing services. FFR is a type of balancing service, which provides dynamic and non-dynamic response, to counter deviations in frequency from 50 Hz. This particular service is considered here because it provides a viable route to market for smaller providers unable to participate in other balancing services e.g. Mandatory Frequency Response (usually provided by large generators).

Non-dynamic FFR is a discrete service, which accepts or provides a set amount of power, triggered at a defined frequency deviation. It is not considered here, as it is not normally provided by battery storage. Dynamic FFR provides or accepts power to/from the grid proportional to the frequency deviation on a second-by-second basis. It consists of three different services: primary, secondary and high response [33]. Primary and secondary services act when grid frequency falls below 50 Hz; primary responds first, followed by secondary which sustains its response for longer. High services act when the frequency rises above 50 Hz.

FFR services are provided over 4-hourly time periods called Electricity Forward Agreement (EFA) blocks. There are six of these each day, with the first one beginning at 23:00. FFR providers receive two types of hourly payments: availability fee and nomination fee. The former is a fixed fee paid for every hour that a provider is available for FFR, the latter is paid for every hour that the provider is called upon to provide FFR. Finally, arbitrage is the process of generating profits through trading electricity in wholesale markets, this involves buying electricity when prices are low and selling when prices are high.

1.4. Modelling FFR Market

GB's FFR market is a monthly auction process in which prospective providers submit tenders detailing how much power they can supply/accept, during which EFA blocks they can be available and what availability/nomination fees they require for this service. These tenders are then assessed by NG and either accepted or rejected. The question of whether a particular tender will be accepted or rejected is a binary classification problem. This type of problem is studied in machine learning and involves using supervised learning models. Several studies have explored similar classification problems; for example [34], [35] built a system for online auction fraud detection and [36], [37] use Naïve Bayes (NB) classifiers to predict whether items will sell on eBay and their final prices. NB classifiers are built upon Bayes' probability theorem. They have the advantages of being fast and easy to implement; however, they require features to be independent [38].

1.5. Contributions of this Work

Previous works assumed that participation in competitive markets is always granted, which is unrealistic. This work addresses this gap by presenting a novel technique, using machine learning, to determine the possible set of outcome(s) and probabilities of battery storage bidding in a competitive market. These outcomes are then propagated through an MILP optimisation model to create a set of possible scenarios, from which the most likely can be ascertained. This technique allows more realistic modelling of battery storage participation in competitive markets.

The novel contributions are:

- Historical FFR post-tender reports are analysed in detail to uncover market trends which give insight into the optimal FFR bidding strategy.
- Different classifiers are proposed to predict the outcomes of frequency response market auctions. They are tested and compared to determine which one is most appropriate for this situation. The chosen classifier is used to predict market outcomes and probabilities of battery storage making specific bids. Previous studies assume that such bids are always accepted. Here, we explore other possibilities and their probabilities.

- The set of predicted market outcomes are fed to an MILP model to assess the potential revenues and their associated probabilities of occurring, via a novel methodology. This methodology builds upon work in the literature using a penalty term for ancillary service unavailability; here, two penalty terms (representing the loss of ancillary service income during the unavailability) are used for the different levels of FFR provision and are risk-weighted.

- The real-time usage of an battery storage device for FFR is simulated allowing our methodology to be examined in real-time. The real-time performance under different levels of risk is studied.

The rest of this paper is organised in the following way: Section 2 gives a description of the models used for market classification and battery optimisation. Section 3 presents the results and discussion of analysing historic market data, comparing different classifiers, optimising the battery storage bidding strategy, and exploring real-time usage of battery for FFR. Finally, Section 4 presents the concluding remarks.

2. Model Description

2.1. FFR Market Classifier

This section presents the inputs and tuning of the classifiers tested and developed to classify FFR market bids. In the case of the FFR market, the training data with which to build the classifier is relatively small; between May 2018 and February 2020 the number of monthly dynamic FFR bids has varied between 26 and 356. The list of features is also short, consisting of:

1. The tendered EFA blocks (1-6)

2. Availability/nomination fees

3. Power provided for the FFR services

It is assumed that information regarding the company and type of generator and connection are not considered in the tender assessment process. In other words, that NGESO has no particular company/technology bias. The six EFA blocks are input as individual features taking on a value of 1 or 0, depending on whether the tendered service will be provided in that block: $t_n^{EFA} \in \{0, 1\}$ where $n \in \{1, 2, 3, 4, 5, 6\}$.

The power, P^x, provided for the services (primary P^p, secondary P^s and high P^h) is split into two separate levels: the maximum power provided when grid frequency deviation is a) 0.2 - 0.5 Hz from 50 Hz and b) when the deviation is greater than 0.5 Hz. These will be denoted $P^x_{0.2}$ and $P^x_{0.5}$ respectively, and frequency deviations referred to simply as "events". The ratio of $P^x_{0.5}/P^x_{0.2}$ is constant at 2.5, with only 1% of tenders between May 2018 and February

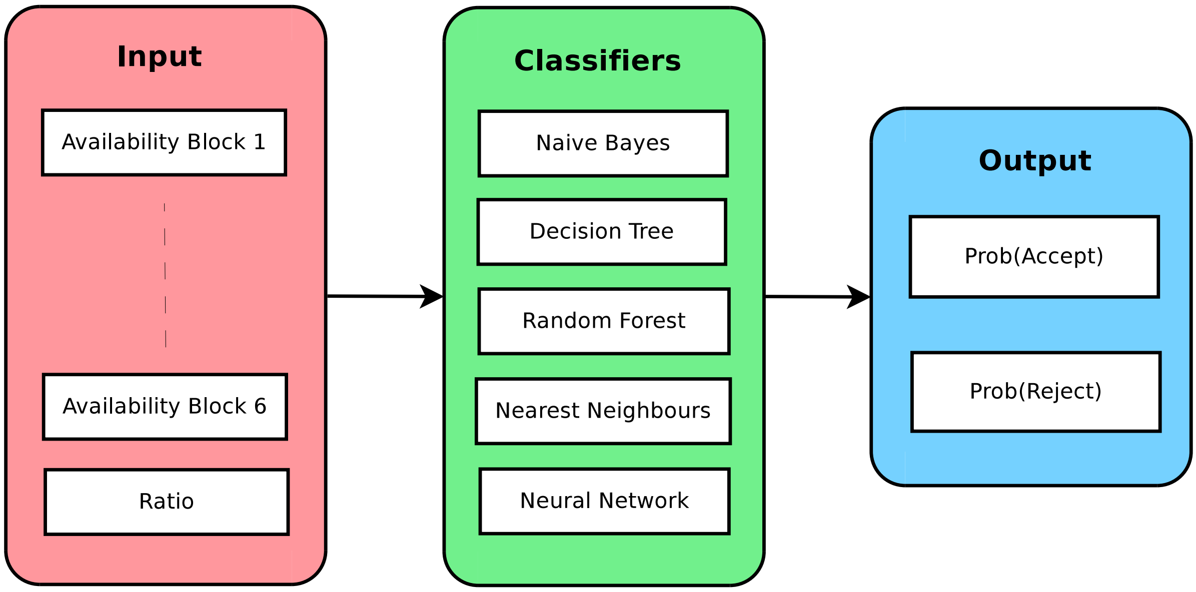


Figure 1: Schematic diagram showing inputs and outputs of classifier model

2020 falling outside of the range 2.5 ± 0.05. Hence only one of these needs to be used as an input for the classifier. Additionally, for over 80% of all tenders, and 93% for more recent ones (December 2019 - February 2020), the same values of $P^x_{0.2}$ and $P^x_{0.5}$ are given for all three services: ie. $P^p_{0.5} = P^s_{0.5} = P^h_{0.5} = 2.5 \times P^p_{0.2} = 2.5 \times P^s_{0.2} = 2.5 \times P^h_{0.2}$. Therefore to represent at least 80% of all tenders, only one power value, nominally $P^p_{0.5}$, is required. This will simply be denoted, P, henceforth. Furthermore, it was observed that P and availability/nomination fees are not independent. In order for all classifier inputs to be independent, these two features were replaced with one feature, which is the ratio of availability fee to P, referred to henceforth as Ratio. The nomination fee was not considered because it is non-zero for fewer than 1% of tenders.

For this work the following types of classifiers were tested and compared: Naive Bayes (using a Multinomial, alpha=1.0), Decision Tree (maximum depth = 10), Random Forest (maximum depth = 10), Nearest Neighbours (number of neighbours = 5) and Neural Networks. Specifications of the hyperparameters used to tune the classifiers are given in brackets. These were optimised by performing repeated, stratified K-fold testing on test data (repeats = 10, number of splits = 5) whilst varying the hyperparameters to maximise the average accuracy scores. This was done using Python's scikit-learn module [39]. Figure 1 presents a schematic representation of the classifiers, showing the model inputs and outputs. The inputs represent a market bid and the outputs are the possible results of the market auction: reject or accept the bid.

Table 1: Values of storage parameters for a lithium ion battery.

Parameter	Value
Power-Capacity Ratio	2
Charge/Discharge Efficiency	90%
Range of SOC	20-100%

2.2. *Battery Storage Device*

Battery storage devices can participate in the FFR market by submitting bids, as previously outlined; in this section their parameters and FFR market bidding strategy are presented. Battery storage devices can be parametrised by their maximum power to capacity ratios, usable capacities (state-of-charge, SOC) and efficiencies. This is shown below in Table 1 for lithium ion batteries. These values are derived from several literature sources [40]–[42] and are approximate because in reality they vary depending on battery usage and age.

FFR auction bids are typically split into three different parts, such that there are 8 possible auction outcomes which could occur due to combinations of different parts of the bid being accepted or rejected. These are summarised in Figure 2. The classifier is used to determine whether or not each part of the bid is accepted, and with what probability; this is used to determine the probabilities of the 8 auction outcomes. The notation adopted here uses the numbers 1 and 0 to represent an accepted or rejected part, respectively. For instance, 100 refers to an outcome in which only the first part of the bid is accepted. Having quantified the probability of each possible classification, 500 scenarios (each having one of the possible 8 outcomes) will be randomly generated according to the classification probabilities.

These generated scenarios will then be applied to an MILP optimisation model in order to examine how the methodology (quantifying the probability of each FFR market classification) affects the value of storage participating in both FFR and arbitrage markets. In this model, a storage device is able to perform arbitrage in the N2EX day-ahead market [43]; the methodology describing the arbitrage optimisation is outlined in the following section. It will be assumed the FFR auction results for the following month are already known at the time of the arbitrage optimisation, since these are released on the twelfth business day of the current month.

2.3. *Optimisation Model*

The optimisation model will maximise the profits of battery storage performing arbitrage, given certain FFR market outcomes. Different auction outcomes, n, will be fed into the optimisation model where each will be parametrised by each hour, t, it's providing FFR in and the power available for FFR, P_n and $P_n/2.5$ (at grid events of > 0.5 Hz and 0.2-0.5 Hz respectively). For each outcome, n, an hourly time series, $t_{nt} \in \{0, 1\} \forall\, n, t$, is developed, where a value of 1 or 0 relates to providing or not providing FFR, respectively. This depends on auction outcome and which parts of the bid (relating to providing FFR in different EFA blocks) are accepted or rejected.

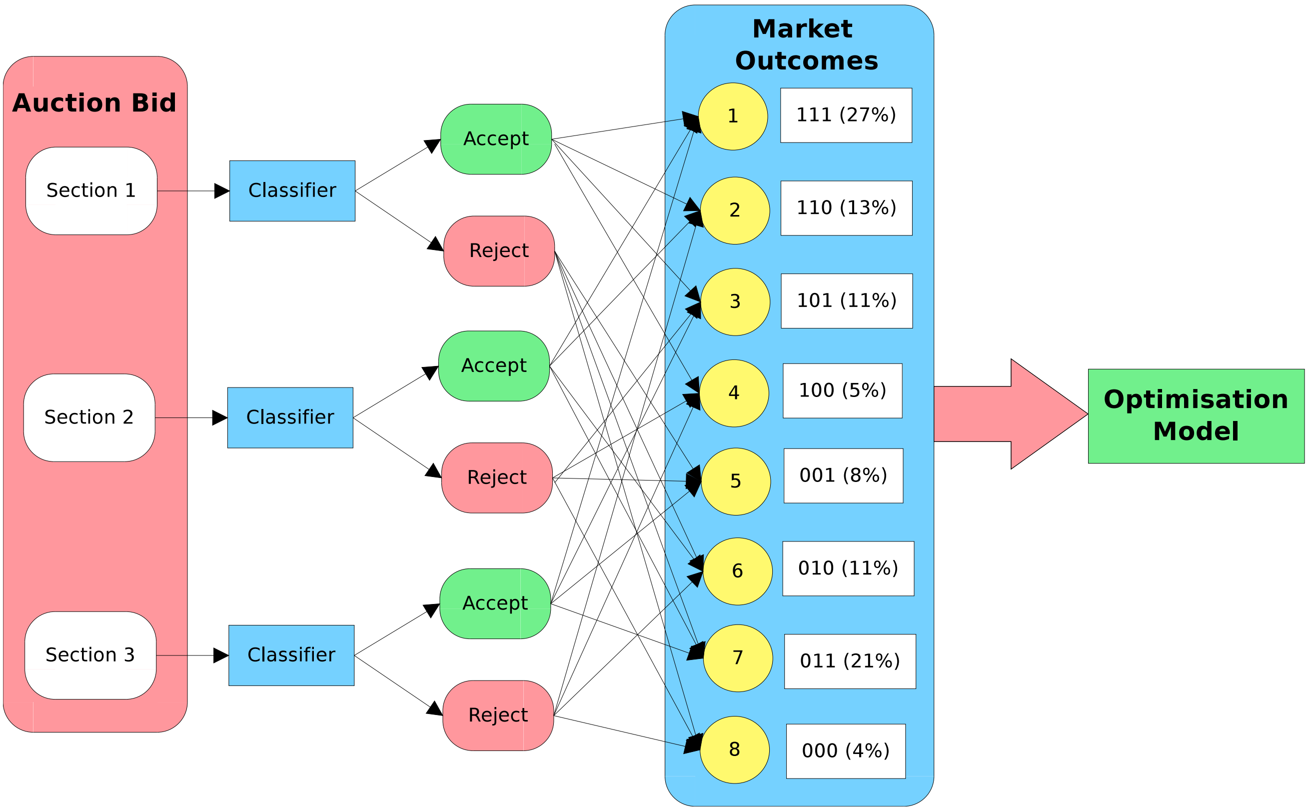


Figure 2: Schematic showing how auction bids (typically split into three parts) feed into the classifier resulting in various different market outcomes with associated probabilities. These are pushed through an MILP optimisation model.

The power used to charge or discharge the storage must remain within its maximum limits, as is expressed by Equations 1 and 2.

$$0 \leq P^c_{nt} \leq \bar{P}_n \qquad \forall\, n, t \tag{1}$$

$$0 \leq P^d_{nt} \leq \bar{P}_n \qquad \forall\, n, t \tag{2}$$

where P^c_{nt}, P^d_{nt} and $\bar{P}_n$ are charging and discharging power (at time t, for outcome n) and maximum power (for outcome n), respectively. Additionally, the capacity, X_{nt}, of the storage must remain within its minimum and maximum limits: $\underline{\mathrm{X}}_n$ and $\bar{X}_n$. However, when it is providing FFR it should also have sufficient spare/available capacity to provide $\frac{P_n}{2}$; this is since the maximum time an FFR provider may be continuously called upon to provide power services is 30 minutes [44]. Equations 3 and 4 represent this mathematically.

$$\underline{\mathrm{X}}_n \leq X_{nt} \leq \bar{X}_n \qquad \forall\, n, t \tag{3}$$

$$\underline{\mathrm{X}}_n + \frac{P_n}{2} \leq X_{nt} \leq \bar{X}_n - \frac{P_n}{2} \qquad \forall\, n, t \tag{4}$$

The capacity of the device at the end of time period t, will be equal to the capacity at the end of the preceding period plus the effect of any charging or discharging that occurred at t. Hence:

$$X_{nt} = X_{n,t-1} + \eta^c_n P^c_{nt} - \frac{P^d_{nt}}{\eta^d_n} \qquad \forall\, n, t \tag{5}$$

In order to maximise the day-ahead arbitrage profits, the following equation is minimised:

$$min \sum_{n,t} \underbrace{p^{DA}_t \left(P^c_{nt} - P^d_{nt}\right)}_{\text{Arbitrage}} + \underbrace{\lambda_{nt} t_{nt} \left(\alpha_{nt}\rho_{0.5} + \beta_{nt}\rho_{0.2}\right)}_{\text{FFR Penalties}} \tag{6}$$

subject to (1)-(3), (5). The first term represents the costs incurred in the day-ahead market, with p^{DA}_t representing the day-ahead buy/sell price, whilst the second term represents penalties associated with being unable to provide the contracted FFR services. These are summed over all outcomes, n, and time periods, t, in the following month. The penalty for FFR unavailability is forfeiting the settled availability fee, λ_{nt}, for that hour and outcome (if this happens on more than three occasions NG may consider the tendered unit unsuitable for providing FFR in future months). Additionally, $\rho_{0.2}$ and $\rho_{0.5}$ are constants representing the probabilities of being called upon for FFR services during 0.2-0.5 Hz and > 0.5 Hz events. Finally, $\alpha(t)$ and $\beta(t)$ are binary variables set by the following conditions:

$$\alpha_{nt} = \begin{cases} 1 & : X_{nt} \leq \underline{X}_n + \frac{P_n}{2} \\ 1 & : X_{nt} \geq \bar{X}_n - \frac{P_n}{2} \\ 0 & : else \end{cases} \qquad \forall\, n,t \tag{7}$$

$$\beta_{nt} = \begin{cases} 1 & : X_{nt} \leq \underline{X}_n + \frac{(P_n/2.5)}{2} \\ 1 & : X_{nt} \geq \bar{X}_n - \frac{(P_n/2.5)}{2} \\ 0 & : else \end{cases} \qquad \forall\, n,t \tag{8}$$

such that $\alpha(t)$ and $\beta(t)$ are equal to one if the storage device doesn't have sufficient usable/unused capacity to provide FFR at the two usable levels. If this occurs during an FFR time period, $t_{nt} = 1$, there is a risk of losing λ_{nt} which is weighted by the probability of being called upon. Outside of the FFR periods, $t_{nt} = 0$, these terms disappear and $\alpha(t)$ and $\beta(t)$ can take any value without risking the penalty.

It is important to make the distinction between the two FFR frequency deviation levels because the probabilities of being required to provide/accept $\frac{P_n}{2}$ MWh and $\frac{(P_n/2.5)}{2}$ MWh differ significantly. In [45] it was found that between 2014 and 2018, in GB, the average number of a) high (+0.2 to +0.5 Hz) events is 1.8 per day and b) low (-0.2 to -0.5 Hz) events is 0.9 per day. There were no $> \pm$ 0.5 Hz events during this period. Additionally, 80% of these high events (a greater percentage for low) were observed to last 30 seconds or less. Future estimates for 2030 predict an increase in the number of 0.2-0.5 Hz events, but with severe events, > 0.5 Hz, only occurring in the most extreme low-inertia scenario [45]. Therefore it seems reasonable to assume that the grid may require powers of $\pm(P_n/2.5)$ MW at least once a day, but $\pm$ P MW very rarely. The values of $\rho_{0.2}$ and $\rho_{0.5}$ cannot accurately be ascertained, however a few deductions can be made: $\rho_{0.2} > \rho_{0.5}$ and $\rho_{0.5} \ll 1$. Varying these will affect the bidding strategy and will be explored later.

For the sake of simplicity the storage device will be considered a deterministic price-taker in the day-ahead market. In reality this is not the case, as explored in preliminary work. However, the difference between deterministic and non-deterministic revenue in the N2EX day-ahead market was found to be 12%, since prices follow a predictable daily pattern. As the main focus here is realistically modelling ancillary services and exploring the trade-offs of the different revenue streams, it is acceptable to use a deterministic arbitrage approach. Furthermore, the size of the storage is small, 4 MW, so its effects on the day-ahead market price are negligible.

3. Results and Discussion

3.1. FFR Market Trends

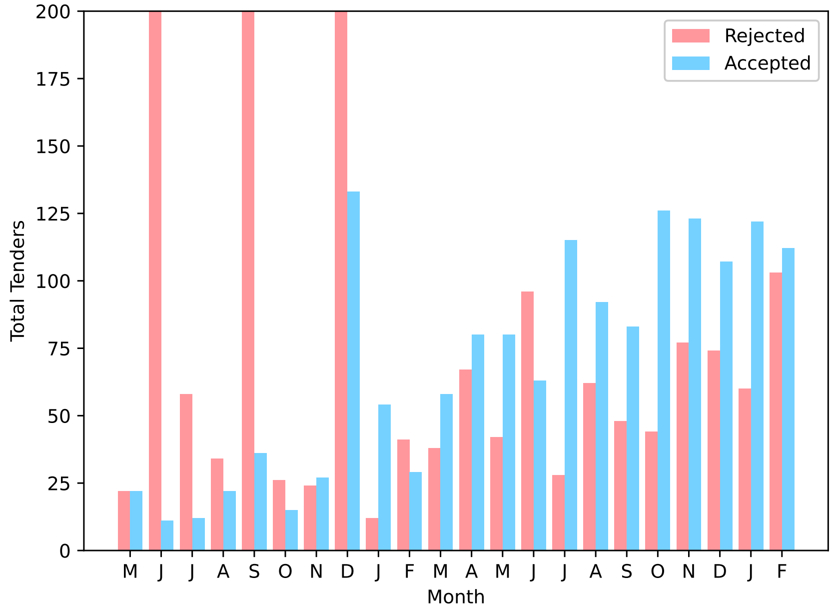
FFR Post-tender reports were examined from May 2018 to February 2020. Figure 3 shows the total amount of accepted and rejected a) tenders and b) power (P rather than P/2.5) each month over this period. It can be seen that both of these quantities have increased over time, which is as would be expected with increasing renewable generation and lower system inertia [46].

In Figure 4 the historical trends have been split up into the six 4-hourly EFA blocks; these start at 23:00 - 3:00 for block one and finish at 19:00 - 23:00 for block six, with the remaining blocks evenly distributed between these. The trends shown here are only for the accepted tenders, and represent a) total accepted tenders, b) total accepted power, P and c) Ratio (the ratio of availability fee to power): this is an average value across all accepted tenders per month and per block. It can be seen that the general trend, across all blocks, is for the number of accepted tenders and power volume to increase with time. However, it can be seen that the values of these, and their individual patterns, vary for the different blocks. Also, it can be gleaned that some of the blocks mirror each other, namely one and two, and three and four. Blocks five and six also follow similar patterns to one another, however, to a lesser extent.

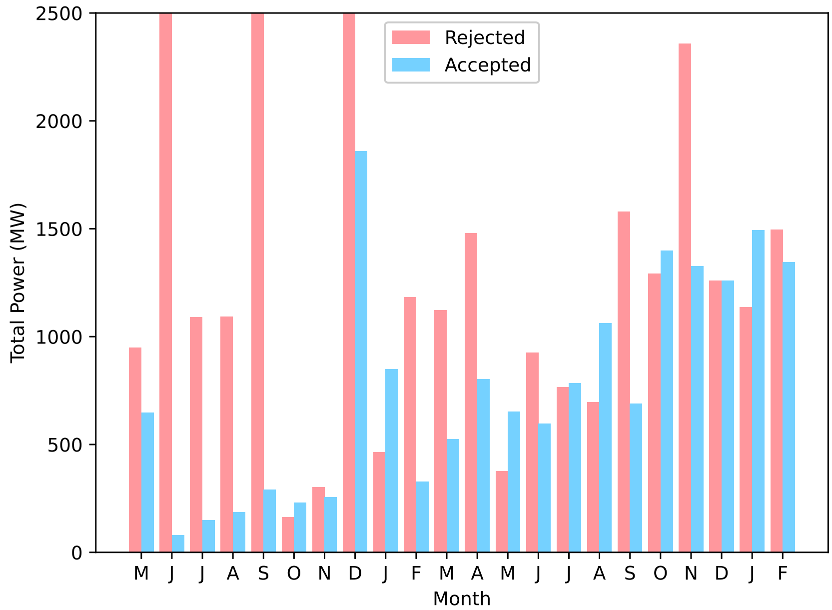
Upon closer inspection of the raw tender data [44], it can be seen that most tenders are submitted as three separate entries: blocks 1 and 2 ($B_{1\&2}$), blocks 3 and 4 ($B_{3\&4}$), and blocks 5 and 6 ($B_{5\&6}$). This can be understood by looking at Figure 4(c). The higher the ratio, the greater the availability fee payment per given P. Historically, with the exception of block five, the ratios of the blocks are all very similar. However, in more recent times the ratios for $B_{5\&6}$ are significantly greater than the others, and lowest for $B_{1\&2}$. Therefore to maximise revenue, a savvy bidder should submit higher availability fees for the later blocks and lower for the earlier ones. Hence, this tactic which has been uncovered through historical analysis will be incorporated into the storage profit optimisation in Section 3.3. This will allow the optimisation and bidding strategy to be much more realistic than in previous ancillary service studies.

3.2. Classifier

Historic data was edited to remove any null entries and any non-dynamic services. As previously described, the feature list consists of availability for blocks 1-6 and Ratio. Repeated, stratified K-fold testing (repeats = 10, number of splits = 5) was performed on January 2020 data which contains 115 entries. This was done for each of the classifier types and results are presented as box plots of accuracy score in Figure 5. The Decision Tree, Random Forest and Nearest Neighbours classifiers perform better than Naive Bayes and Neural Network, as they have higher median, lower and upper quartile, and maximum and minimum values.

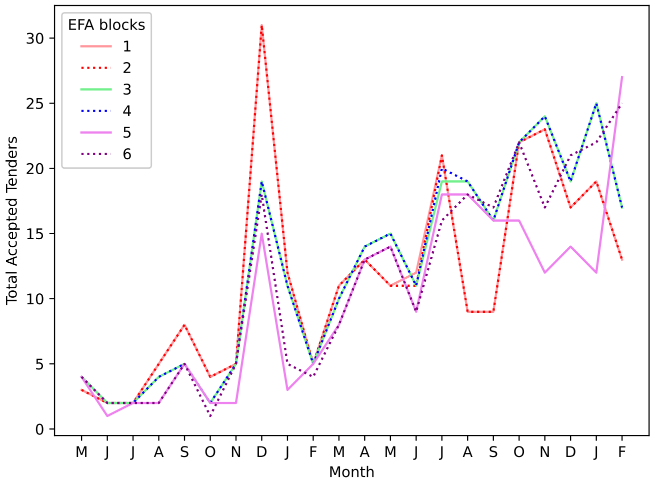


(a) Total accepted and rejected tenders (May 2018 - February 2020)

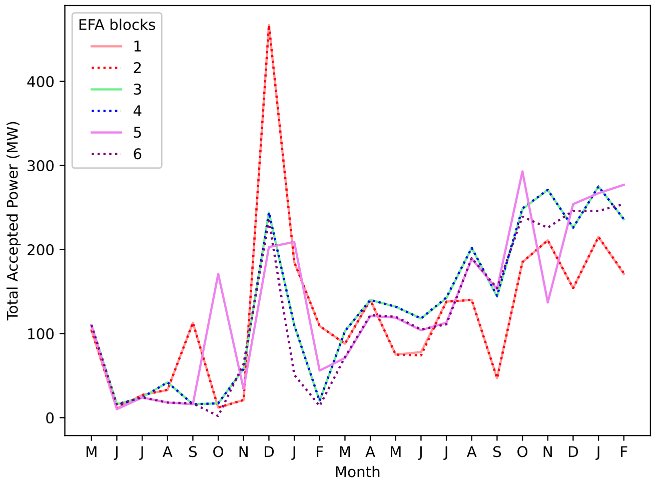


(b) Historic total accepted and rejected powers from May 2018 to February 2020

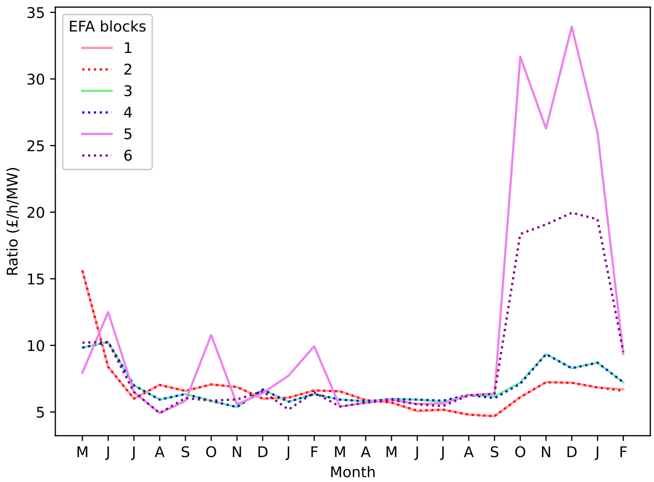
Figure 3: Total amount of a) accepted and rejected tenders and b) accepted and rejected power, P, each month (May 2018 to February 2020).



(a) Tenders



(b) Power



(c) Ratio

Figure 4: Total accepted a) tenders, b) power and c) ratio of availability fee to power across the six EFA blocks (May 2018 to February 2020).

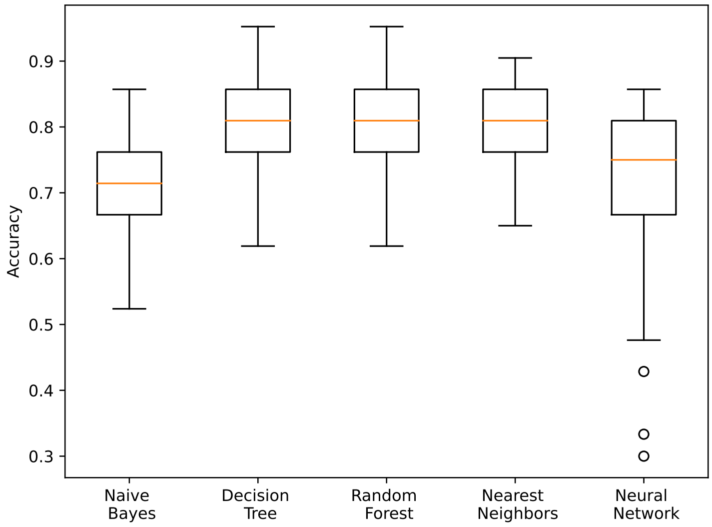


Figure 5: Accuracy score for different types of classifier based on January 2020 data.

Table 2: Accuracy of classifiers.

Classifier	Accuracy December 2019	Accuracy January 2020	Accuracy February 2020
Naive Bayes	0.55	0.78	0.5
Decision Tree	0.60	0.73	0.64
Random Forest	0.63	0.72	0.61
Nearest Neighbours	0.67	0.66	0.56
Neural Network	0.65	0.33	0.5

Further testing was performed by training the classifiers on November 2019, December 2019 and January 2020 data, and then testing them on December 2019, January 2020 and February 2020 data (i.e. testing each month on its consecutive month). This reflects how they would be used in reality, because only historic data is available at the time of bidding for the next auction. The accuracy scores of the classifier predictions are displayed in Table 2. It can be seen that accuracy values are significantly lower than those obtained through K-fold testing. This is to be expected, as the previous section showed that the number of accepted tenders, power and Ratio varies from month to month. Despite this, the Decision Tree and Random Forest classifiers managed to perform relatively well with all accuracy scores above 0.6.

Hypothetical tenders were made for $B_{1\&2}$ with Ratio varying from 1 to 50. These were then tested on the different classifiers, after they had been trained on January 2020 data, to examine the classifier predictions as Ratio is varied. The results of this are presented in Figure 6; red regions correspond to predictions of tenders being accepted, and blue regions to tenders rejected. Since NG accept the tenders which are most economic for them [47], it would be expected that tenders with a smaller ratio have a higher probability of being accepted, and those with a larger ratio a

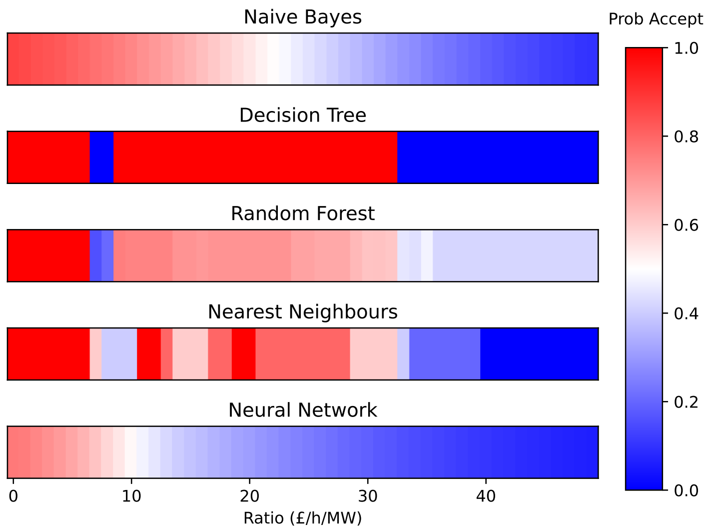


Figure 6: Probability of hypothetical tender acceptance, based on January 2020 data.

higher probability of being rejected. This trend is generally predicted by the classifiers. However, the Decision Tree, Random Forest and Nearest Neighbour classifiers predict that some tenders with low Ratios will be rejected. This may be due to overfitting, sensitivity to outliers or lack of testing data.

As described in the methodology section, probabilities associated with different market outcomes will be propagated through the MILP model. For this particular application we require the probabilities of the classifications rather than the classifications themselves. Despite giving the best performances when predicting the classifications, Decision Tree, Random Forest and Nearest Neighbours have a tendency to predict their probabilities as either 0.0 or 1.0, as shown in Figure 6). This is not useful for this particular application, which aims to quantify the uncertainty in market bid classification; probabilities of 0.0 or 1.0 suggest full certainty which is unrealistic for this application. It must be noted, however, that for the purpose of pure classification these classifiers are the most suitable. Naive Bayes is chosen over Neural Network for the following analysis since it has a smaller interquartile range for accuracy score (from the repeated, stratified K-fold testing) which suggests it may be more reliable. Additionally, Neural Network performed poorly when trained on December and tested on January data.

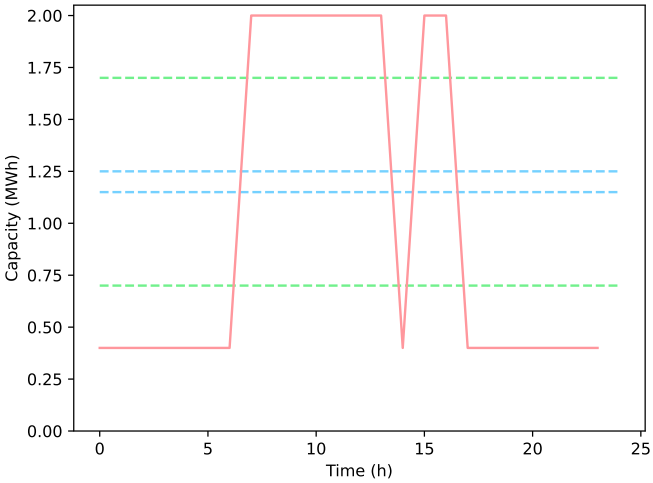
3.3. Battery Storage Optimisation

In this section the optimum bidding strategy for an battery storage device able to perform both arbitrage and FFR power services will be explored. As previously mentioned, they are able to participate in the day-ahead arbitrage market and make tenders for the monthly FFR dynamic services auction, which will be either accepted or rejected in advance of each upcoming month. After learning whether or not these tenders have been accepted and for which EFA blocks, the optimum strategy to buy/sell electricity in the market can be determined using Equation 6. The storage device will be modelled as a lithium ion battery using parameter values given in Table 1; the maximum capacity will be 2 MWh, and maximum power 4 MW. Power values of P = 1 MW, 1.25 MW and 1.5 MW will be considered for FFR services, as these allow the battery to provide the maximum high and low responses for the maximum time of 30 minutes. It was seen that designating realistic values to $p_{0.2}$ and $p_{0.5}$ is difficult, and requires a thorough grid frequency analysis outside the scope of this work. Values of 0.8 and 0.2 were chosen, respectively, for all the optimisations in this subsection: the effects of changing these are explored in the following subsection. These reflect the fact that frequency deviations of > 0.5 Hz are unlikely, whilst deviations between 0.2 and 0.5 Hz have historically occurred on average twice a day [48].

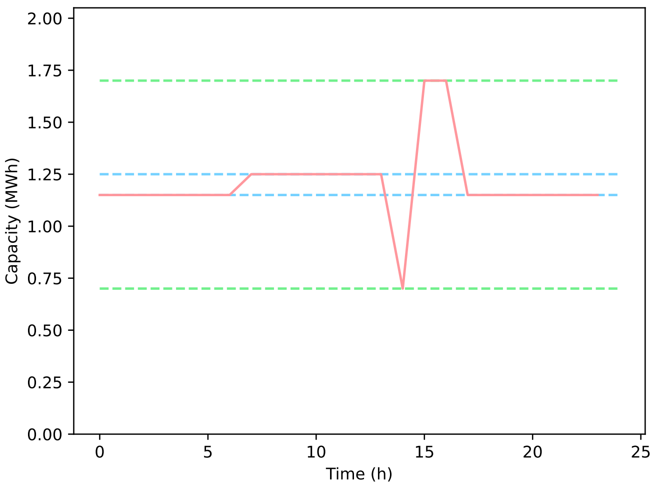
Figure 7 shows an example of the optimised daily capacity profile for a) when the storage device is only performing arbitrage and b) when it is performing both arbitrage and FFR services. The green and blue dotted lines represent the ranges between which it can deliver the maximum possible required power services at the P and P/2.5 levels respectively. The probability of being required to provide/accept P MW is very low, as this only occurs at frequency deviations > 0.5 Hz. Hence the probability-weighted penalty for being unable to provide it is also low. Therefore, at certain time periods the arbitrage profits are larger than this weighted penalty (the loss of income due to not being able to provide FFR which is the availability fee) and the optimisation algorithm decides to risk being penalised in order to reap the arbitrage rewards. This can be seen in Figure 7(b) at time periods 15-17.

In Section 3.1, it was found that successful FFR tenders were split up into three separate parts for $B_{1\&2}$, $B_{3\&4}$, and $B_{5\&6}$. The highest Ratio was submitted for $B_{5\&6}$, and lowest for $B_{1\&2}$. Hence the storage device will submit tenders with this same structure. To determine which availability fee should be submitted for each power P (1, 1.25, 1.5 MW), and each pair of blocks, an OLS regression was used (accepted power against accepted availability fee). The mean availability fee predicted for each power was then determined. One consequence of structuring tenders in this way, is that some parts of the tender may be accepted and others rejected. To quantify the probability of this, the Naive Bayes classifier developed in Section 3.2 is called upon. The mean availability fee values, for each of the above situations, were fed into the classifier which estimated their probabilities of being accepted; this is presented in Table 3. This information was then used to probabilistically generate 500 post-tender scenarios with 8 possible outcomes, as shown in Figure 2.

Figure 8 shows the results of generating these scenarios for the P = 1 MW case. Figure 8(a) displays the percentage of generated scenarios with each market outcome and Figure 8(b) shows the total income generated by FFR and arbitrage for each of these outcomes. The most commonly occurring outcome is all three parts accepted, and the least common all three parts rejected. This is expected, since these outcomes have the highest and lowest combined



(a) Arbitrage



(b) Arbitrage and FFR services

Figure 7: Optimum daily capacity profile of battery storage device performing a) arbitrage and b) arbitrage and FFR services.

Table 3: Calculated mean availability fees from Feb 2020 data and their probability of being accepted, as determined by the classifier.

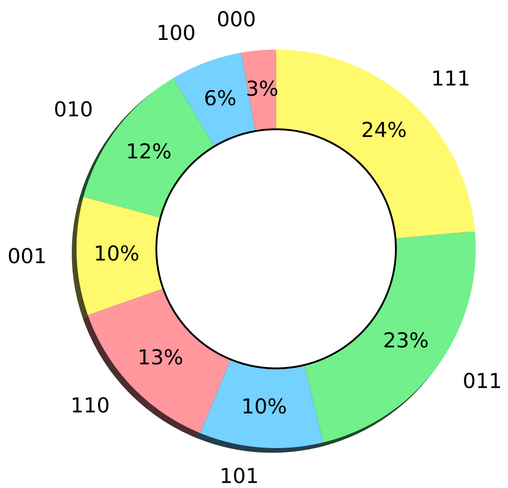
Power	EFA Blocks	Availability Fee (£/h)	Probability Accept (%)
1 MW	1 and 2	5.30	56
	3 and 4	5.40	72
	5 and 6	15.70	67
1.25 MW	1 and 2	7.10	55
	3 and 4	7.20	71
	5 and 6	17.60	68
1.5 MW	1 and 2	8.70	55
	3 and 4	9.10	71
	5 and 6	19.60	69

probabilities, respectively.

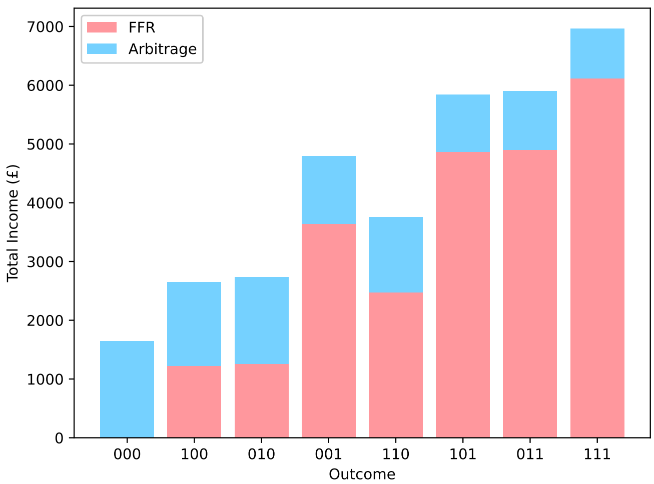
In Figure 8(b), it can be seen that the maximum income generated through FFR ($\sim$ £6,000) which occurs for 111, is much greater than the maximum arbitrage income, which occurs for 000, $\sim$ £1600. This confirms that FFR is a more lucrative revenue stream, and therefore securing accepted tenders should take priority over performing arbitrage. Additionally, it confirms that performing FFR in $B_{5\&6}$ is more lucrative than in the other blocks, since income from 001 > 110. Hence, these blocks should take precedence. Another interesting observation is that as FFR profits increase, arbitrage profits decrease. Despite this, arbitrage profits are still significant and non-negligible for all FFR outcomes. Therefore it should not be discounted as a revenue stream and still stands to provide an advantageous, additional source of income.

This same analysis was repeated for the P = 1.25 MW and P = 1.5 MW cases, in order to determine which value of P maximises potential revenue, whilst minimising the worst-case scenario, 000. Figures 9 and 10 compare the percentage of scenarios with each market outcome and total incomes for both of these. It can be seen that as P increases, total income increases; this is because a higher availability fee can be accepted. However, arbitrage income decreases as P increases: for 000 arbitrage income is £627 for P = 1.25 MW and £416 for P = 1.5 MW. As P increases there is less usable capacity available for arbitrage, so this finding makes sense. The pie charts show that the percentages of scenarios with each outcome are very similar for the P = 1 MW, P = 1.25 MW and P = 1.5 MW cases; this is expected since the acceptance probabilities, given in Table 3, are similar. Therefore these do not influence the optimum choice of P. Consequently, the optimum choice of P is the one which maximises the total potential revenue: this is found to be P = 1.5 MW, due to it achieving the highest FFR payments.

The optimum market bidding strategy, in terms of availability fee (or Ratio), for a fixed value of P = 1 MW, is also determined. In order to explore the effects on total income of varying the availability fees, the previous scenario generation and optimisation procedure was repeated for P = 1 MW. Each time availability fees were varied, for the different blocks, they were pushed through the classifier (as Ratio) to determine the different acceptance probabilities.

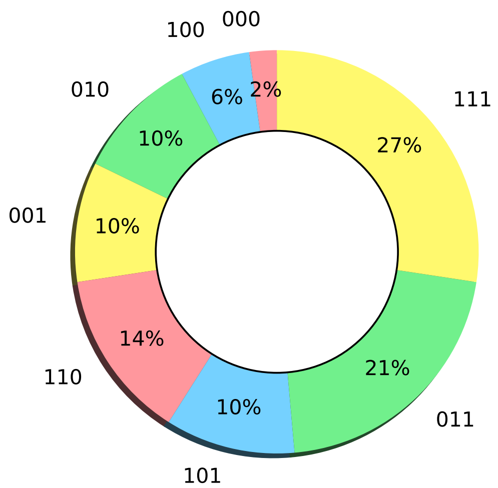


(a) Percentage of scenarios with each market outcome

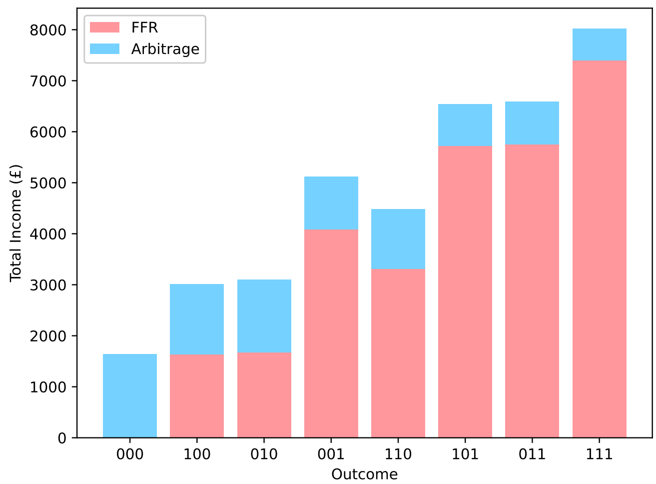


(b) Total Income

Figure 8: P = 1 MW case. Percentage of scenarios with each market outcome and the total income generated by FFR and arbitrage for each outcome.

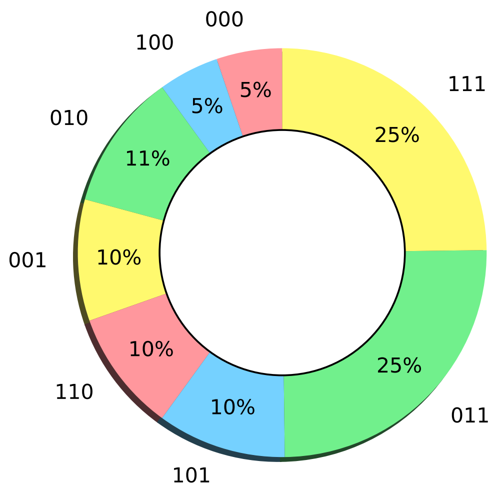


(a) Percentage of scenarios with each market outcome

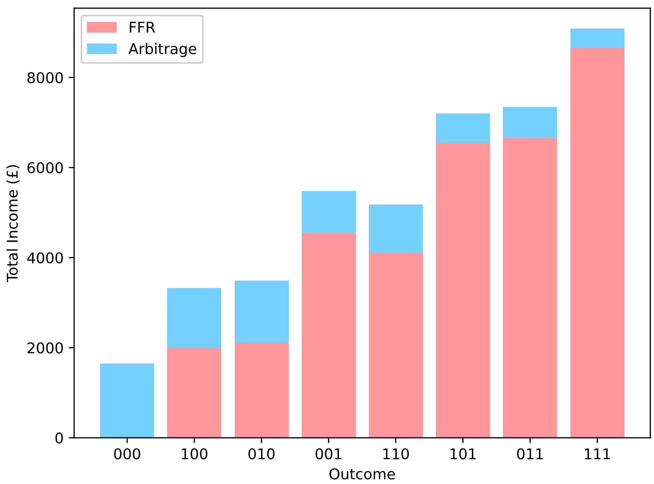


(b) Total Income

Figure 9: P = 1.25 MW case. Percentage of scenarios with each market outcome and the total income generated by FFR and arbitrage for each outcome.



(a) Percentage of scenarios with each market outcome



(b) Total Income

Figure 10: P = 1.5 MW case. Percentage of scenarios with each market outcome and the total income generated by FFR and arbitrage for each outcome.

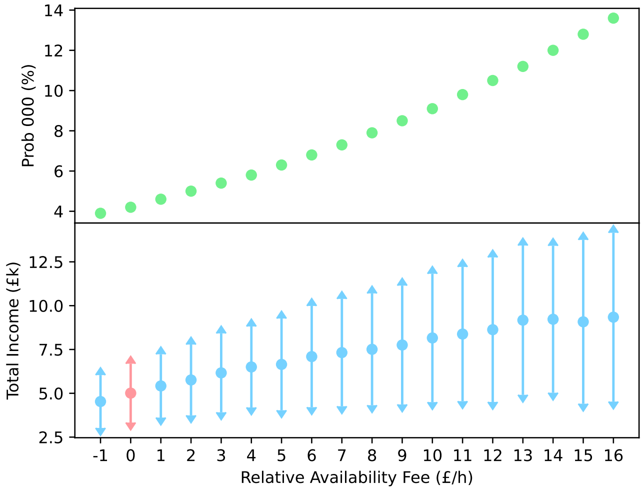


Figure 11: Above: Probability of outcome 000 occurring, as availability fee is increased. Below: Mean and standard deviation of the total income for 500 probabilistically generated scenarios using different availability fees.

This was then used to generate 500 scenarios, each with one of the 8 outcomes shown in Figure 2, but different probabilities. The optimisation procedure was then carried out for each of the 500 scenarios, and a mean total income and standard deviation was calculated. The results of this are presented in Figure 11, along with the probabilities of the worst-case outcome 000. The reference case is the one presented in Table 3 for 1 MW, and is shown in red. The relative availability fees were generated by adding +£X to each part of the reference case availability fees. The set of availability fees considered is [£5.30 + X, £5.40 + X, £15.70 + X], where $X \in Z : Z \in [-1, 16]$.

It can be seen that as the availability fee increases, mean total income also increases. This makes sense, as a greater accepted availability fee leads to a greater FFR income. However, the probability of the worst-case scenario, 000, also increases with availability fee. Hence, this is a riskier strategy. Additionally, standard deviation also increases, reflecting the fact that the results of the market auction are less predictable as availability fee increases. It must be noted that inaccuracies associated with the classifier predictions are not considered here. These will increase the unpredictability of the market outcomes, and consequently the risk associated with bidding for high availability fees.

Finally, the losses due to assuming that FFR bids are always accepted are quantified. In Table 4 for each value of P, the income gained in the best-case scenario, 111, is presented alongside the mean income. This is calculated as the mean of the 500 generated scenarios, using the availability fees and probabilities presented in Table 3. It can be seen that mean income is significantly lower than best-case income. For P values of 1, 1.25 and 1.5 respectively, the mean income is 28%, 29% and 28% lower than the best-case income. This means that models assuming FFR market acceptance could overestimate revenue by $\sim$28%.

Table 4: Best-case and mean FFR incomes under different output power scenarios.

P (MW)	Best-case Income (£)	Mean Income (£)
1	6963	5010
1.25	8021	5722
1.5	9084	6524

3.4. Real-Time FFR Provision

In order to determine the real-time FFR usage of an a battery storage device, grid frequency data from NG was analysed [44], [48]. This data has a one second resolution and gives the actual grid frequency in Hz. From this, the frequency deviation from 50 Hz each second was calculated; the response of the battery is proportional to this. The methodology for determining the corresponding storage power output/input is outlined in [26]. It is found that a storage device providing FFR, regardless of whether it is also performing arbitrage, must be balanced in real-time. This may be done via bilateral contracts or by buying/selling electricity in NG's balancing market. The costs associated with doing this are found to be negligible compared with FFR income.

For this analysis it is assumed that a 2 MWh, 4 MW battery is providing FFR during all EFA blocks at a level of P = 1.5 MW, which was found to be the most lucrative. Its arbitrage strategy is optimised using the model described in Section 2.3, and the values of $\rho_{0.2}$ and $\rho_{0.5}$, which control the level of arbitrage, are varied. The real-time capacity levels of the storage device performing a) FFR and b) arbitrage at the different levels over three days are shown in Figure 12. The solid black lines represent the total capacity as a function of time, due to arbitrage and FFR usage. The change in capacity of the device due to arbitrage usage is shown by the blue line. The change in capacity due to FFR is given by the blue and yellow areas, corresponding to reducing and increasing the capacity relative to the arbitrage capacity, respectively. Black dashed lines show upper and lower capacity limits of the storage device.

It can be seen that for values of 1/1 for $\rho_{0.2}$ and $\rho_{0.5}$, the level of arbitrage is kept within a tight band around the capacity mid-point. As these are relaxed to 0.8/0.2, arbitrage occurs outside of this tight band, but within the upper and lower capacity limits. For values of 0/0 and 0.2/0.2, a larger amount of arbitrage occurs taking the capacity to its upper and lower limits. This is not acceptable whilst performing FFR, since it leaves no spare/usable capacity to be used for FFR services. Hence, these values should not be used.

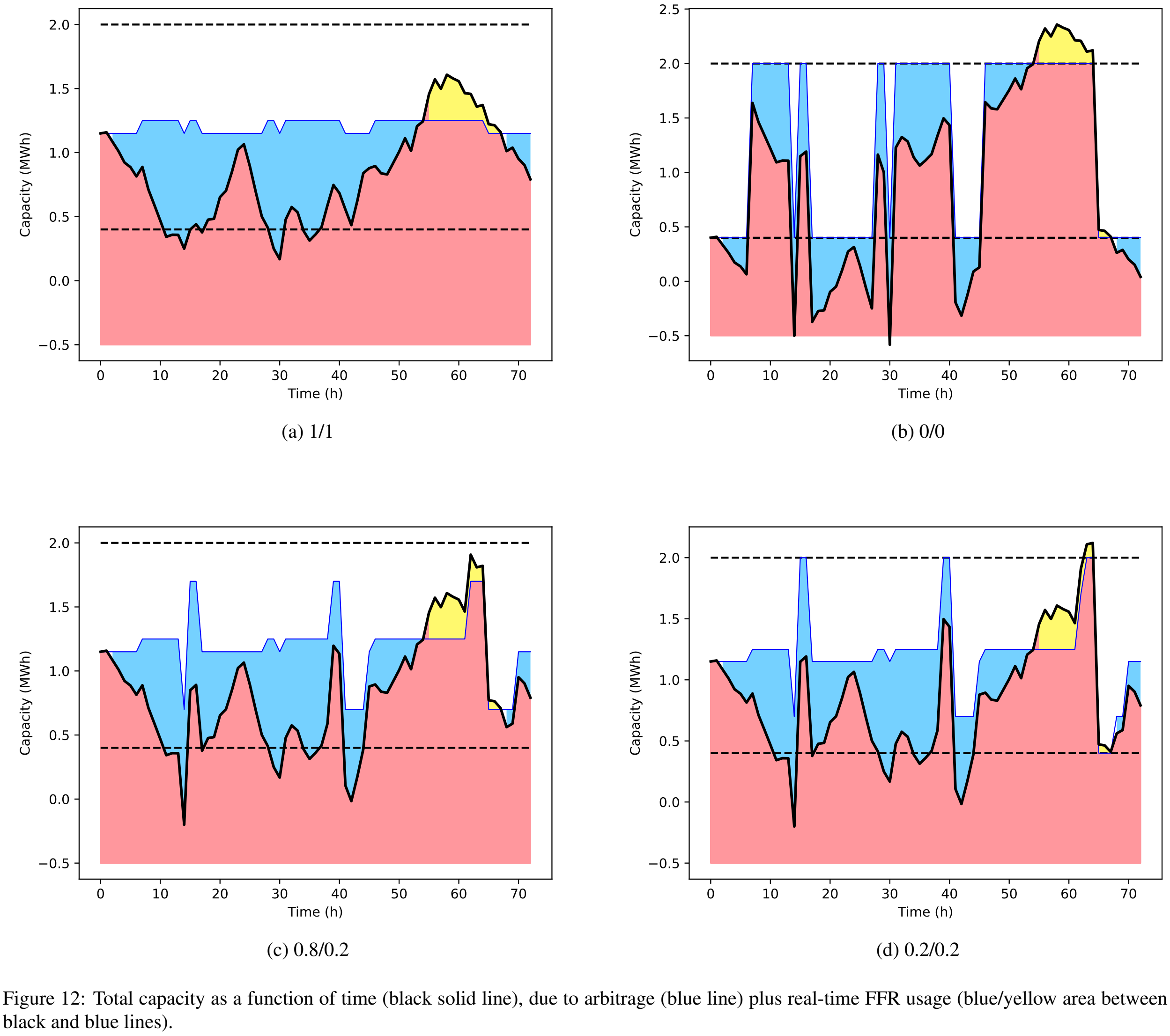
Table 5 quantifies some key findings for each of the four scenarios plus the no arbitrage scenario over the 72 hour period. These are: the amount of time each scenario can provide FFR for (without additional real-time charging or discharging) and the additional/excess capacity which must be acquired/removed in order to keep the storage device between its upper and lower limits. It can be seen that for all scenarios, including when no arbitrage is performed, the battery is not available to provide FFR across all time periods; it must therefore be balanced in real-time in order

Table 5: Findings from scenarios of real-time FFR provision.

$\rho_{0.2}/\rho_{0.5}$	FFR Availability	Additional Capacity Required (MWh)	Excess Capacity to Remove (MWh)
1/1	85%	0.83	0
0/0	47%	11.32	2.42
0.8/0.2	81%	2.23	0
0.2/0.2	78%	2.23	0.23
No Arbitrage	82%	1.19	0

to keep its capacity within its usable limits. For the very tight level of arbitrage (values of 1/1 for $\rho_{0.2}$ and $\rho_{0.5}$) FFR availability is actual greater than for no arbitrage, and for the 0.8/0.2 case availability is only 1% lower. Whilst this analysis should be carried out over longer time-periods, initial results suggest that performing arbitrage over a small band of capacity is acceptable and feasible. Additionally, the previous section has shown that even performing a small amount of arbitrage (with values of 0.8/0.2 for $\rho_{0.2}$ and $\rho_{0.5}$) can bring in significant revenue (£400 - £1600) whilst simultaneously providing FFR services.

It must be noted that if storage owners repeatedly fail to provide frequency response when called upon, then they will incur a greater consequence than simply paying a penalty. As previously mentioned, if this happens on more than three occasions NG may consider the unit unsuitable to provide frequency response in future months. Furthermore, if these failures occur on a wider scale, this may lead to market reform and a reassessment of the rules. However, by performing arbitrage across only a small band and performing real-time balancing, as outlined in [26], this risk of failure is minimised. With a sufficient balancing strategy, the battery's capacity should remain close to its mid-point, even with limited arbitrage occurring, enabling it to meet frequency response requirements.



(a) 1/1

(b) 0/0

(c) 0.8/0.2

(d) 0.2/0.2

Figure 12: Total capacity as a function of time (black solid line), due to arbitrage (blue line) plus real-time FFR usage (blue/yellow area between black and blue lines).

4. Conclusion

Ancillary services are necessary for stabilising electricity grids worldwide and battery storage devices present a promising low carbon option for providing these services. The optimal participation of a battery storage device in GB's FFR market, whilst simultaneously performing arbitrage, has been explored here. A novel machine learning methodology for assessing the probability of the battery being accepted to provide FFR, at a certain income level and for particular periods, is presented. The methodology involves testing and comparing classifiers on historic market data and using the most suitable one to determine the probabilities of different outcomes for hypothetical bids made on behalf of the battery, rather than simply assuming market acceptance. This allows FFR participation to be modelled more realistically than in the literature; additionally, this methodology may be applied to other auction market problems. It is found that the expected income is $\sim$28% lower when considering the FFR market as non-deterministic, as opposed to assuming market acceptance.

The outcomes of the machine learning classifier are propagated through an MILP optimisation model which contains two risk-weighted penalty terms associated with being unable to perform FFR. It is iterated 500 times with different FFR outcomes (accepted or rejected) generated probabilistically. Hence, the mean expected income through arbitrage and FFR, and its standard deviation, can be calculated. This method quantifies all possible market outcomes and their probabilities in a way which has not been done previously. The results confirm that FFR is a larger source of revenue than arbitrage for battery storage. However, they also show that simultaneously performing arbitrage over a small, risk-constrained band is economical and feasible in real-time. Future work may include improving the classifier with a learning element, exploring similar markets worldwide and assessing the real-time cost for providing FFR under different arbitrage strategies. Additionally, future work should apply this short-term bid optimisation model to a long-term economic feasibility study; this should provide insight for investors considering using battery storage for ancillary services.

5. Acknowledgements

This work was supported by the UK Engineering and Physical Science Research Council via grant EP/L016818/1 which funds the Centre for Doctoral Training in Energy Storage and its Applications. The authors are also grateful to Drax Power Ltd. for their financial support.

References

[1] G. Gowrisankaran, S. S. Reynolds and M. Samano, "Intermittency and the value of renewable energy", *Journal of Political Economy*, vol. 124, no. 4, pp. 1187–1234, 2016, ISSN: 1537534X. DOI: 10.1086/686733.

[2] J. P. Barton and D. G. Infield, "Intermittent Renewable Energy", vol. 19, no. 2, pp. 441–448, 2004.

[3] W. Su, J. Wang and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources", *IEEE Transactions on Smart grid*, vol. 5, no. 4, pp. 1876–1883, 2013.

[4] M. Yekini Suberu, M. Wazir Mustafa and N. Bashir, "Energy storage systems for renewable energy power sector integration and mitigation of intermittency", *Renewable and Sustainable Energy Reviews*, vol. 35, pp. 499–514, 2014, ISSN: 13640321. DOI: 10.1016/j.rser.2014.04.009. [Online]. Available: http://dx.doi.org/10.1016/j.rser.2014.04.009.

[5] A. Oudalov, D. Chartouni, C. Ohler and G. Linhofer, "Value analysis of battery energy storage applications in power systems BT - 2006 IEEE PES Power Systems Conference and Exposition, PSCE 2006, October 29, 2006 - November 1, 2006", 2206–2211 BN –142440178X, 2006. DOI: 10.1109/PSCE.2006.296284. [Online]. Available: http://dx.doi.org/10.1109/PSCE.2006.296284.

[6] P. Mercier, R. Cherkaoui, S. Member and A. Oudalov, "Optimizing a Battery Energy Storage System for Frequency Control Application in an Isolated Power System", *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1469–1477, 2009.

[7] V. Knap, S. K. Chaudhary, D.-I. Stroe, M. Swierczynski, B.-I. Craciun and R. Teodorescu, "Sizing of an energy storage system for grid inertial response and primary frequency reserve", *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3447–3456, 2015.

[8] J. Liu, J. Wen, W. Yao and Y. Long, "Solution to short-term frequency response of wind farms by using energy storage systems", *IET Renewable Power Generation*, vol. 10, no. 5, pp. 669–678, 2016, ISSN: 17521424. DOI: 10.1049/iet-rpg.2015.0164.

[9] R. Sebastián, "Application of a battery energy storage for frequency regulation and peak shaving in a wind diesel power system", *IET Generation, Transmission and Distribution*, vol. 10, no. 3, pp. 764–770, 2016, ISSN: 17518687. DOI: 10.1049/iet-gtd.2015.0435.

[10] W. W. Kim, J. S. Shin and J. O. Kim, "Operation Strategy of Multi-Energy Storage System for Ancillary Services", *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4409–4417, 2017, ISSN: 08858950. DOI: 10.1109/TPWRS.2017.2665669.

[11] R. Lee, S. Homan, N. Mac Dowell and S. Brown, "A closed-loop analysis of grid scale battery systems providing frequency response and reserve services in a variable inertia grid", *Applied Energy*, vol. 236, no. C, pp. 961–972, 2019. DOI: 10.1016/j.apenergy.2018.1. [Online]. Available: https://ideas.repec.org/a/eee/appene/v236y2019icp961-972.html.

[12] P. Zou, Q. Chen, Q. Xia, G. He and C. Kang, "Evaluating the Contribution of Energy Storages to Support Large-Scale Renewable Generation in Joint Energy and Ancillary Service Markets", *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, pp. 808–818, 2016, ISSN: 19493029. DOI: 10.1109/TSTE.2015.2497283.

[13] E. Sortomme and M. A. El-Sharkawi, "Optimal scheduling of vehicle-to-grid energy and ancillary services", *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 351–359, 2012, ISSN: 19493053. DOI: 10.1109/TSG.2011.2164099.

[14] M. Fisher, J. Apt and J. F. Whitacre, "Can flow batteries scale in the behind-the-meter commercial and industrial market? A techno-economic comparison of storage technologies in California", *Journal of Power Sources*, vol. 420, no. January, pp. 1–8, 2019, ISSN: 03787753. DOI: 10.1016/j.jpowsour.2019.02.051. [Online]. Available: https://doi.org/10.1016/j.jpowsour.2019.02.051.

[15] A. Roos, S. O. Ottesen and T. F. Bolkesjø, "Modeling Consumer Flexibility of an Aggregator Participating in the Wholesale Power Market and the Regulation Capacity Market", *Energy Procedia*, vol. 58, no. 1876, pp. 79–86, 2014, ISSN: 18766102. DOI: 10.1016/j.egypro.2014.10.412. [Online]. Available: http://dx.doi.org/10.1016/j.egypro.2014.10.412.

[16] S. Shafiee, A. Bhuiya, A. U. Haque, H. Zareipour and A. M. Knight, "Economic assessment of energy storage systems in alberta's energy and operating reserve markets", in *2018 IEEE/PES Transmission and Distribution Conference and Exposition (T&D)*, IEEE, 2018, pp. 1–5.

[17] N. Yu and B. Foggo, "Stochastic valuation of energy storage in wholesale power markets", *Energy Economics*, vol. 64, pp. 177–185, 2017.

[18] J. Cho and A. N. Kleit, “Energy storage systems in energy and ancillary markets: A backwards induction approach”, *Applied Energy*, vol. 147, pp. 176–183, 2015, ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.01.114. [Online]. Available: http://dx.doi.org/10.1016/j.apenergy.2015.01.114.

[19] M. Alipour, B. Mohammadi-Ivatloo, M. Moradi-Dalvand and K. Zare, “Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets”, *Energy*, vol. 118, pp. 1168–1179, 2017, ISSN: 03605442. DOI: 10.1016/j.energy.2016.10.141. [Online]. Available: http://dx.doi.org/10.1016/j.energy.2016.10.141.

[20] J. Wang, H. Zhong, W. Tang *et al.*, “Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products”, *Applied Energy*, vol. 205, pp. 294–303, 2017, ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.07.047. [Online]. Available: https://doi.org/10.1016/j.apenergy.2017.07.047.

[21] C. Brivio, S. Mandelli and M. Merlo, “Battery energy storage system for primary control reserve and energy arbitrage”, *Sustainable Energy, Grids and Networks*, vol. 6, pp. 152–165, 2016, ISSN: 23524677. DOI: 10.1016/j.segan.2016.03.004. [Online]. Available: http://dx.doi.org/10.1016/j.segan.2016.03.004.

[22] C. Bordin, H. O. Anuta, A. Crossland, I. L. Gutierrez, C. J. Dent and D. Vigo, “A linear programming approach for battery degradation analysis and optimization in offgrid power systems with solar energy integration”, *Renewable Energy*, vol. 101, pp. 417–430, 2017.

[23] C. Bordin and A. Tomasgard, “Smacs model, a stochastic multihorizon approach for charging sites management, operations, design, and expansion under limited capacity conditions”, *Journal of Energy Storage*, vol. 26, p. 100 824, 2019.

[24] F. Wankmüller, P. R. Thimmapuram, K. G. Gallagher and A. Botterud, “Impact of battery degradation on energy arbitrage revenue of grid-level energy storage”, *Journal of Energy Storage*, vol. 10, pp. 56–66, 2017.

[25] D. Pelzer, D. Ciechanowicz and A. Knoll, “Energy arbitrage through smart scheduling of battery energy storage considering battery degradation and electricity price forecasts”, in *2016 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia)*, IEEE, 2016, pp. 472–477.

[26] F. A. V. Biggins, S. Homan, D. Roberts and S. Brown, “Exploring the economics of large scale lithium ion and lead acid batteries performing frequency response”, *Energy Reports*, 2021, 5th Annual CDT Conference in Energy Storage Its Applications.

[27] S. S. Oren, “Design of ancillary service markets”, in *Proceedings of the 34th Annual Hawaii International Conference on System Sciences*, Jan. 2001, 9 pp.-. DOI: 10.1109/HICSS.2001.926283.

[28] K. Oureilidis, K.-N. Malamaki, K. Gallos *et al.*, “Ancillary services market design in distribution networks: Review and identification of barriers”, *Energies*, vol. 13, p. 917, Feb. 2020. DOI: 10.3390/en13040917.

[29] Y. G. Rebours, D. S. Kirschen, M. Trotignon and S. Rossignol, “A survey of frequency and voltage control ancillary services—part ii: Economic features”, *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 358–366, 2007.

[30] A. G. Isemonger, “The evolving design of rto ancillary service markets”, *Energy Policy*, vol. 37, no. 1, pp. 150–157, 2009.

[31] W. W. Hogan, “Electricity scarcity pricing through operating reserves”, *Economics of Energy & Environmental Policy*, vol. 2, no. 2, pp. 65–86, 2013.

[32] ENTSO-E, *Survey on Ancillary Services Procurement and Electricity Balancing Market Design*, 2018 (accessed 03-2020). [Online]. Available: https://www.entsoe.eu/publications/market-reports/#survey-on-ancillary-services-procurement-and-electricity-balancing-market-design.

[33] National Grid (ESO), “FIRM FREQUENCY RESPONSE TENDER RULES AND STANDARD CONTRACT TERMS NATIONAL GRID ELECTRICITY TRANSMISSION plc”, Tech. Rep., 2019, pp. 1–101.

[34] V. Almendra and D. Enachescu, "A fraudster in a haystack: Crafting a classifier for non-delivery fraud prediction at online auction sites", *Proceedings - 14th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing, SYNASC 2012*, pp. 233–239, 2012. DOI: 10.1109/SYNASC.2012.21.

[35] F. Anowar, S. Sadaoui and M. Mouhoub, "Auction fraud classification based on clustering and sampling techniques", in *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, IEEE, 2018, pp. 366–371.

[36] D. Nicholson and R. Paranjpe, "A Novel Method for Predicting the End-Price of eBay Auctions", *stanford*, pp. 1–5, 2013.

[37] M. R. Khadge and M. V. Kulkarni, "Machine learning approach for predicting end price of online auction", *Proceedings of the International Conference on Inventive Computation Technologies, ICICT 2016*, vol. 2016, pp. 1–5, 2016. DOI: 10.1109/INVENTIVE.2016.7830232.

[38] I. Rish, "An empirical study of the naive Bayes classifier", in *IJCAI 2001 workshop on empirical methods in artificial intelligence*, vol. 3, 2001, pp. 41–46. DOI: 10.1039/b104835j.

[39] F. Pedregosa, G. Varoquaux, A. Gramfort *et al.*, "Scikit-learn: Machine learning in Python", *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[40] CREESA, *Willenhall*, (accessed 03-2020). [Online]. Available: https://www.sheffield.ac.uk/creesa/willenhall/facts.

[41] H. Keshan, J. Thornburg and T. S. Ustun, "Comparison of lead-acid and lithium ion batteries for stationary storage in off-grid energy systems", 2016.

[42] G. Albright, J. Edie and S. Al-Hallaj, "A comparison of lead acid to lithium-ion in stationary storage applications", *Published by AllCell Technologies LLC*, 2012.

[43] Nord Pool, *Historical Market Data: N2EX Day Ahead Auction Prices*, 2020. [Online]. Available: https://www.nordpoolgroup.com/historical-market-data/ (visited on 20/09/2008).

[44] National Grid (ESO), *Frequency response services*, 2020. [Online]. Available: https://www.nationalgrideso.com/balancing-services/frequency-response-services (visited on 01/2019).

[45] S. Homan and S. Brown, "An analysis of grid frequency volatility in great britain", *Under Review*, 2020.

[46] Q. Hong, M. Nedd, S. Norris *et al.*, "Fast frequency response for effective frequency control in power systems with low inertia", *The Journal of Engineering*, vol. 2019, no. 16, pp. 1696–1702, 2019, ISSN: 2051-3305. DOI: 10.1049/joe.2018.8599.

[47] National Grid (ESO), *Firm Frequency Response (FFR) Market Information Report for Aug-18*, 2018. [Online]. Available: https://www.nationalgrideso.com/document/118101/download.

[48] S. Homan and S. Brown, "An analysis of frequency events in great britain", *Energy Reports*, vol. 6, pp. 63–69, 2020, 4th Annual CDT Conference in Energy Storage Its Applications, ISSN: 2352-4847. DOI: https://doi.org/10.1016/j.egyr.2020.02.028. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2352484720301967.