# Optimising investments in battery storage and green hydrogen production

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# Declaration

I confirm that this thesis is entirely of my own work; it is original in content and all sources have been accurately reported and acknowledged. This document has not been submitted at any other institution to obtain an academic qualification. I am aware of the University of Sheffield's guidance on Unfair Means (www.sheffield.ac.uk/ssid/unfair-means).

# Abstract

Energy systems are undergoing a transition towards low-carbon alternatives, but intermittent renewable sources like wind and solar pose challenges. Battery storage and hydrogen technologies, offer potential solutions with numerous benefits. They can enhance grid stability, improve power quality, and decarbonise industries like heavy manufacturing, heating, and shipping. Both batteries and hydrogen complement renewables by storing excess power and using curtailed energy.

To drive the widespread adoption of low-carbon energy technologies, it is crucial to establish its economic viability. This research focuses on optimising the revenues of low-carbon energy investments, specifically battery storage and green hydrogen production. It explores three key areas: determining the optimal usage of these technologies, identifying the best deployment locations, and addressing uncertainties.

In terms of usage, the research analyses various case studies and modelling techniques. It applies optimisation models to energy markets, examines community-owned battery projects, and combines machine learning with optimisation models to maximise battery revenues across different market segments. Additionally, the research explores the optimal investment and usage of PEM electrolysers within wind farms to produce green hydrogen, using optimisation models and real options analysis.

The findings highlight that the revenue-maximising use of energy technologies depends on specific circumstances. Grid-connected battery storage can benefit more from providing ancillary services like Firm Frequency Response than engaging in energy arbitrage. Simultaneously optimising arbitrage within a risk-constrained band can further enhance revenue. For hydrogen storage, wind farms with low Power Purchase Agreement (PPA) prices can increase revenue by using PEM electrolysers to produce hydrogen instead of directly exporting power. The research also provides a methodology to determine threshold prices for wind farms with higher PPAs, aiding their decision-making process to maximise revenue.

Regarding deployment locations, optimisation models identify optimal co-location strategies. Battery storage paired with solar is found to generate maximum revenue in southeast England, northwestern England, and north Wales. For PEM electrolysers co-located with onshore wind, optimal locations are southern Scotland (specifically, the Lanarkshire area) and mid-east England (around Lincolnshire).

To address uncertainties, the research employs two modelling techniques. Real options analysis proves effective for making long-term investment decisions under uncertainty, improving the value of investments. It demonstrates that employing this approach can significantly enhance the financial viability of low-carbon energy projects. Additionally, scenario-based stochastic optimization (SBSO) is used for day-to-day scheduling, reducing curtailed wind energy and increasing profits in a case study involving a wind farm with battery storage and hydrogen electrolysis.

Future research can further enhance revenue modelling and optimisation of low-carbon energy systems by investigating battery and electrolyser degradation rates, exploring revenue streams for other ancillary service markets, improving Balancing Mechanism modelling, and developing more accurate forecasting price methods. These efforts will contribute to establishing the economic viability and efficient integration of energy storage technologies in low-carbon energy systems.

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# List of publications

## Journal publications

- F. Biggins, S Homan, J. Ejeh *et al.*, "To trade or not to trade: Simultaneously optimising battery storage for arbitrage and ancillary services," *Journal of Energy Storage*, vol. 50, p. 104 234, 2022

- F. Biggins, M. Kataria, D. Roberts *et al.*, "Green hydrogen investments: Investigating the option to wait," *Energy*, vol. 241, p. 122 842, 2022

- F. Biggins, J. O. Ejeh and S. Brown, "Going, going, gone: Optimising the bidding strategy for an energy storage aggregator and its value in supporting community energy storage," *Energy Reports*, vol. 8, pp. 10 518–10 532, 2022

- F. A. Biggins, D. Travers, J. O. Ejeh *et al.*, "The economic impact of location on a solar farm co-located with energy storage," *Energy*, vol. 278, p. 127 702, 2023

## Conference proceedings

- F. Biggins, S Homan, D Roberts *et al.*, "Exploring the economics of large scale lithium ion and lead acid batteries performing frequency response," *Energy Reports*, vol. 7, pp. 34–41, 2021

- F Biggins and S Brown, "Optimising onshore wind with energy storage considering curtailment," *Energy Reports*, vol. 8, pp. 34–40, 2022

- F. A. Biggins, J. O. Ejeh, D. Roberts *et al.*, "Optimising a wind farm with energy storage considering curtailment and uncertainties," in *Computer Aided Chemical Engineering*, vol. 51, Elsevier, 2022, pp. 79–84

- J. O. Ejeh, F. A. Biggins and S. F. Brown, "Value of aggregator-led community energy storage systems with degradation constraints," in *Computer Aided Chemical Engineering*, vol. 50, Elsevier, 2021, pp. 1453–1458

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# Chapter 1

# Introduction

This chapter outlines the key research motivations and puts the work into context. Next follows a discussion of uses and types of battery and hydrogen production technologies; the specific technologies studied within this project are outlined and justified. The aims and contributions of the research are then presented, followed by the structure of the remaining thesis.

## 1.1 Motivation

The imminent threat posed by climate change is one of the largest geopolitical causes for concern in modern history. It is feared that extreme and erratic weather conditions, increasing pollution levels and depletion of natural resources will deteriorate the quality of many people's lives, intensify societal inequalities and create a state of global civil unrest. Consequently, reducing greenhouse gas emissions, which strongly augment the effects of climate change, has become a matter of global importance [9]. Many countries, including the UK, have pledged to cut down on harmful emissions, particularly of carbon dioxide, and are funding a great deal of research into strategies to accomplish this [10]. One of the key technologies identified as playing an important role in decarbonisation is energy storage [11].

Integrating energy storage into electricity grids can improve their flexibility and stability, due to its ability to bridge the gap between electricity production and demand [12]. As nations increasingly shift towards intermittent renewable generation, to achieve decarbonisation targets, this gap may increase [13]. For example, in the UK, the recent 2050 net zero carbon emissions target will further the expansion of renewables and curb the usage of fossil-fuel based power-plants [14]. Whilst these measures will help to mitigate against the effects of climate change, they will equally result in larger electricity supply and demand discrepancies [15]. Since energy storage has the potential to neutralise these discrepancies [16]–[19], it is likely to become an important technology for low-carbon grids. Furthermore, references [20] and [21] show that for electricity systems with high wind power penetration, energy storage can improve both system reliability and stability.

There are many different types of energy storage technologies, each with its own attributes and set of suitable applications [22]–[24]. In Figure 1.1, a comparison of power rating and energy capacity for the main storage technologies is shown. The discharge time duration as a function of power rating is also indicated. Shorter term storage, such as types of lithium ion batteries and flywheels are suitable for improving power quality of electrical grids, whereas longer term storage systems are suitable for capacity services. Additional factors such as efficiency, cost (capital and operational) and lifetime may also affect the suitability of these technologies to various applications.

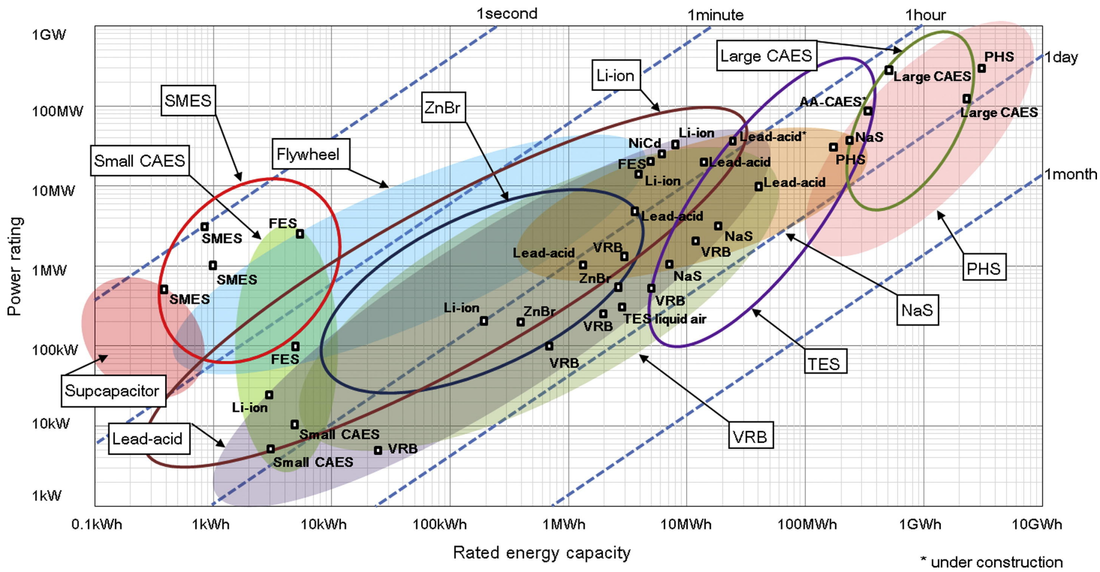



Figure 1.1: A comparison of energy capacity and power rating for different energy storage technologies [23]. Note: SMES = superconducting magnetic energy storage; ZnBr = zinc bromine; NaS = sodium sulphur; PHS = pumped hydro storage; CAES = compressed air energy storage; VRB = vanadium redox battery; TES = thermal energy storage

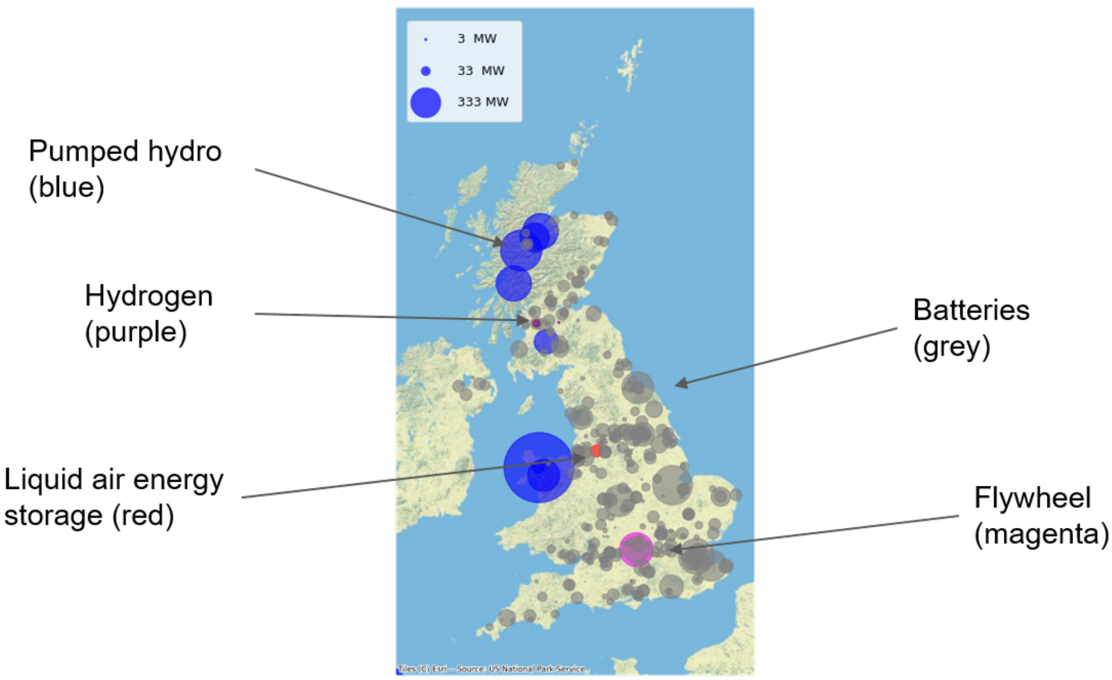



Figure 1.2: Currently deployed and pipeline energy storage in GB. Data adapted from [25].

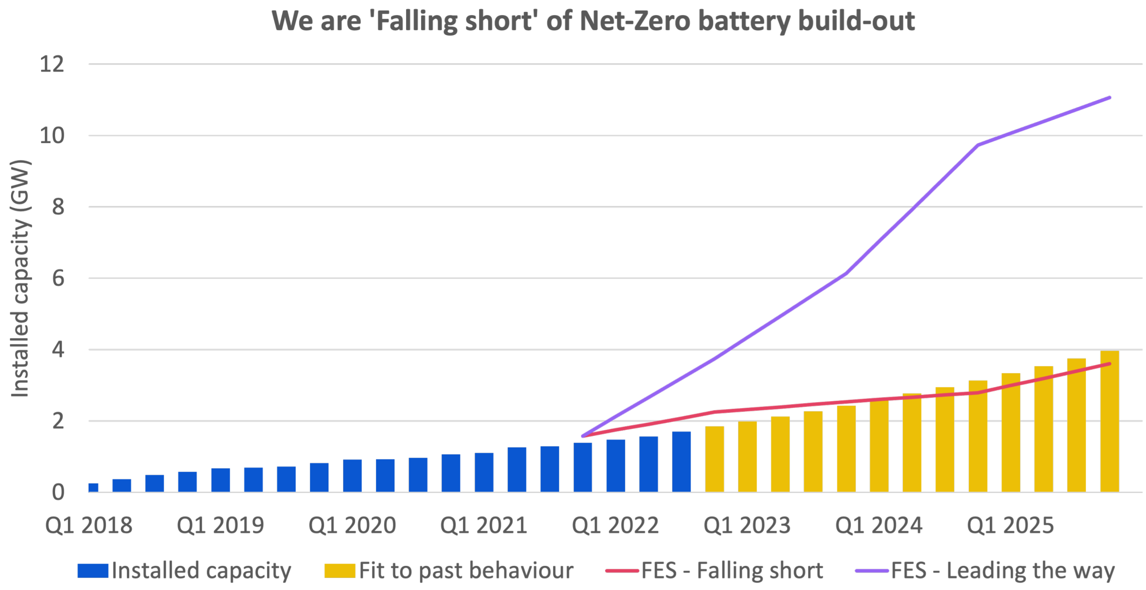



Figure 1.3: Installed battery capacity in GB with future build-out (based on past behaviour) compared against National Grid's Future Energy Scenarios 'Falling short' and 'Leading the way'. Data adapted from [26], [27].

In Great Britain different types of large-scale energy storage technologies have been deployed, or are in the process of getting planning permission. Figure 1.2 shows the type, location and size of currently deployed and pipeline energy storage in the UK, using data from Great Britain's (GB's) Renewable Planning Database [25]. It can be seen that there are several very large pumped hydro storage facilities; the largest of these is Dinorwig in north Wales, with an installed capacity of 1728 MW. The rest of GB's energy storage is dominated by batteries; a large number of battery projects of varying sizes can be seen. There are a few other types of energy storage deployed or planned in GB including liquid air storage, hydrogen and a large flywheel facility, but the vast majority of storage projects are pumped hydro or batteries.

Figure 1.3 shows Great Britain's historically installed battery capacity (data taken from [27]) and future build-out based upon historical rate. These are compared against two of National Grid's Future Energy Scenarios:

- **Falling short**: this is the worst-case scenario, in which we fall short of our Net-Zero targets.
- **Leading the way**: this is the best-case scenario in which we achieve Net-Zero.

It can be seen that if battery build-out continues along its historical trajectory, we will fall short of Net-Zero targets and have to deal with the catastrophic consequences. Of course, battery storage is only one of the many required technological developments to reach Net-Zero. Nonetheless, Figure 1.3 shows that within this sector a step-change in battery deployment rate is needed for GB to achieve its climate goals.

Furthermore, according to Energy Systems Catapult GB's requirement for low carbon flexible capacity by 2030 is 30 GW and increases to 60 GW by 2050, to integrate renewable generation and provide energy security [28]. Hence, to achieve this level of installed capacity, there needs to be much greater deployment of energy storage. Additionally in the most recent BloombergNEF New Energy Outlook report, they estimate that 245 GWh battery storage should be deployed each year to 2030 and hydrogen must scale rapidly to provide up to 22% of total energy consumption (compared with 0.002% in 2021) [29]. Additionally, the UK government published a target in 2021 to generate 5 GW of low carbon hydrogen production capacity by 2030 [30]; this is in comparison with 0.02 GW hydrogen projects registered with the Renewable Planning Database. Therefore, this project is specifically focused on battery storage and hydrogen, since the deployment of these technologies needs to be accelerated to meet the above targets.

The economics of batteries and hydrogen will play an important role in determining their deployment. If they are not economical, pose too many risks, or are faced by policy barriers, then their deployment will remain low [31]. Under these circumstances, the deployment targets might not be reached, and nations may fall short of their decarbonisation targets. According to [32], there is a conflict between the technical benefits that these low-carbon technologies can bring, to power and energy systems, and the challenge of economically compensating these services within current market frameworks.

In [33] the authors suggest that optimising the usage of batteries, to maximise revenue, can improve their attractiveness to investors. The authors of [34] show that by optimising energy storage profits in different revenue streams, namely demand management and response, and arbitrage, its payback period can be reduced, thereby making it a more attractive investment. Additionally, in [35] the authors use an optimisation model to determine the maximised value that battery storage can generate performing frequency services; they use this to determine the optimal sized battery to invest in. These are just some examples of how optimisation models have been used to help influence investment decisions in energy storage; many more studies are discussed in the literature review in Chapter 3.

Due to the urgent need to decarbonise and expand battery and hydrogen production deployment, this research focuses on optimising their usage to maximise revenue. The results can be used to drive more informed investment decisions in these technologies, and are therefore of interest to organisations operating in the battery storage and hydrogen production space. Since energy storage is a key part of decarbonising energy systems, it is hoped that this research will play a part in enabling a cleaner, more sustainable future.

## 1.2 Aims and contributions

The main goals of this project are to bring attention to the importance of battery storage and hydrogen production and encourage increased investments in these technologies. Additionally, the findings will provide valuable insights for organisations operating in the field of energy storage, enabling them to make more informed decisions.

To optimise the economic aspects of low-carbon energy investments, this research focuses on addressing various fundamental questions, such as:

1. How can energy storage be optimally be used to generate revenue?
2. Where is the optimal location to deploy battery storage and hydrogen production to maximise revenue?
3. How can uncertainties in economics calculations be addressed?

Each of these questions addresses a particular aspect of optimising energy storage economics, with the overall aim of informing a potential investor or decision-maker; they are the key research questions examined in this project, and are referred to as R1, R2 and R3, respectively, throughout the remainder of this thesis. Firstly, it is necessary to examine how energy storage can generate revenue e.g. through what mechanisms/markets, and how can this be optimised. Secondly, when deciding whether or not to deploy energy storage, consideration of its potential location(s) is necessary. If energy storage can generate greater revenue in some locations compared with others, this is important information that a potential investor should be informed of. Finally, there are uncertainties associated with any investment, and energy storage is no different. It is therefore necessary to study these uncertainties and consider their economical impact. A discussion of specific literature relating to these questions and highlighting knowledge gaps is presented in Section 3.

## 1.3 Thesis outline

This thesis is prepared in *by publication* format. The remainder of the thesis is structured in the following way: Chapter 2 presents general background underpinning the project. It discusses different types of energy storage and mechanisms for generating revenue, with specific discussion of Great Britain's electricity markets, since it is used as a case study. A review of studies in the literature optimising the economics of energy storage is presented in Chapter 3. These are organised by mechanism for revenue generation. There is also discussion of studies optimising the location of energy storage co-located with renewables, and studies that optimise energy storage economics under uncertainty.

Chapter 4 introduces each publication and explicitly states the contributions of each author. The publications are ordered to address R1, R2 and R3 in turn, and discussion is included to clarify how the publications specifically explore these questions. Chapter 5 concludes the prelude to publications. It discusses the research and its importance, and then evaluates how future work can address remaining knowledge gaps. Finally, concluding remarks are presented. Chapters 6 - 11 present each publication in full.

# Chapter 2

# Background

This section firstly introduces different types of batteries and hydrogen electrolysers and their uses. Next there is an explanation of how energy storage can be used to generate revenue. Finally, since Great Britain (GB) is used as a case study for this project, it is necessary to introduce the relevant markets, that energy storage can participate in, and their operation.

## 2.1 Batteries

### 2.1.1 Uses of batteries

This project explores primarily large, utility-scale batteries, which an investor may use for a variety of applications to generate profits. As outlined in [36], there are many different services that can be offered by grid-connected, utility-scale batteries; these are summarised in Figure 2.1. It can be seen that there are four main categories of services provided:

1. Those that benefit system operation by improving power quality. For example, frequency regulation keeps grid frequency within its mandated limits, and black start services restore power following a power loss.

2. Services that reduce system costs by negating or deferring investments in system infrastructure. For example, peak shifting, also referred to as peak shaving, is a process that involves flattening out electricity generation and demand. The idea of peak shifting is to use batteries to charge up overnight (increasing generation during this time) and discharge in the evening (lowering generation during the peak) deferring the need for grid infrastructure improvements.

3. Maximising the output of solar and wind generation, for instance, by storing excess power that would otherwise be curtailed.

4. Providing back-up generation for mini-grids, which has historically relied on diesel generators.

Additionally, alongside these technical benefits, there are also potential economical benefits of investing in batteries. In [37] and [38] they study how batteries can be used for various applications to generate profits. These applications fall into one of two categories: behind-the-meter applications and front-of-the-meter applications. Figure 2.2 visualises these two main categories for generating profits. Behind-the-meter applications involve the battery owner directly using it for their own benefit, such as electricity bill reduction, improving self-sufficiency and providing

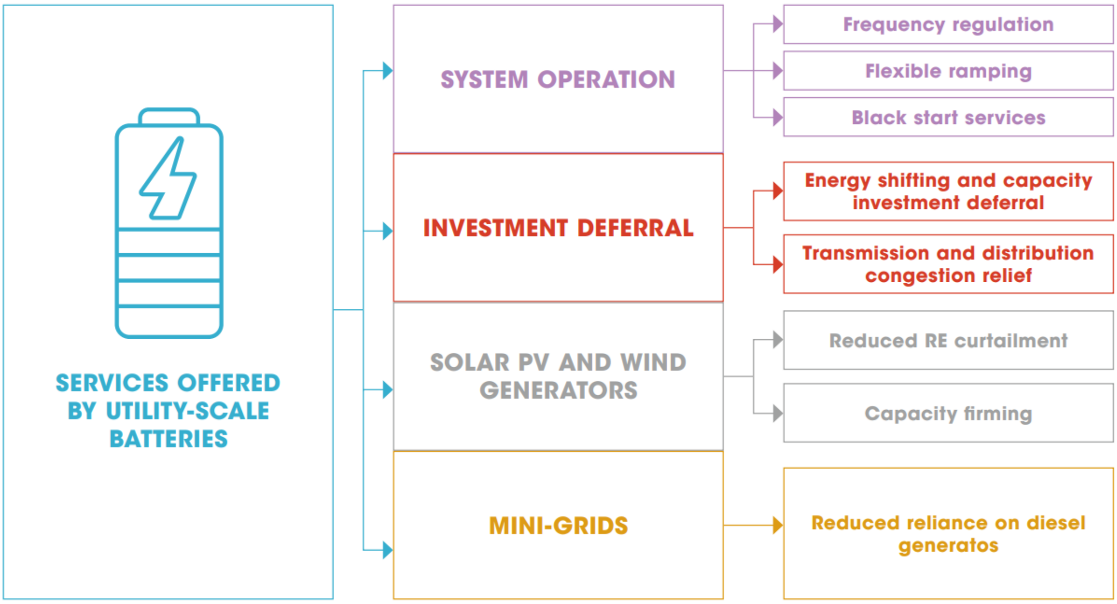



Figure 2.1: Services offered by utility-scale batteries [36].

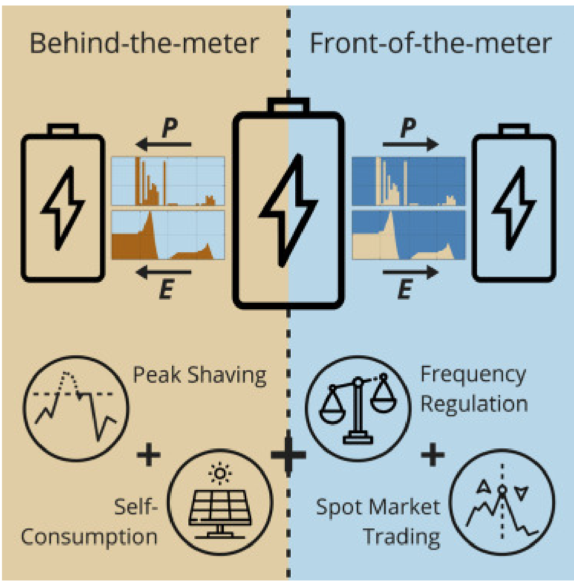



Figure 2.2: Batteries can be used to generate profits through behind-the-meter and front-of-the-meter applications [37].

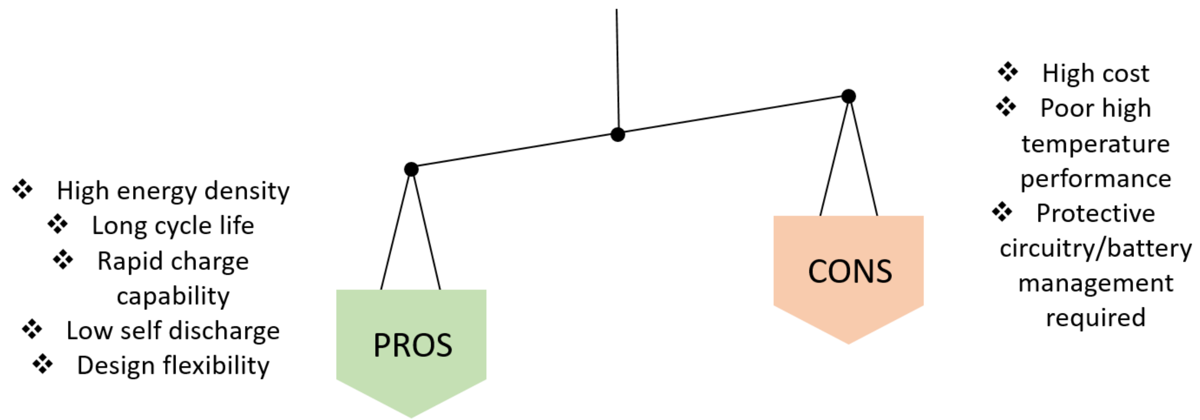



Figure 2.3: Pros and cons of Lithium ion batteries, adapted from [39].

back-up power. Front-of-the-meter applications involve exporting power to transmission or distribution networks, for services such as arbitrage (buying electricity when wholesale prices are cheap, selling when they are expensive), or frequency regulation.

There are many different types of battery technologies that can perform these applications. The most common types of batteries, as discussed in [36] and [39], include Lithium ion, lead acid, sodium sulphur and flow batteries. Of these technologies, Lithium ion is found to have the greatest installed capacity. According to the International Energy Agency, in 2020 Lithium ion batteries comprised 93% of the total battery storage mix [40]. Due to their prevalence, this project will hence focus on optimising investments in **Lithium ion batteries**.

### 2.1.2 Lithium ion batteries

Lithium ion batteries have high volumetric densities, due to high operating voltages $\approx 4$ V [41]. This has long since made them a popular choice for portable electronic devices. They are also a popular choice for electric vehicles, due to their aforementioned high energy density, low self-discharge and high cycle life [42], [43]. Lithium ion batteries are also gaining increasing attention for use in grid applications, as energy storage can facilitate a shift towards low-carbon electricity grids and Lithium ion batteries are a mature and trusted technology [44], [45].

The advantages and disadvantages of Lithium ion batteries are displayed in Figure 2.3. As previously mentioned, its high energy density lends this technology to applications in portable electronics and electric vehicles. This has led it to become a mature and trusted battery technology. However, one of the key drawbacks of Lithium ion batteries are their high costs [39]. Whilst this is expected to decrease [46], it may still pose a barrier for potential investors. Therefore, the use of optimisation modelling to schedule battery operation and maximise profits is an invaluable tool to encourage investment and improve deployment [33], [35].

## 2.2 Hydrogen

### 2.2.1 Uses and production of hydrogen

Hydrogen is another type of energy storage with a variety of applications. For instance, there is a growing global market for hydrogen vehicles [47]. Hydrogen also has the potential to replace fossil fuels as a feedstock in industry, such as steel and chemicals and cement [48]. Natural gas grids may also be able to support hydrogen - either blended or by itself - to decarbonise heating

[49]. Additionally, hydrogen has the potential to decarbonise the shipping industry by replacing conventional greenhouse gas emitting maritime fuels [50]. Therefore it is expected to become a hugely important type of energy storage, as nations pursue decarbonisation targets. However, in order to achieve these targets hydrogen must be produced in a way that is sustainable and does not emit greenhouse gases.

There are different methods for producing hydrogen. The method that offers the lowest cost is steam methane reforming, but it has a significant drawback as it releases carbon dioxide. This makes it an unsustainable choice, unless it is combined with carbon capture and storage (CCS) technologies. The most cost effective method involves steam methane reforming, however this releases carbon dioxide and is not a viable option, unless carbon capture and storage (CCS) technologies are used in conjunction [51]. Biomass gasification, sometimes referred to as *blue hydrogen*, is the most energy efficient hydrogen production method that doesn't use fossil fuels [52]; however, it too releases carbon dioxide and must be retrofitted with CCS technologies which are expensive [53]. The process of renewable electrolysis, referred to as *green hydrogen*, has the greatest decarbonisation potential. This is since renewable generation has no carbon emissions, and the only by-product of electrolysis is oxygen. However, there are various challenges such as high costs and unreliable production, facing this technology that should be overcome to improve its deployment.

The deployment of green hydrogen has historically been neglible in comparison with other production methods; it made up 1% of total hydrogen production in 2018 [54]. One of the issues facing green hydrogen is that it requires renewable generation, for which there is already a high demand to decarbonise electricity grids [55]. High costs also pose a barrier for deployment, these include capital expenditure (CAPEX) to purchase the electrolyser components and electricity costs during its operation [56]. According to a 2019 report by Wood Mackenzie, CAPEX and electricity costs represent 14% and 73% of total costs, respectively; the remaining 13% is financing costs and operations and maintenance [57]. In order for greater investments in green hydrogen to occur, investors need to be confident that they can achieve profits with this costly technology. Modelling and optimisation models are a key tool that can schedule electrolyser operation, to improve reliability and maximise profits.

### 2.2.2 Electrolysers

Electrolysers are devices that use electrical energy to split a water molecule into hydrogen and oxygen molecules. They can be powered by renewables, non-renewables, or the electricty grid, which may be a mix of renewables and non-renewables at any one time. The lowest carbon option, which will be considered in this project, is powering an electrolyser directly from renewables. In order to meet the requirements for economical and efficient renewable hydrogen production the electrolyser must have the following characteristics:

1. High hydrogen production efficiency.
2. Able to respond to quick power fluctuations from variable renewable generation.
3. Low minimum load for times when renewable generation is low.
4. Long lifetime to minimise replacement costs for the stack.

There are three main types of electrolyser used in industry, these are: alkaline, proton exchange membrane (PEM), and solid oxide electrolysers (SOC). The advantages and disadvantages of these electrolysers are presented in Figure 2.4 [52], [58], [59]. Alkaline electrolysers are

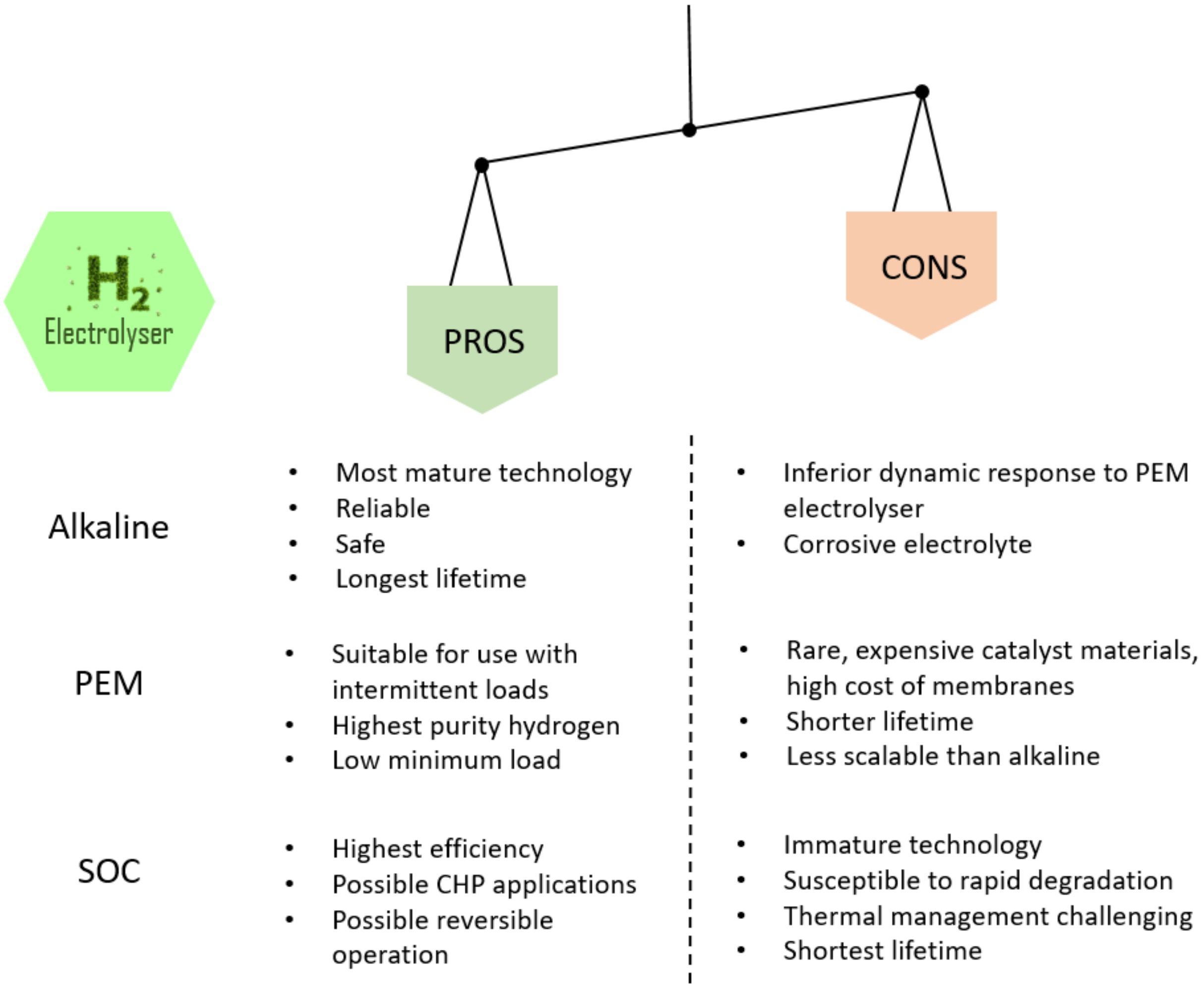



Figure 2.4: Pros and cons of different electrolysers, adapted from [52], [58], [59]. PEM = proton exchange membrane; SOC = solid oxide electrolyser.

the most mature technology, typically used for hydrogen production with a constant input load. They are safe and reliable, and have a longer lifetime than the other electrolysers. However, alkaline electrolysers have a slow start up time, $\approx$ 15 minutes, and a minimum load of 20-40% of the electrolyser's nominal power [52], [60]. Therefore, they are not well-suited to be powered by intermittent renewables, as they may switch off (into idle or standby mode) when generation fluctuates below this minimum load and take a relatively long time to start up again. This could lead to lower hydrogen production and decreased revenue.

PEM electrolysers can respond quickly when powered by variable loads, and are therefore well suited to being paired with renewables [61]. They also have a low minimum load, 0-10% of the electrolyser's nominal power, this means that they can still operate at times of low generation [60]. PEM electrolysers also have the advantage of producing high purity hydrogen. However, the lifetime of PEM electrolysers are lower than alkaline, $\approx$ 60,000 hours for the stack for PEM, compared with $\approx$ 90,000 hours for alkaline [62]. They are also relatively expensive due to rare and expensive material requirements.

SOC electrolysers are still in the early stages of development. They have the potential to achieve high efficiencies, 76 - 81% compared with 51 - 60% and 46 - 60% for alkaline and PEM [63]. They do not use expensive materials, and enhance efficiency by using waste heat. They currently face technical challenges such as fast degradation of the stack, thermal stress caused by intermittent loads and a shorter lifetime than the other electrolysers. Also they require high temperatures, which could affect economic viability. Based upon the advantages and disadvantages of each electrolyser, PEM is the best choice for producing green hydrogen. This project will therefore focus on optimising investments in **PEM electrolysers**.

## 2.3 Revenue generation

### 2.3.1 Mechanisms

The main revenue generation mechanisms for grid connected energy storage, that will be explored within this project are:

1. **Arbitrage** - the process of generating profits through trading energy in wholesale markets, this involves buying energy when prices are low (using this to charge up a battery, or other type of storage device) and selling when prices are high (discharging or releasing the stored energy).

2. **Ancillary services** - the set of services that contribute towards maintaining a stable electricity grid. For instance, maintaining grid frequency and voltage within its mandated limits. Energy storage can perform ancillary services by releasing power (discharging) and taking in power (charging) as and when it is required.

3. **Co-location with renewables** - energy storage can maximise the revenue of renewables by making use of otherwise curtailed power and renewable power can also be used to produce green hydrogen, which can be sold at a profit.

### 2.3.2 Great Britain's electricity markets

Great Britain (GB) is used as a case study in this project, therefore it is necessary to define and explain the various markets in GB that energy storage can interact with. Electricity is traded in wholesale markets up to one hour before the procurement period, then any discrepancies are balanced by GB's Electricity System Operator, National Grid (NG). A range of different services are used by National Grid to maintain power reliability and quality. Grid frequency must be maintained at 50 Hz $\pm 1\%$ on a second-by-second basis, using services known as Frequency Response. Firm Frequency Response (FFR) 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 energy 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. 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 surpasses 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, energy arbitrage is the process of generating profits through trading energy in wholesale markets, this involves buying energy when prices are low and selling when prices are high.

Energy trading can occur bilaterally or on exchanges. A bilateral contract is an agreement between two parties (eg. a supplier and generator) to exchange energy under a set of specified conditions [64]. These are difficult to model as data is not readily available. The two main exchanges are APX and N2EX where electricity can be traded for next day delivery and usage [65]. Within each of these exchanges electricity can be sold in a day-ahead auction market (which closes one day ahead of delivery at 9:50am UK time), or an intra-day market (where trading occurs continuously up to one hour before delivery). The day-ahead market is much more liquid than the intra-day market, which means that market price is more likely to reflect intrinsic value [66]. Additionally, prices are less volatile in the day-ahead market, hence this is less risky for participants to trade in and will be considered here rather than the intra-day market.

In real-time, the predicted electricity usage might not align with actual usage. This could lead to an electricity shortage or surplus. In this event, it is up to National Grid to balance supply and demand on a second-by-second basis. It does so by accepting offers (generation increases and demand reductions) and bids (generation reductions and demand increases) made in real-time. This is referred to as the Balancing Mechanism. Balancing Mechanism trading is performed in half hourly intervals and market closure to submit bids/offers is 30 minutes before the start of each interval.

## 2.4 Summary

This chapter delved into batteries and hydrogen electrolysers and their applications. It explored how energy storage can generate revenue, with a focus on Great Britain's market. Large utility-scale batteries offer services to improve power quality, reduce costs, and enhance renewable energy output. Behind-the-meter and front-of-the-meter applications cater to personal benefits and grid services, respectively.

Lithium-ion batteries dominate due to their reliability and high energy density. However, their cost can be a deterrent. Modelling can be used to optimize battery usage and boost their profitability, making them more enticing for investors.

Hydrogen's potential lies in decarbonizing hard to electrify industries: industry, heating, and shipping. However, the most common production methods release carbon dioxide - renewable electrolysis, or green hydrogen, is a more sustainable option since it has no emissions. PEM electrolysers are the most suitable type for this purpose since they can handle intermittent loads and yield high purity hydrogen. Nonetheless challenges including high costs and production reliability need addressing. Optimisation can enhance electrolyser profitability and attract investment.

Revenue generation mechanisms for energy storage include arbitrage, ancillary services, and co-location with renewables. Arbitrage capitalises on price differentials, ancillary services maintain grid stability, and co-location optimises use of renewable generation. In Great Britain, energy storage can participate in each of these mechanisms: through providing ancillary services for National Grid ESO (the Electricity System Operator) and trading in exchanges, such as N2EX.

# Chapter 3

# Literature review

Within this chapter, studies in the literature examining how battery storage and hydrogen prodiction can be used to optimise revenues are presented. Then there is a discussion of studies that optimise the locations of energy storage co-located with renewables. Finally, studies that optimise under uncertainty are discussed, and a summary of the literature review is presented. Some sections within this chapter have been extracted from the publications, presented in full in Chapters 6 - 11. Whenever this is the case it is explicitly indicated, such that the reader can avoid repetition.

## 3.1 Arbitrage

This section is extracted from Chapter 5, with some re-wording. Many studies in the literature have examined the profitability of energy storage arbitrage in different electricity markets. Depending on the size of the assets, these studies can be divided into two categories. In the first category, it is assumed that the power capacity of these assets is small compared to the total power demand hence, the operation of these assets has a negligible effect on market prices. The assets are referred to as "price-takers". The second category addresses larger assets whose operation affects market demand more significantly and consequently prices; these are "price-makers". A summary of the studies optimising energy arbitrage is shown in Figure 3.1; these are categorised by the modelling technique used.

### 3.1.1 Price-taker optimisation

The authors of [67] present a cost analysis of lithium ion battery, compressed air and pumped hydro storage performing arbitrage in the Californian electricity market as a function of its efficiency, modelling the energy storage as a price-taker. They do this by implementing a genetic algorithm method. This is an iterative technique, based upon natural selection, that evolves towards an optimal solution [68]. The authors of [67] find that lithium ion batteries do not generate enough revenue to break-even, however pumped hydro storage is an economical option. The authors of [69] determine the arbitrage value of storage in the PJM region of the United States from 2002 to 2007. They use a linear optimisation model that schedules the battery charge/discharge to perform arbitrage in order to maximise profits, with perfect and imperfect forecasting of market prices. It was found that this value depends strongly on storage device parameters, namely its efficiency and capacity, as well as external factors such as fuel price and mix. A lower-band for the profit created through arbitrage was determined, using rudimentary forecasting techniques, and it was highlighted that significant value could still be captured.

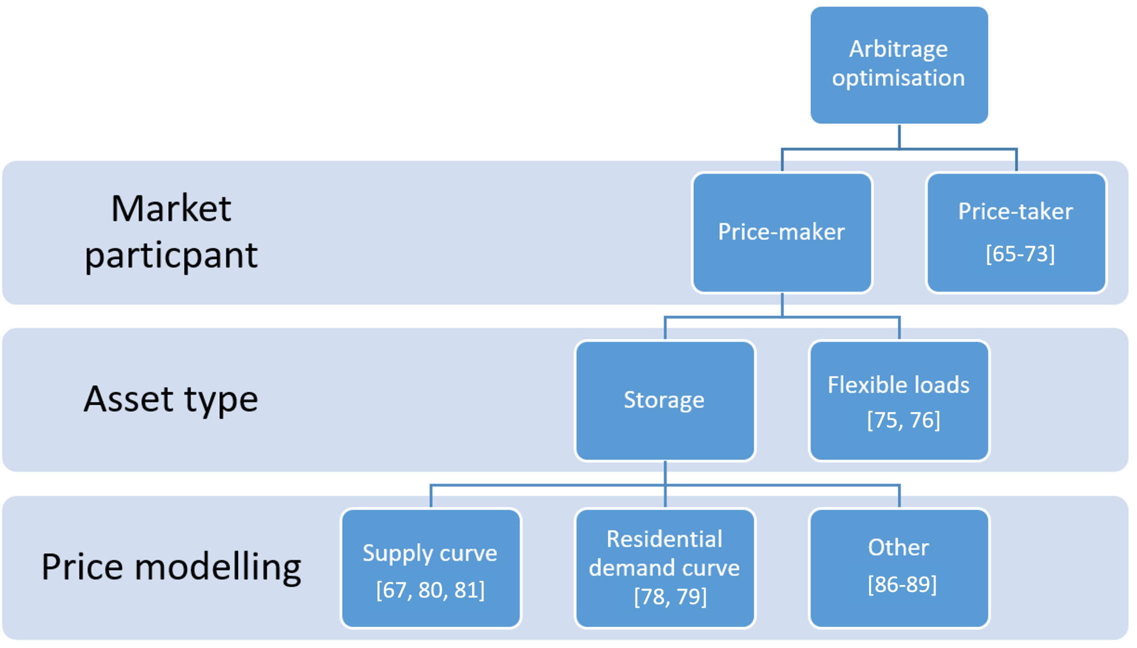



Figure 3.1: Categorisation of references optimising energy arbitrage.

In [70], they consider a consumer load aggregator with control of electrical energy storage; the aggregator acts as an intermediary between the storage device owners, electricity end-users and electricity markets. The aggregator participates in day-ahead and real-time electricity markets; their objective is to use the storage to minimise the costs associated with providing consumers with their required loads. A novel Model Predictive Control (MPC) framework was proposed to minimise costs in the real-time market, by considering both known price and load in the current time-period and projected prices and loads (and their associated uncertainties) for future periods. The authors of [71] propose a risk-constrained, bi-level approach to optimise bids and offers made by energy storage owners, whilst [72] model the optimal operation of an energy storage device under stochastic market prices. The latter demonstrate the efficacy of their mathematical theorem but do not apply it to a numerical example. In [71] they use linearisation techniques to formulate the non-linear bidding model into a mixed-integer linear program that is easier to solve. They use a 2 day horizon to determine the optimum state-of-charge of the storage at the end of the first day to maximise profits the second day.

In [73], the uncertainties of market prices, demand and renewable generation are considered, and a probabilistic model is proposed to optimise an aggregator's bidding curves in the Iberian day-ahead and intra-day markets using fixed and flexible load, battery storage, wind and solar generation. Results show that the probabilistic method is found to generally produce greater profits than the non-probabilistic optimisation method. Although it is a riskier method and might lead to occasional losses. In [74] they explore the strategy of an aggregator with storage who can both perform arbitrage and bid in the capacity market, determining the optimal allocation between these two revenue streams. This optimal allocation is found to be variable and depends on the cost of flexible load reduction. Finally, in [75] they present a community level case study, where an aggregator procures electricity for a number of households with PV. The aggregator has access to a battery which is assumed to be owned by a distribution system operator (DSO) and/or the aggregator. A linear optimisation model is developed to reduce costs and carbon emissions under two scenarios: firstly, the aggregator has total control and performs arbitrage, secondly a "peak shaving" scenario optimises for both aggregator and DSO. Little difference is observed between the two scenarios, therefore "peak shaving" is recommended to prevent too large loads on the distribution transformer.

These studies highlight the ability of storage to create value through arbitrage in different markets and under different operating strategies. However, they assume that market prices are unchanged by the participation of the storage. The authors of [76] optimise the scheduling of price-maker distributed energy resources (DERs) in the Spanish electricity market; they do this by applying a mixed-integer linear programming model to maximise the profits of an aggregator with control over the DERs. Results suggest that even for small aggregations their knock-on effect on market price should be examined. Hence, in order to best assess the profitability of aggregated resources, they should be treated as price-makers. This is an interesting finding, however the analysis is limited to the Spanish electricity market; it should be applied to other electricity markets, for example in Great Britain, for comparison.

### 3.1.2 Price-maker optimisation

The market bidding strategies of price-maker flexible loads are explored in [77], [78]. In [77] they use a mixed-integer linear program to optimise the bidding strategy of an energy retailer participating in the Nordic day-ahead electricity market under varying levels of risk. Results showed that greater profits could be achieved as risk is increased. Additionally, the authors demonstrate the economic value that flexibility, in this case flexible loads rather than energy storage, can bring. In [78], they examine the case of economic bidding in the day-ahead electricity market. This is unusual because most of the literature focuses on the specific case of self-scheduling bidding (bids for a certain volume of energy with no price component) rather than the more general, but complicated, economic bidding (bids containing both an energy quantity and upper price limit). The economic bids are formulated as step-wise increasing functions with increasing price and energy; the authors use linearisation techniques to reformulate the optimisation model into a mixed-integer linear programming model to improve solver efficiency. They show that the economic price-maker bidding approach outperforms self-scheduling bidding for flexible loads.

Energy storage is typically less flexible in its bidding strategy than time-shiftable loads [79]. This is because hourly bids and offers are interdependent; a storage operator can only offer to generate electricity if their earlier purchase bids have been accepted. For this reason, self-scheduling bids are generally preferred. Several studies have addressed the optimal self-scheduling of price-maker energy storage facilities [69], [80]–[83]. These studies can be split into two groups, depending on their method for modelling the relationship between storage operation and market price.

The first method models this relationship using a residual demand curve, which is defined as the total demand curve minus demand from all other suppliers [80], [81]. It illustrates how volume of electricity sold by the supplier in consideration, in this case a storage operator, varies as a function of market price. An example of a residual demand curve is illustrated in Figure 3.2 for a singular firm, and is compared against market supply and demand. It can be seen that when market clearing price is at the supply-demand equilibrium point (in this example \$66) all demand is met and there is no residual demand. However, for a small change in market price residual demand increases substantially, this can be seen by the flatness of the residual demand curve. This method is applied to storage operator bidding strategies in [80] and [81]; it is particularly useful for price-maker modelling when electricity demand is elastic i.e. demand is highly responsive to a change in price.

The second method is more straightforward and may be used when electricity demand can be considered inelastic [83]. This is the case when day-to-day electricity demand does not vary significantly, despite fluctuations in price. The authors of [85] examine electricity demand

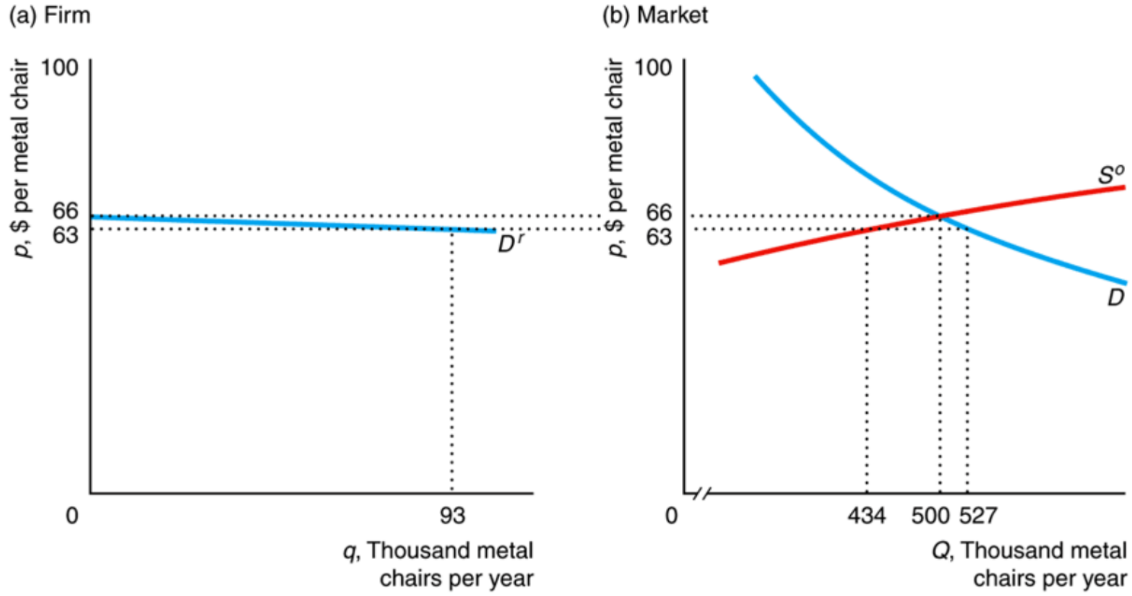



Figure 3.2: Residual demand curve for a single firm (left), market supply and demand curve (right) [84].

elasticity in the United States, and [86] present a review paper examining residential demand elasticity. Both studies find that short-term electricity demand is highly inelastic, although long-term trends are more elastic. Therefore, for modelling storage operation in short-term markets, such as day-ahead and intra-day markets, the inelastic assumption can generally be made. It is then sufficient to model the relationship between market price and storage operation using a supply curve. In [69] they use historical data to construct linear supply curves for each month, whereas in [82] actual hourly demand and generation curves are used to model the impacts of storage charging and discharging. These two approaches assume that the supply curves are always known in advance with perfect forecasting.

The authors of [83] improve upon this work by considering the uncertainties associated with predicting future supply curves. They do this by using historical data to construct nominal, maximal and minimal supply curves, where 90% of this data is encapsulated between the upper and lower bounds. Additionally, the level of risk-aversion of the energy storage operator can be incorporated into the model and can influence the storage strategy chosen. Reference [87] presents a price-based unit commitment model which uses historic market resilience data and approximates this as a step-wise function to reduce computational complexity. In [88] they reduce this even further by introducing a method to maximise the profitability of price-aware energy storage without invoking linear optimisation. They find that for 0.4 GW of storage operating in the British day-ahead market, not accounting for price-maker effects incurs a 5% error on profits. Finally, game-based methods may be used to optimise the scheduling of price maker market participants, as in [89]–[91]. However, such methods are generally used to analyse strategic behaviour rather than for developing bidding strategies, and hence will not be explored further here.

In conclusion, it can be seen that a wide array of literature relating to energy storage arbitrage optimisation already exists. From reviewing the literature, it is inferred that modelling bids as price-makers can improve revenue, compared to price-taker bidding for large storage. Additionally, since electricity demand has previously been shown to be inelastic in the short-term, it is sufficient to use a supply curve to model the relationship between market price and storage operator bid.

However, a couple of gaps in the literature have been identified. The majority of these studies do not explore in any depth the technological and economical aspects of the energy storage. Most studies are highly mathematical with little technical discussion. For example, there is little discussion of the costs involved with installing and maintaining a grid connected energy storage facility, nor the expected lifetimes of such projects. Hence, it is unclear if the profits achieved through arbitrage are actually sufficient to make these projects economically viable, ie. whether a positive Net Present Value (NPV) can be attained.

Additionally, some of the previous studies on energy arbitrage are quite old and the economic analysis is out-dated. Since the price of energy storage has changed drastically over recent years [92], [93], it is necessary to reassess the economic viability of these devices. Details regarding the types of energy storage modelled eg. their parameters, and how to optimise these has been neglected from the preceding studies. The methodology presented in these studies is however, highly valuable, and will be used as the basis for the arbitrage optimisation model developed here. This will be used in conjunction with other revenue streams, as discussed in the following section, and applied to novel case studies. For example, exploring how energy storage arbitrage can bring value to renewable generation and community storage owners.

## 3.2 Ancillary services

This section firstly explores studies modelling battery storage providing a type of ancillary service known as frequency response, which batteries are very well suited to. Then optimisation models that maximise the revenues of energy storage providing ancillary services are examined.

### 3.2.1 Frequency response

This subsection is extracted from Chapter 6, with some re-wording. Due to their fast response and high ramp-rate, battery storage systems have been identified as an attractive choice to provide frequency response. Frequency response involves absorbing or generating power to maintain grid frequency within its operational limits. Several studies have demonstrated the effectiveness of energy storage for frequency response, showing its potential to improve power quality and stability in power grids. For example, [94] finds energy storage can provide inertial response and frequency regulation similar to that of conventional power plants, and [95] shows that it can effectively provide short-term frequency control.

In [96] the authors assess the profitability of energy storage providing frequency response services. The authors simulate a battery performing frequency response and optimise its size to maximise NPV. They find that batteries can improve grid stability and are suitable for performing multiple ancillary services at once i.e. multitasking. They suggest that even if frequency control is not a battery's main purpose, it may still be profitable to reserve a portion of the storage for this.

In [97] the authors find that energy storage can smooth power fluctuations due to wind generation and consumer load, and [98] propose a model for energy storage to enhance smoothing of frequency fluctuations in power grids. Finally, [99] 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 frequency response services; however they have mostly considered things from the point of view of a grid operator, rather than a storage device owner.

In [100], 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.

### 3.2.2 Ancillary serivces optimisation

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, [71], [74], [101]–[107]. For example the authors of [101] and [102], optimised the usage of electric vehicles (EVs) and stationary batteries, respectively, to generate revenue in energy 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 [74] they 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 [103], 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. They find that the majority of the revenue is generated through providing fast responding grid balancing services. The authors of [104] use a stochastic process, to model market prices under uncertainty, then present an optimisation model for energy storage scheduling. The results find that the majority of revenue comes from providing ancillary services, additionally they show that a high power-to-energy ratio is optimal.

The authors of [105] take a different approach to this, using backward induction to determine a storage operator's optimum strategy in energy and ancillary markets. In both [106] and [71], they 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 [107] they present a control strategy 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. They 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 [108] they assess the profitability of energy storage providing power services to the grid. The authors calculate the Net Present Value (NPV) of battery storage performing three different power services: load levelling (maintaining transmission grid capacity within its limits and negating the need to upgrade transmission systems), frequency response and peak shaving (managing peaks in demand). Frequency response is found to provide the greatest revenue for the battery owner.

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 [74] and [107] 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.

## 3.3 Co-location with renewables

This section firstly discusses why co-locating energy storage with renewables can be advantageous, and then examines studies in the literature that optimise the scheduling of energy storage co-located with renewables. The following subsections then explore studies in the literature that also optimise the locations of energy storage co-located with renewables. Firstly, studies optimising the locations of energy storage alongside solar are discussed. This is followed by a disussion of studies optimising hydrogen production alongside wind generation.

### 3.3.1 Co-location with renewables

Whilst energy storage does not necessarily need to be co-located alongside renewable generation to reap aforementioned grid benefits, there are other unique advantages to co-location. These include attractive economics, through shared inverters and grid connection costs, and improved operation, such as the battery capturing clipped power that may otherwise be lost [109], [110] and co-locating energy storage alongside renewables can reduce power curtailment [111]. Furthermore, examining whether the economics of a renewables can be improved by adding energy storage is of interest to commercial partners and renewable owners.

Recent studies in the literature have presented models to optimise the scheduling of battery storage [112], [113] and hydrogen electrolysis [114]–[116] co-located with renewables. In particular, [112] optimise the sizing of the batteries in a number of different generation mixes and they calculate the levelised cost of energy (LCOE) and break-even time. The authors of [113] minimise the electricity costs of a microgrid with solar, wind and diesel generation, battery storage and demand management. The proposed two stage mixed-integer linear programming model is found to reduce costs by shifting loads and reducing the size of the required storage.

In [114], they optimise the number of electrolysers to maximise profits whilst taking into account the different modes of operation. They find that 13 electrolysers (2.10 MW/unit) is the optimal number for a 50 MW wind farm: fewer than this and available wind capacity is not fully used, greater than this the investment cost is substantial. Deng and Jiang optimise the size of wind-hydrogen systems to supply refuelling stations; they aim to increase usage of wind power whilst also matching demand [115]. Results show that when wind generation is low, power should be imported from the grid to avoid supply shortage. Carr et al. also optimise the scheduling of a wind-hydrogen refuelling station, with the aim of maximising profits and minimising demand shortfall [116]. They demonstrate performance benefits of their optimisation model, including reducing wind curtailment, which would otherwise be wasted. This is an important factor to model, since growing renewable penetration will increase curtailed power [117]. However, only the latter two studies take into account renewable curtailement [115], [116].

One aspect of storage co-location with renewables, that is not considered in the above studies is the optimal choice of location. This is since renewable generation will vary with location, and hence affect the suitability for co-location. Additionally, in Great Britain, in common with other countries (for example Germany, Spain and Poland [118]), there are a number of independent, regional grid operators that are responsible for the distribution of electricity around a particular region of the national grid. In GB there are 14 operators known as Distribution Network Operators (DNOs). These are operated independently and hence each DNO may impose a different set of charges on the distribution grid users, which may be consumers or generators. This is important because a renewable site may face different charges for exporting power depending on which DNO region it is located in [119].

The following subsection, hence, explores studies in the literature examining choice of location for solar farms, with and without storage. Next, studies that optimise the locations of wind-hydrogen production sites are examined.

### 3.3.2 Solar-storage location

This subsection is extracted from Chapter 7. The optimal choice of location for solar farms is a research area currently receiving a great deal of attention, for example [120]–[127]. These studies can be broadly split up into two categories: those that consider location within an electrical network, and those that consider geographical location. The first category optimises locations of power-grid connections, to reduce power losses and improve voltage profile [120], [121], the latter of which presents a novel algorithm to improve system performance, and to minimise connection costs [122]. These studies are valuable from purely a grid point-of-view; however, they do not consider factors such as geography, weather and socio-economics, which may vary regionally and affect optimal choice of location.

In the second category, the studies look at large areas; for instance, the authors of [123] and [124] study the optimal locations of PV in Brazil and PV-wind hybrid in Iran, respectively. Both use Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) to rank locations according to factors such as climate, environment, geography and economics. TOPSIS is a method used to compare options and make decisions based on multiple criteria. It finds the best choice by considering how well each option performs against best and worst-case scenarios. Other papers using similar ranking methods include [125] and [126], which study the deployment of solar farms in India and Bali, respectively. In [127], the authors use GIS analysis to identify suitable locations for solar farms in the UK; they find that by not considering local planning permission and grid constraints, area overestimations may occur up to 97%.

Studies looking at the optimal location for solar with energy storage are found to be significantly less common than those looking at just solar; examples of these include [128]–[130]. Both [128] and [129] consider the optimal network connection, rather than geographical location, for the installation of solar and ES. The authors of [130] on the other hand, model the performance of solar and molten salt storage in three locations in Egypt, to identify the optimum one. The network connection studies are too small in their scope when considering optimal location within an entire country, since they do not consider differences in geography or weather, and the latter study only considers three locations. In [131] and [132], they look at the optimum battery size in different locations, when co-located with solar and within a PV-microgrid, respectively. However, the former only studies two sites, whilst the latter looks at network connections over a small region. Instead of these approaches we should be looking at the impact of location on a large scale (i.e. country-wide) considering a large number of possible sites. This is because both sunlight and Distribution Network Operators can vary regionally around a country - both of which affect site economics and should therefore be considered.

### 3.3.3 Wind-hydrogen location

This subsection is extracted from Chapter 8. Many recent papers have identified potential locations for low-carbon hydrogen production; these are presented in Table 9.1, which shows the country or region considered, along with the hydrogen production method(s) and any notable methods or results. The majority of these studies focus on producing green hydrogen from renewables, however some also consider other methods such as biomass gasification. In References [133] - [146] all consider at least one method of green hydrogen production: electrolysis powered by solar and/or wind generation. Most of these papers map potential hydrogen production across a whole country, for example [133] and [134] map solar electrolysis potential in Algeria and Turkey respectively. On the other hand [135], [136] and [137] map wind and solar electrolysis in

Table 3.1: Comparison of studies mapping potential low-carbon hydrogen production sites.

| Ref. | Country/Region | Hydrogen Production Method | Other Notes |
|---|---|---|---|
| [133] | Algeria | Solar electrolysis | GIS based multi-criteria decision making model to identify most suitable sites |
| [134] | Turkey | Solar electrolysis | Calculates production potential considering different natural water sources. |
| [135] | Sistan & Baluchistan, Iran | Solar, wind electrolysis | Assesses investment costs in solar and wind. |
| [136] | Birjand County, Iran | Solar electrolysis | Inclusion of fuel cell to re-electrify hydrogen; System size and location optimised for rural areas. |
| [137] | Yazd province, Iran | Wind electrolysis | Multi-criteria decision making model considers economics and Co2 reductions. |
| [138] | Qatar | Solar, wind electrolysis | Fuzzy logic to choose best location. |
| [139] | Afghanistan | Wind electrolysis | Calculates decrease in Co2 emissions and payback period. |
| [140] | Iran | Solar electrolysis | Calculates levelised cost of electricity and capacity factor of sites. |
| [141] | Australia | Solar, wind electrolysis | Assesses regional economic potential; Considers hydrogen production from fossil fuels. |
| [142] | Ukraine | Wind electrolysis | Analyses social benefits of wind-hydrogen investment. |
| [143] | Togo | Solar, wind electrolysis, biomass gasification | Wind not sufficient, biomass has greatest production potential. |
| [144] | Turkey | Solar electrolysis | Compares production potential using 3 different electrolysers. |
| [145] | Pakistan | Solar, wind electrolysis, geothermal, biomass and municipal solid waste | Biomass has greatest availability followed by solar and municipal solid waste. |
| [146] | Scotland | Offshore wind electrolysis | Identifies sites where existing infrastructure could enable hydrogen transportation. |

different provinces within Iran.

One common methodology among papers in the literature is the use of weather data to determine electrical output from renewables and consequently estimate green hydrogen potential in the different locations. Another notable feature in decision making for hydrogen production location is project economics. In [135] they calculate the cost per kWh of producing solar and wind power in the locations with the greatest solar and wind potential, respectively. However, they do not consider the costs of producing hydrogen, nor how this varies with location. References [137] and [138] calculate the levelised cost of hydrogen (LCOH) in several locations using weather station data in Qatar and Iran, respectively.

References [139] and [140] calculate levelised cost of electricity (LCOE) from wind generation in Afghanistan and solar generation in Iran, respectively. The former study calculates LCOH in the city identified as having the lowest LCOE. In [136], Zhang et al. calculate total life-cycle costs for grid-independent systems, considering hydrogen tank storage. These studies highlight the value of considering economics when choosing locations for hydrogen production. They show that there is regional variation in economics, due to varying solar and/or wind resources, and a potential investor must take this into account when choosing a location. However, they do not consider hydrogen transport to end-user, which is an important practical factor.

The authors of [147] and [148] analyse hydrogen infrastructure options in Germany to transport hydrogen from production site (renewable electrolysis) to vehicle refuelling stations. They find that transportation costs are low relative to production costs, however pipeline infrastructure is nonetheless a significant upfront investment. It should therefore be taken into consideration when selecting a suitable green hydrogen site. Another essential element for making the case for green hydrogen deployment is optimising its production and scheduling. A green hydrogen investor/owner would wish to to maximise its potential profits, therefore profit optimisation methods should also be examined and applied. This element is missing from existing studies that optimise wind-hydrogen location.

## 3.4 Optimising under uncertainty

The discussion thus far has mostly involved deterministic optimisation models. In other words, it is assumed that factors such as electricity price and renewable generation are known in advance; this is usually unrealistic. Therefore, to more accurately assess the value that energy storage can bring, uncertainties should be taken into account. There are several techniques in the literature that can be applied to optimise decision making and scheduling under uncertainty. In [149], [150] and [151] the authors review the main methodologies that have been developed for this purpose. These include:

- **Stochastic optimisation** - this method involves optimising when there is randomness present in the problem being optimised. For example, this could be used to schedule a battery alongside solar when there is an element of randomness (e.g. imperfect weather forecasts) in the solar generation out-turn.
- **Robust optimisation** - this method aims to make decisions that are feasible under all potential (uncertain) scenarios, and optimal for the worst-case scenario. It is particularly useful for strategic decisions that may be fixed for long periods of time, such as planning a chemical plant. This is since hedging against the worst-case scenario improves the chances of success [152].
- **Fuzzy mathematical programming** - similar to stochastic optimisation, this method involves optimisation under randomness. However, random parameters are considered as

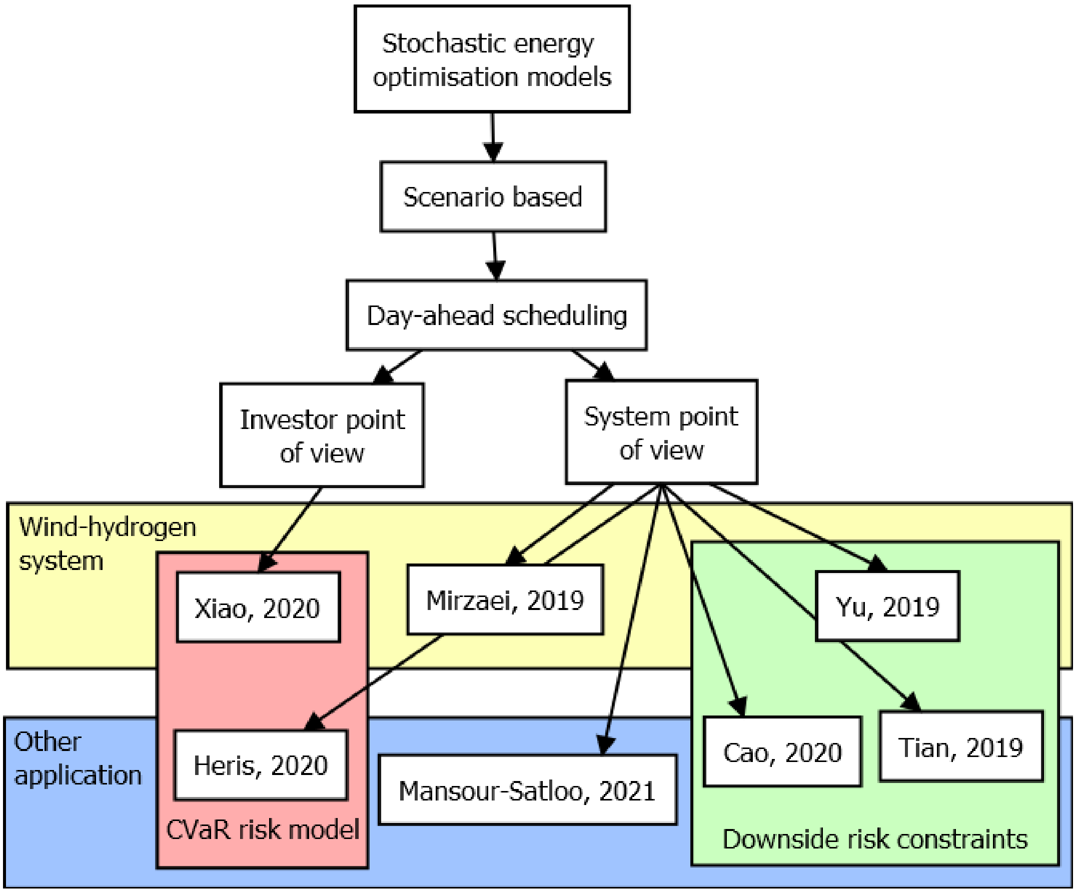



Figure 3.3: Categorisation of studies presenting a scenario-based stochastic optimisation model for energy storage.

fuzzy numbers [150]. These are numbers that do not have a precise value, but are rather a set of numbers represented by a function.

- **Real options analysis** - this method involves analysing potential decisions made over a project's lifetime at each stage, considering all potential realisations of uncertain parameters. It is a useful method when planning projects where there is flexibility, for example to wait or delay the project, at each time step.

The following subsections discuss studies in the literature that apply these methods to optimise energy storage.

### 3.4.1 Stochastic optimisation

There are a number of recent studies optimising the scheduling of renewable energy - energy storage systems under uncertainties using stochastic optimisation. As summary of recent studies using stochastic approaches to optimise the day-ahead scheduling of energy storage is shown in Figure 3.3 In [153], the authors consider uncertainties in wind generation and electricity price and present a scenario-based stochastic optimisation (SBSO) model which evaluates financial risk. They find that a hydrogen electroyser can increase the value of a wind system, the extent of which depends on hydrogen price. The authors of [154] present a similar model that also evaluates financial risk under uncertainty. In this case they optimise the scheduling of an energy system comprising of power, gas, heating and a hydrogen system, with uncertainties arising from the wind output of wind turbines. Results show that total system operation cost was reduced by including the hydrogen.

[155] and [156] present SBSO models which minimise operation costs of a system with wind generation and HS, the latter study also considers demand response. Both of these papers consider uncertainties in wind generation, whilst [155] also considers uncertainties in demand. The efficacy of these models at reducing the risk of uncertainties is demonstrated. [157] presents a SBSO model to minimise operation costs of an intelligent parking lot with HS and renewable generation. They present a Pareto set of solutions for different levels of risk aversion. [158] presents a hybrid robust-stochastic model to optimise an energy system with wind, hydrogen and battery storage. The model takes into account uncertainties in electricity price, load and wind speed. The hybrid approach is found to allow the system operator greater flexibility to manage uncertainties, also it is robust to the highest levels of uncertainty. Although for high robustness levels, operational costs increased. Incorporating hydrogen into the system, however, reduced operating costs. Finally, [159] presents a stochastic optimisation model to schedule an energy system, with wind, electrical and heat storage. They examine how heat demand response (flexible scheduling of heating) affects operational costs, for different levels of risk. It is found that by including flexible heating in the system, system costs are reduced, and that by considering risks (for example, disadvantageous electricity prices) the results are robust to uncertainties.

These studies highlight the value of SBSO models for scheduling wind-hydrogen systems under uncertainties. However, they do not consider curtailed wind, which is an important issue as renewable penetration increases. This is because electricity transmission lines can only transport a limited amount of power, and excess renewable generation is curtailed (e.g. it is not allowed to flow and is wasted) - this problem grows with more renewables on the system. Nor do they consider other forms of energy storage, such as battery storage. Additionally, with the exception of [153], they optimise from a system operator point of view rather than that of an investor.

Several studies address using curtailed wind for a hydrogen electrolyser. For example, [160] explore different approaches for handling curtailed wind. They find that investing in an electrolyser is both a profitable and environmentally friendly approach. However, they do not consider uncertainties in wind power or electricity price. The authors of [161] present a machine learning model to predict curtailed power which is used for an electrolyser and battery storage. However, they optimise from a system operator point of view rather than that of an investor. On the other hand, [162] present a chance-constrained model that optimises the size of a wind-hydrogen system from an investor's perspective. Their methodology allows flexibility for the decision variables to not satisfy the constraints at a given probability level; thus adverse conditions can be accounted for. However, they do not model different curtailment or electricity price scenarios nor do they incorporate battery storage.

### 3.4.2 Robust optimisation

In [163] the authors apply robust optimisation to a power system with energy storage and renewables, to schedule the storage. The objective is to lower system congestion at peak demand, with the robust model considering the most severe scenario. It is found that the energy storage scheduling is able to reduce congestion, and it is therefore suggested that storage can facilitate more renewables without the need for expensive network upgrades. In [164] they use robust optimisation to plan the size and position of energy storage based upon a real power distribution network. The authors find that including storage and optimising it using the robust approach, compared against a deterministic approach, lowers the annual operational cost of the network by 29.9% even considering the storage CAPEX. These studies highlight the economic benefit that energy storage can bring to a system operator, however, they do not consider things from an energy storage investor point of view.

The optimised profits of energy storage using a robust optimisation approached are studied in [165] and [166]. The former maximises the profits of a hybrid thermal energy storage system, results show that optimised strategies are robust against uncertain market prices [165]. The latter maximises the profits of compressed air energy storage, they find that total profits are improved by 30.3% and 54.28% compared against deterministic optimisation in optimistic and pessimistic cases, respectively [166]. Whilst these studies consider an investor point of view, they do not consider battery storage or hydrogen production. Additionally, renewable co-location and curtailment is not addressed in these studies.

### 3.4.3 Fuzzy mathematical programming

In [167], the authors apply fuzzy programming method to determine the optimal capacities for a combined heat and power (CHP) system to minimise costs. The model uses fuzzy set theory to account for uncertainties associated with energy demands (electrical and thermal) and gas and power prices. They apply this to the case of a typical hospital - to determine the optimal capacity of a CHP system - and find that considering uncertainties led to a positive return on investment. The authors of [168] use a fuzzy cuckoo search algorithm (CSA) to optimise the economic dispatch of a power system with 40 generation units. The proposed method is also tested on systems with 10, 26 and 6 generation units and is found to optimise power system costs with lower computational time than genetic algorithm (GA) and particle swarm optimisation (PSO) methods. Neither of these studies consider battery storage or hydrogen production.

There are studies in the literature applying fuzzy mathematical programming to energy storage optimisation models [169]–[172]. However, there are much fewer of them compared against stochastic optimisation and robust optimisation. In [169] they optimise the scheduling of a PV-battery system using fuzzy optimisation to maximise the economics, whilst addressing uncertainties in PV generation. It was found that using this algorithm could generate savings, however these were small $\approx 0.07\%$. The authors of [170] use multi-objective optimisation model to minimise costs and emissions of a hybrid energy system, consisting of PV, battery storage and a fuel cell. They then apply a fuzzy mathematical approach to select the optimal solution to the model. They find that using demand response (shifting flexible demand to preferable time periods, and away from peak time periods) the system's costs and emissions can be reduced. This study is useful from a system operator point of view, but not for an investor.

In [171] they apply a fuzzy optimisation model to maximise the profits of an energy storage aggreagtor performing vehicle-to-grid. Vehicle-to-grid involves using electric vehicle batteries to both charge and discharge to the grid, in order to make money. The method addresses uncertainties in market price and amount of energy stored within the vehicle batteries. Compared against a deterministic optimisation approach, the fuzzy model generates higher profits and lower battery degradation costs for the aggregator. Finally, the authors of [172] apply a fuzzy optimisation model to maximise the profits and sizing of battery storage participating in ancillary service markets in Texas. They consider market uncertainties, and demonstrate the model's effectiveness compared against a deterministic equivalent. These are both interesting and relevant studies, however, they do not model hydrogen production, nor do they model renewable co-location and curtailment.

### 3.4.4 Real options

This subsection is extracted from Chapter 9. Real options is a useful approach for assessing the value of a project where there is inherent uncertainty and flexibility. The term real options refers to decisions, or *options*, made by an investor over a project's lifetime. Several of these are outlined in [173] and include, but are not limited to: invest, delay, expand, switch, suspend, contract or abandon. By analysing the real options at each step of a project, the risk of uncertainty can be managed by changing its course towards a more favourable direction.

Real options analysis doesn't directly improve an investment, but it provides a framework to make better decisions - which can improve investments. It does so by considering hypothetical scenarios, where options are taken at different times, e.g. delay 1 year vs 2 years. Then systematically applying a set of potential future outcomes (e.g. price trajectories, technology improvements, interest rates) to determine the profitability of each scenario and outcome. Analysis can then be performed on the possible set of outcomes for each scenario. This then helps investors to make decisions based on the mean and standard deviation of the outcomes for a scenario. A risk-averse investor is likely to choose the scenario with a low profit standard deviation and minimal outcomes resulting in losses (e.g. invest in 5 years time once more information has been learned). Conversely, a risk taker might choose a scenario with a few very high potential outcomes but more loss-making outcomes (e.g. invest now whilst there are more unknowns).

Interest in the application of real options in the energy sector is rising due to the limitations of traditional techniques [174]. In particular, there are a number of studies relating specifically to energy storage, as outlined in [175]. However, only 2 of these have been identified as relating to hydrogen production [176], [177]. Kroniger and Madlener use a real options approach to analyse the decision to run a wind-hydrogen system with or without a fuel cell to convert the hydrogen back to electricity [176]. Converting the hydrogen is found to be unprofitable; it is preferable to directly produce hydrogen. This study could be developed by considering a wider range of hydrogen prices, and electrolyser parameters with their predicted future evolution. Schmitz and Madlener consider the options associated with using kite-based wind energy to generate hydrogen. The authors use a binomial lattice approach to evaluate options and Monte Carlo simulation for uncertainties (compressed air price, hydrogen price and storage cost) [177]. It is found that for the three case studies considered their values are improved by considering a real options approach. This is an interesting case study, however, it is lacking in technical details particularly regarding the electrolysis unit and its operation.

Li et al. use real options to assess the optimal building strategy of hydrogen refuelling stations [178]. They find that the interaction between speed of infrastructure availability and adoption needs to be considered to avoid sub-optimal decisions. This is an interesting study, however, we are more concerned with the production of hydrogen than its use here. Secondly, Franzen and Madlener assess the option to expand a wind-hydrogen system by a 5 MW module at each time step [179]. They use a cascaded binomial tree to model the decision steps and Monte Carlo simulation for uncertainties in revenue (due to the stochastic nature of wind). By considering real options the valuation of the system significantly improves compared with a classical net present value calculation. Whilst this is a valuable contribution to the literature, there are several points which need addressing. Firstly, the sensitivity of the revenue to hydrogen prices should be analysed. Secondly, it is expected that advancements in PEM electrolyser technology will decrease their CAPEX and improve their energy consumption which will affect their future value and should be accounted for.

### 3.4.5 Discussion of approaches

Each of the four approaches discussed above provide different methods for optimising under uncertainty. Stochastic optimisation and fuzzy mathematical programming are used for scheduling problems, for example when to charge or discharge a battery. Models using these approaches optimise day-to-day decisions (e.g. what time is best to schedule discharge), rather than longer term investment/planning decisions. Out of these two approaches, there are more studies in the literature that apply stochastic optimisation to energy storage scheduling problems, compared with fuzzy mathematical programming. In particular, a large number of studies were found that used scenario-based stochastic optimisation models to the day-ahead scheduling optimise energy storage (as shown in Figure 3.3). Since it is a well-established modelling technique, it is applied in this work for day-to-day storage optimisation. Furthermore, gaps in the stochastic optimisation approach were identified (not considering an investor point of view, not considering curtailment, not considering systems with batteries and electrolysers) and are addressed here.

For longer term project decisions, such as whether or not to invest in a particular technology, robust optimisation and real options analysis techniques are used. The robust optimisation method has the advantage of hedging against the worst-case scenario, whereas real options analysis allows greater flexibility in decision making (by considering potential decisions at all steps in a project's lifetime, rather than making all of the decisions at the start of the project). One particular advantage of the real options approach is that specific investment decisions, such as: invest now, delay project, expand project etc. can be explored in detail and optimised. Therefore, real options analysis is chosen as the approach for optimising long-term investment decisions, over robust optimisation, due to its decision making flexibility and increasing interest in the literature.

## 3.5 Literature summary

This literature review has studied papers that optimise batteries and hydrogen electrolysis to maximise revenues. It looked at three different mechanisms for generating revenue: arbitrage, ancillary services and co-locating alongside renewables. For the latter, it also examined studies that optimise the choice of location - since renewable generation varies with location. Finally, the literature review presented studies optimising energy storage under uncertainty since prices cannot be perfectly predicted.

By analysing studies in the literature, the following gaps and limitations have been identified:

- Many studies have looked at how batteries can perform arbitrage, however, the majority model them as price-takers rather than price-makers. Additionally, most studies do not examine the NPV of large scale battery projects and whether or not they are actually profitable investments.

- The route to market for energy storage owners is also neglected. For ancillary service markets this is often a complicated auction process. However, previous work has not considered this.

- Renewable curtailment is not often included in energy storage scheduling optimisation models.

- There are few studies in the literature optimising the location of solar co-located with battery storage; existing studies only consider small regions or a limited number of locations.

- Studies optimising the locations of wind-hydrogen systems should also consider transport to end-users and schedule optimisation to maximise profits.

- The application of real options analysis to analyse investments in hydrogen electrolyser is not widely studied. These models should also account for future changes in hydrogen price, electrolyser CAPEX and energy consumption.

- Scenario-based stochastic optimisation models should consider renewable curtailment and its associated uncertainties, and assess the potential revenue obtainable using a combination of battery storage and/or a hydrogen electrolyser.

The research presented in the following publications aims to address these gaps in the literature in order to improve upon existing revenue optimisation strategies for batteries and hydrogen electrolysis. This is to boost their profitability and attract investment in these sustainable technologies.

# Chapter 4

# Overview of publications

## 4.1 Optimising energy storage revenue

The first two publications address R1: *How can energy storage optimally be used to generate revenue?* Publication 1 maximises the arbitrage profits of a battery storage aggregator participating in GB's day-ahead and balancing markets. This is applied to a community storage case study, whereby mutual benefits for community and aggregator are identified. Publication 2 maximises the profits of a battery owner simultaneously performing arbitrage in GB's day-ahead market and providing a frequency response ancillary service.

### 4.1.1 Publication 1

#### Information

F. Biggins, J. O. Ejeh and S. Brown, "Going, going, gone: Optimising the bidding strategy for an energy storage aggregator and its value in supporting community energy storage," *Energy Reports*, vol. 8, pp. 10 518–10 532, 2022

This full length article is published in the Elsevier journal, Energy Reports. Elsevier has confirmed that the article can be publicly posted as long as it is embedded within the thesis and appropriately acknowledged.

#### Credit author statement

I performed the computational work outlined in this manuscript. I developed the methodology and the code, and performed results analysis. Dr Jude Ejeh generated Figure X based upon a flow chart that I designed; I performed all other visualisations, and drafted the manuscript. Jude and Professor Sol Brown reviewed and edited the manuscript; Sol supervised the project.

#### Summary

This publication applies linear and quadratic optimisation models to examine the value derived by an aggregator, using energy storage for arbitrage in Great Britain's day-ahead and balancing energy markets. The optimum arbitrage strategy is determined when the aggregator is considered a price-taker and a price-maker with access of up to 500 MW battery storage. It was found that the choice of price-taker or price-maker made negligible different in the day-ahead market. In the balancing market the price-maker profits were 10.9% higher for 500 MW storage when prices were perfectly forecasted, however, choice of strategy made neglible difference for imperfect forecasting. We then applied the model to a community-owned energy storage case study to determine the potential value an aggregator with partial access to the storage could obtain. Results showed that household electricity bills could be improved by this arrangement. In particular, households could improve their profits by up to $13.2\%$ in winter months if aggregator access is allowed.

### 4.1.2 Publication 2

#### Information

F. Biggins, S Homan, J. Ejeh *et al.*, "To trade or not to trade: Simultaneously optimising battery storage for arbitrage and ancillary services," *Journal of Energy Storage*, vol. 50, p. 104 234, 2022

This full length article is published in Elsevier journal, Journal of Energy Storage. Elsevier has confirmed that the article can be publicly posted as long as it is embedded within the thesis and appropriately acknowledged.

#### Credit author statement

I performed the computational work outlined in the manuscript. This involved data analysing, developing machine learning and optimisation models, analysing and visualising results. Dr Sam Homan helped me to develop the methodology to analyse and model Firm Frequency Response (FFR) data, through a series of conversations. He gave me advice on where to locate and how to use the data and taught me relevant background theory on FFR. I prepared the manuscript draft. Sam, Dr Jude Ejeh and Professor Sol Brown reviewed and edited the manuscript; Sol supervised the project.

#### Summary

This publication presents a novel methodology to optimise the profits of a battery storage owners simultaneously using the battery to provide ancillary services (in GB's FFR market) and arbitrage (in GB's day ahead market). A machine learning classifier is applied to predict outcomes and associated probabilities of the FFR auction market, the results of this are propagated through an arbitrage optimisation model. We find that it is both feasible and economical to simultaneously use a battery for both arbitrage and ancillary services. However arbitrage should be performed across a small band of the battery's capacity to avoid unavailability penalties. We find that by considering the auction market as a deterministic process, as often done in the literature, the expected income is overestimated by $\approx 28\%$. Our methodology avoids this overestimation and provides battery storage owners with a useful and realistic framework to optimise their profits.

## 4.2 Optimising battery storage and hydrogen production location

The second two publications address R2: *Where is the optimal location to deploy energy storage to maximise revenue?* Publication 3 explores how the optimised profits of a solar farm with battery storage varies with location and the potential consequences on the future of co-located battery storage deployment, using Great Britain as a case study. Publication 4 identifies the most advantageous locations to produce green hydrogen, based upon wind-hydrogen profit optimisation in different locations around Great Britain.

### 4.2.1 Publication 3

#### Information

F. A. Biggins, D. Travers, J. O. Ejeh *et al.*, "The economic impact of location on a solar farm co-located with energy storage," *Energy*, vol. 278, p. 127 702, 2023

This full length article is published in the Elsevier journal, Energy. Elsevier has confirmed that the article can be publicly posted as long as it is embedded within the thesis and appropriately acknowledged.

#### Credit author statement

I performed the majority of the computation work; Dr Jude Ejeh developed the solver method, which solves the optimisation model. I analysed and visualised the data, and drafted the manuscript. Dr Dan Travers developed the methodology to predict solar generation and provided hourly profiles for solar generation prediction and out-turn, under the supervision of Professor Alastair Buckley. Jude, Dan, Alastair, Dr Rachel Lee and Professor Sol Brown reviewed and edited the manuscript, and the project was supervised by Sol.

#### Summary

This publication applies a mixed integer linear programming optimisation model to explore how the maximised profits of a solar farm with and without battery storage varies around Great Britain. It was found that profit variation, due to the addition of a battery, reflected regional Use-of-System charges. Hence, these charges favour co-locating a battery with solar in some regions rather than others. In particular, the regions where a battery could add the most value were those that had fewer existing solar farms. Net Present Value calculations found that it is only profitable to add small batteries (0.1 MWh/0.1 MW) to a solar farm, and that this is only profitable in regions containing 25% of GB's solar farms. To encourage increased co-location of solar and storage, the differential between non-intermittent generation and intermittent generation payments should increase.

### 4.2.2 Publication 4

#### Information

F. A. V. Biggins, J. O. Ejeh, D. Roberts *et al.*, "Mapping the potential of onshore green hydrogen for industry decarbonisation," *Under Review*, 2022

#### Credit author statement

I performed the computational work, analysis and visualisation presented in this publication. I developed the methodology and drafted the manuscript. Professor Sol Brown supervised the project. It was reviewed and edited by Dr Diarmid Roberts, Dr Jude Ejeh and Sol.

#### Summary

This publication applies an optimisation model to identify locations in Great Britain where green hydrogen production, via onshore wind electrolysis, can generate the greatest profits. These results are compared against maps of current and future renewables, onshore wind curtailment and locations of potential industrial hydrogen demand, to identify the most advantageous locations to produce green hydrogen. Two locations with favourable economics, under base case conditions, are identified. These are southern Scotland, around Lanarkshire, and mid-east England, around Lincolnshire. The former region houses many wind farms, some of which are heavily curtailed, therefore hydrogen electrolysis could provide a useful pathway for otherwise curtailed power. The latter region is located in close proximity to large potential industrial demand sites, thereby lowering transport infrastructure costs to end-users. For the specific scenarios modelled in this study, hydrogen price should be at least £3.50/kg to encourage production of green hydrogen; for prices lower than this, adding an electrolyser to a wind farm is not an economical investment.

## 4.3 Addressing uncertainties

The final two publications address R3: *How can uncertainties in economics calculations be addressed?* Two different approaches to optimising under uncertainty are examined here. The first approach, applied in publication 5, uses real options analysis to examine long-term investment decisions, such as: invest now, wait to invest, abandon investment. The second approach, applied in publication 6, uses a stochastic-based scenario optimisation model to optimise battery storage and hydrogen production scheduling in the short-term, under uncertain power generation, curtailment and price conditions.

### 4.3.1 Publication 5

#### Information

F. Biggins, M. Kataria, D. Roberts *et al.*, "Green hydrogen investments: Investigating the option to wait," *Energy*, vol. 241, p. 122 842, 2022

This full length article is published in the Elsevier journal, Energy. Elsevier has confirmed that the article can be publicly posted as long as it is embedded within the thesis and appropriately acknowledged.

#### Credit author statement

I developed the code used in this publication, based upon the work of masters student Mohit Kataria. I performed all simulations, results and analysis, generated the visualisations and drafted the manuscript. The methodology identified by Mohit is based upon [181]. Mohit developed a model for his masters project that applies real options to battery investments. I based my model upon his work, re-formulating his code, adapting it for green hydrogen investments and adding in levels of complexity. Specifically, I updated the code to take consider more than one exercise threshold and loop over multiple parameters. Mohit was invaluable in this work, as his project formed its basis; his project was supervised by Dr Diarmid Roberts and Professor Sol Brown. I reviewed the literature and drafted the manuscript. Diarmid and Sol reviewed and edited the manuscript; Sol supervised the project.

#### Summary

This publication applies real options (RO) analysis to assess the value of investing in green hydrogen for a wind farm. It considers uncertainties in hydrogen price, CAPEX and energy consumption, and identifies cases where immediate investment is beneficial. For other cases, it was found that the value of the investment could be improved by waiting. A specific case study is examined, consisting of a medium sized wind farm, with 20 turbines and a PPA of £0.055/kWh. It was found that by waiting to invest until hydrogen prices reached £4.40/kg, the expected value added by a 1000 kW PEM electrolyser increases from -£664 000 to £0. The average wait time is 17 months; however, if the turbine owner waits an average of 32 months, improvements in CAPEX and energy consumption reduce the required hydrogen price to £3.10/kg. Our model is robust to varying input parameters; additionally, it is simple to use and apply for wind farm owners and can be adapted for varying levels of risk aversion.

### 4.3.2 Publication 6

#### Information

F. A. Biggins, J. O. Ejeh, D. Roberts *et al.*, "Optimising a wind farm with energy storage considering curtailment and uncertainties," in *Computer Aided Chemical Engineering*, vol. 51, Elsevier, 2022, pp. 79–84

This book chapter is published in ESCAPE 32 conference proceedings published by Elsevier. Elsevier has confirmed that the article can be publicly posted as long as it is embedded within the thesis and appropriately acknowledged.

#### Credit author statement

I performed the computational work outlined in this manuscript. I developed the methodology and the code, and performed results analysis and visualisation. Input electricity price data for the model was generated by Aaron Yeardley using a Gaussian Process (GP), additionally he wrote a couple of sentences about GPs for the manuscript. I drafted the rest of the manuscript. It was reviewed and edited by Aaron, Dr Diarmid Roberts, Dr Jude Ejeh and Professor Sol Brown; the project was supervised by Sol.

#### Summary

This publication applies a scenario-based stochastic optimisation (SBSO) model to schedule a wind farm with battery storage (BS) and/or a hydrogen electrolyser (HE) to maximise profits. It considers uncertainties in wind generation and curtailment, and GB's day-ahead market prices. The mean expected income with and without the battery and electrolyser is determined, along with the % usage of curtailed wind, that would otherwise be wasted. It was found that HE increases mean expected income and curtailed wind utilisation significantly more than BS. However, by combining HE and BS curtailed wind utilisation increases from 68% to 95%, compared with HE alone. Our model can be applied to other renewable generators and used to determine the suitability of battery and electrolyser for maximising profits and making optimal use of curtailed generation, under generation, curtailment and price uncertainties.

# Chapter 5

# Conclusion

## 5.1 Discussion

Low-carbon, flexible energy technologies will play a vital role in the decarbonisation of electricity grids, which will be required to meet climate goals and mitigate against global warming. Unfortunately reports from Energy Systems Catapult, BloombergNEF and National Grid's Future Energy Scenarios estimate that we are falling short of our target build-out of batteries and low-carbon hydrogen required to meet GB's climate goals, such as achieving Net-Zero by 2050. To be in with a chance of achieving these goals and mitigating against catastrophic climate change, a step change in battery and hydrogen deployment is needed.

However, the deployment of these technologies depends largely on how economically attractive they are. With this is mind, the aim of this project has been to optimise investments in low-carbon energy technologies, specifically lithium ion batteries and PEM electrolysers. This is in order to help potential investors make more informed decisions. Additionally, this analysis has highlighted whether current market conditions are sufficient to achieve the required deployment or whether further incentives will be necessitated.

The work carried out in this project addressed three main research questions, to optimise the economics of battery storage and hydrogen production investments: How can energy storage optimally be used to generate revenue? Where is the optimal location to deploy it? How can uncertainties in economic calculations be addressed? Through addressing these questions, various gaps in the literature have been examined; this section firstly discusses how these gaps have been addressed, then presents the findings with respect to the research questions.

### 5.1.1 Contributions of this work

A review of the literature revealed that whilst many studies have optimised the usage of batteries for arbitrage and ancillary services, few of these examine the route to market for battery owners. This is addressed by applying an aggregator arbitrage model to community-owned battery storage as a novel business model proposition (Publication 1) and by using a machine learning classifier to predict the outcomes of one of GB's ancillary service auction markets (Publication 2). Results presented in Publication 1 revealed that the community-aggregator arrangement could be mutually beneficial, with household electricity bill savings increased by up to 13.2% in winter months by allowing aggregator access. This publication also challenged one of the assumptions commonly made in the literature, that battery storage arbitrage can be modelled as a price-taker rather than a price-maker. It was found that this assumption holds true in GB's day-ahead and balancing markets for arbitrage performed using 500 MW battery storage. Publication 2 found that considering auction markets as deterministic, as done in the literature, can overestimate expected income by $\approx 28\%$. The methodology presented in this publication provides a more realistic framework to optimise profits in this type of market.

Additionally, it was found that there are very few studies in the literature optimising the location of solar co-located with battery storage; existing studies only consider small regions or a limited number of locations. Publication 3 addressed this gap, and found that in GB regional Use-of-System charges favour the addition of batteries in regions containing few existing solar farms. For a case study conducted exploring the addition of a 0.1 MWh/0.1 MW battery, the expected Net Present Value is only positive in regions containing 25% of GB's solar farms.

The literature review found that optimising the locations of green hydrogen production is a growing research area. However, these locational studies neglect to optimise production scheduling to maximise profits, and few consider transport of hydrogen to end-users. Futhermore, the application of real options analysis to optimise investments in hydrogen electrolysers is not widely studied. In particular, existing studies in this field do not account for future changes in hydrogen price, electrolyser CAPEX and energy consumption. These gaps in the literature are addressed in Publications 4 and 5, respectively. Publication 4 identified two regions in Great Britain where, under base case conditions, adding a PEM electrolyser to a wind farm enhanced economics: southern Scotland, around Lanarkshire, and mid-east England, around Lincolnshire. Additionally, these regions were either close to heavily curtailed wind farms, and could thus use curtailed wind that would otherwise be wasted, or industrial centres of demand, minimising transport requirements. Publication 5 found that the application of real options analysis to green hydrogen investments could improve expected value added. It can be easily applied and used to advice a wind farm owner about whether they should invest, or wait to invest in an electrolyser, and under what conditions an investment should be triggered to maximise profits, given different levels of risk-aversion.

Another element often neglected in optimisation models in the literature is renewable curtailment. This has been addressed by developing a scenario-based stochastic optimisation model, presented in Publication 6, that optimises scheduling of both a battery and hydrogen electrolyser co-located with curtailed onshore wind. The model considers uncertainties in wind generation, curtailment and market prices. Results show that an electrolyser allows greater usage of curtailed wind and increases mean expected income compared with a battery. However, these factors are maximised when both electrolyser and battery are employed.

### 5.1.2 Conclusions

Based upon the research conducted in this project, the following recommendations are made in response to the research questions.

1. **How can energy storage optimally be used to generate revenue?**

   This varies from case to case. However, for grid connected battery storage it was found (in Publication 2) that ancillary services, namely Firm Frequency Response, are a more lucrative source of revenue than arbitrage. However, simultaneously performing arbitrage over a small, risk-constrained band can maximise revenue.

   For hydrogen production, it was found (in Publication 5) that for wind farms with a Power Purchase Agreement of £0.03/kWh or lower, adding a PEM electrolyser, and using wind generation to produce hydrogen rather than directly exporting power, is expected to improve revenue, relative to no electrolyser, even in a pessimistic scenario. Wind farms with greater PPAs should wait for threshold prices, that can be determined using the methodology determined here, before adding an electrolyser to improve their mean expected income.

2. **Where is the optimal location to deploy battery storage and hydrogen production to maximise revenue?**

   It was found (in Publication 3) that battery storage co-located with solar can maximise revenue, at the time of modelling, when located in south-east England (particularly in London), north-west England or north Wales.

   The optimal locations to deploy a PEM electrolyser, co-located with onshore wind, in order to maximise revenue were found to be southern Scotland, around Lanarkshire, and mid-east England, around Lincolnshire (Publication 4).

3. **How can uncertainties in economics calculations be addressed?**

   Long-term investment decisions, made under uncertain conditions, are found to be economically improved by employing real options analysis (Publication 5). This method involves waiting until certain criteria (threshold conditions), that are optimised, are met before investing or, if the criteria are not met, abandoning the investment.

   For day-to-day scheduling of flexible energy technologies, it was found (in Publication 6) that a scenario-based stochastic optimisation model can be used maximise mean expected income under uncertainty.

## 5.2 Limitations and future work

In future research, there are several areas that could be explored to enhance the modelling and optimisation of battery storage and hydrogen production revenues. These areas include modelling battery and electrolyser degradation rates, investigating additional types of ancillary service markets, improving the modelling of the Balancing Mechanism, and developing better forecasting methods.

The work carried out in this project could have been improved with the following:

- **Modelling battery and electrolyser degradation:** To improve the accuracy of low-carbon energy system modelling, it is important to consider the impact of degradation of batteries and electrolysers over time. Battery degradation is affected by various factors, including charge-discharge cycles, temperature, depth of discharge, and operating conditions. Similarly, electrolysers may experience degradation due to operating conditions and the type of electrolyte used. Future work could focus on incorporating degradation into the optimisation model, enabling more accurate assessment of the long-term performance and economic viability of low-carbon energy systems. Additionally, including degradation into the model could change the optimum usage of battery storage and hydrogen production. Heavy cycling of batteries causes them to degrade faster, so the model might opt for strategies that cycle the battery less - generating less revenue in the short-term but more in the long-term.

- **Exploring more different types of ancillary service markets:** Ancillary service markets play a vital role in grid stability and reliability. This work optimised bidding in the Firm Frequency Response market. However, this service is being retired by National Grid ESO in the future to be replaced by different services - namely Dynamic Containment, Dynamic Regulation and Dynamic Moderation. These services have different clearing prices to Firm Frequency Response and are procured in daily, rather than monthly, auctions. Therefore, future work should develop a model to optimise the bidding in these markets at day-ahead granularity. Simultaneously optimising across the three new services, considering factors such as clearing price, battery throughput (average energy import/export for each service affecting degradation and state-of-charge), and the feasibility of also doing wholesale trading would be particularly interesting. On a more general, less GB-specific level, it would be valuable to develop an ancillary services optimisation methodology that can address the question: which service is the optimum one the participate in at a given moment in time?

- **More realistic modelling of the Balancing Mechanism:** The Balancing Mechanism is an key component of grid operation, ensuring the balance between electricity supply and demand in real-time. Similar to ancillary services, acceptance to buy/sell power in the Balancing Mechanism is not guaranteed. There is a chance that bids/offers in the service will be rejected. A more realistic way of modelling revenues in the Balancing Mechanism would take into account the probability of being accepted. Additionally, there is a locational aspect to Balancing Mechanism revenues - with battery storage in certain parts of the country having higher acceptance rates than others. Incorporating this into the locational studies would allow more accurate insights into the impact of location on economics.

- **Better forecasting methods:** Accurate forecasting of market prices and renewable generation is critical for optimising low-carbon energy revenues. However, forecasting remains a challenging task due to the inherent variability and uncertainty in these factors. Future research could focus on developing advanced forecasting methods, such as machine learning techniques, statistical models and/or weather prediction algorithms. By improving the forecasting techniques, future revenues of battery storage and hydrogen production can more accurately be determined. Additionally, with strong forecasting methods in place, scenario analysis could be run to determine optimal low-carbon energy revenues under a variety of different scenarios. For example, how much money would batteries make in a scenario with high renewable generation buildout vs low buildout.

- **Application of real options analysis to battery investments:** There are many investment decisions that need to be made over a battery project's lifetime which lend themselves to real options analysis. For example, once the battery has fully degraded ie. reached the end of its life, should it be replaced or should the land and grid connection be sold on? Additionally, at what point should the battery be replaced, after it has degraded to 60% or 70% of its initial capacity? A battery owner might also use real options analysis to decide whether to use a cap and floor arrangement if using an external aggregator or optimiser to operate the battery. These are just a few examples of case studies where application of real options analysis could improve battery project decision making in future work.

Overall, by considering these future research directions, we can advance the modelling and optimisation of low-carbon energy technologies, leading to more efficient and sustainable integration of renewable energy sources into the grid.

# Chapter 6

# Going, going, gone: optimising the bidding strategy for an energy storage aggregator and its value in supporting community energy storage


## Abstract

Energy storage aggregation can bring many advantages to electrical power systems; these include improving flexibility, lowering system costs and reducing the need for carbon-intensive peaking plants. In this work linear and quadratic optimisation models are applied to examine the value derived by an aggregator, using energy storage for arbitrage in Great Britain's day-ahead and balancing energy markets. The optimum arbitrage strategy is determined when the aggregator is considered a price-taker and a price-maker with access of up to 500 MW battery storage. In the day-ahead market the choice of price-taker or price-maker strategy made negligible difference, however, in the balancing market the price-maker profits were 10.9% higher for 500 MW storage when prices were perfectly forecasted. For imperfect forecasting, the choice of strategy made a negligible difference. A sensitivity analysis challenged the modelling assumptions. System parameters that had the greatest impact on results were the battery efficiency (more efficient, higher profits) and its duration (shorter duration, higher profits). The model was then applied to investigate the potential value that can be obtained by an aggregator with partial access to a community-owned energy storage. Results showed that household electricity bills could be improved by this arrangement. In particular, households that use their batteries less during the winter months, could improve their profits by up to 13.2% if aggregator access is allowed.



### Keywords

Energy Storage; Aggregator; Optimisation; Energy Dispatch; Community Storage.


## 6.1 Introduction and literature review

### 6.1.1 Benefits of energy storage aggregation

Integrating energy storage devices into the electricity grid will improve its flexibility and stability. This is due to their ability to bridge the gap between electricity generation and usage [182] which is becoming more pronounced as the UK is increasingly shifting towards intermittent renewable sources [183]. In particular, the recent introduction of the 2050 net-zero carbon emissions target will further the expansion of renewables and curb the usage of fossil fuel-based power plants [14]. Whilst this measure will help to mitigate the effects of climate change, it will equally result in larger discrepancies between electrical supply and demand. Since energy storage has the potential to curb these discrepancies, it is likely to become an important technology in a low-carbon future [16]. Furthermore, references [184] and [21] show that for electricity systems with high renewable penetration, energy storage can improve system reliability and stability.

Control of energy storage devices is often overseen by "aggregators"; these are intermediaries acting between storage device owners, electricity end-users and electricity markets. They schedule the charging and discharging of storage devices in order to maximise their profits; these can be generated through energy arbitrage in wholesale markets and/or partaking in ancillary service markets, such as frequency response. Research has shown that aggregator-led control of storage devices can improve power system reliability [185] and benefit from economies of scale, by managing information centrally [186], [187]. However, storage device owners may not wish to hand over control of their devices to aggregators, in which case the use of financial incentives may be necessitated. The authors in [187] explore the value brought to a system by different types of storage (residential, industrial and commercial) and how this could translate into payments for their owners. It was found that larger payments were required for residential owners, as the highest savings were realised under local usage of their storage, and therefore such owners would need a greater incentive to give out their storage for system-beneficial aggregation.

### 6.1.2 Optimising aggregator profits

There are several ways in which energy storage aggregators can make these profits: ancillary services, behind-the-meter services and arbitrage. Several studies have explored the economics of energy storage performing ancillary services. For instance, in [5] they compare the economics of lithium ion and lead acid batteries providing frequency response; lithium ion batteries with high power density were found to be the most profitable. In [188] they examine the economics of pumped hydro storage participating in the day-ahead market as well as performing ancillary services; this type of storage is only found to be economical when there is existing infrastructure. Cost models for lithium ion batteries providing behind-the-meter services are compared in [189] and it was found that there is little publicly available data to accurately estimate costs and more work needs to be done to address these uncertainties.

Many studies have also examined the profitability of aggregators performing energy arbitrage in different electricity markets. Depending on the size of the aggregator's assets, these studies can be divided into two categories. In the first category, it is assumed that the power capacity of these assets is small compared to the total power demand hence, the operation of these assets has a negligible effect on market prices. The assets are referred to as "price-takers". The second category addresses larger assets whose operation affects market demand more significantly and consequently prices; these are "price-makers". A summary of the studies optimising energy arbitrage is shown in Figure 6.1; these are categorised by the modelling technique used.

### 6.1.3 Price-taker optimisation

An example of study based on the price-taker category is [67]. The authors present a cost analysis of energy storage performing arbitrage in the Californian electricity market as a function of its efficiency. They find that lithium ion batteries do not generate enough revenue to break-even, however pumped hydro storage is an economical option. The authors of [69] determine the

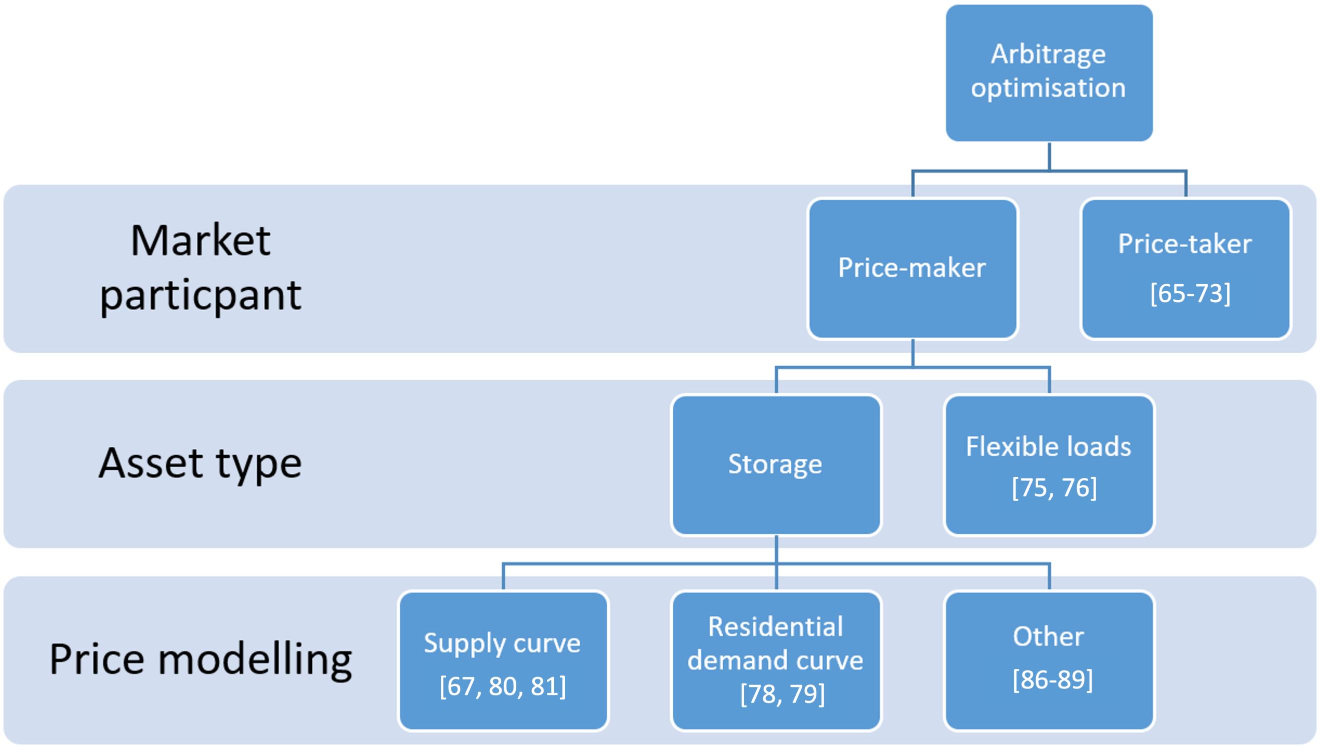



Figure 6.1: Categorisation of references optimising energy arbitrage.

arbitrage value of storage in the PJM region of the United States from 2002 to 2007. It was found that this value depends strongly on storage device parameters, namely its efficiency and capacity, as well as external factors such as fuel price and mix. A lower-band for the profit created through arbitrage was determined, using rudimentary forecasting techniques, and it was highlighted that significant value could still be captured. In [70], they consider a consumer load aggregator with control of electrical energy storage, who participates in day-ahead and real-time electricity markets. Their objective was to use the storage to minimise the costs associated with providing consumers with their required loads. A novel Model Predictive Control (MPC) framework was proposed to minimise costs in the real-time market, by considering both known price and load in the current time-period and projected prices and loads (and their associated uncertainties) for future periods. The authors of [71] propose a risk-constrained, bi-level approach to optimise bids and offers made by energy storage owners, whilst [72] model the optimal operation of an energy storage device under stochastic market prices. In [73], the uncertainties of market prices, demand and renewable generation are considered, and a probabilistic model is proposed to optimise an aggregator's bidding curves in the day-ahead and intra-day markets using fixed and flexible load, battery storage, wind and solar generation. In [74] they explore the strategy of an aggregator with storage who can both perform arbitrage and bid in the capacity market, determining the optimal allocation between these two revenue streams. Finally, in [75] they present a community level case study, where an aggregator procures electricity for a number of households with PV. The aggregator has access to a battery which is assumed to be owned by a distribution system operator (DSO) and/or the aggregator. A linear optimisation model is developed to reduce costs and carbon emissions under two scenarios: firstly, the aggregator has total control and performs arbitrage, secondly a "peak shaving" scenario optimises for both aggregator and DSO. Little difference is observed between the two scenarios, therefore "peak shaving" is recommended to prevent too large loads on the distribution transformer.

These studies highlight the ability of storage to create value through arbitrage in different markets and under different operating strategies. However, they assume that market prices are unchanged by the participation of the storage. The authors of [76] optimise the scheduling of price-maker distributed energy resources (DERs), and suggest that even for small aggregations their effect on market price should be examined. Hence, in order to best assess the profitability of aggregated resources, they should be treated as price-makers.

### 6.1.4 Price-maker optimisation

The market bidding strategies of price-maker flexible loads are explored in [77], [78]. In [77] they found that their bidding strategy was influenced by two risk factors: low-profit risk and volume deviation risk. Additionally, they saw that when the load was more sensitive to changes in spot-price, average spot-price was reduced leading to lower electricity costs. This highlights the consumer benefit of having flexible loads, such as storage devices. In [78], they examine the case of economic bidding in the day-ahead electricity market. This is unusual because most of the literature focuses on the specific case of self-scheduling bidding (bids for a certain volume of energy with no price component) rather than the more general, but complicated, economic bidding (bids containing both an energy quantity and upper price limit). They show that the economic price-maker bidding approach outperforms self-scheduling bidding for flexible loads.

Energy storage is typically less flexible in its bidding strategy than time-shiftable loads [79]. This is because hourly bids and offers are interdependent; a storage operator can only offer to generate electricity if their earlier purchase bids have been accepted. For this reason, self-scheduling bids are generally preferred. Several studies have addressed the optimal self-scheduling of price-maker energy storage facilities [69], [80]–[83]. These studies can be split into two groups, depending on their method for modelling the relationship between storage operation and market price. The first method models this relationship using a residual demand curve, which is defined as the total demand curve minus demand from all other suppliers [80], [81]. It illustrates how market price varies as a function of electricity volume submitted by the storage facility. This method is described in [80] and [81] and is particularly useful for price-maker modelling when electricity demand is elastic.

The second method is more straightforward and may be used when electricity demand can be considered inelastic [83]. This is the case when day-to-day electricity demand does not vary significantly, despite fluctuations in price. In practice, this assumption can generally be made. It is then sufficient to model the relationship between market price and storage operation using a supply curve. In [69] they use historical data to construct linear supply curves for each month, whereas in [82] actual hourly demand and generation curves are used to model the impacts of storage charging and discharging. These two approaches assume that the supply curves are always known in advance with perfect forecasting. The authors of [83] improve upon this work by considering the uncertainties associated with predicting future supply curves. They do this by using historical data to construct nominal, maximal and minimal supply curves, where 90% of this data is encapsulated between the upper and lower bounds. Additionally, the level of risk-aversion of the energy storage operator can be incorporated into the model and can influence the storage strategy chosen. Reference [87] presents a price-based unit commitment model which uses historic market resilience data and approximates this as a step-wise function to reduce computational complexity. In [88] they reduce this even further by introducing a method to maximise the profitability of price-aware energy storage without invoking linear optimisation.

### 6.1.5 Contributions of this work

This work addresses the economics of energy storage aggregation. It will consider a consumer load aggregator with energy storage which it uses purely for arbitrage. The main novelty comes from the application of this system setup, to investigate how an aggregator can add value to community energy storage through a partial access arrangement. Previous work has modelled either the use of community storage at a local level to optimise for community usage [190], [191] or for grid services such as arbitrage [75], [192]. The benefit of using the storage device simultaneously for these two purposes has not yet been explored. The arrangement presented here optimises the ratio of the storage quotas for each of these two applications and finds specific scenarios which are mutually beneficial to both the aggregator and community.

It is hoped that this work will lead to increased research into different approaches for energy storage deployment, ownership and control. It should be noted that battery degradation is not considered here as preliminary work found it to have little impact on the bidding strategy and profitability over the time frame considered in this model [8]. However, for simulations over a longer period, the degradation and remaining useful life should be considered [193].

Contributions of this work are as follows:

- The model proposed by [70] is applied to schedule a load aggregator's arbitrage bids in Great Britain's day-ahead and real-time markets when they have access to battery storage.
- The model is adapted to consider the aggregator as a price-maker, using the supply curve method identified in the literature. The choice of price-taker or price-maker strategy for scheduling the storage is explored, along with the effects of changing battery size and time of year.
- A sensitivity analysis is performed to challenge modelling assumptions, including battery duration and efficiency, load characteristics and whether or not actual market prices are affected by aggregator bidding.
- We then apply this model to study a novel arrangement where an aggregator has partial access to a community owned battery storage. Scenarios are identified that are mutually beneficial for the community and aggregator.

The rest of this paper is organised in the following way: Section 6.2 explains the formulation of the model, the data sources used and their manipulation. Section 6.3 presents the results and discussion, which are split into three sub-sections: Section 6.3.1 compares the price-maker and price-taker optimisation strategies, Section 6.3.2 presents a sensitivity analysis to challenge the assumptions made and Section 6.3.3 presents the community-owned storage case study. Finally, concluding remarks are given in Section 6.4.

## 6.2 Model Description

### 6.2.1 Model overview

In this model, the bidding strategy of an energy storage aggregator performing arbitrage is optimised. The aggregator considered here acts as an electricity distributor, providing a range of customers with their required electrical loads. Such aggregator must purchase the electricity in wholesale markets, which they can then sell to the customers. The bulk of the electricity is bought in the day-ahead market, as the required hourly quantities and prices can usually

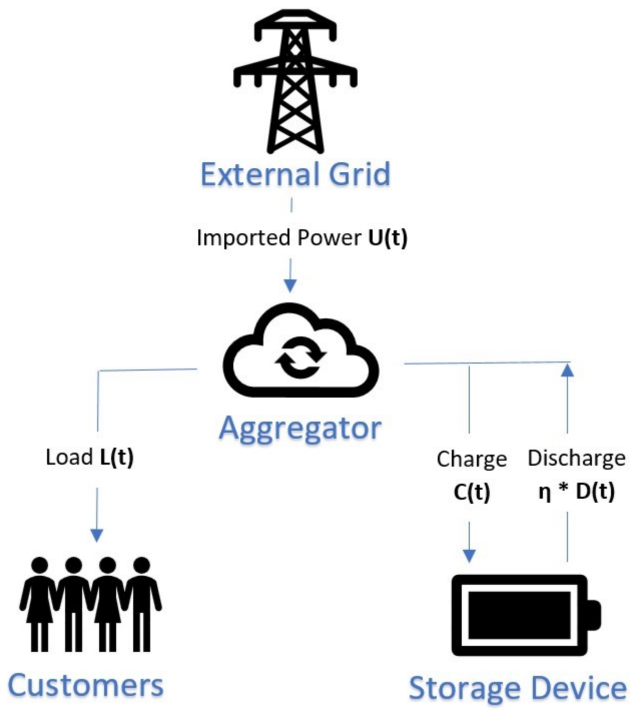



Figure 6.2: An aggregator imports power at time t to provide to a set of customers, whose power usage constitutes load L(t). They have access to an energy storage device which can be used for power management.

be predicted with a reasonable degree of accuracy. Any real-time discrepancies between the predicted and actual electricity demand are balanced in the real-time market, where additional electricity can be bought, and excess sold.

The aggregator has access to energy storage, which can be used to minimise their costs; smart scheduling of the storage can shift electricity purchasing to hours when prices are low, and consequently reduce purchasing requirements for hours when prices are high. A schematic diagram of the aggregator's distribution network is shown in Figure 6.2. For the first case study (results presented in 6.3.1 and 6.3.2), the aggregator has one central battery which it uses to maximise profits whilst delivering load to 1000 customers. The community case study (results in 6.3.3) has a different architecture to this: each of the 1000 households has its own smaller battery (rather than one central battery) which can be aggregated.

The optimum arbitrage strategy is determined when the aggregator is considered a price-taker and a price-maker. The price-taker and price-maker optimisation models are applied to a case study in Great Britain (GB) to examine their potential value. A sensitivity analysis is then carried out to challenge some of the assumptions. Finally, the price-taker model (selected over price-maker, since traded quantities are low, maximum storage power 1 MW) is applied to a community storage case study. The potential of an aggregator to improve the profits of the community, through a partial sharing scheme, is examined.

### 6.2.2 Price-taker optimisation model

The day-ahead profits of the aggregator are optimised by minimising Equation 6.1, where $\hat{p}_t^{DA}$A is the predicted day-ahead market price at time $t$, and $\hat{P}_t^{imp}$ is the predicted power purchased in the market. It is assumed that the day-ahead market price is independent of $\hat{P}_t^{imp}$, in other words the aggregator is a price-taker. Power purchased by the aggregator is equal to predicted customer load, $\hat{L}_t$, plus power purchased to charge the storage, $\hat{P}_t^{p+}$, minus power discharged from the storage, $\hat{P}_t^{p-}$. This is represented by Equation 6.2. $\hat{P}_t^{imp}$ may be negative, in cases when $P_t^{p-}$ is greater than $\hat{L}_t$, and power being sold in the market.

$$min \sum_{t=0}^{47} \hat{p}_t^{DA} \hat{P}_t^{imp} \tag{6.1}$$

$$\hat{P}_t^{imp} = \hat{L}_t + \hat{P}_t^{p+} - \hat{P}_t^{p-} \qquad \forall t \tag{6.2}$$

Once the optimum value of $\hat{P}_t^{imp}$ has been determined and the day-ahead bidding is finalised, the actual day-ahead prices are finalised. In GB's Nord Pool (N2EX) day-ahead market trading closes at 9:50am GB time one day before delivery; results are then finalised at 10am and actual market price is $p_t^{DA}$. It is assumed that the aggregator's bids are accepted. Total day-ahead storage savings are calculated using Equation 6.3, where the first term represents costs incurred in the day-ahead market when there is no storage and the second term represents costs when there is storage.

$$\sum_{t=0}^{47} p_t^{DA} \hat{L}_t - \sum_{t=0}^{47} p_t^{DA} \hat{P}_t^{imp} \tag{6.3}$$

The real-time profits are optimised by applying the model predictive control algorithm proposed in [70]. This works by implementing Algorithm 1, which aims to minimise power purchased in the real-time market. In GB this market is known as the Balancing Mechanism (BM); trading in the BM occurs in 30 minute intervals with market closure 30 minutes before the start of each interval. It is assumed that actual customer load, $L_t$, is known at this time. Power purchased in the BM is equal to the required power in real-time, $P_t^{imp}$, minus the power purchased in the day-ahead market, $\hat{P}_t^{imp}$. $P_t^{imp}$ is equal to $L_t$ plus power purchased to charge the storage, $P_t^{p+}$, minus power discharged from the storage, $P_t^{p-}$. The storage charging/discharging strategy can be altered in real-time to minimise BM costs. Predicted BM price is given by, $\hat{p}_t^{BM}$, once bidding is finalised the actual BM price, $p_t^{BM}$, is learned. Storage savings in the BM for time period $t$, relative to no storage, are then calculated using Equation 6.4.

$$p_t^{BM}(P_t^{imp} - \hat{P}_t^{imp}) - p_t^{BM}(L_t - \hat{L}_t) \qquad \forall t \tag{6.4}$$

**Algorithm 1** Real time optimisation

**Solve** DA model for all $t \in T$ **while** $t \in T$ **do**

**Obtain** load at current time period $L_t$

**Forecast** real-time settlement price $\hat{p}_t^{BM}$ at current time $t$, and future load and price: $\hat{L}_t$, $\hat{p}_{t'}^{BM}$ at time $t' \in T''$ where $T'' = \{t+1, ..., t+48\}$

**Solve** real time optimisation model:

$$min\Big[\hat{p}_t^{BM}(P_t^{imp} - \hat{P}_t^{imp}) + \sum_{t'=t+1}^{t+48} \Big(\hat{p}_{t'}^{BM}(P_{t'}^{imp} - \hat{P}_{t'}^{imp})\Big)\Big] \tag{6.5}$$

subject to :

$$P_t^{imp} = L_t + P_t^{p+} - P_t^{p-} \qquad \forall\, t \tag{6.6}$$

$t = t + 1$

**end**

Constraints on the energy storage device are given by Equations 6.7-6.10. Equation 6.7 determines the capacity of the storage at the end of time period $t$, $X_t$, which depends upon the capacity at the end of period $t-1$ and the charging and discharging in $t$; $\eta^c$ and $\eta^d$ are the charging and discharging efficiencies, respectively. Equations 6.8 and 6.9 maintain capacity and charging/discharging powers between their minimum and maximum values. Equation 6.10 prevents the storage from simultaneously charging and discharging.

$$X_t = X_{t-1} + \eta^c P_t^{p+} - \frac{P_t^{p-}}{\eta^d} \qquad \forall t \tag{6.7}$$

$$\underline{X} \le X_t \le \bar{X} \qquad \forall t \tag{6.8}$$

$$0 \le P_t^{p+} \le \bar{P}^c, \qquad 0 \le P_t^{p-} \le \bar{P}^d \qquad \forall t \tag{6.9}$$

$$P_t^{p+} P_t^{p-} = 0 \qquad \forall t \tag{6.10}$$

A summary of the aggregator's arbitrage optimisation procedure is shown in Figure 6.3. It can be seen that the day-ahead optimisation is firstly solved for the first day. Then the real-time model is solved for the first day in 48 half-hour periods, implementing the current solution for storage operation at each time step. The model iterates over each day until the final day is reached. It is terminated, then storage operation and day-ahead and balancing mechanism expenditures are calculated.

### 6.2.3 Price-maker optimisation model

Up until now, it has been assumed that the aggregator's bids in the wholesale markets have had a negligible effect on market prices. However, this may not be the case particularly if the load and storage are large. To model the bidding of a price-maker, the relationship between market price and energy quantity traded must be known. This can be represented by a supply curve. Here, supply curves were constructed using data from N2EX [194] and fitting linear regression models to the data (price vs. quantity bought) for each month. Making daily, weekly or even hourly supply curves might be a more accurate method for analysing price-maker bidder. This is because

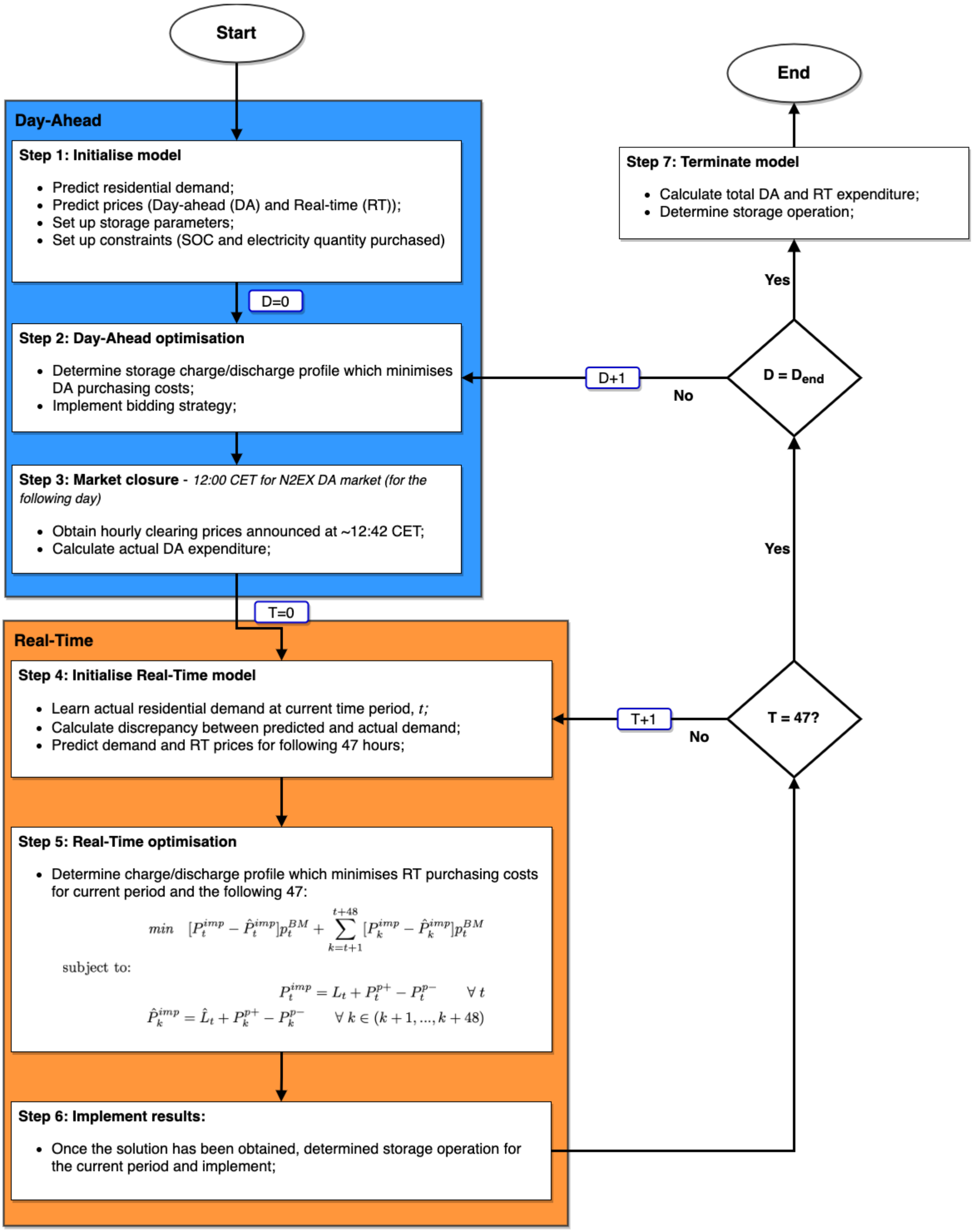



Figure 6.3: Flow chart showing the day-ahead and real-time optimisation procedure for the aggregator.

prices are strongly affected by weather conditions which can vary greatly from day-to-day, and even hour-to-hour. However, there are insufficient data points to construct such detailed supply curves.

A relationship between price $p_t$ and quantity purchased $P_t^{imp}$ is then obtained using Equation 6.11:

$$p_t = aP_t^{imp} + b \qquad \forall t \tag{6.11}$$

where a is gradient, and b intercept of supply curve. The change in price $\delta p_t$ due to the purchased quantity $P_t^{imp}$ is proportional to the gradient, such that $\delta p_t = aP_t^{imp}$. Hence, the day-ahead objective function, given by minimising Equation 6.1, can be amended to:

$$min \sum_{t=0}^{47} (\hat{p}_t^{DA} + a\hat{P}_t^{imp})\hat{P}_t^{imp} \tag{6.12}$$

which can be solved using a quadratic solver: in this case BARON [195]. The same technique was also used to update the real-time objective function where $\hat{p}_t^{BM}$ was replaced with $\hat{p}_t^{BM} + a^{BM}(P_t^imp - \hat{P}_t^{imp})$ where $a^{BM}$ is the gradient of the balancing market supply curve.

### 6.2.4 Community storage optimisation model

The community considered here comprises of 1000 households with heterogeneous installed PV and 1 kW sized lithium ion battery storage scaled to the size of maximum solar power (0.68 kW – 0.94 kW). For each household, $i$, at time, $t$, their load is represented by $L_{ti}$, and their generated solar power, $S_{ti}$. They are able to use $x\%$ of their battery along with their PV to reduce household electricity bills. The remaining $(100 - x)\%$ of the battery is used by an aggregator who uses this for arbitrage in the day-ahead market. In return, the aggregator offers a percentage of their profits to the community.

The aggregator optimises their $(100 - x)\%$ of the battery in the day-ahead market by minimising Equation 6.13, subject to Equations 6.14 and 6.7-6.10 for each battery storage device, $i$, where $P_{ti}^{imp}$ is power imported for each device at time, $t$. For each battery, the aggregator can access minimum and maximum capacities and a maximum power of $\underline{X}(100-x)\%$, $\bar{X}(100-x)\%$, $\bar{P}(100 - x)\%$, respectively.

$$min \sum_{t=0}^{47} \sum_{i=0}^{1000} \hat{p}_t^{DA} P_{ti}^{imp} \tag{6.13}$$

$$P_{ti}^{imp} = P_{ti}^{s+} - P_{ti}^{s-} \qquad \forall t, i \tag{6.14}$$

The community optimises their $x\%$ of the battery by operating it in real-time alongside their PV to minimise their electricity bills. They are on a time of day electricity (TIDE) tariff, in this work the TIDE tariff provided by Greenenergy is modelled [196], [197]. This tariff provides customers with low electricity prices (£0.09/kWh) between 00:00 – 07:00, medium prices (£0.16/kWh) between 07:00 – 16:00 and 20:00 – 24:00, and high prices (£0.32/kWh) on weekdays between 16:00 – 20:00, on weekends the high prices are replaced by medium prices.

At each moment in time each household learns their current electricity load, L, PV generation, PV, electricity price, p, and amount of available power to charge and discharge their battery, C and D. The procedure to minimise the electricity bill for each household is presented by the flow chart in Figure 6.4. It is repeated at each time period, t, as new information is learned. The minimum and maximum capacities and maximum power of the battery that the households can

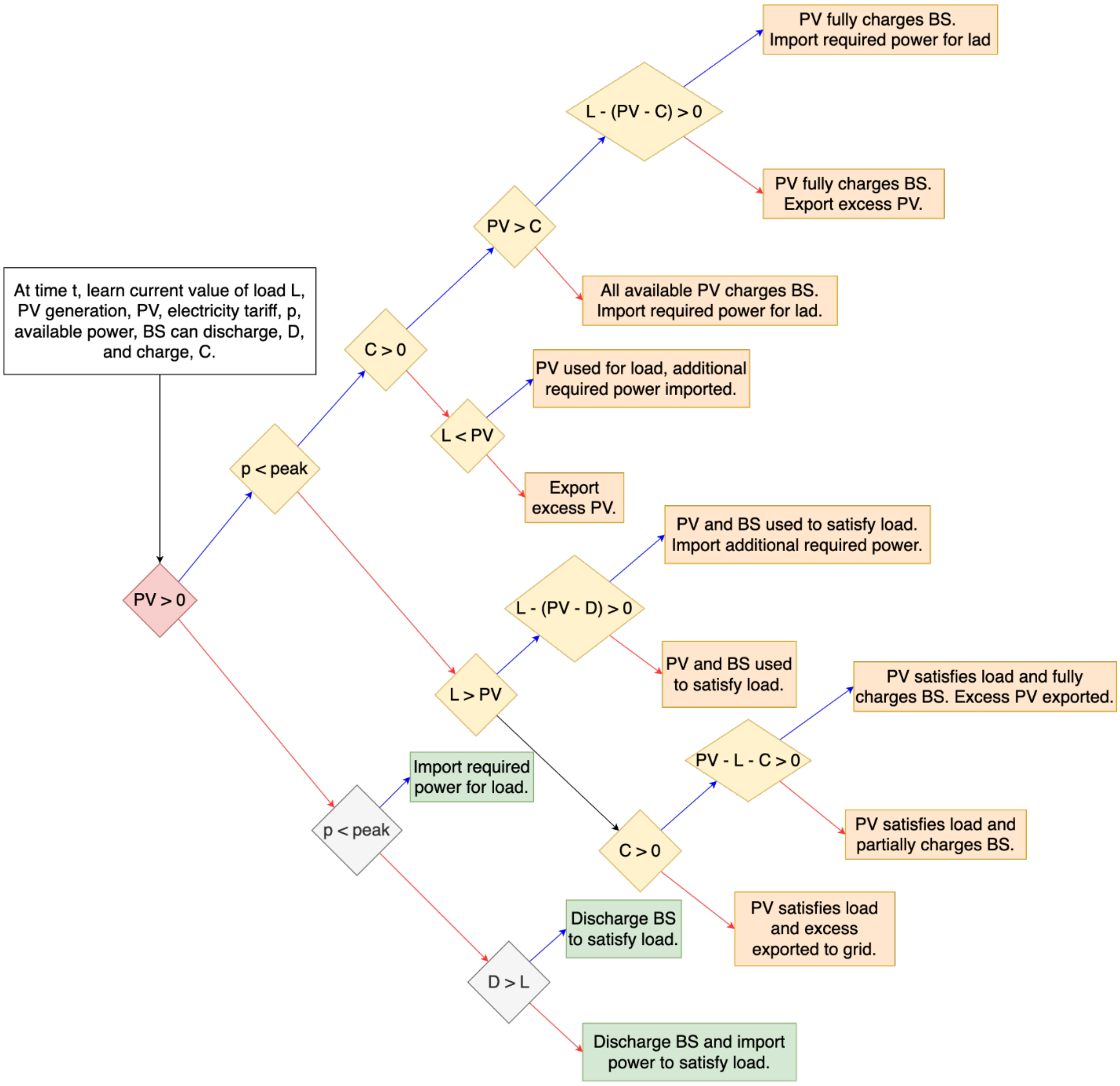



Figure 6.4: Flow chart showing the procedure to minimise the community electricity bills for each household. This is repeated at each time, t, as load, generation and price are learned. Blue arrow represents 'yes', red arrow represents 'no'; boxes are orange/yellow when there is PV generation, and grey/green when there is no PV.

access is $\underline{X}x\%$, $\bar{X}x\%$ and $\bar{P}x\%$, respectively.

### 6.2.5 Data sources and manipulation

Data for historic day-ahead prices was obtained from Nord Pool (N2EX) for 2019 [194]. The dataset contains information about the electricity quantities traded each hour and the finalised price. This market has hourly resolution, however to make it compatible with other data sources, it was sub-sampled into half-hourly resolution by assuming that the price was constant throughout each hour. To realistically model the aggregator's bidding strategy, it is assumed that they do not have perfect knowledge of trading price in advance. Therefore, the day-ahead price must be accurately forecasted. It was found in preliminary work that a 2-week rolling average prediction method was more accurate than Gaussian Process (GP) forecasting, with RMSE scores of 8.64 and 11.60 for January 2019 predictions respectively. The GP was trained on data from January 2017 to December 2018, using a unique clustering method and training parameters such as generation mix, weather and demand [198].

Balancing mechanism data was obtained from National Grid [199]. In order to predict these prices SARIMA (Seasonal Auto-regressive Integrated Moving Average) models were tested, as these have been applied in the literature [200], [201]. These were initially tested on balancing mechanism data from September 21st 2016 to the end of 2017. A SARIMA (2,1,2)(0,1,2,24) model was found to have the lowest AIC (Alkaike Information Criterion) value on initial tests. However, this model was found to give an RMSE (Root Mean Squared Error) of 99.7 for price predictions, whereas simply using the same predictions as for the day-ahead market (2-week rolling average method) gave an RMSE of 34.4. Therefore, for the sake of simplicity the day-ahead rolling average predictions for the day-ahead market were also used as the predictions for the balancing market. It is not unreasonable to assume that these two markets will follow similar patterns, since hours with greater electricity demand (and hence higher prices) may be more likely to have greater discrepancies in real-time.

Data for modelling residential load is obtained from ELEXON [202]. This dataset gives daily average load profiles for different types of consumer e.g. residential, commercial, industrial, on specified electricity price tariffs for a weekday, a Saturday and a Sunday. In this work we use the residential load profiles for consumers on a flat tariff (electricity price is a constant rate for all times) and an Economy 7 tariff (electricity price is lower for 7 hours during the night and higher during the day).

The predicted load was taken to be the number of customers on the flat tariff multiplied by the average flat tariff profile, plus the number of customers on the Economy 7 tariff multiplied by the average Economy 7 profile. Actual load was generated by adding random noise to the average profiles for the different customers. This is represented by Equation 6.15, where $L_{t,i}$ is the actual load for customer $i$ and time $t$, $\hat{L}_t$ is their predicted load and $N(0,1)$ is the standard normal distribution. Total load is the sum of actual load for each customer, the absolute value of this is taken to avoid any negative loads being generated.

$$L_{ti} = \hat{L}_t + N(0,1)\hat{L}_t \qquad \forall t, i \tag{6.15}$$

It was observed that when adding random noise for each customer (1000 customers modelled), the actual load averaged out to the predicted load due to random noise cancelling out. Therefore, to introduce an element of unpredictability, 100 random profiles were generated and each multiplied by 10; it was assumed that each generated profile represented 10 customers. In the sensitivity analysis in Section 6.3.2, these assumptions are challenged.

For the community storage optimisation model the load was generated randomly using Equation 6.11. It was assumed that the community were all on time-of-use electricity tariffs, such that they can use their PV and battery to reduce their bills. Therefore, their load profiles were modelled using the Economy 7 residential profiles for predicted load, $\hat{L}_t$. In this case study, random noise was added for each of the 1000 customers, since each customer optimises their bills individually, it does not matter whether their collective loads average out to the predicted load.

The solar PV profiles were modelled using real household solar panel data that was provided for this work [203]. The data set contains information about location, size and hourly generation (from Jan 2016- Dec 2017) for each site These sites are located across GB, therefore to model a local community k-means clustering was employed to select a cluster of profiles located close together. This is discussed further in Section 6.3.3. For each of the households, they were randomly assigned one of these solar profiles along with 1 kW battery, with a 4-hour duration. This size of the battery was chosen such that its power was of a comparable size to the peak solar output; the solar profiles have a peak output in the range 0.68 kW – 0.94 kW. The batteries are modelled as a 4-hour duration battery, as in the recent PNNL report [204], with a minimum capacity of 20% and charging and discharging efficiencies of 90% [205], [206]. The households can export excess solar power for a price of 5p/kWh, this is a typical export price that could be expected under the UK's Smart Export Guarantee scheme [207], [208].

## 6.3 Results and Discussion

### 6.3.1 Price-taker vs. price-maker

For the comparison of the price-taker and price-maker optimisation models it is assumed that the aggregator has access to a large capacity of battery storage; this may be an aggregation of many smaller batteries (as in the community storage application) or fewer large scale batteries. To understand the scale of energy storage in Great Britain, Figure 6.5 shows energy storage currently deployed, under construction and with planning permission submitted or granted. This data is retrieved from the Renewable Planning Database [25].

The locations, size and type of storage are displayed; grey represents battery storage, blue is pumped hydro, pink is flywheel storage, red is liquid air energy storage and purple is hydrogen storage. It can be seen that there are some very large-scale hydro storage facilities; the largest is Dinorwig in North Wales with a capacity of 1728 MW. It can also be seen that there are many more battery storage projects than any other type of energy storage. The largest battery storage project in the database has a capacity of 550 MW and currently planning permission has been submitted. Therefore, in this Section battery storage up to 500 MW will be considered in the optimisation model.

Figure 6.6 shows the savings made by the aggregator in January 2019 using the battery storage, compared with not using it, for different sized batteries each with a 4-hour duration. This is shown for the price-taker (PT) and price-maker (PM) optimisation models using imperfect price forecasting (IF) and perfect forecasting (PF) methods. The IF methods use a 2-week rolling average method (using historic day-ahead prices as inputs) for predicting both day-ahead and balancing mechanism prices. The PF cases use the actual prices. Savings are calculated using Equations 6.3 and 6.4 and summing over all periods in January 2019. It is assumed that the actual day-ahead and balancing market prices are affected by the aggregator's bidding, i.e. price-maker, and are determined using the method in Section 6.2.3, such that $p_t$ -¿ $p_t + aP_t$, where $p_t$ is the market price, a supply curve gradient and $P_t$ quantity traded in the market.

In Figure 6.6 the solid bars are the savings in the day-ahead market, and the striped bars are the additional savings in the balancing mechanism. Several things can be observed; firstly, for the IF cases, there is very little difference in savings between the PT and PM optimisation models. Secondly, the savings in the balancing mechanism are negligible compared with those in the day-ahead market for the IF cases. For the PF cases there are significant savings in the balancing market – greater than in the day-ahead market – and these are higher for the PM model than the PT model; for 500 MW storage, balancing market savings are 10.9% higher for the PM model than the PT model when prices were perfectly forecasted. However, there is also a negligible difference between the PM and PT models in the day-ahead market for the PF cases. The difference in day-ahead savings for IF and PF is relatively small, compared with the difference in savings in the balancing mechanism; this difference increases with storage size.

These results that in reality, when prices are not perfectly known in advance, battery storage arbitrage in the day-ahead market is a reliable source of income. Having perfect knowledge of day-ahead prices can slightly improve this income, but even using a basic prediction technique such as a 2-week rolling average allows high savings to be made ( £45,000 for 1000 MWh storage over 1 month in winter). Additionally, for the storage sizes considered here, which are comparable to GB's large scale battery storage, using a price-maker optimisation model makes

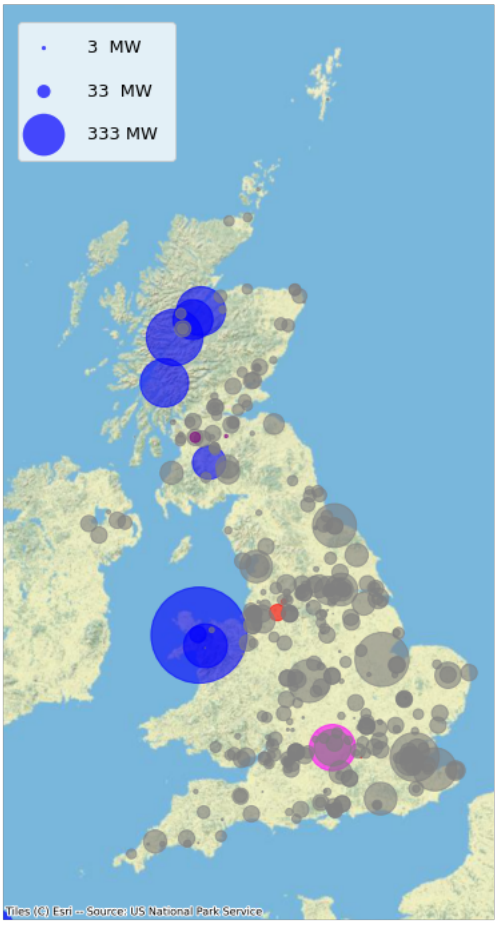



Figure 6.5: Energy storage in Great Britain, either operational, under construction or planning permission submitted or granted. Grey = battery storage, blue = pumped hydro, pink = flywheel, red=liquid air storage, purple = hydrogen storage.

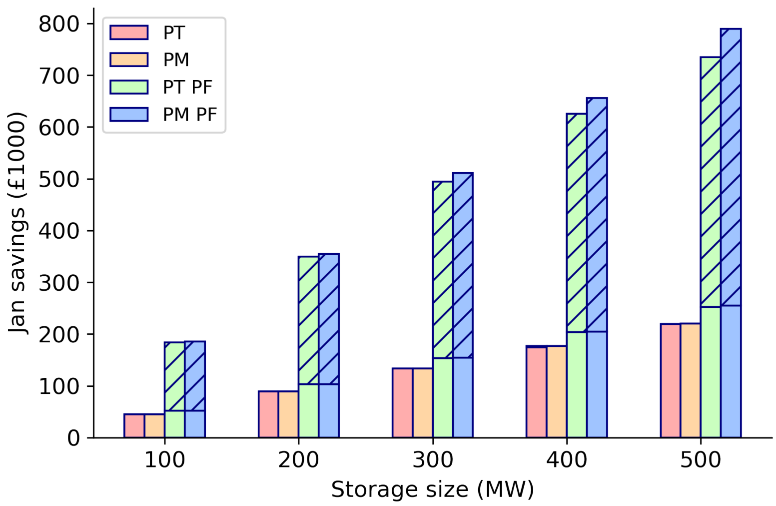



Figure 6.6: Monthly aggregator savings, relative to no storage, for different sized storage and different optimisation strategies. PT= price-taker, PM = price-maker, PF = perfect forecasting. Solid bar represents profits in day-ahead market and striped bar balancing mechanism.

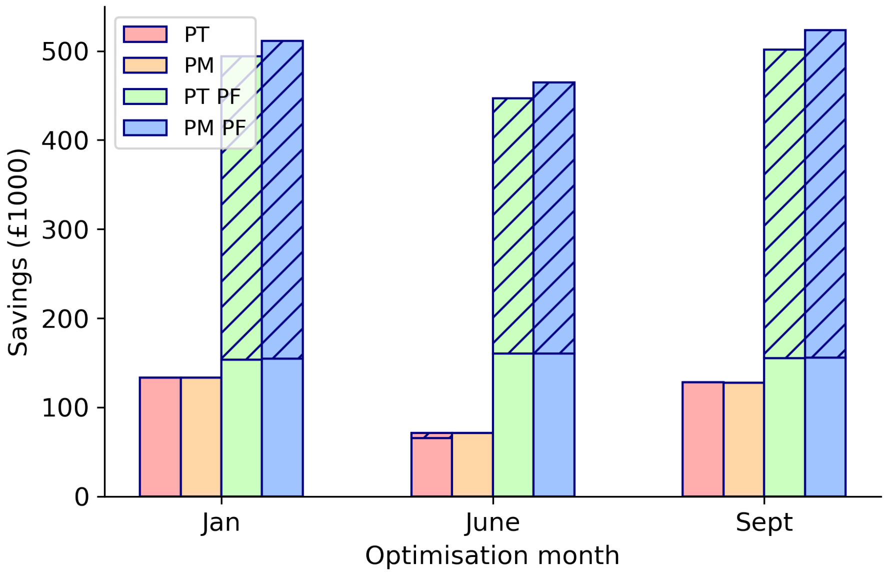



Figure 6.7: Monthly aggregator savings, relative to no storage, for 300 MW sized storage over different months and optimisation strategies. PT= price-taker, PM = price-maker, PF = perfect forecasting. Solid bar represents profits in the day-ahead market and striped bar balancing mechanism.

negligible difference to overall savings in the day-ahead market. This is since the electricity volumes traded in this market are vast (around 500 TWh are traded each year [209]) and hence the effects of a battery storage aggregator's bids are negligible. Therefore, for the sake of reducing computational complexity it is advised that for arbitrage optimisation models in this market, a price-taker strategy is employed. Finally, these results show that if balancing market prices are known in advance this is a very lucrative market for battery storage to perform arbitrage in. However, accurately predicting these prices is very complex.

The PT and PM optimisation models are applied to June and September using 300 MWh, 4-hour duration battery storage (this size storage was chosen since for January there was an observable deviation between PT and PM strategies); the results of this are presented in Figure 6.7. For these months, it is also observed that there is a negligible difference in day-ahead savings for the PT and PM optimisation models. As for January, there is an increase in PM savings for the case of perfect forecasting. However, as previously stated it is unrealistic to assume these are known perfectly in advance. For the imperfect forecasting cases, it can be seen that day-ahead savings are lower in June than in January and September, and there is a larger difference between perfect and imperfect forecasting savings. It was found that the Mean Average Percentage Error (and Root Mean Squared Error) for January, June and September were 10.35% (£0.0060/kWh), 15.46% (£0.0060/kWh) and 16.06% (£0.0052/kWh), respectively. One explanation for the differences observed is that in June the prediction errors occurred during hours when arbitrage is likely to occur e.g. hours with minimum/maximum prices, whereas for January and September prediction errors occurred during hours when arbitrage is less likely to occur and hence had a lesser impact on overall profitability.

### 6.3.2 Sensitivity analysis

In this section assumptions made previously about battery and load parameters are challenged to examine whether they affect the conclusions. The base case against which results are compared

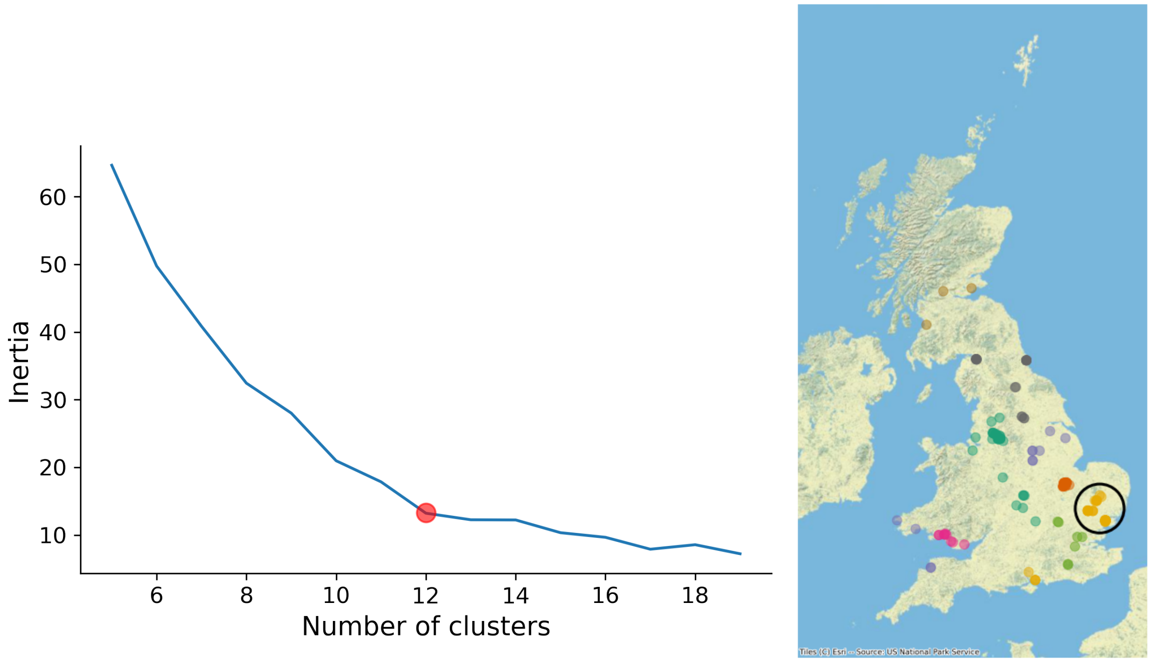
Table 6.1: Sensitivity analysis comparing assumptions made about battery, load generation and prices against the January 300 MWh, 4-hour duration, 90 % efficient battery base case.

| Sensitivity analysis | DA savings (£1000) | RT savings (£1000) | Total savings (£1000) | % change compared to base |
|---|---|---|---|---|
| Base case | 133.47 | 0.1 | 133.57 | - |
| 8 hour duration battery | 76.64 | 2.37 79.01 | -41% | |
| 2 hour duration battery | 169.09 | -5.12 | 163.97 | 23% |
| 1 hour duration battery | 181.78 | -17.24 | 164.55 23% | |
| 85% efficiency battery | 80.73 | 0.72 | 81.45 | -39% |
| 95% efficiency battery | 182.97 | -2.69 | 180.28 | 35% |
| load 75% flat tariff | 133.47 | 0.1 | 133.58 | 0% |
| load 25% flat tariff | 133.46 | 0.1 | 133.56 | 0% |
| load generation 10 profiles * 100 | 133.47 | 0.1 | 133.57 | 0% |
| load generation 1000 profiles | 133.47 | 0.1 | 133.57 | 0% |
| load generation N(0,2) | 133.47 | 0.1 | 133.57 | 0% |
| savings calculated using price-taker prices | 135.87 | 1.74 | 137.61 | 3% |

is the imperfect forecasting price-taker optimisation model for January. The base case battery is 300 MWh (chosen as it was the middle value, and used for comparing the different months) with a duration of 4 hours and charging and discharging efficiency of 90%; the customer load is generated as outlined in Section 6.2.5, assuming 50% are on the flat tariff and 50% on the Economy 7 tariff. This is varied in the sensitivity analysis by changing the percentage of customers on the flat tariff vs Economy 7, the number of profiles randomly generated and the standard deviation of the random noise. It is assumed that the actual price is altered by the aggregator's bids. The change to aggregator savings, relative to the base case, is determined for each of these parameters as they are varied in turn. Table 1 presents the results of this sensitivity analysis.

It can be seen that as battery duration is increased to 8 hours there is a 41% reduction in savings compared to the base case. This is since it takes the battery longer to charge/discharge so the volumes of electricity that can be traded are reduced, hence arbitrage profits are lower. Inversely, as battery duration is decreased savings increase by 23%. However, the increase in savings realised by reducing battery duration from 2 hours to 1 hour is less than 1%. A shorter duration battery can reliably generate more profits in the day-ahead market, however it is seen to make greater losses in the less-predictable balancing market. This is since a disadvantageous bid, made under incorrect predictions, is costlier when greater electricity volumes are traded. As expected, for a less efficient battery the savings are significantly decreased, and similarly increased for a more efficient battery savings increase.

It can be seen in Table 1 that the effects of altering the load have a negligible effect on the total savings. Specifically, the load was altered by: varying the number of customers on the flat tariff vs Economy 7, the number of generated profiles and the random noise added to each profile. This is since the aggregator makes savings relative to the no storage case by using the battery storage for arbitrage. Any increase in cost for the aggregator due to increasing the size and randomness of the load is incurred for both the case with and without the storage, and the relative difference between the two remains the same. However, there is a difference in savings when the prices are assumed to the price-taker e.g. unaffected by the aggregator's bids. When the prices are price-taker the aggregator's savings are greater since their bids do not adversely affect their profits.




(a) Inertia

(b) Clusters

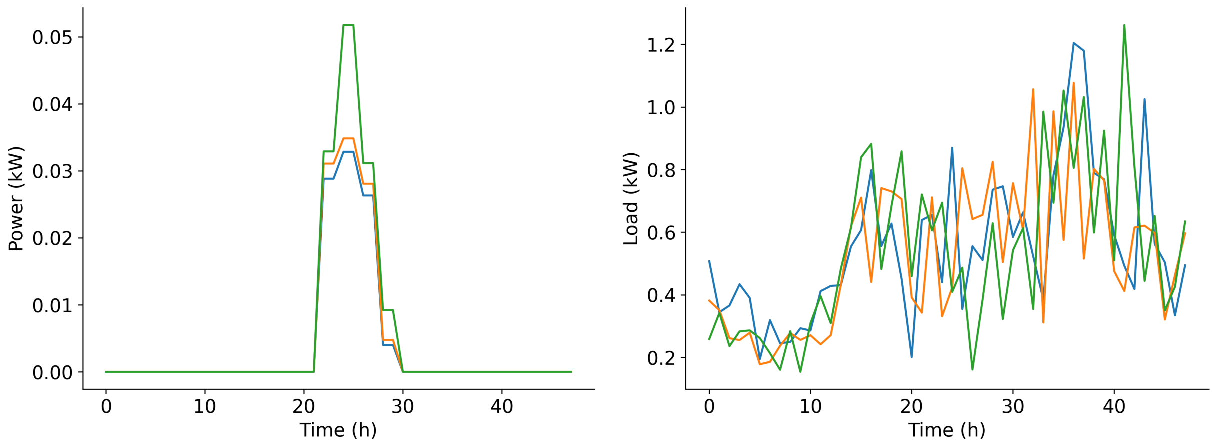
Figure 6.8: Left: inertia as a function of number of clusters for the k-means clustering, 12 clusters chosen as optimum; Right: the different locational clusters (for no. clusters = 12) represented by different colours, cluster with most points highlighted.

### 6.3.3 Community storage optimisation

Residential solar profiles were clustered using k-means clustering to represent local communities. To determine the optimum number of clusters, the inertia was determined over a range of clusters; this describes the spread of points away from the central point (the lower the inertia the closer together the points). The optimum number of clusters was chosen as 12 (indicated by Figure 6.8 (left)) since this is the elbow point where inertia is sufficiently low, whilst not having too many clusters to maintain a sufficient number of sites in each one. Figure 6.8 (right) shows the locations of the solar profiles, and the colour represents the cluster that they have been grouped into; this is shown for the optimum number of clusters, 12. The cluster that contains the most profiles has been highlighted; it contains 34 profiles.

The solar profiles for the community storage model were randomly selected from these 34 profiles for each of the 1000 households. The first 3 solar and load profiles generated on the first day of January shown in Figure 6.9. It can be seen that the solar generation is relatively low on this day, compared with yearly peak PV outputs in the range 0.68 kW – 0.94 kW for these profiles. Additionally, there is variation in solar profiles within the cluster, which may be due to factors such as PV size, orientation, cloud cover etc. By considering these different profiles, and generating random load profiles, our model captures a range of different household behaviours, battery usage profiles and bill savings.

In Figure 6.10 the left-hand side figure shows the load of one household over 2 days in June (dashed blue line), its PV generation (orange line), and imported power (solid blue line); the right-hand side figure shows the power to (positive) and from (negative) the battery over the same time period. The times when the electricity tariff is at its peak are highlighted in red. These are shown for June since there is greater solar generation, hence the electricity bill minimisation procedure may be seen more clearly. It can be seen that the solar generation satisfies the household load and reduces required power import. Additionally, in hours with high generation




(a) PV (b) Load

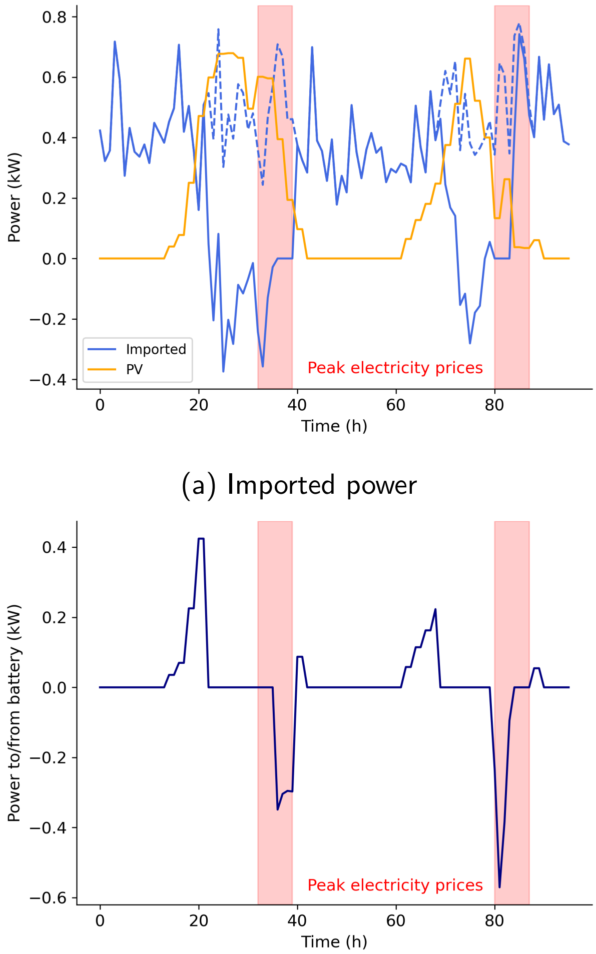
Figure 6.9: First 3 PV and load profiles generated for the first day in January 2019.

some power can be exported. The battery storage is charged by the solar during hours outside of peak electricity prices, and discharges to satisfy the load during these times. The average household savings in January 2019 due to the battery storage, relative to the case where there is no battery, is shown in Figure 6.11. These are determined for varying levels of x (community share of battery) and percentage of profits paid by aggregator. It should be noted that for these simulations the aggregator participates in the day-ahead market, and is considered a price-taker with imperfect price forecasting; these are predicted using a 2-week rolling average.

In January when the aggregator pays 20% of their profits, the community make the greatest savings by having 90% access to their batteries and sharing 10% of them with the aggregator. However, as the percentage of aggregator profits paid increases, the community can improve their savings by allowing the aggregator increased access. For the case of a 60% profit payment, the community can make greatest savings by using 70% of their batteries and offering up 30% to the aggregator. For an 80% profit payment, greatest community savings are made when they use 50% of their batteries and offer up 50%. In this case, the households can improve their savings by an average of 13.2% compared with the no sharing scenario (x = 100%). It should be noted that these are conservative estimates of aggregator profits, since their profits could be improved with more sophisticated forecasting techniques and participation in other markets, such as intraday and the balancing mechanism.

For the months of June and September the average household savings, when the aggregator pays them 60% of their profits, are greatest when the aggregator has 10% access and no access to the storage, respectively; this can be seen in Figure 6.12. This may be due to the fact that during these months there is more solar generation, compared with January. According to data from the Met Office, the 10-year average of daily sun hours in Great Britain in January is 1.8 hours, compared with 6.8 and 5.1 hours for June and September respectively [210]. Therefore, during these months the households use their batteries more and can achieve greater electricity bill reduction, lessening the need for sharing with an aggregator. Although there are more sunlight hours, and hence solar generation, in June than September, there is less need for residential heating and lighting therefore electricity usage is lower in June. This may explain why the community bill savings with the storage are greater in September than in June, as electricity bills are higher in September.

A mutually beneficial sharing arrangement between community and aggregator could be established over winter months, when solar generation is low. This would allow the community to improve their monthly savings during the months when they get little use of their batteries.

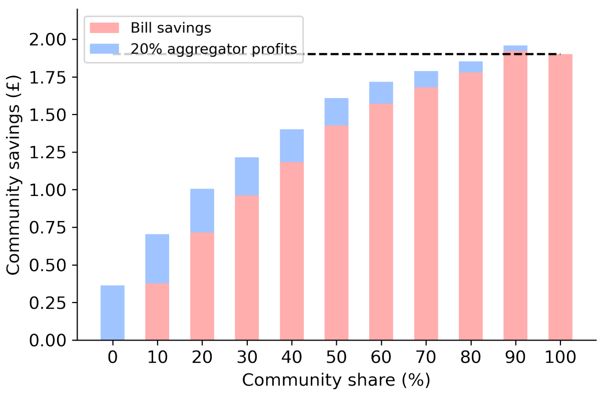



(a) Imported power

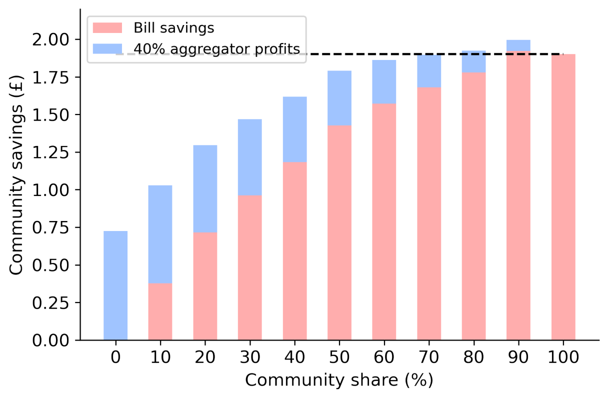


(b) Battery

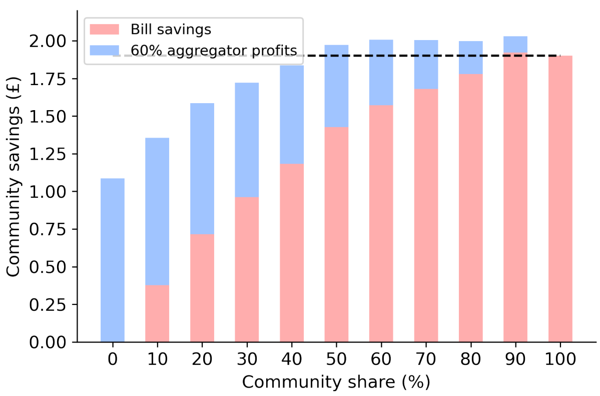
Figure 6.10: Top: imported power and generated PV for one household in June, dashed blue line is load which is satisfied using PV, battery and imported power; Bottom: power to and from the battery. Red areas represent times when electricity price is at peak.



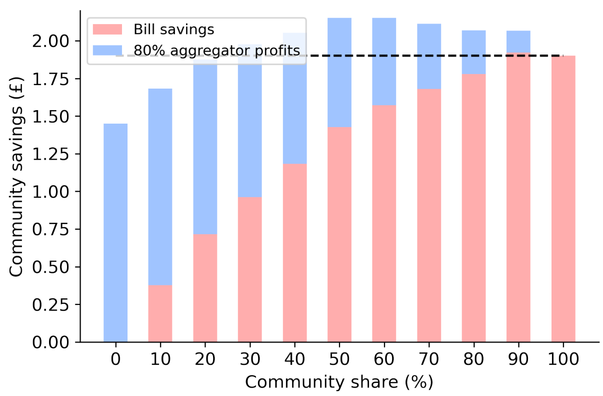

(a) 20%




(b) 40%

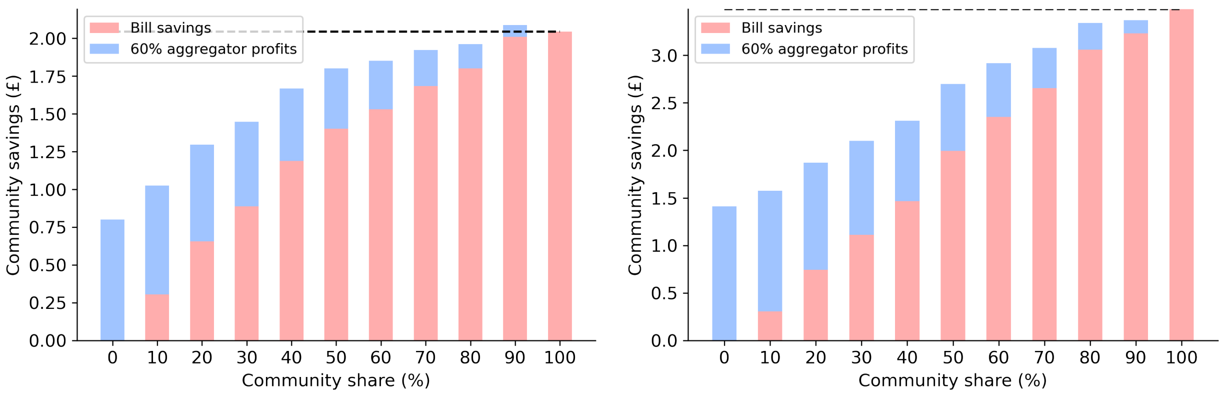



(c) 60%




(d) 80%

Figure 6.11: Average household savings in January 2019, relative to the case when they have no battery storage, as their share of the battery and the percentage of aggregator profits paid to the community are varied.




(a) June (b) Sept

Figure 6.12: Average household savings in June 2019 (left) and September 2019 (right), relative to the case when they have no battery storage, as their share of the battery is varied and the aggregator pays 60% of their profits.

The aggregator would get access to a proportion of battery storage for arbitrage, and would keep a share of the profits e.g. 40% or 20%, whilst paying the community 60% or 80% respectively. It should also be noted that for these calculations it has been assumed that the aggregator only participates in the day-ahead market with imperfect and simplistic price forecasting. In reality, if they were to employ more sophisticated forecasting models and participate in more markets, their profits and hence community savings could be improved. Additionally, the households are assumed to use a complex bill minimisation procedure (as shown in Figure 6.3) to schedule their share of the battery storage. If the households were to employ a more basic procedure for scheduling their batteries then their bill savings, compared with no storage, could be lower and hence the benefit of partially sharing with an aggregator would be increased.

This work may be applied to any location within the UK. The results might change slightly, due to different solar profiles in different locations. For example, in northern Scotland there are fewer daily sun hours in winter, compared with the chosen cluster in South-East England, and greater daily sun hours in summer. It is expected that the value brought by an aggregator in winter would therefore increase (due to the households having less usage of their batteries) and decrease in the summer (households having greater usage of their batteries). However, the general trend observed, that the sharing scenario could be a useful way to generate community savings over winter, is expected to hold in any location in the UK. This is since it is a relatively small country and weather patterns and seasons are generally similar throughout. Furthermore, this model could be applied to any other country or region where an aggregator can participate in wholesale arbitrage markets and residential households may make bill savings using battery storage.

## 6.4 Conclusion

In this work, the trading strategy of an energy storage aggregator is examined in GB's day-ahead and balancing markets under price-taker and price-maker scenarios. This was done by applying linear and quadratic optimisation models to examine the value derived by the aggregator, using energy storage for arbitrage in Great Britain's electricity markets. It was found that in the day-ahead market, the difference in profits between a price-taker and price-maker scheduling is negligible; for the balancing market, the price-maker scheduling can improve profits by 10.9%

for 500 MW storage when prices are perfectly forecasted. However, it is not realistic to assume perfect forecasting. A sensitivity analysis revealed that profits are most affected by battery efficiency - increased with increasing efficiency - and duration - decreased with increasing duration. Varying the load and whether or not actual prices are affected by the aggregator's bids had very little difference on overall profits.

This model was applied to a case study where a community of households with PV and battery storage allowed the aggregator partial access to the storage in exchange for a percentage of the aggregator's profits. The households used their own share of the storage to reduce electricity bills. Results showed that the greatest average bill savings were made in September, due to high solar generation and residential load. The lowest savings were made in January when the average daily hours of sunlight was low - 1.8 hours in Great Britain. In January, it was beneficial for households to allow the aggregator access to their storage. The aggregator was found to improve community profits by up to 13.2%. Additionally, it should be noted that this is a lower estimate of the value an aggregator could bring, due assumptions that the households were able to perform a complex bill lowering procedure, and that the aggregator only participates in the day-ahead market using a simplistic price forecasting technique.

The work in this paper may be applied in other locations; both in the UK and in other countries/regions where an aggregator can perform arbitrage in wholesale markets and communities can use battery storage for electricity bill reduction. In addition, it would be interesting to examine different forecasting methods for balancing market prices to try to improve the accuracy of forecasts and increase aggregator profits in this market in turn. Future work could also involve using other procedures to model household storage usage and bill savings. For example, employing a more simplistic approach to storage usage, such as charge during certain hours, discharge during certain hours. Additionally, exploring the effects of altering the size and duration of household batteries is of interest.

# Chapter 7

# To trade or not to trade: simultaneously optimising battery storage for arbitrage and ancillary services


## 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.


## 7.1 Introduction

### 7.1.1 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 [15]. 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 work suggests that renewable intermittency can be abated with the use of energy storage; [17] finds energy storage to increase the value of electricity generation, [211] finds it to reduce operational costs of a micro-grid, and [19] 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 [108] and [96] 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, [94] finds energy storage can provide inertial response and frequency regulation similar to that of conventional power plants, and [95] shows that it can effectively provide short-term frequency control. In [97] the authors find that it can smooth power fluctuations due to wind generation and consumer load, and [98] propose a model for energy storage to enhance smoothing of frequency fluctuations in power grids. Finally, [99] 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 [100], 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, [71], [74], [101]–[107]. 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 [101] and [102], 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 [74], 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 [103], 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 [104] use a stochastic process, to model market prices under uncertainty, then present an optimisation model for energy storage scheduling.

The authors of [105] take a different approach to this, using backward induction to determine a storage operator's optimum strategy in electricity and ancillary markets. In both [106] and [71], 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 [107] 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 [74] and [107] 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 [212] and [213] 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 [214] and [215] 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, [216] 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 $\approx 10$ 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.

### 7.1.2 Ancillary Services

A number of studies, for example, [217], [218] and [219], 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 [220]. 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 [221] 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 [222]. 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.

### 7.1.3 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 [199]. 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.

### 7.1.4 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 [223], [224] built a system for online auction fraud detection and [225], [226] 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 [227].

### 7.1.5 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 7.2 gives a description of the models used for market classification and battery optimisation. Section 7.3 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 7.4 presents the concluding remarks.

## 7.2 Model Description

### 7.2.1 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

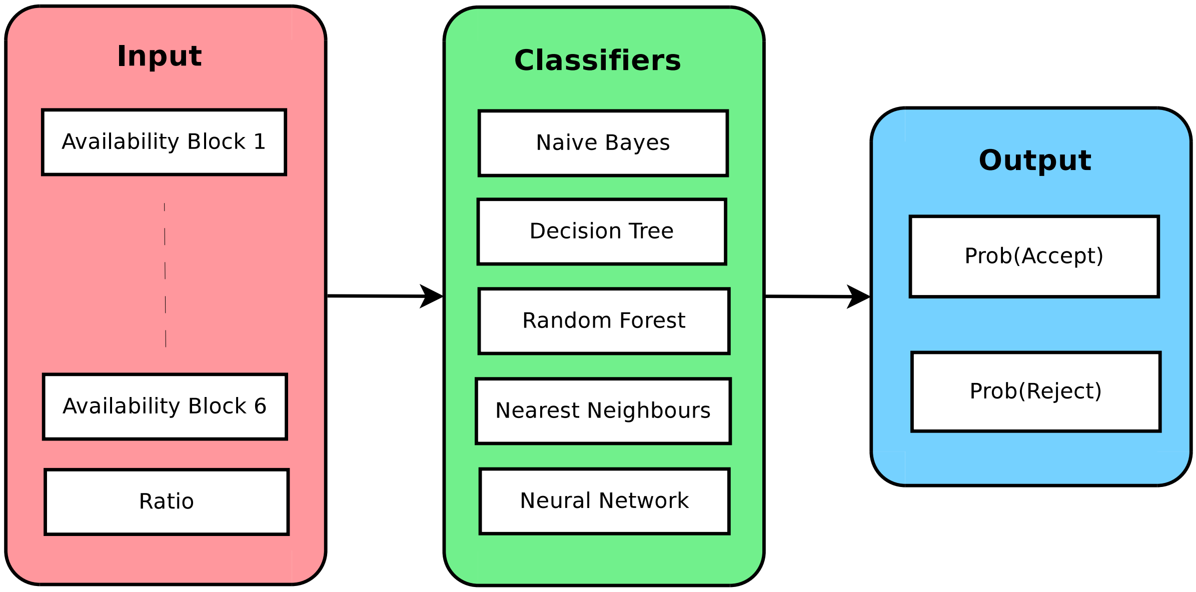



Figure 7.1: Schematic diagram showing inputs and outputs of classifier model

- 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 2020 falling outside of the range $2.5 \pm 0.05$. 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 [228]. Figure 7.1 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.

### 7.2.2 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 7.1 for lithium ion batteries. These values are derived from several literature sources [205], [206], [229] 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

Table 7.1: Values of storage parameters for a lithium ion battery.

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

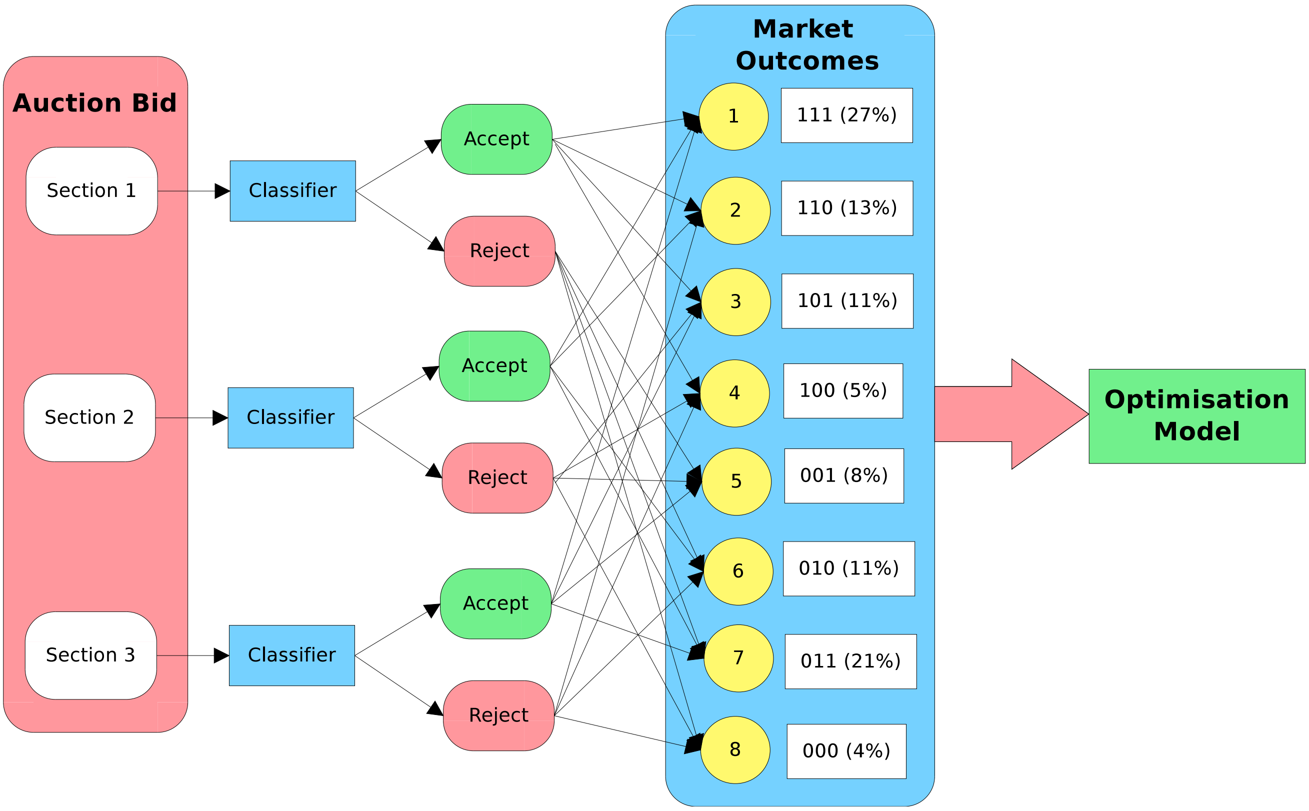



Figure 7.2: Schematic showing how auction bids (typically split into three parts) feed into the classifier resulting in various different market outcomes with associated probabilities. These are pushed through an MILP optimisation model.

auction outcomes which could occur due to combinations of different parts of the bid being accepted or rejected. These are summarised in Figure 7.2. 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 [194]; 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.

### 7.2.3 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.

The power used to charge or discharge the storage must remain within its maximum limits, as is expressed by Equations 8.1 and 8.2.

$$0 \leq P^c_{nt} \leq \bar{P}_n \qquad \forall\ n,t \tag{7.1}$$

$$0 \leq P^d_{nt} \leq \bar{P}_n \qquad \forall\ n,t \tag{7.2}$$

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: $\underline{X}_n$ 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 [230]. Equations 8.3 and 8.4 represent this mathematically.

$$\underline{X}_n \leq X_{nt} \leq \bar{X}_n \qquad \forall\ n,t \tag{7.3}$$

$$\underline{X}_n + \frac{P_n}{2} \leq X_{nt} \leq \bar{X}_n - \frac{P_n}{2} \qquad \forall\ n,t \tag{7.4}$$

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:

$$X_{nt} = X_{n,t-1} + \eta^c_n P^c_{nt} - \frac{P^d_{nt}}{\eta^d_n} \qquad \forall\ n,t \tag{7.5}$$

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

$$min \sum_{n,t} \underbrace{p^{DA}_t \left(P^c_{nt} - P^d_{nt}\right)}_{\text{Arbitrage}} + \underbrace{\lambda_{nt} t_{nt} \left(\alpha_{nt}\rho_{0.5} + \beta_{nt}\rho_{0.2}\right)}_{\text{FFR Penalties}} \tag{7.6}$$

subject to (8.1)-(8.3), (8.5). 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, $\lambda_{nt}$, 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:

$$\alpha_{nt} = \begin{cases} 1 & : \ X_{nt} \leq \underline{X}_n + \frac{P_n}{2} \\ 1 & : \ X_{nt} \geq \bar{X}_n - \frac{P_n}{2} \\ 0 & : \ else \end{cases} \qquad \forall\, n, t \tag{7.7}$$

$$\beta_{nt} = \begin{cases} 1 & : \ X_{nt} \leq \underline{X}_n + \frac{(P_n/2.5)}{2} \\ 1 & : \ X_{nt} \geq \bar{X}_n - \frac{(P_n/2.5)}{2} \\ 0 & : \ else \end{cases} \qquad \forall\, n, t \tag{7.8}$$

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 $\lambda_{nt}$ 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 [231] 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 $>$ ± 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 [231]. 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 ± 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.

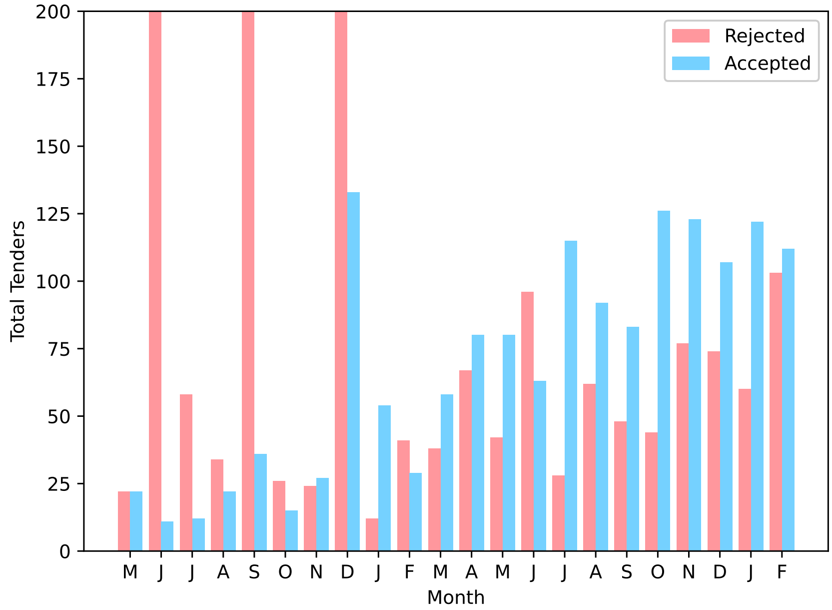
For the sake of simplicity the storage device will be considered a deterministic price-taker in the day-ahead market. In reality this is not the case, as explored in preliminary work. However, the difference between deterministic and non-deterministic revenue in the N2EX day-ahead market was found to 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.

# 7.3 Results and Discussion

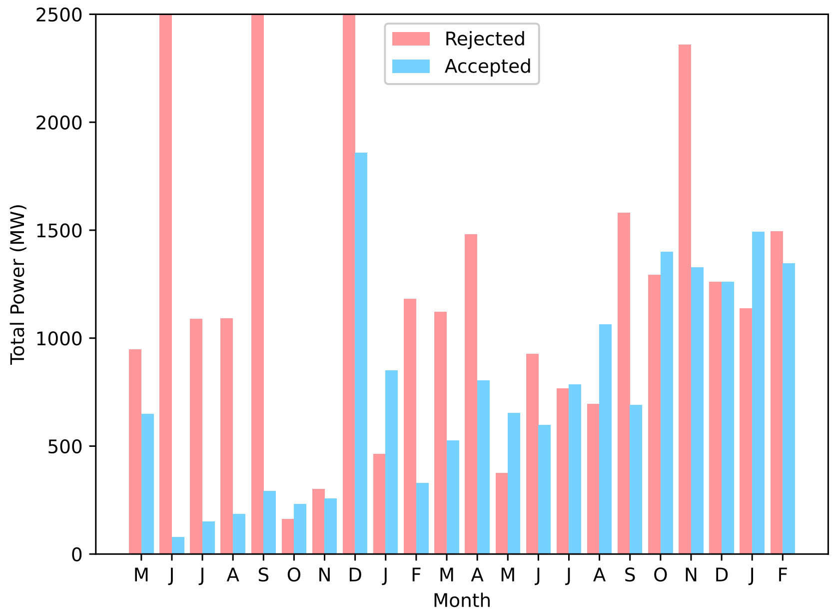
## 7.3.1 FFR Market Trends

FFR Post-tender reports were examined from May 2018 to February 2020. Figure 7.3 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 [232].

In Figure 7.4 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

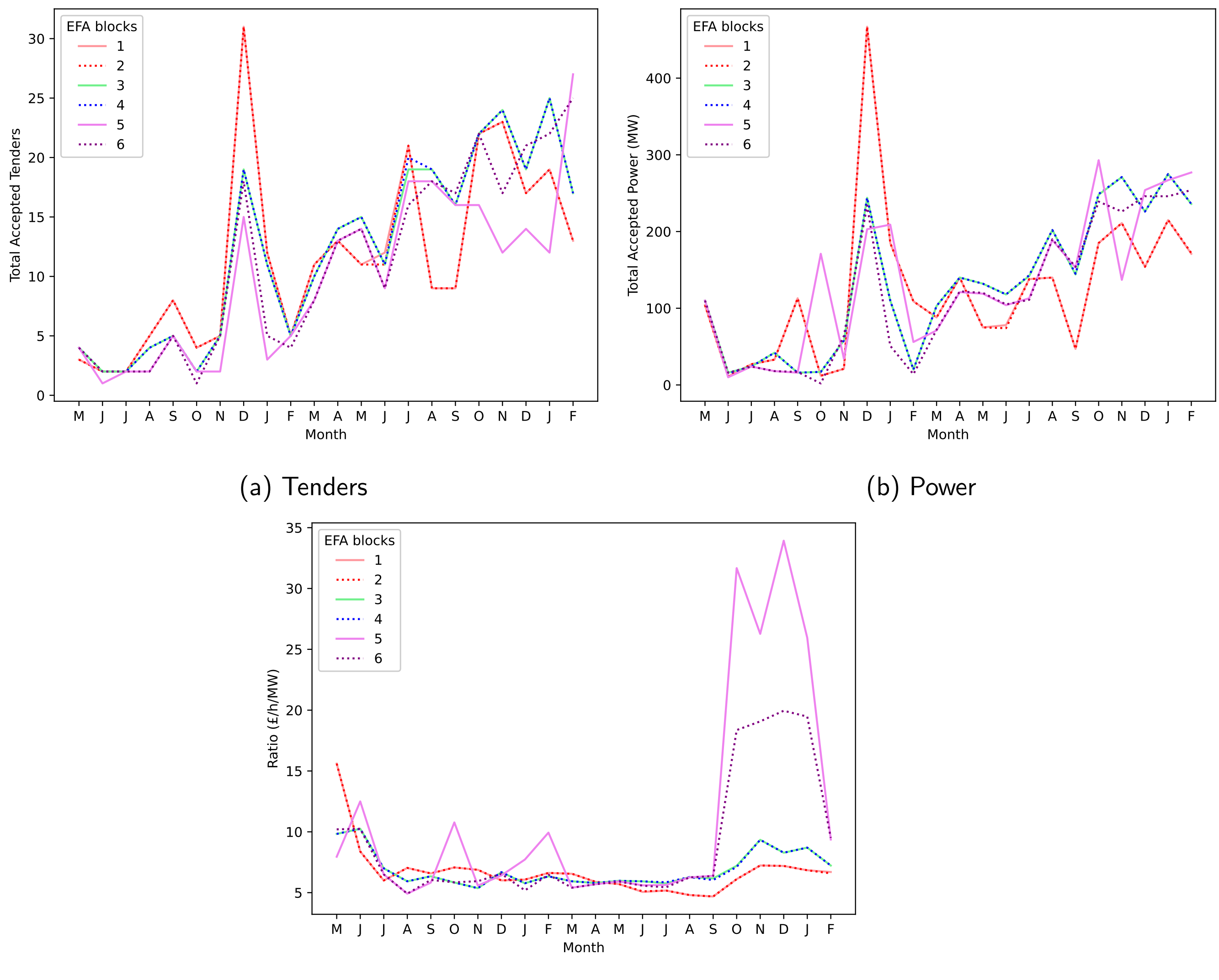



(a) Total accepted and rejected tenders (May 2018 - February 2020)




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

Figure 7.3: 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 7.4: Total accepted a) tenders, b) power and c) ratio of availability fee to power across the six EFA blocks (May 2018 to February 2020).

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 [230], 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 7.4c. 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 7.3.3. This will allow the optimisation and bidding strategy to be much more realistic than in previous ancillary service studies.

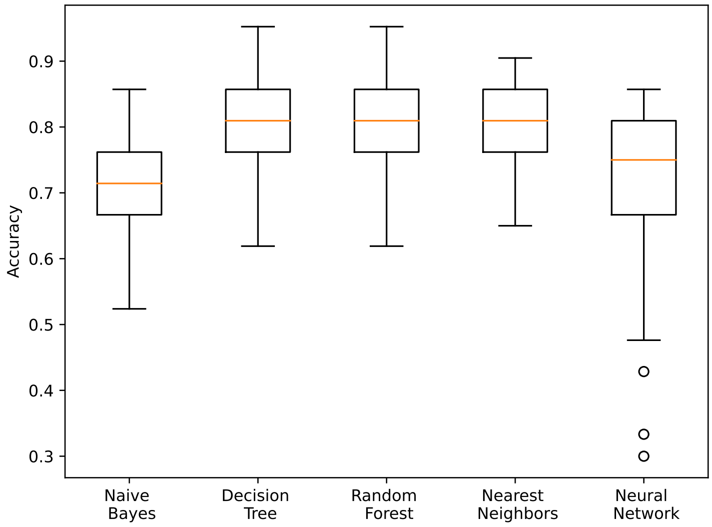



Figure 7.5: Accuracy score for different types of classifier based on January 2020 data.

Table 7.2: Accuracy of classifiers.

| Classifier | Accuracy | | |
|---|---|---|---|
| | December 2019 | January 2020 | 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 |

### 7.3.2 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 7.5. 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.

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 7.2. 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 7.6; red regions correspond to predictions of tenders being accepted, and blue regions to tenders rejected.

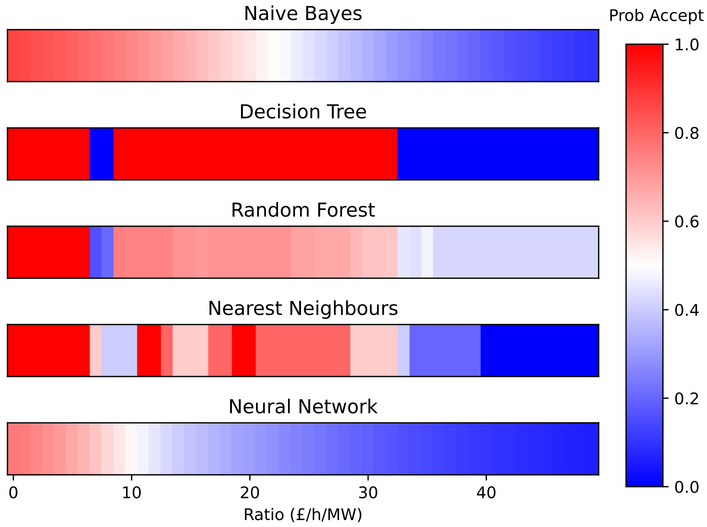



Figure 7.6: Probability of hypothetical tender acceptance, based on January 2020 data.

Since NG accept the tenders which are most economic for them [233], it would be expected that tenders with a smaller ratio have a higher probability of being accepted, and those with a larger ratio a 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 7.6). 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.

### 7.3.3 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 7.6. The storage device will be modelled as a lithium ion battery using parameter values given in Table 7.1; 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

Table 7.3: 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 |

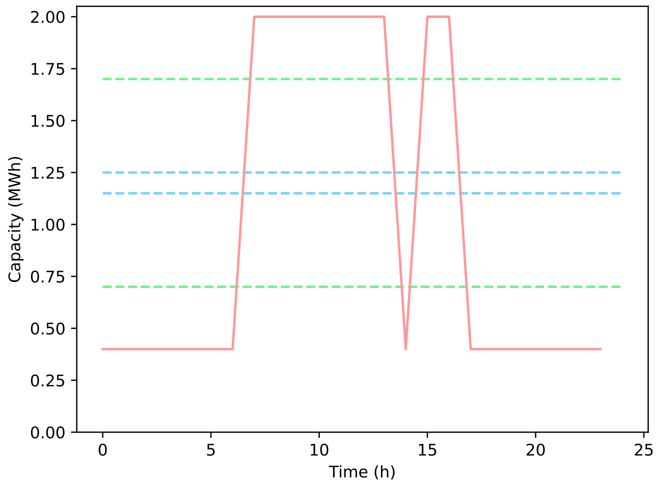
analysis outside the scope of this work. Values of 0.8 and 0.2 were chosen, respectively, for all the optimisations in this subsection: the effects of changing these are explored in the following subsection. These reflect the fact that frequency deviations of ¿ 0.5 Hz are unlikely, whilst deviations between 0.2 and 0.5 Hz have historically occurred on average twice a day [234].

Figure 7.7 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 7.7b at time periods 15-17.

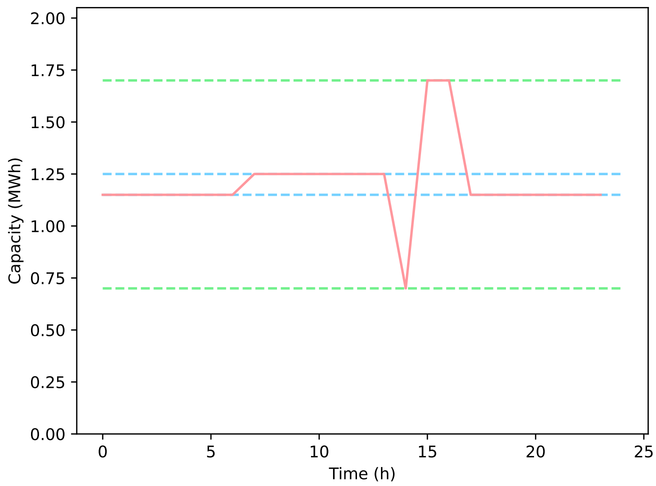
In Section 7.3.1, it was found that successful FFR tenders were split up into three separate parts for $B_{1\&2}$, $B_{3\&4}$, and $B_{5\&6}$. The highest Ratio was submitted for $B_{5\&6}$, and lowest for $B_{1\&2}$. Hence the storage device will submit tenders with this same structure. To determine 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 7.3.2 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 7.3. This information was then used to probabilistically generate 500 post-tender scenarios with 8 possible outcomes, as shown in Figure 7.2.

Figure 7.8 shows the results of generating these scenarios for the P = 1 MW case. Figure 7.8a displays the percentage of generated scenarios with each market outcome and Figure 7.8b 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 probabilities, respectively.

In Figure 7.8b, 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

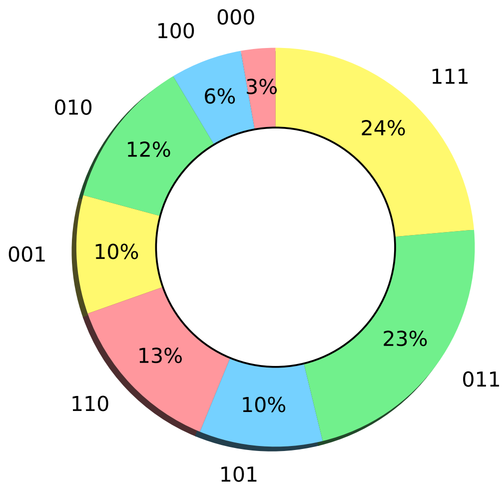



(a) Arbitrage

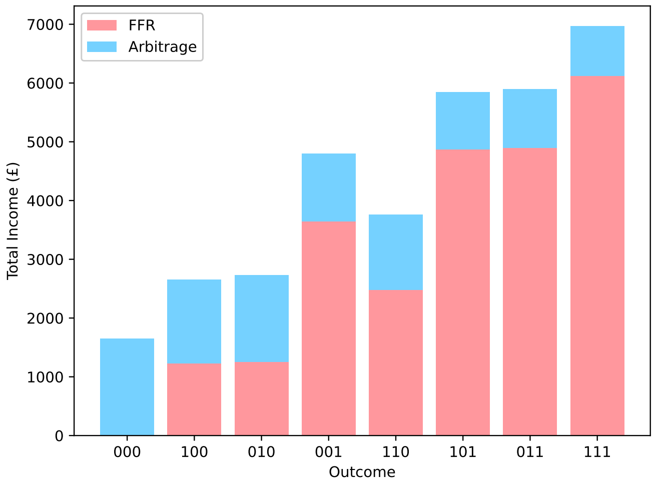



(b) Arbitrage and FFR services

Figure 7.7: Optimum daily capacity profile of battery storage device performing a) arbitrage and b) arbitrage and FFR services.




(a) Percentage of scenarios with each market outcome

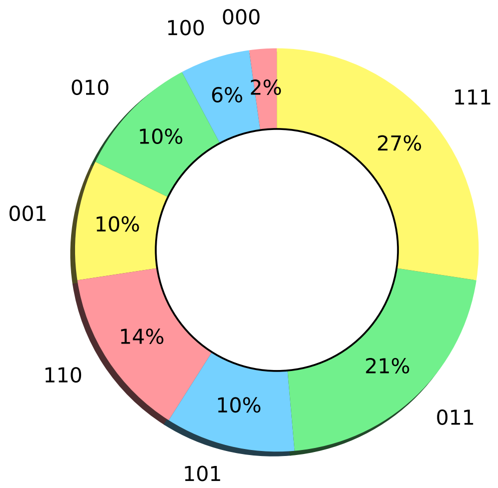



(b) Total Income

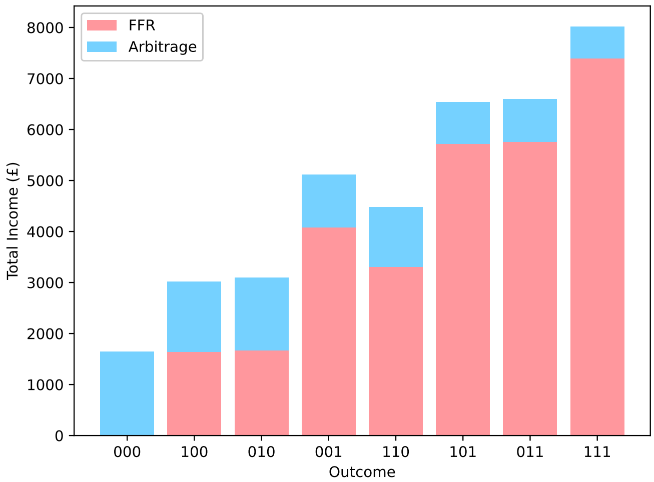
Figure 7.8: P = 1 MW case. Percentage of scenarios with each market outcome and the total income generated by FFR and arbitrage for each outcome.

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 7.9 and 7.10 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 7.3, are similar. Therefore these do not influence the




(a) Percentage of scenarios with each market outcome

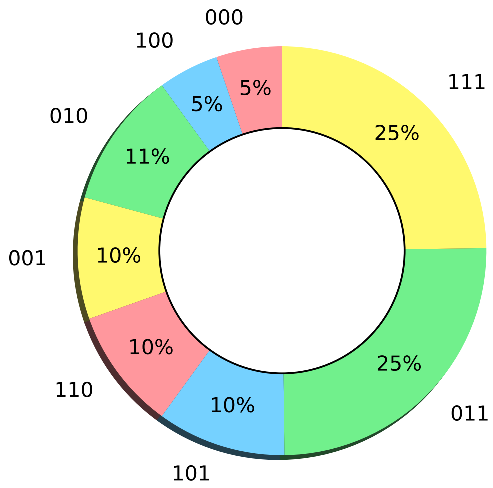



(b) Total Income

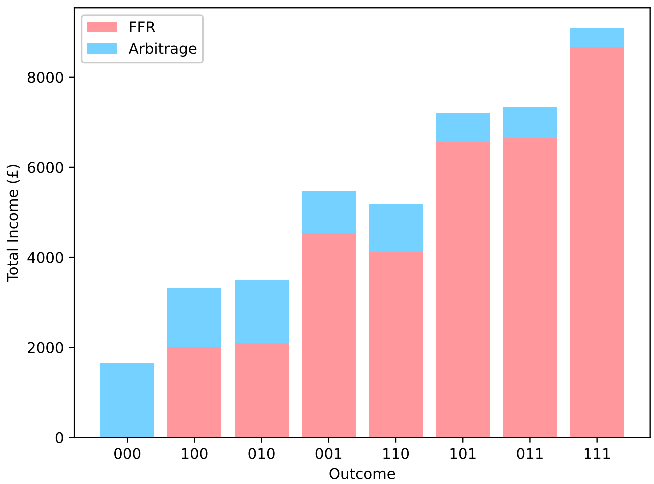
Figure 7.9: P = 1.25 MW case. Percentage of scenarios with each market outcome and the total income generated by FFR and arbitrage for each outcome.

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. This was then used to generate 500 scenarios, each with one of the 8 outcomes shown in Figure 7.2, 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 7.11, along with the probabilities of the worst-case outcome 000. The reference case is the one presented in Table 7.3 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 $X \in Z : Z \in [-1, 16]$.




(a) Percentage of scenarios with each market outcome




(b) Total Income

Figure 7.10: P = 1.5 MW case. Percentage of scenarios with each market outcome and the total income generated by FFR and arbitrage for each outcome.

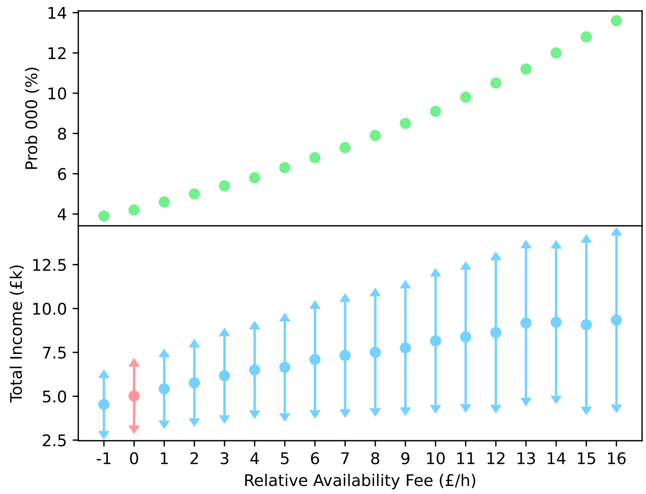



Figure 7.11: Above: Probability of outcome 000 occurring, as availability fee is increased. Below: Mean and standard deviation of the total income for 500 probabilistically generated scenarios using different availability fees.

Table 7.4: 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 |

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 7.4 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 7.3. 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%.

### 7.3.4 Real-Time FFR Provision

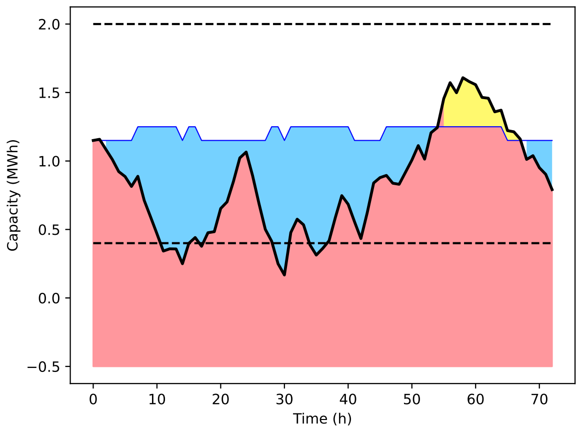
In order to determine the real-time FFR usage of an a battery storage device, grid frequency data from NG was analysed [230], [234]. This data has a one second resolution and gives the actual grid frequency in Hz. From this, the frequency deviation from 50 Hz each second was calculated; the response of the battery is proportional to this. The methodology for determining the corresponding storage power output/input is outlined in [216]. 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 7.2.3, 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 7.12. 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.

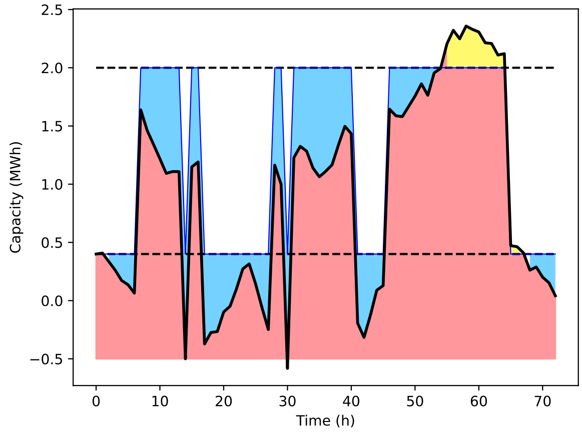
It can be seen that for values of $1/1$ for $\rho_{0.2}$ and $\rho_{0.5}$, the level of arbitrage is kept within a tight band around the capacity mid-point. As these are relaxed to 0.8/0.2, arbitrage occurs outside of this tight band, but within the upper and lower capacity limits. For values of 0/0 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 7.5 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 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.

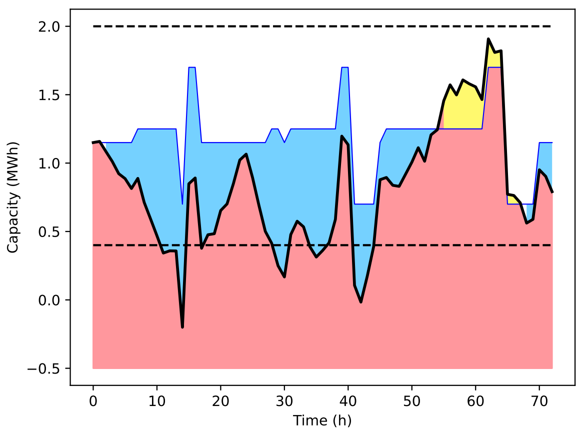
It must be noted that if storage owners repeatedly fail to provide frequency response when called upon, then they will incur a greater consequence than simply paying a penalty. As previously mentioned, if this happens on more than three occasions NG may consider the unit unsuitable to provide frequency 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 [216], 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.



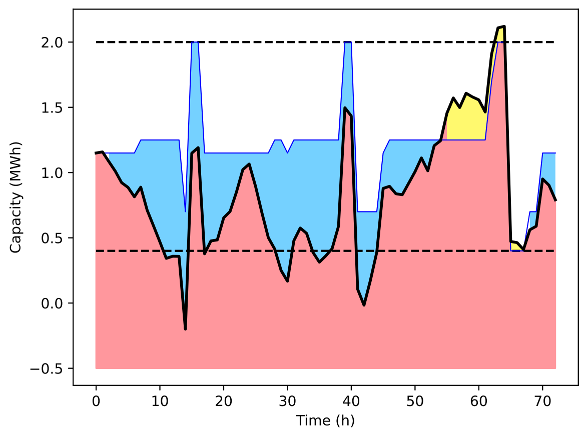

(a) 1/1




(b) 0/0




(c) 0.8/0.2




(d) 0.2/0.2

Figure 7.12: 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).

Table 7.5: 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 |

## 7.4 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.

# Chapter 8

# The economic impact of location on a solar farm co-located with energy storage


## Abstract

Deploying energy storage (ES), alongside renewable generation, can help to decarbonise electricity grids. A key aspect of deploying these is choosing a suitable location, which is both geographically feasible and economical. Previous studies identify locations with suitable geographies; here we focus on the economic impact of location. We explore how the maximised profits, determined using a mixed integer linear programming (MILP) optimisation model, of a solar farm co-located with ES vary in different regions around Great Britain (GB) as a case study. We perform a cost-benefit analysis from the point of view of a distribution-connected solar farm owner. Real solar generation data is used, along with a weather model, to accurately represent forecast and actual output. For solar farms without ES profits are higher in locations with greater solar irradiance. However for sites with ES we find greater profit variation, primarily due to different distribution charges. For the majority of GB, ES does not add sufficient value to offset its high upfront costs and is not worth adding to solar sites. Additionally, it is found to be uneconomical to add ES to most existing solar farms, despite many studies highlighting the grid benefits this would bring. We recommend that distribution network operator and market pricing better reflects the value which ES can bring to the electricity system economical to add to solar sites. To encourage increased co-location distribution operators should offer greater a differential between non-intermittent generation and intermittent generation payments, in particular at times of high system demand.



### Key Words

Energy Storage; Solar PV; MILP Optimisation; Locational Study; Local Constraints


## 8.1 Introduction

### 8.1.1 Overview

Climate change is a major geopolitical issue, and the transition from fossil fuels to renewables is crucial [9]. Solar photovoltaics (PV) are a key component of this transition, accounting for

11% of renewable electricity generation in the UK [235]. Energy storage (ES) is also important, as it can mitigate fluctuations in renewable output and enable optimal use of variable electricity sources [236]–[238].

ES can be economically beneficial for renewable generators and grid operators by creating value through energy arbitrage and lowering system costs [239].

Co-locating ES alongside renewables can also provide additional benefits such as attractive economics, improved operation, and reduced power curtailment. In this work, we explore the economic impact of location on solar PV farms co-located with ES in Great Britain, to assess the feasibility of deploying ES under current market conditions. Whilst ES does not necessarily need to be co-located alongside renewable generation to reap aforementioned grid benefits, there are other unique advantages to co-location. These include attractive economics, through shared inverters and grid connection costs, and improved operation, such as the battery capturing clipped power that may otherwise be lost [109], [110]. Co-locating ES alongside renewables can also reduce power curtailment [111].

In this work we will explore the economic impact of location on solar PV farms co-located with ES across Great Britain (GB). We will calculate the maximum obtainable income with and without ES, and hence the value it can bring. The aim is to study how feasible it is to deploy ES, particularly alongside solar PV, since previous work has shown how important this for decarbonisation, improving power quality and reducing grid system costs. The following section will explore literature on the topic of optimising the location of solar farms and the scheduling of co-located ES and solar.

### 8.1.2 Literature Review

The optimal choice of location for solar farms is a research area currently receiving a great deal of attention, for example [120]–[127]. These studies can be broadly split up into two categories: those that consider location within an electrical network, and those that consider geographical location. The first category optimises locations of power-grid connections, to reduce power losses and improve voltage profile [120], [121], the latter of which presents a novel algorithm to improve system performance, and to minimise connection costs [122]. These studies are valuable from purely a grid point-of-view; however, they do not consider factors such as geography, weather and socio-economics, which may vary regionally and affect optimal choice of location.

In the second category, the studies look at large areas; for instance, the authors of [123] and [124] study the optimal locations of PV in Brazil and PV-wind hybrid in Iran, respectively. Both use Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) to rank locations according to factors such as climate, environment, geography and economics. Other papers using similar ranking methods include [125] and [126], which study the deployment of solar farms in India and Bali, respectively. In [127], the authors use GIS analysis to identify suitable locations for solar farms in the UK; they find that by not considering local planning permission and grid constraints, area overestimations may occur up to 97%.

Few studies have explored the optimal location for solar PV farms co-located with energy storage (ES), with most focusing solely on solar. Some studies, such as [128] and [129], consider network connection optimization rather than geographical location. Another study, [130], models the performance of solar and molten salt storage in three locations in Egypt. However, these studies are limited in scope and do not consider differences in geography or weather. Studies such as [131] and [132] explore the optimal battery size in different locations but only on a small scale. It is important to investigate the impact of location on a larger scale, considering numerous possible sites throughout the country.

Recent developments in energy storage (ES) technology are important for optimizing the location of ES with solar. Reviews on ES technologies, such as [240] and [241], should be taken into account. Lithium ion batteries are found to be more efficient than lead acid and flow batteries, with flow batteries having the greatest number of cycles. Costs of lithium iron phosphate, lithium nickel manganese cobalt oxide, and lead acid batteries are similar, with LFP being slightly more economical. Redox flow batteries are less economical. Whilst this study focuses on co-located battery storage with solar, it should be noted that the methodology can be applied to other types of storage.

Optimised ES scheduling is crucial to maximise profits for the solar co-located site. Mixed Integer Linear Programming (MILP) and Convex Optimisation (CO) algorithms are used in [242] and [243] to minimise the electricity bills of consumers on particular tariffs with access to solar and storage. Larger grid-scale systems with access to wholesale markets, as considered in this work, are studied in [69] and [70]. The latter uses a Model Predictive Control (MPC) algorithm to optimise ES in day-ahead and real-time wholesale markets. Other studies expand upon these by including market uncertainties [72], [73] and battery degradation [214], [215]. However these studies do not consider batteries co-located with solar. In [244] they optimise the economics of lithium ion and lead acid batteries co-located with grid connected solar with consideration of degradation. They find that the levelised cost of energy and net present cost of energy are lower for the lead acid battery, suggesting that this is the more economical battery chemistry to use in combination with grid connected solar.

Finally, there are several methods for calculating the value added by ES (in this case, by co-locating it with solar); these can be split into different categories. In [245], [246] and [244] they present a Net Present Value (NPV) analysis to assess the value of ES performing arbitrage and different batteries in distribution substations, respectively. On the other hand, [247] and [244] present methods to calculate Levelised Cost of Storage/Energy (LCOS/LCOE), respectively, in order to compare the effects of different technical characteristics of ES on its economics. Another method to assess the value of storage is Real Options (RO) analysis, as considered in [2], [248] and [249]. Since NPV is the most ubiquitous method, it will be used here.

### 8.1.3 Locational Factors GB

The criteria for solar farm site suitability in the UK is presented in [127]; these are geographical (including land slope), weather related and constraints due to network connections. Since this work is interested in identifying the optimal region, which will be a large area rather than a specific site, finer details such as distance from network connections, rivers, woodland and urban areas will be omitted. Additionally, as the aim is to find the region where profits can be maximised only factors affecting this will be considered. These are:

- Weather - Solar irradiance and cloud cover will affect solar farm power output, and hence total income made through selling this in wholesale markets.
- Regional Electricity Grid Charges - These are outlined subsequently and will also affect the total income.

In common with other countries, in GB there are a number (14) of licensed DNOs (Distribution Network Operators), illustrated in Figure 8.1, which are responsible for the distribution of electricity around a particular region of the national grid. These are operated independently and hence each DNO may impose a different set of charges on the distribution grid users, which may be consumers or generators. This is particularly important because a solar farm may face different charges for exporting power depending on which DNO region it is located in [119].

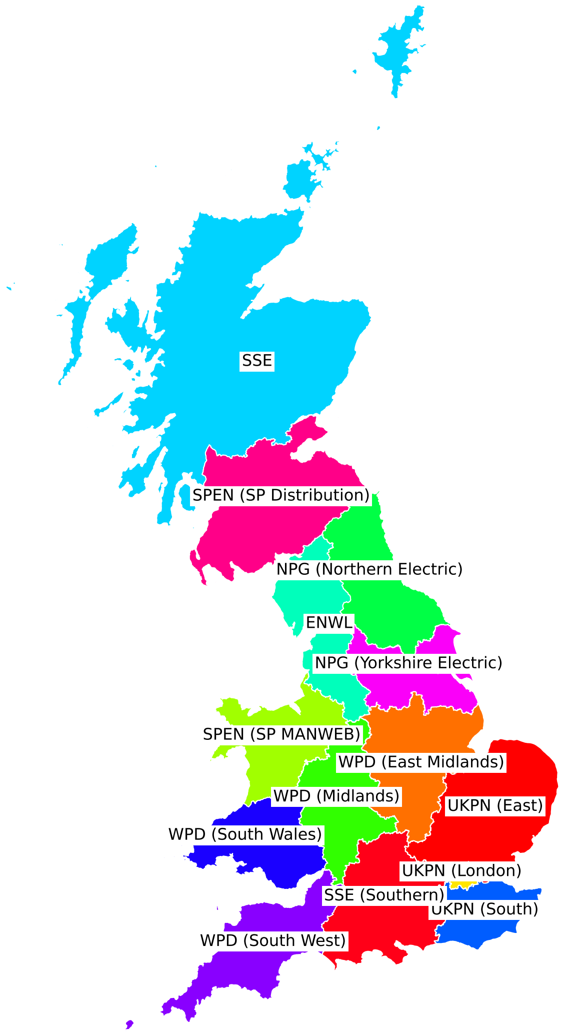



Figure 8.1: Map showing the 14 different DNOs and their regions in GB.

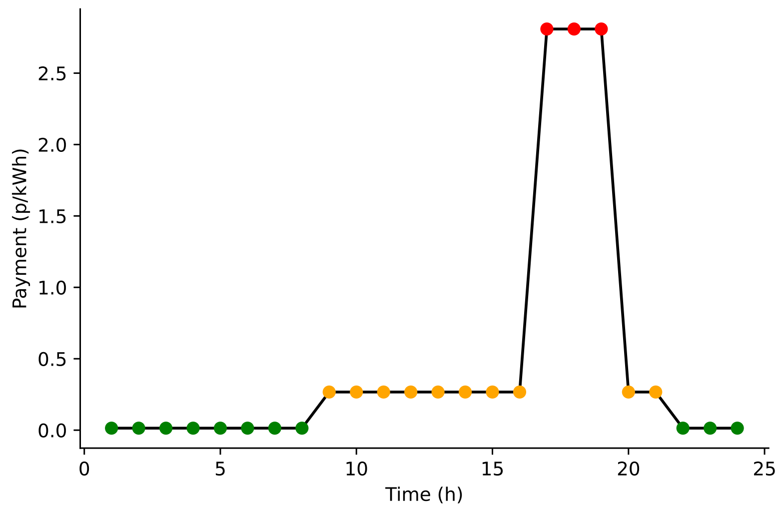



Figure 8.2: Red, amber and green time bands for Western Power Distribution (East Midlands)

Information on Use-of-System charges imposed by each DNO can be found on their websites [250]–[255]. Negative charges are given to generators for exporting power to the distribution networks, with intermittent generators receiving a set payment and non-intermittent generators receiving varying payments following a red, amber, and green charging structure. Figure 8.2 shows this for Western Power Distribution (East Midlands). It should be noted that at weekends these payment structures differ slightly: there are normally no red time bands. Weekly time series of payments were generated for each DNO, considering the full weekly structures.

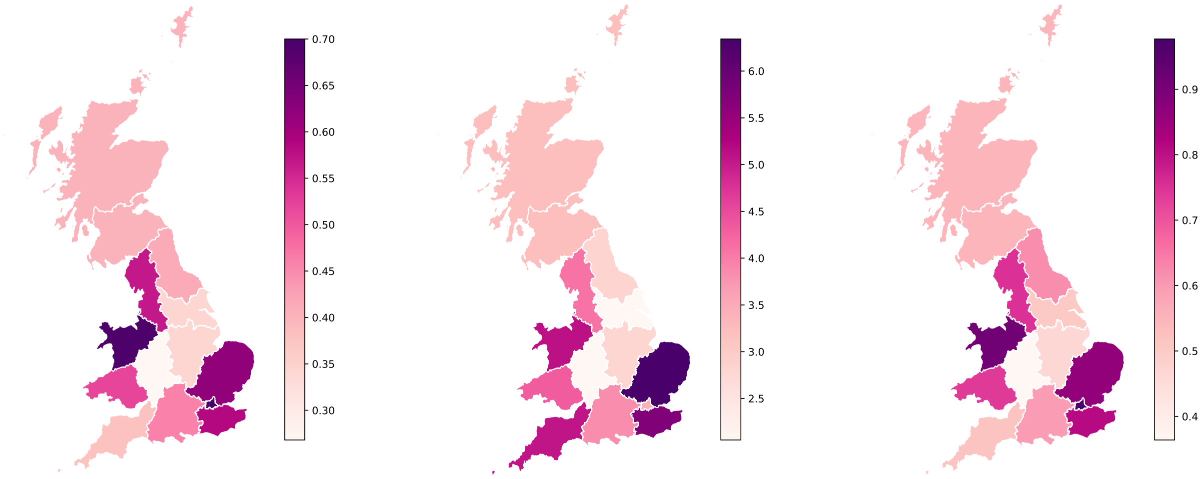
In Figure 8.3 the payments received by the different generator types are shown for the different DNO regions. It can be seen that there is a distinct difference between the payments received in the different regions for both intermittent and non-intermittent generators. Additionally, the mean payments received by non-intermittent generators is greater than for intermittent, and the red time band payments are significantly greater. Since ES is defined as non-intermittent [256], by co-locating storage with solar the red payment band can be taken advantage of.

### 8.1.4 Contributions of this Work

This work builds upon grid scale battery storage optimisation models in the literature, such as [70], and co-located with solar, in as [244]. Whilst many research papers have answered the question - what's the best way to use batteries to generate revenue? Far fewer papers have considered - where is the best location to locate a battery to generate revenue? Yet, location is an important factor to consider when it comes to practically deploying these devices.

Novelty lies within the exploration of how the battery's economics varies with its location on country-wide scale. This work addresses a gap in the literature - previous studies optimising the location of solar with battery storage are few and far between, and limited to a local scale, or else limited to a small number of possible locations. It brings together two important deployment considerations usually studied separately: economics and location. Another key strength is that the model can easily be replicated and applied to different case studies, making it a useful tool for decision-making for battery storage projects. Additionally, it has implications that are important to solar farm owners and investors interested in this technology, and policy-makers wishing to predict the future solar-storage landscape. The novel contributions of this work are as follows:

- This study will explore the economic impact of location on solar co-located with storage on a large, country-wide scale considering a large number of possible sites. Specifically, it




(a) Int (b) Max (c) Mean

Figure 8.3: DNO payments (p/kWh) for intermittent generators (Int), non-intermittent generators red band (Non-Int Max) and non-intermittent generators mean (Non-Int Mean).

studies Great Britain (GB) using historical solar generation data and corresponding market price data from 2016-2017, with locational charging prices from the most recently available reports (2020-2021).

- A novel MILP optimisation model is introduced to determine the scheduling of ES with solar which maximises profits in day-ahead and balancing markets, whilst considering location dependent distribution grid charges. This is a non-deterministic model with solar output and market prices unknown ahead of time.

- The locational study will examine the effects of changing ES size (maximum power and capacity rating) on its NPV in different regions, to determine optimal size to maximise value.

The rest of this paper is structure as follows: Section 2 presents the methodology, this includes prediction models for solar output and market prices, as well as the MILP optimisation model; Section 3 presents the results and discussion; finally, Section 4 presents the conclusions and future work.

## 8.2 Methodology

In this section we firstly outline the source and manipulation of the solar data, and the weather model applied to predict solar generation. Then we discuss electricity markets in Great Britain and the methods employed to predict prices. Next, we present models to optimise co-located ES revenues in the day-ahead and real-time markets. Finally, we outline how we determined the economic feasibility of installing ES in each location.

### 8.2.1 Solar Sites

Data regarding 150 solar panel sites in GB has been provided for this work [257]. The data set contains information about location, size and hourly generation (from 2016-2017) for each site. For this work each of these solar sites is scaled up to have the same maximum power output (1 MW - as this is representative of a distribution connected solar farm [25]) so that direct comparisons between sites can be made. The co-located ES will be smaller than the maximum solar output, since average yearly solar in GB has a load factor of 0.112 [235]. Preliminary analysis of solar data suggests that the storage should be sized on the order $10^{-1}$ MW for a 1 MW sized solar farm.

In [258] a weather model is developed and used to predict hourly solar generation for each of these sites using information about their location, size and elevation. It uses a Gradient Boosted Tree machine learning model (based on methods in [259], [260]) that was trained using historical weather forecast and solar outturn data to forecast solar outturn and, therefore, solar PV generation at different sites in the UK. The weather forecast data included irradiance, air temperature, humidity, wind speed, and wind direction (data from the European Centre for Medium-Range Weather Forecasts [261]). It was found that including all of these variables improved accuracy. The model also considered time of day, year, and solar geometry, as well as time-lagged variables to improve performance further.

### 8.2.2 Electricity Markets

Energy trading can occur bilaterally or on exchanges. A bilateral contract is an agreement between two parties (eg. a supplier and generator) to exchange energy under a set of specified conditions [64]. These are difficult to model as data is not readily available. In GB the two main exchanges are European Power Exchange and Nord Pool (N2EX) where electricity can be traded for next day delivery and usage [65]. Within each of these exchanges electricity can be sold in a day-ahead auction market (which closes one day ahead of delivery at 9:50am UK time), or an intra-day market (where trading occurs continuously up to one hour before delivery). The day-ahead market is much more liquid than the intra-day market, which means that market price is more likely to reflect intrinsic value [66]. Additionally, prices are less volatile in the day-ahead market, hence this is less risky for participants to trade in and will be considered here rather than the intra-day market.

In real-time, it is up to National Grid to balance supply and demand on a second-by-second basis. It does so by accepting offers (generation increases and demand reductions) and bids (generation reductions and demand increases) made in near real-time. This is referred to as the Balancing Mechanism. Balancing Mechanism trading is performed in half hourly intervals and market closure to submit bids/offers is 30 minutes before the start of each interval. For a solar generator that has sold its predicted output in the day-ahead market, it must settle any discrepancies in actual output in the balancing market.

When solar is co-located with ES there is the option to shift energy trading to times when prices are more advantageous; the optimisation procedure to maximise profits through this means is presented in the following section. Since market prices are not known in advance, they must be predicted. Day-ahead market prices generally follow a certain daily pattern and hence can be predicted reasonably accurately using a simple 7-day rolling average method. The MAPE (Mean Absolute Percentage Error) for this method using N2EX data from 2016 to 2018 was found to be $11\%$ [194]. Balancing market prices are very difficult to predict. Some studies in the literature use SARIMA (Seasonal Auto-regressive Integrated Moving Average) models [200], [201]. However, when this was tested on National Grid's Balancing Mechanism it did not perform well [199]. A

SARIMA(2,1,2)(0,1,2,24)[1] model was found to give an RMSE (Root Mean Squared Error) of 99.7, whereas simply using the same predictions as for the day-ahead market gave an RMSE of 34.4. It is not unreasonable to assume that these two markets will follow similar patterns, since hours with greater electricity demand (and hence higher prices) may be more likely to have greater discrepancies in real-time. Hence, the 7-day rolling average day-ahead values were used as predicted prices for both markets.

### 8.2.3 Day-ahead optimisation model

This section presents the MILP optimisation model used to maximise the day-ahead profits of ES co-located with solar in GB, with consideration of local DNO pricing structures. The equations governing the MILP are outlined as follows. Equations 8.1 and 8.2 ensure that the power used to charge/discharge each ES, n, at time, t, does not exceed its maximum limit.

$$0 \leq P^c_{nt} \leq \bar{P}_n \qquad \forall\, n, t \tag{8.1}$$
$$0 \leq P^d_{nt} \leq \bar{P}_n \qquad \forall\, n, t \tag{8.2}$$

The capacity of each ES at the end of time period, $t$, is described by Equation 8.3; it depends upon the capacity at the end of time period $t-1$, plus/minus the effects of charging/discharging in the current time period. Equation 8.4 maintains capacity within its maximum and minimum limits, and Equation 8.5 states that charging power may not exceed predicted solar output power.

$$X_{nt} = X_{n,t-1} + \eta^c_n P^c_{nt} - \frac{P^d_{nt}}{\eta^d_n} \qquad \forall\, n, t \tag{8.3}$$
$$\underline{X}_n \leq X_{nt} \leq \bar{X}_n \qquad \forall\, n, t \tag{8.4}$$
$$P^c_{nt} \leq \hat{S}_{nt} \qquad \forall\, n, t \tag{8.5}$$

Power exported to the grid is described by Equation 8.6, and is equal to predicted solar output, minus ES charging and plus ES discharging.

$$\hat{P}^{exp}_{nt} = \hat{S}_{nt} - P^c_{nt} + P^d_{nt} \qquad \forall\, n, t \tag{8.6}$$

Finally, the objective function is given by Equation 8.7; it maximises day-ahead profits, due to predicted market prices and time-band dependent DNO payments, subject to equations (8.1) - (8.6).

$$\mathit{max} \sum_{nt} \Big( \hat{p}^{DA}_t + \sum_r \mu_{rn} p^{DNO}_{rt} \Big) \hat{P}^{exp}_{nt} \tag{8.7}$$

### 8.2.4 Real-time optimisation model

For the real-time optimisation, the MPC algorithm proposed in [70] is adopted and developed here; it works by implementing the following algorithm.

[1]Other SARIMA models were tested on September 2016 data however this one was chosen as it had the lowest AIC (Alkaike Information Criterion) value.

**Algorithm 2** Real time optimisation

**Solve** DA model for all $t \in T$ **while** $t \in T$ **do**

**Obtain** solar output at current time period $S_{nt}$ **Forecast** real-time settlement price $\hat{p}_t^{BM}$ at current time $t$, and future solar generation and price: $\hat{S}_{nt}$, $\hat{p}_{t'}^{BM}$ at time $t' \in T''$ where $T'' = \{t+1, ..., t+24\}$ **Solve** real time optimisation model:

$$\begin{aligned} \textit{max} \sum_n \Bigg[ \Big( \hat{p}_t^{BM} + \sum_r \mu_{rn} p_{rt}^{DNO} \Big) (P_{nt}^{exp} - \hat{P}_{nt}^{exp}) \\ + \sum_{t'=t+1}^{t+24} \Big( (\hat{p}_{t'}^{BM} + \sum_r \mu_{rn} p_{rt'}^{DNO}) (P_{nt'}^{exp} - \hat{P}_{nt'}^{exp}) \Big) \Bigg] \end{aligned} \tag{8.8}$$

subject to equations (8.1) - (8.4) for $T' = \{t, ..., t+24\}$, equations (8.5) - (8.6) for $T'' = \{t+1, ..., t+24\}$, and:

$$P_{nt}^c \leq S_{nt} \qquad \forall\, n, t \tag{8.9}$$

$$P_{nt}^{exp} = S_{nt} - P_{nt}^c + P_{nt}^d \qquad \forall\, n, t \tag{8.10}$$

$t = t + 1$

**end**

Optimisations are carried out over 1 year from November 2016 to November 2017, corresponding to the solar data. Day-ahead and balancing market price data corresponding to this (November 2016 to November 2017) is used, since it is more realistic to use price data corresponding to the same time periods as the solar generation data. This is because factors affecting solar output, such as weather, will also affect market prices (via change in electricity demand and national renewable generation) and this needs to be taken into account.

The DNO payment data is taken from the most recent reports (2020-2021). We use more recent data for DNO payments, since these payments are decided upon before the start of each year and do not vary with factors such as solar output. Therefore, more recent data is preferred to capture more recent trends in use-of-system charges. On the other hand market prices, such as day-ahead and balancing market prices, may vary as a function of solar generation/weather; hence, day-ahead and balancing market prices need to correspond to solar generation data. The resolution of this model is hourly, since both day-ahead market prices and solar generation data have hourly resolution. Balancing market prices are half-hourly, therefore every other price, corresponding to half past the hour, was omitted. Most DNO time bands start and end on the hour; any other time band commencements not on the hour were rounded to the nearest hour.

In the optimisation models for both day-ahead and real-time markets, we assume that future prices and solar generation are unknown and we lack perfect knowledge of the future, which reflects the real-world operation of an ES optimiser. We also assume that the ES trading has no impact on prices and is considered a price-taker rather than a price-maker, which is valid when traded volumes are small relative to the total market. Previous research has shown that when price forecasting is imperfect, there is no significant difference in modelling storage as a price-maker or price-taker for storage capacities up to 500 MW in both day-ahead and real-time markets [3]. For the sake of simplicity the ES is modelled as a price-taker.

Table 8.1: Costs associated with installation and maintenance of lithium iron phosphate (LFP) and lithium nickel manganese cobalt oxide (NMC) batteries, and their lifetime, in 2020 and estimates for 2030 in brackets [204]. A conversion of $\$1 = £0.78$ is used to convert these to pounds.

| | LFP | NMC |
|---|---|---|
| Storage Block (\$/kWh) | 182 (109) | 194 (116) |
| Balance of System (\$/kWh) | 42 (30) | 37 (26) |
| Power Equipment (\$/kW) | 85 (73) | 85 (73) |
| Controls and Communication (\$/kW) | 40 (28) | 40 (28) |
| System Integration (\$/kWh) | 50 (36) | 51 (42) |
| Construction and Commissioning (\$/kWh) | 61 (50) | 63 (51) |
| Project Development (\$/kWh) | 73 (60) | 75 (62) |
| Grid Integration (\$/kW) | 31 (25) | 31 (25) |
| Operations & Maintenance Fixed (\$/kW-yr) | 4.40 (3.61) | 4.51 (3.70) |
| Operations & Maintenance Variable (\$/kWh) | 0.5125 | 0.5125 |
| Lifetime | 10 | 10 |

### 8.2.5 NPV calculations

The economic viability of installing ES in each location is also explored through calculations of its Net Present Value (NPV). This is of interest when a) deciding whether the install ES with a pre-existing solar farm, or b) deciding whether or not to include ES in plans for an upcoming solar farm. In [204] they present a report summarising a cost analysis of ES technologies based upon 2020 data, along with estimates for 2030. These were projected from the 2020 values by considering each technology's current state of development and using low, medium and high learning rates. Data was obtained from an extensive study of the literature, conversations with vendors, and responses to questionnaires.

The installation and maintenance costs associated with lithium iron phosphate (LFP) and lithium nickel manganese cobalt oxide (NMC) batteries is presented in Table 8.1. This is shown for 2020, with estimated values for 2030 in brackets. It can be seen that the prices of these batteries are incredibly similar; for the purposes of this work LFP batteries will be considered, since they perform the same or better than NMC on all cost metrics except for $C^{BOS}$. The typical lifetimes of these batteries are given in Table 8.1; they can also be calculated as the amount of time before capacity degrades to 80% of its initial value. The installation cost associated with ES, n, is shown in Equation 8.11, and the yearly maintenance costs for year, y, in 8.12.

$$C_n^i = (C^{SB} + C^{BOS} + C^{SI} + C^{PD} + C^{CC})\bar{X}_n + (C^{PE} + C^{COMS} + C^{GI})\bar{P}_n \qquad \forall\, n \tag{8.11}$$

$$C_{ny}^m = C_y^{OMV}\bar{X}_n + C^{OMF}\bar{P}_n \qquad \forall\, n \tag{8.12}$$

The NPV of an ES project can be calculated using the following equation:

$$NPV_n = -C_n^i + \sum_{y=1}^{Y} \frac{(I_{ny} - C_{ny}^m)}{(1+r)^y} \qquad \forall\, n \tag{8.13}$$

where $r$ represents the discount rate and $Y$ the end of project lifetime in years. The cash flow is equal to yearly ES income minus operations and maintenance costs, where yearly income is shown in Equation 8.14 and is comprised of income from 1) the day-ahead market, 2) DNO payments and 3) the balancing market (this may be negative). In the final year the ES's residual value is also included as income; this is shown in Equation 8.15.

$$I_{ny} = I_{ny}^{DA} + I_{ny}^{DNO} + I_{ny}^{BM} \qquad \forall\, n \tag{8.14}$$
$$I_{nY} = I_{nY}^{DA} + I_{nY}^{DNO} + I_{nY}^{BM} + R_n \qquad \forall\, n \tag{8.15}$$

The residual value is calculated using the declining balance method of depreciation, as described in [262]. It can be calculated using Equation 8.16, where $a$ is acceleration of depreciation and $L$ is useful battery lifetime. Here, double depreciation, $a = 2$, is used since it is assumed battery value degrades quickly. The useful lifetime is calculated as: $L = Y + Y^{2ndlife}$. In other words, the lifetime of the project considered here (shown in Table 8.1) plus the second life lifetime. In [263] they assess the 2nd-lifetime of nickel metal hydride (NiMH) and lithium-ion batteries used for different purposes; an average value of 7 years can be calculated from this and will be used here.

$$R_n = C_n^i(1 - \frac{a}{L})^Y \qquad \forall\, n \tag{8.16}$$

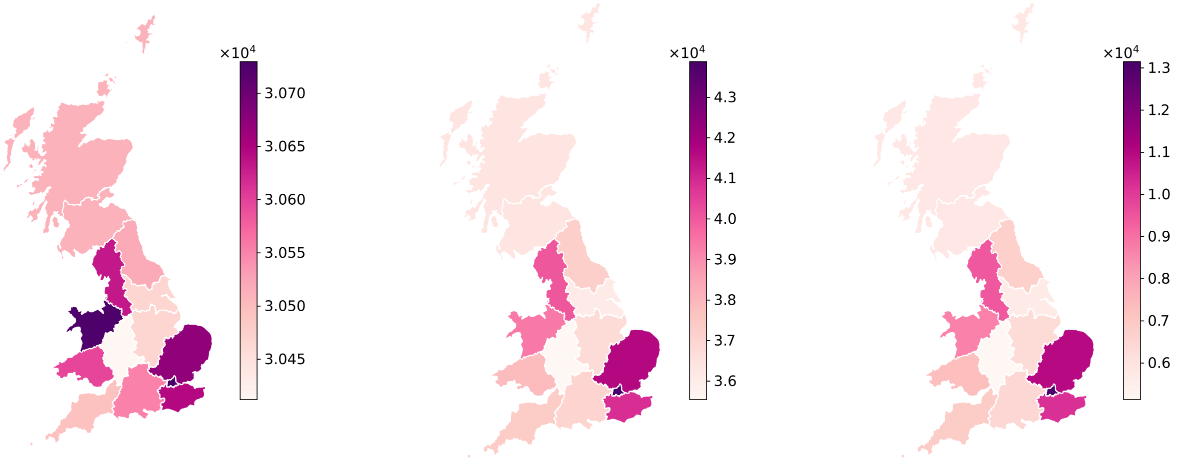
# 8.3 Results and Discussion

In this section we firstly explore the effects of location on the economics of a solar site, under the assumption that the solar generation is the same in all locations. This allows us to directly compare the effect of locational prices on economics. Then we remove this assumption and also examine the region differences due to weather. We then examine the economics required for a profitable co-located site, the effects of economies of scale and the minimum installation costs for profitable economics. Finally we discuss implications and limitations of this work.

## 8.3.1 Locational Effects

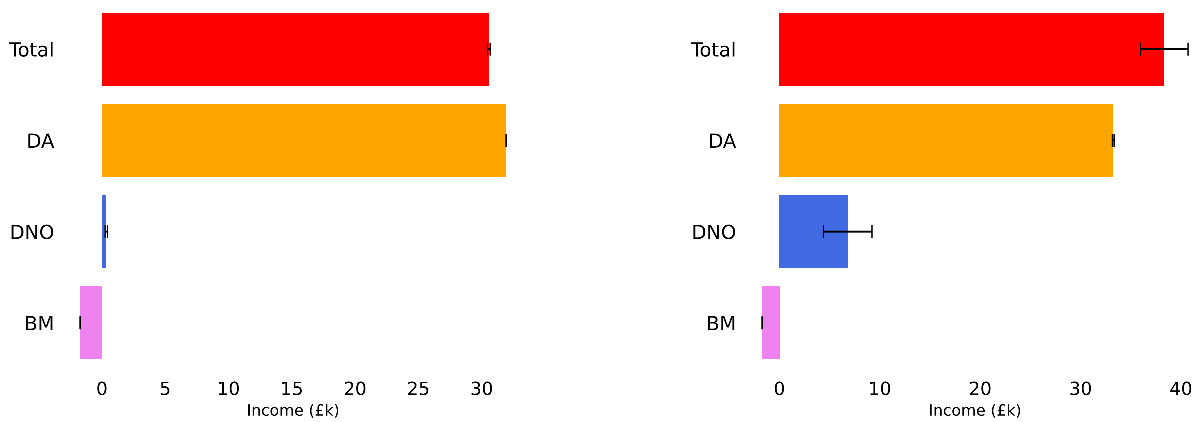
For the initial simulations each solar site was co-located with ES with parameter values: $P_n$ = 0.4 MW, $X_n$ = 0.2 MWh, $\underline{X}_n$ = 0.04 MWh, $\eta_n^d = \eta_n^c$ = 0.9. Figure 8.4 shows the results of when one arbitrarily chosen solar site was replicated in each of the DNO regions. In other words, each region contained one site with the same predicted/actual solar generation profile. The purpose of doing this is to compare directly the change in income due to different DNO payments. The mean and standard deviation of income through the different revenue streams: day-ahead market (DA), balancing market (BM) and DNO payments, is also shown in Figure 8.5 for PV only and PV with ES.

Several things can be inferred from these results; firstly, the regional variation in income for PV only is very small ($\sim$ £250), and the bulk of the income comes from the DA market with very little DNO contribution. However, when storage is included a much larger variation in regional income is observed ($\sim$ £7,000). Additionally, the inclusion of ES improves total income significantly; this is seen in all three revenue streams but in particular due to DNO payments. The consequences of this are that when considering locational options for PV only, regional income differences are not important. However, when looking to either install ES with existing PV or construct a new PV farm with ES, these regional differences will have a great impact on the site's economics (under current market conditions).



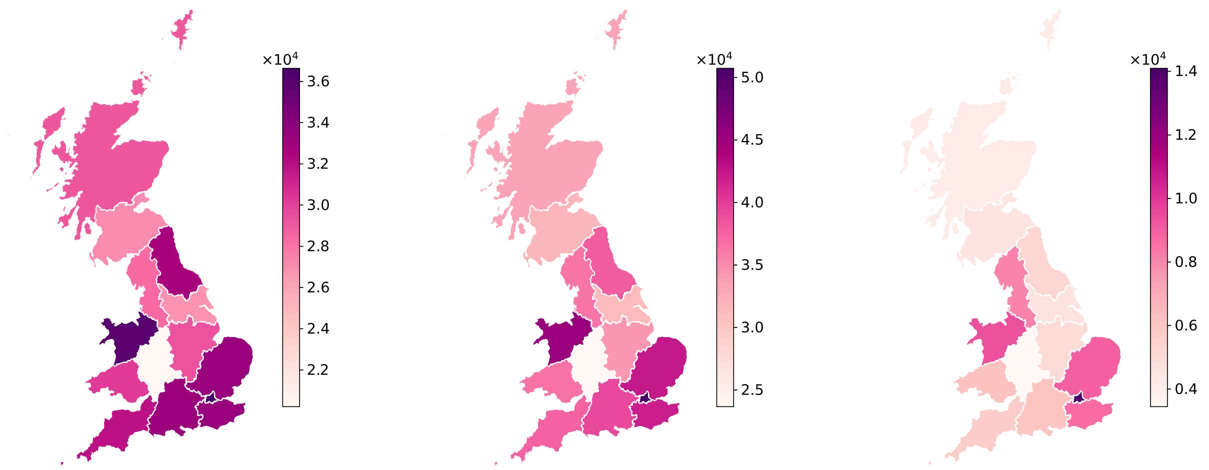

(a) PV (b) PV with ES (c) ES

Figure 8.4: Total yearly income (£) for one repeated solar profile in each region for PV only, PV with ES and improvement in income due to ES.




(a) PV (b) PV with ES

Figure 8.5: Income breakdown for PV (left) and PV with ES (left) in day-ahead (DA) and balancing (BM) markets, due to DNO payments and total.




(a) PV (b) PV with ES (c) ES

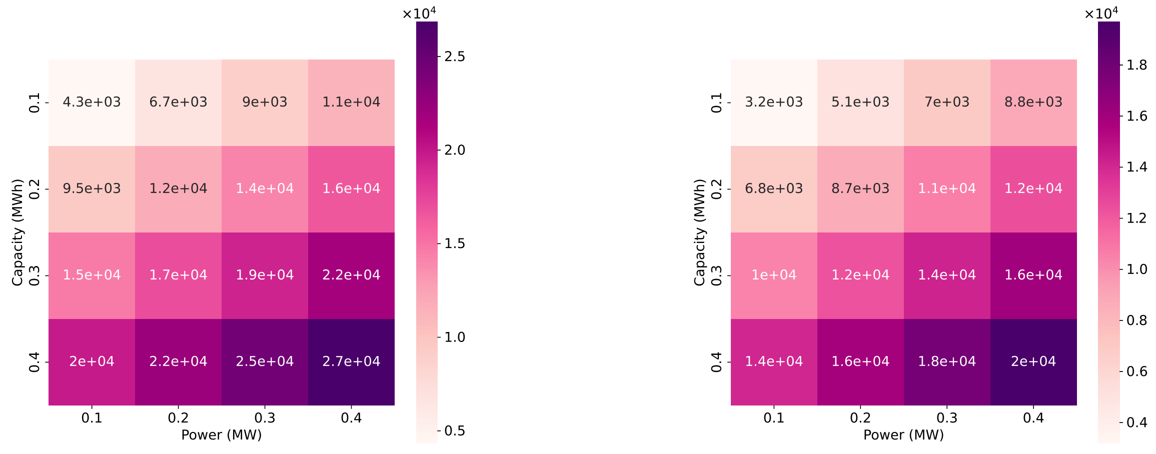
Figure 8.6: Average total yearly income (£) across each region for PV only, PV with ES and improvement in income due to ES.

All 150 sites were used for the next simulation. Each one was located and its associated DNO identified, then they were all optimised using their unique solar profiles. The results of this therefore combine the regional DNO effects, previously discussed, with regional differences due to weather which affect the solar output. In Figure 8.6 the average yearly income per site in each of the different DNO regions is presented. It can be seen that there is greater variation in PV income now that different solar profiles in each region have been used. As expected, the general trend is that PV in the southernmost regions generate high incomes due to improved solar irradiance. The outlier is the Western Power Distribution Midlands DNO region, which generates the least income. It can be seen in Figures 8.3 that this region receives the lowest DNO payments. Additionally, the solar generation of sites within this region may compound this effect; for example, previous work suggests that inland solar sites may make greater financial losses in the balancing market [258]. The ES income follows the same trends as seen in Figure 8.4, confirming that when deciding whether to include storage the DNO payments are the most important factor, rather than the output of the solar itself.

## 8.3.2 Economic Viability

Figure 8.7 shows the yearly ES income required (each year over its lifetime) to make NPV zero; this is done for LFP batteries using 2020 and 2030 cost values. A conversion rate of 0.78 pounds to one dollar has been used. In the previous section, ES incomes for a 0.2 MWh/0.4 MW battery were in the range $0.4 - 1.4 \times 10^4$; an LFP battery of this size needs to have an income of $1.7 \times 10^4$ or $1.4 \times 10^4$, using 2020 and 2030 prices respectively, in order to have a zero NPV. This is therefore are not profitable under current (2020) market conditions without additional incentives. However, it appears that smaller sized batteries could be profitable, hence, simulations will be done for 0.1 MWh/0.1 MW, 0.1 MWh/0.2 MW and 0.2 MWh/0.1 MW ES.

In Figure 8.8 the average NPV for ES installed with solar in each region is shown. This is done using 2020 LFP battery costs and for different sized ES. It can be seen that ES is profitable in London, however, as this is a highly urban area it is unlikely for a solar farm to be installed




(a) 2020

(b) 2030

Figure 8.7: Yearly ES income (£) required to make NPV zero for different sized Lithium-ion batteries.

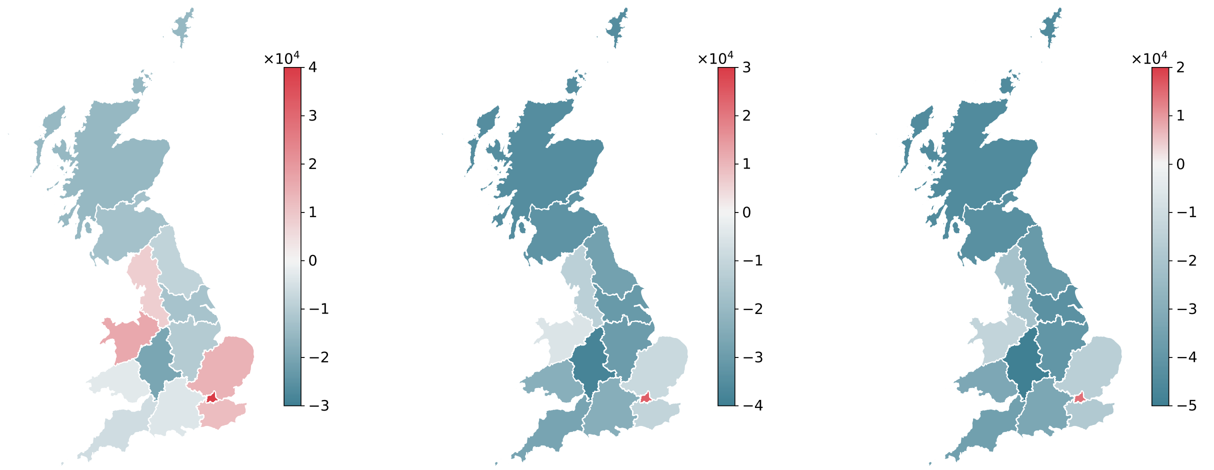
here. For regions in south-east England and north Wales ES becomes profitable when it is smaller e.g. 0.1 MWh/0.1 MW, although north Wales is also impractical due to its mountains. In other regions and for larger storage it is not profitable to co-locate ES with a solar farm.

Figure 8.9 compares the average NPV values (for 0.1 MWh/0.1 MW) against the number of existing solar sites in each region as of June 2020; this data is obtained from the UK's Renewable Energy Planning Database [264]. We see that in the regions where ES is profitable there are relatively few solar farms - 25% of the total. In regions with the most solar farms, e.g. the South West, it is not profitable to add ES. One possible reason for this may be that due to the high capacity of solar generation in these regions there is less need for ES, and hence there is less need for advantageous DNO payments. Conversely, for regions where large scale solar is impractical due to population density (London) and mountains (North Wales), ES is more highly valued. This may be because their distribution grids have greater need for the support that energy storage can offer, for instance dispatchable generation and balancing services.

### 8.3.3 Economies of scale

The results presented thus far have modelled small-scale storage, $10^{-1} - 10^{0}$ MW. This is small relative to grid storage; according to the most recent Renewable Planning Database (April 2022), currently operational battery storage in the UK ranges from 0.1 - 50 MW, with larger projects submitted for planning permission [25]. Additionally, there is 2828 MW of pumped hydro storage in the UK. The largest of these, Dinorwig (1728 MW), provides fast acting response to balance the grid [265]. In comparison with these storage projects, the batteries modelled here are small. However, we are more concerned with performing a cost-benefit analysis from the point of view of a distribution-connected solar farm owner, than a transmission scale investor.

It is worth considering how the economics of adding battery storage to a solar farm varies as its scale increases. In particular, it is interesting to analyse whether it would benefit from economies of scale. In Figure 8.10 the relative CAPEX (%) per MWh storage, compared against 1 MWh, is shown for different duration LFP batteries as duration increases to 10 and 100 MWh. It can be seen that increasing the size of the battery decreases the unit cost, particularly for




(a) 0.1 MWh/0.1 MW

(b) 0.1 MWh/0.2 MW

(c) 0.2 MWh/0.1 MW

Figure 8.8: Average NPV across each region using 2020 lithium ion battery costs for different sized ES.

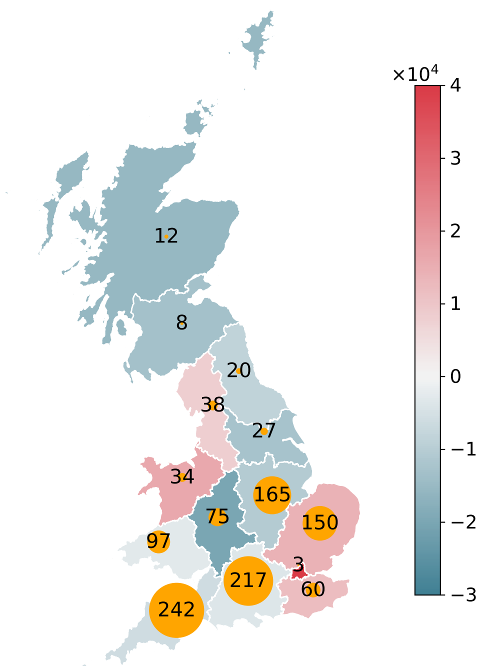



Figure 8.9: Number of pre-existing solar sites in each DNO region as of June 2020. Plotted on 0.1 MWh/0.1 MW lithium ion battery average NPV (£).

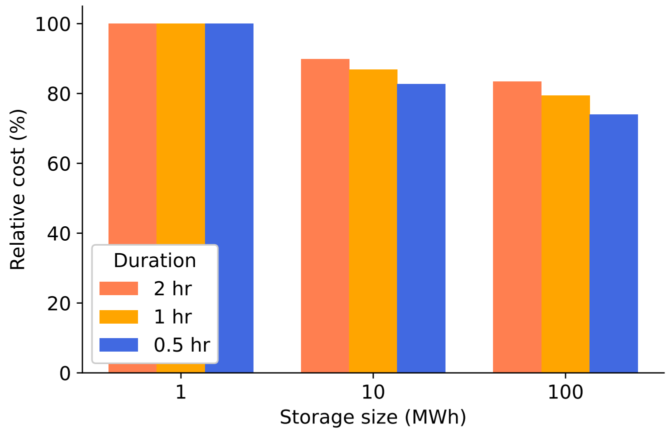



Figure 8.10: Relative CAPEX (%) per MWh storage compared against 1 MWh, for different duration LFP batteries, as scale increases from 1 MWh to 10 and 100 MWh [204].

Table 8.2: Mean NPV and standard deviation for different solar and storage of different scale factors.

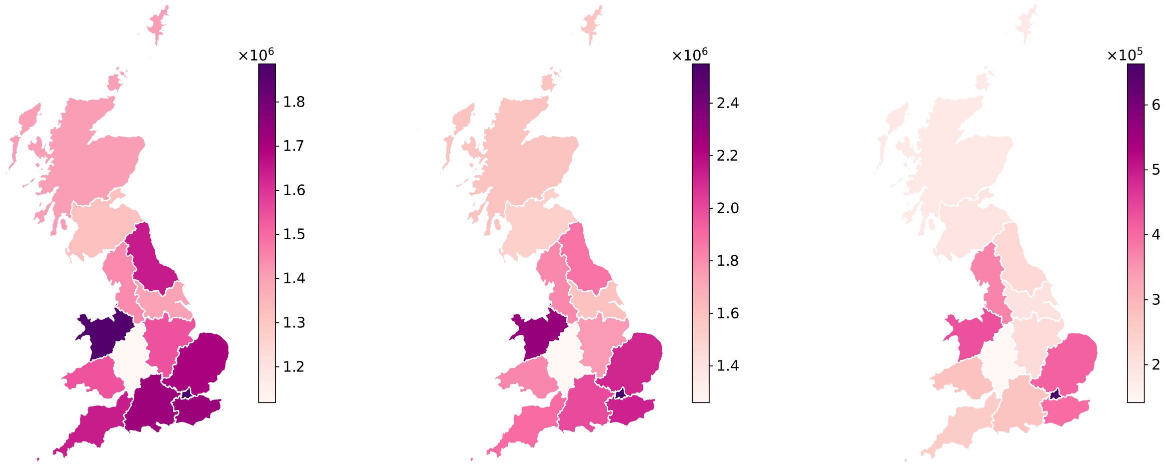
| Max solar output, battery power/capacity | Mean NPV (£) | Std NPV (£) |
|---|---|---|
| 1 MW, 0.4 MW/0.2 MWh | -6.02 $\times 10^4$ | 1.35 $\times 10^4$ |
| 50 MW, 20 MW/10 MWh | -2.38 $\times 10^6$ | 6.68 $\times 10^5$ |

lower duration/higher power batteries. This is since costs that scale with kW, shown in Table 8.1, such as controls and communication, and grid integration decrease relative to size [204]. It is likely that NPV is overestimated for the batteries in the previous section due to a decrease in size leading to an increase in relative costs. Hence, causing these batteries to also be an uneconomical investment for a solar farm participating in day-ahead and balancing markets.

To examine the effects of economies of scale, the simulations in Section 3.1 were repeated with solar and storage scaled by a factor of 50. The maximum output of the solar farms is 50 MW (representative of the maximum sized operating solar farms in the UK [25]) and the storage has maximum power 20 MW and capacity 10 MWh. The results of this are presented in Figure 8.10 and Table 8.3. In Figure 8.10 it can be seen that the scaled-up ES income follows the same geographic trends observed in Section 3.1. This is unsurprising as the optimised scheduling of the storage unchanged, the only difference is the magnitude of energy quantities exported. Table 2 compares the mean NPV and its standard deviation for the small-scale storage and the scaled-up storage. This calculation factors in the ES CAPEX, that is relatively reduced for the scaled-up battery. For both cases mean NPV is negative. However, it can be observed that the scaled-up battery benefits from economies of scale; if there were no economies of scale, it would be expected that mean NPV would be 50 times that of the small scale storage $\approx -3 \times 10^6$. Despite the slight improvement, it is still not economical for a solar farm owner to add ES for arbitrage.

### 8.3.4 Minimum installation cost

The cost of lithium-ion batteries fluctuates due to various factors, including raw material prices, manufacturing scale, technological advancements, and government policies and incentives. This means that the prices used here might not reflect current market values. Therefore, it is instructive to flip the research question and ask: at what cost does it become profitable to add




(a) PV (b) PV with ES (c) ES

Figure 8.11: Average total yearly income (£) across each region for PV only, PV with ES and improvement in income due to ES. Scaled up by factor 50, in comparison with Figure 6.

Table 8.3: Mean minimum installation costs (£/kWh) required to make NPV zero.

| Power (kW) | Capacity (kWh) | Duration (h) | Mean minimum installation costs (£/kWh) |
|---|---|---|---|
| 100 | 50 | 0.5 | 394 |
| 100 | 100 | 1 | 410 |
| 100 | 200 | 2 | 258 |

ES to a solar PV site?

We calculate the minimum installation cost at which it becomes profitable to add ES by rearranging Equation 13 with NPV equal to zero. The results are shown in Table 3, for different battery durations. It should be noted that these values include all aspects of installation costs, including system integration, project planning, power equipment etc. as well as the material cost of the battery.

Adding a 1-hour duration (100 kW/100 kWh) battery to a solar PV site becomes profitable when the installation cost reaches or falls below £410/kWh. However, as the duration increases to 2-hours, a lower installation cost of £258/kWh is required to generate a profit. This is because while the energy capacity of a 2-hour battery doubles that of a 1-hour battery, the profits are less than double, making a cheaper cost necessary for a profitable installation. The minimum installation cost for a 0.5-hour duration battery is similar to that of a 1-hour battery, at £394/kWh. Although material costs are lower for a 0.5-hour battery, the profits are also lower.

In Figure 8.12 we show how the mean minimum installation costs vary for the different DNO regions. As seen previously, greater income can be achieved in London, the south-east and north Wales. In these regions, the minimum installation costs required for ES to become profitable are much higher. In London, the mean cost is £839/kWh. Adding ES in these regions is still beneficial when material and manufacturing costs are high. In the West Midlands, installation costs must fall below £100/kWh to be profitable to add ES to a PV site.

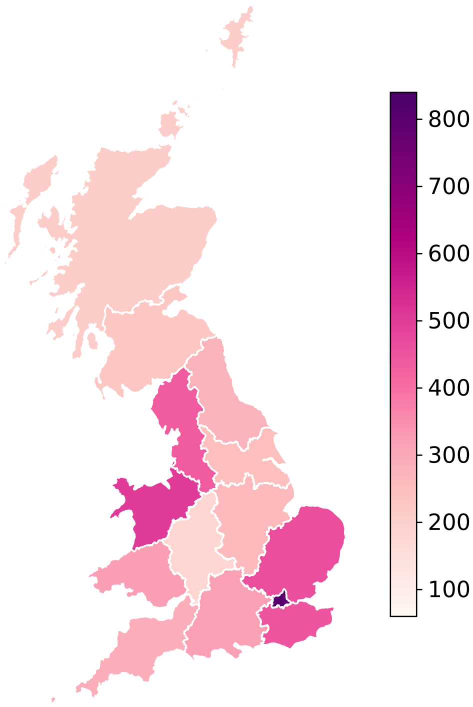



Figure 8.12: Mean minimum installation cost (£/kWh) in each DNO region for a 1-hour (100 kWh/100 kW) battery.

### 8.3.5 Discussion

The findings suggest that under the studied market conditions it is uneconomical to add ES to most existing solar farms in the UK for arbitrage. Consequently the unique benefits of co-locating ES with solar, such as capturing clipped power and reducing curtailment, may not be realised. To encourage increased co-location, there should be greater cost benefits for the solar farm owner. These might include greater differential Use-of-System pricing to favour non-intermittent generation over intermittent generation. Specifically, ES investments could be encouraged by increasing Use-of-System payments during red time bands, when demand is at its peak.

Interestingly, it was observed that due to the regional nature of GB's DNO Use-of-System charges, it is more economical to incorporate ES in some regions than others. However, the regions where adding ES is economically favorable do not correspond to those with the most existing solar sites, nor those with the greatest solar irradiance. This is an unusual observation, and reflects the fact that in GB different regional operators may set their own pricing. Similar analysis may be performed in regions outside of GB, where differences in regional market structures lead to differing locational economics. In [266] the authors explore the economics of hybrid renewable-storage systems participating in 7 different US wholesale markets; these include CAISO (California Independent System Operator), ERCOT (Electric Reliability Council of Texas) and NYISO (New York Independent System Operator), amongst others. The net value is found to differ regionally, and also as a function of battery duration and capacity, and year. A review of Distribution System Operators (DSOs) in Europe shows that some countries have a larger number of DSOs (Germany, Spain, Poland), whereas other countries have 1 (Croatia, Greece, Ireland) [118]. Examining these further is outside of the scope of this work, but it would be interesting to explore whether similar regional effects are observed within these countries.

Limitations of this study are that it only considers battery revenues from merchant markets, namely the day-ahead market and Balancing Mechanism. In reality, a battery might also generate revenue by participating in ancillary service market. For example, it could participate in frequency response and reserve markets during times when it is not trading in merchant markets. Additionally, this model does not consider battery degradation. Heavily battery cycling (charging and discharging) leads to accelerated degradation and reduces its lifetime. This can be expensive, due to the cost of replacing the battery. Often batteries have warranties in place to limit cycling. It would be interesting future work to include revenues from ancillary service markets and to also include some degradation constraints in the optimisation model, to examine how these factors affect the economics.

Finally, it is acknowledged that changes will shortly be taking place in the way distribution grids function. DNOs will be transitioning towards DSOs (Distribution System Operators); this reflects the transition towards more decentralised electricity grids, with local generation and changes in usage patterns. The DSOs will have more control over the local grids and use smart technologies for the management of the network [267]. It is unclear what the consequences will be for the Use-of-System charges, however, there is emphasis on supporting low carbon technologies, such as ES, in local electricity grids [268]. Hence, it is expected that the upcoming changes will improve the profitability of ES. Specifically, for co-location of ES with solar to become more economically advantageous for solar farmers, it is recommended to increase the differential between non-intermittent generation and intermittent generation payments, and increase non-intermittent payments during red time bands.

## 8.4 Conclusion

In this work we have presented a mixed integer linear programming (MILP) optimisation model to explore the economic impact of location on a solar farm co-located with energy storage (ES). The model combines economics and location (usually considered separately). It is easy to replicate and apply to different case studies, making it a useful tool for decision-making for battery storage projects. This work is of interest to distribution-connected solar owners and organisations considering investing in low-carbon energy assets. We determine how the maximum achievable profits of a solar farm with and without ES in different regions around Great Britain (GB) vary, and in which regions ES adds more value. Our results show that solar farms without ES are more profitable in regions with higher solar irradiance and profits are relatively unaffected by differences in local grid charges. On the other hand for solar farms with ES the regional profits are more varied and strongly affected by local charges.

We find that ES adds greater value in regions where there are fewer existing solar farms. These are often regions where it is geographically impractical to build solar farms. Additionally net present value (NPV) calculations show that it is only profitable to add small ES (0.1 MWh/0.1 MW) to a solar farm. This is only profitable in select regions containing 25% of GB's total existing solar farms. Hence for the majority of these it is not economical to add ES. These findings are important because recent studies suggest that we should be adding more ES to solar; since it can reduce clipping and curtailment, and optimises its usage. Our findings suggest that solar owners could lose out on these benefits unless distribution network and market pricing is changed to favour ES, specifically by increasing the differential between non-intermittent generation and intermittent generation payments.

Future work may look at studying the degradation of ES due to its co-location with solar. It may be interesting to examine how including degradation in the optimisation function affects its profits and lifetime, and if this in turn affects its optimum location. Future work may also aim to predict future distribution grid charges, using historic trends, and repeating this analysis as and when any changes are made. Modelling the future volatility of day-ahead and balancing market prices is also an area of development which will influence the value of ES. Finally, the model outlined here may be applied to any other country, or countries, where there is variation in regional distribution grids. It is hoped that work will bolster the deployment of ES, particularly co-located with solar, to improve power grids and enable the decarbonisation of electricity systems.

# Chapter 9

# Mapping green hydrogen potential for industry decarbonisation

## Abstract

Green hydrogen can decarbonise sectors in industry that have been historically reliant on fossil fuels, such as steel, paper and chemical production. However, its high costs relative to other hydrogen production methods has hindered its deployment. This work seeks to support increased deployment, by developing and applying a method to optimise profits and identifying the most advantageous locations to produce green hydrogen via onshore wind electrolysis, using Great Britain as a case study. We identify two regions with favourable economics, under the base case scenario: Lanarkshire in southern Scotland, and mid-east England, around Lincolnshire. The former region houses many wind farms, some of which are heavily curtailed, therefore hydrogen electrolysis could provide a useful pathway for otherwise wasted power. The latter region is located in close proximity to large potential industrial demand sites, thereby lowering transport infrastructure costs to end-users. In Great Britain, iron and steel, and chemical and cement production are the largest current carbon emitters that can be decarbonised with hydrogen. For the specific scenarios modelled in this study, the hydrogen price should be at least £3.50/kg to encourage production of green hydrogen; for prices lower than this, adding an electrolyser to a wind farm is not an economical investment. Mean levelised cost of hydrogen was calculated as £3.33/kg - £4.41/kg for the range of cost scenarios studied.

### Keywords

Green hydrogen; optimisation modelling; mapping; industry decarbonisation; onshore wind; wind electrolysis.

## 9.1 Introduction and literature review

### 9.1.1 Decarbonisation and green hydrogen

Many countries and unions around the world have outlined legally binding targets to reduce carbon emissions, including Canada, Japan and the EU [269]. The UK has recently introduced a new legally binding target to reduce emissions by 78% (relative to 1990) by 2035, ahead of its net zero target in 2050 [270]. In order to achieve this target substantial change is required: the use of fossil fuels must be avoided, unless carbon capture technology is in place. One potential solution is to replace fossil fuels with green hydrogen.

Among the many "colours" of hydrogen, green hydrogen refers specifically to that produced via water electrolysis powered by renewables [271]. It is an attractive alternative to natural gas, that can be produced and combusted with no greenhouse gas emissions. Green hydrogen can sustainably diversify energy systems by decarbonising sectors that have been historically reliant on fossil fuels, such as: industry, transport and buildings [272]. In particular, it can replace fossil fuels in sectors within industry, such as steel and chemical production, that are especially challenging to decarbonise. It is versatile and is well suited to store energy from renewables, providing a useful pathway for curtailed power [273].

However, green hydrogen is a relatively new technology and hence questions still remain about its optimal deployment. One barrier to large-scale deployment is cost: in comparison with other types of hydrogen its production costs are significantly higher [271], [274]. Hence, an important area of research is finding strategies to maximise profits and minimise costs associated with green hydrogen production, to incentivise its deployment.

Another issue is location; this will affect its economics since some regions will have greater natural resources, and hence renewable production potential, than others. Additionally, when choosing a location there should be consideration of the hydrogen economy as a whole: for instance, it should be feasible to store and transport to its end-users, and the value of using existing renewables should also be examined [275]. With this in mind, the following section presents a review of recent literature studying firstly the spatial aspects of green hydrogen production. Secondly we examine literature exploring its transport and storage, and finally, we present literature optimising its economics. In this study the end-users of the green hydrogen are carbon intensive industries that may be decarbonised with hydrogen.

### 9.1.2 Locations for hydrogen production

Kakoulaki et al. [276] found that 81% of studied regions (in the EU and UK) have the potential to match electricity demand with renewables, and still have excess electricity leftover for green hydrogen production. This suggests a high potential for green hydrogen production using existing renewables. Many recent papers have identified potential locations for low-carbon hydrogen production; these are presented in Table 9.1, which shows the country or region considered, along with the hydrogen production method(s) and any notable methods or results. The majority of these studies focus on producing green hydrogen from renewables, however some also consider other methods such as biomass gasification. In [133] - [146] they consider at least one method of green hydrogen production: electrolysis powered by solar and/or wind generation. Most of these papers map potential hydrogen production across a whole country, for example [133] and [134] map solar electrolysis potential in Algeria and Turkey respectively. On the other hand [135], [136] and [137] map wind and solar electrolysis in different provinces within Iran. One common methodology among papers in the literature is the use of weather data to determine electrical output from renewables and consequently estimate green hydrogen potential in the different locations.

Another notable feature in decision making for hydrogen production location is project economics. In [135] the authors calculate the cost per kWh of producing solar and wind power in the locations with the greatest solar and wind potential, respectively. However, they do not consider the costs of producing hydrogen, nor how this varies with location. References [138] and [137] calculate the levelised cost of hydrogen (LCOH) in several locations using weather station data in Qatar and Iran, respectively. References [139] and [140] calculate levelised cost of electricity (LCOE) from wind generation in Afghanistan and solar generation in Iran, respect-

Table 9.1: Comparison of studies mapping potential low-carbon hydrogen production sites.

| Reference | Country/Region | Hydrogen Production Method | Other Notes |
|---|---|---|---|
| [133] | Algeria | Solar electrolysis | GIS based multi-criteria decision making model to identify most suitable sites |
| [134] | Turkey | Solar electrolysis | Calculates production potential considering different natural water sources. |
| [135] | Sistan & Baluchistan, Iran | Solar, wind electrolysis | Assesses investment costs in solar and wind. |
| [136] | Birjand County, Iran | Solar electrolysis | Inclusion of fuel cell to re-electrify hydrogen; System size and location optimised for rural areas. |
| [137] | Yazd province, Iran | Wind electrolysis | Multi-criteria decision making model considers economics and carbon reductions. |
| [138] | Qatar | Solar, wind electrolysis | Fuzzy logic to choose best location. |
| [139] | Afghanistan | Wind electrolysis | Calculates decrease in carbon emissions and payback period. |
| [140] | Iran | Solar electrolysis | Calculates levelised cost of electricity and capacity factor of sites. |
| [141] | Australia | Solar, wind electrolysis | Assesses regional economic potential; Considers hydrogen production from fossil fuels. |
| [142] | Ukraine | Wind electrolysis | Analyses social benefits of wind-hydrogen investment. |
| [143] | Togo | Solar, wind electrolysis, biomass gasification | Wind not sufficient, biomass has greatest production potential. |
| [144] | Turkey | Solar electrolysis | Compares production potential using 3 different electrolysers. |
| [145] | Pakistan | Solar, wind electrolysis, geothermal, biomass and municipal solid waste | Biomass has greatest availability followed by solar and municipal solid waste. |
| [146] | Scotland | Offshore wind electrolysis | Identifies sites where existing infrastructure could enable hydrogen transportation. |

ively. The former study calculates LCOH in the city identified as having the lowest LCOE; this was found to range from 2.118 to 2.346 $/kg depending on scenario and whether degradation was considered. Zhang et al. [136] calculate total life-cycle costs for grid-independent systems, considering hydrogen tank storage. For a 3 kW electrolyser system, mean total life-cycle cost is found to range from 1,678,360 - 4,115,720 $. These studies highlight the value of considering economics when choosing locations for hydrogen production. They show that there is regional variation in economics, due to varying solar and/or wind resources, and a potential investor must take this into account when choosing a location. However, they do not consider hydrogen transport to end-user, which is an important practical factor. Baufumé et al. [147] and Reuß et al. [148] analyse hydrogen infrastructure options in Germany to transport hydrogen from production site (renewable electrolysis) to vehicle refuelling stations. They find that transportation costs are low relative to production costs, however pipeline infrastructure is nonetheless a significant upfront investment. It should therefore be taken into consideration when selecting a suitable green hydrogen site.

### 9.1.3 Transport and storage

Hydrogen transport is considered in a few of the locational studies presented in Table 9.1: [133], [141] and [146]. In [133] they do not perform economic calculations, however part of their location selection criteria is to reduce distance to roads/railways and power lines, minimising potential infrastrucutre costs. They estimate the yearly demand for hydrogen vehicles in different locations. In [141] they estimate the NPV of a project considering the necessary infrastructure, including the amount of power and water required for the electrolyser, their transportation, and the transportation of the produced hydrogen. The high cost of hydrogen transmission favours its production to be located near ports - under the assumption that it will be exported. Likewise [146] does not consider economics but accounts for hydrogen transportation by considering how existing oil and gas pipelines could transport hydrogen from offshore wind sites.

The storage of hydrogen, in particular for seasonal usage, is a factor that should also be considered. Recent studies in the literature explore the possibility of using underground, geological storage [277]–[279]. In particular, [277] examines using aquifers, depleted oil and gas fields and salt caverns for hydrogen storage. Whereas, [278] explores the possibility of depleted oil and gas fields, and [279] simply depleted natural gas reservoirs. This research area is in its infancy, and as highlighted by [277], more research should be done to improve understanding of reactions that can occur between the hydrogen and the geological structures. In [280], they use the UK as a case study to assess the geological storage potential of off-shore gas fields. The authors find that the estimated storage capacity far exceeds the estimated seasonal demand for hydrogen (based upon domestic heating demand) and frees up land space onshore for other large-scale storage applications, such as carbon storage or compressed air energy storage. For non-seasonal hydrogen demand, for example industry or transport, there is less need to store hydrogen for long periods of time.

### 9.1.4 Optimising hydrogen economics

Another essential element for making the case for green hydrogen deployment is optimising its production and scheduling. A green hydrogen investor/owner would wish to maximise their potential profits, therefore profit optimisation methods should also be examined and applied. Green hydrogen systems are typically able to participate in electricity markets - buying and/or selling electricity, and/or providing ancillary services - as well as selling hydrogen. Therefore, a profit seeking investor may wish to examine the trade-offs between selling electricity and hydrogen, especially if they participate in time-varying electricity markets, to ensure they maximise returns on their investment.

There have been several recent studies exploring this topic. For example, the authors of [116] present a model of a wind-hydrogen refuelling station that maximises profits and minimises demand shortfall. The refuelling station participates in a time-varying electricity market and the electrolyser is able to use otherwise curtailed wind power; the optimisation procedure is found to improve profits. In [281], the authors optimise the schedule and sizing of a hydrogen refuelling station which is able to participate in electricity and ancillary service markets. Additionally, [114] optimise the scheduling of an alkaline electrolyser, taking into account its different operative modes (idle, standby, production).

Another factor worth considering that affects economics is renewable curtailment. In [6] it is found that adding an electrolyser to a curtailed onshore wind site improves profits, more so than adding an equally sized battery, and allows greater usage of curtailed wind. The authors of [282] map wind curtailment in Great Britain. They find that onshore wind is much more highly curtailed, up to 32 % for sites in Scotland, than offshore wind, with annual rates of 0-0.63 %. Hydrogen electrolysis could be both an economical and environmentally beneficial (due to not wasting curtailed power) pathway to use curtailed wind, of which there is already a great deal of in Scotland which is forecast to increase with growing renewable penetration.

### 9.1.5 Contributions of this work

From the above it is clear that developing a framework for locating green hydrogen production is an important field that is gaining momentum. It is important to assess locations on a country-wide scale with considerations of renewable resources and transportation to end-users. Additionally, this should be combined with an optimisation model from the point-of-view of a renewables owner or investor to determine the maximum achievable profits. In reality, if an investment is not profitable and/or there are no incentives, it is unlikely to occur, even if the resources and infrastructure are in place. The contributions of this work are therefore:

1. Mapping hydrogen demand for decarbonising industry, using the UK as a case study. Comparing these against locations of existing renewable generation to identify potential hydrogen clusters.

2. Applying an optimisation model to maximise the economics of a wind-hydrogen system in different locations across Great Britain.

3. Analysis of the above GIS layers corresponding to: where existing renewable resources and hydrogen demand are located, and the locations of the most economical investments.

It should be noted that hydrogen storage is not considered in this study. This is because we focus on its potential for decarbonising industry, which is not seasonal. For seasonal applications of hydrogen, such as residential heating, its storage should be taken into account. Additionally, this study does not explicitly model modes of transport between hydrogen production and demand locations. It is outside of the scope of this work, with the main contribution being the application of the optimisation model to various locations. However, there is a qualitative discussion of transport options. Finally, Northern Ireland is omitted from the optimisation study, which analyses Great Britain, rather than the UK. This is since Norther Ireland has a different grid transmission system operator and charging structure compared with Great Britain.

The remainder of the paper is as follows: Section 2 presents the methodology, firstly for mapping potential demand and production sites, then for the optimisation model. Section 3 presents the results and discussion, within this section maps for hydrogen demand, production and economics are compared. Additionally, this is compared against locations where onshore wind is most heavily curtailed. The conclusion is presented in Section 4.

# 9.2 Methodology

## 9.2.1 Mapping hydrogen demand

The hydrogen demand for industry is mapped by identifying processes where fossil fuels can be replaced by hydrogen and locations where these processes occur. In [48] the authors present a method for identifying potential hydrogen demand for energy-intensive industrial processes; the industries found to have hydrogen potential are summarised in Figure 9.1.

The UK's National Atmospheric Emissions Inventory contains data for carbon emissions from large point sources, corresponding to industrial units [283]. Information regarding location of the unit, its sector and carbon emissions per year is available. The sectors are compared against those found to have hydrogen potential, and the individual units corresponding to these are identified. The locations of these units and the size of their current carbon emissions are mapped. These are the locations where there is expected to be hydrogen demand in the future, as these industries are obliged to decarbonise. The size of their emissions gives an indication as to the hydrogen demand requirement - however quantifying this is outside of the scope of this work.

Figure 9.2 shows the total yearly carbon emissions from industrial point sources in the UK [283]. These are grouped by industry type and ranked in descending order of emissions. The industries in blue text can be decarbonised with hydrogen, based on [48]. It can be seen that the top three emitters are production of: power, oil and gas, and petroleum; they represent 61% of yearly industrial point source emissions. The former can be decarbonised using renewable electricity production alongside energy storage, whilst demand for petroleum, oil and gas should decrease as fossil-fuel based vehicles are replaced by electric vehicles, and heat is decarbonised. Hydrogen can, at least in part, decarbonise the next three greatest emitting industries: iron and steel, chemicals and cement, along with smaller emitters, such as minerals, paper, lime and non-ferrous metals. These industries represent 27% of all industrial point source carbon emissions, therefore hydrogen can play an important role in decarbonising industry. However, hydrogen alone is not sufficient and other technologies will be required to decarbonise and/or reduce the top three emitters. Additionally, further research should be conducted on methods to reduce emissions from the remaining 12% of industrial carbon emitters.

## 9.2.2 Mapping green hydrogen production

Green hydrogen is produced via electrolysis, powered by renewable generation. In order to map potential sites for green hydrogen production, we identify the locations of existing and future renewable generation sites. This gives an indication of where renewable electrolysis could occur, using existing renewable infrastructure. Additionally, the yearly electricity output of each potential site is estimated. This allows a comparison of the production potential for the different sites; the greater the yearly output, the greater the potential green hydrogen production.

The Renewable Plannning Database (RPD) contains information regarding all renewable energy projects in the UK sized over 150 kW [25]. Specifically, it can be used to identify: type of project (e.g. solar, wind, biomass etc.), size, location and development status (e.g. planning submitted, approved/rejected, under construction etc.). In order to map potential green hydrogen locations in the UK, the RPD is used to identify current and future (development status: operational, under construction, planning permission granted) wind and solar projects.

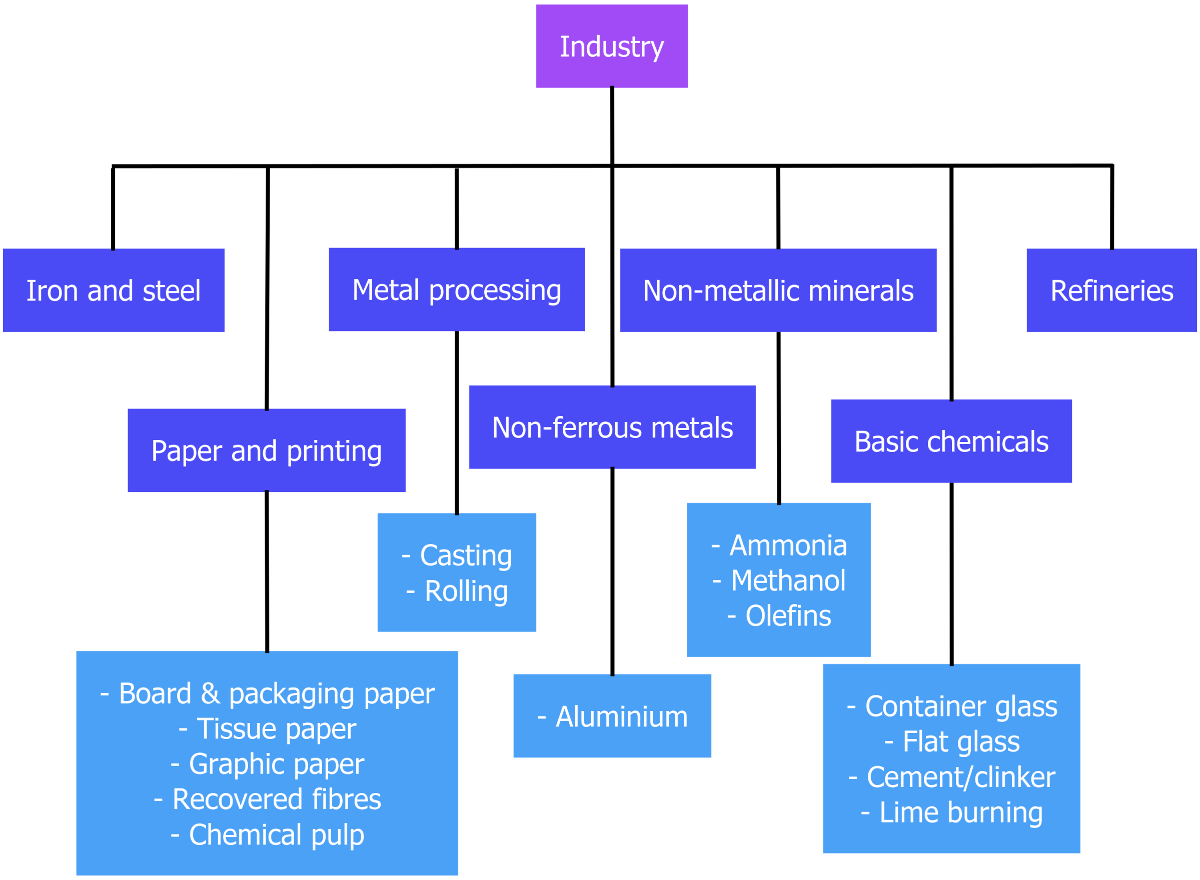



Figure 9.1: Carbon intensive industries that can be decarbonised with hydrogen. Adapted from [48].

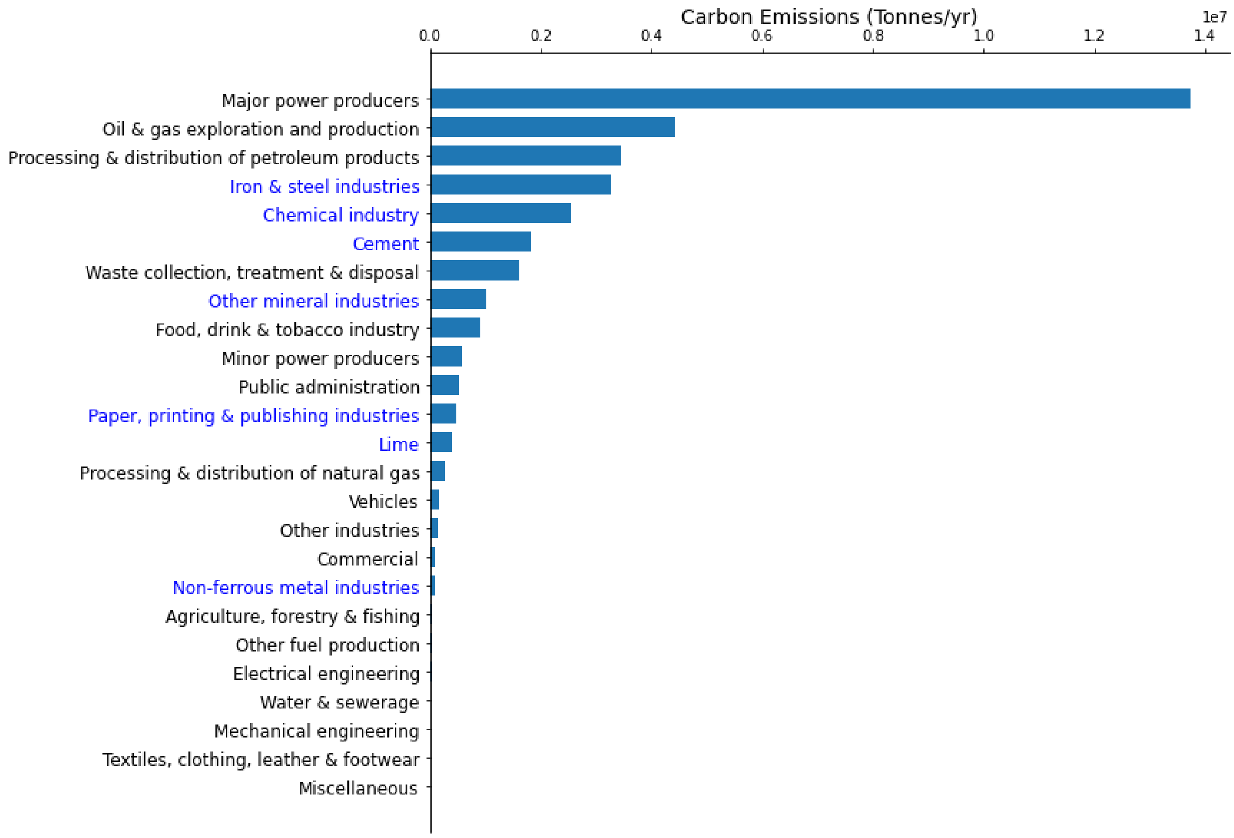



Figure 9.2: Total yearly carbon emissions from industrial point sources in the UK by sector, data adapted from [283]. Industries in blue text can be decarbonised with hydrogen.

The yearly output is estimated for each project using the UK's average yearly load factors for onshore and offshore wind and solar [284]. These are $28.1\%$, $45.7\%$ and $11.2\%$, respectively. For each renewable site, the installed power is multiplied by its respective load factor and 8760 hours in one year.

### 9.2.3 Optimising wind-hydrogen economics

For a renewables owner to invest in an electrolyser, to produce green hydrogen, it must be economical. To assess whether or not an investment is economical, we present a simple optimisation model to maximise the profits a renewables owner could achieve. An onshore wind case study is presented. It uses openly available wind data, recorded at weather stations around the UK [285]. We explore how for the owner economics could vary regionally based upon a) variation in wind generation, and b) variation in local Use-of-System charges. These Use-of-System charges vary due to different Distribution Network Operators (DNOs) setting their own local charges, this is discussed further in [286]. It should be noted that this methodology is easily applied to solar and offshore wind. Onshore wind was selected as a case study for this work due to the availability of onshore weather station data and the higher load factor of wind compared to solar generation.

In order to optimise the profits of the onshore wind owners with an electrolyser, Equation 9.1 is maximised for each wind site, $i$, over a time period, T. The first term represents the profits from exporting power, where $w_{it}$ is wind power generation at site, $i$, and time, $t$, $e_{it}$ is power to the electrolyser, $p^{PPA}$ is power purchase agreement (PPA) price[1] and $p_{it}^{DNO}$ is DNO Use-of-System price. The second term represents the profits due to selling hydrogen, where $EC$ is the

[1]Renewable generators typically have a PPA contract whereby they sell exported power at a fixed price.

energy consumption in units of kWh/kg to produce 1 kg of hydrogen, and $p^h$ is the hydrogen sell price.

$$max \sum_{it} \big(w_{it} - e_{it}\big)\big(p^{PPA} + p_{it}^{DNO}\big) + \frac{e_{it}}{EC}p^h \tag{9.1}$$

In this model, the site may only export power, since a previous study found that import tariffs were too high and it was only optimal to export [6]. This constraint is imposed by Equations 9.2 and 9.3. Additionally, power to the electrolyser must not surpass its nominal power and must not be negative, as shown by Equation 9.3.

$$w_{it} - e_{it} \geq 0 \qquad\qquad \forall\, i, t \tag{9.2}$$

$$0 \leq e_{it} \leq \bar{e} \qquad\qquad \forall\, i, t \tag{9.3}$$

The output of the optimisation model is the optimised schedule of the electrolyser, $e_{it}$, for each site. This can be used to calculate the Net Present Value (NPV) of the electrolyser, at each site, and hence determine whether or not it is an economical investment. The NPV of an electrolyser can be calculated using Equation 10.3.

$$NPV_i = -C_i + \sum_{y=1}^{Y} \frac{(I_{iy} - O_{iy})}{(1+r)^y} \qquad\qquad \forall\, i \tag{9.4}$$

where $r$ represents the discount rate and $Y$ the end of project lifetime in years. The CAPEX, $C_i$, is subtracted at the start of the investment, and the cash flow is equal to yearly income improvement, $I_{iy}$ minus OPEX, $O_{iy}$. Yearly income improvement is calculated using Equation 9.5, where $E_{iy}$ is the yearly income when there is an electrolyser and $N_{iy}$ is the yearly income when there is no electrolyser. $E_{iy}$ and $N_{iy}$ are determined using Equations 9.6 and 9.7, respectively; the factor of 1/2 is used to convert power (kW) to electricity (kWh) over each half-hour time period.

$$I_{iy} = E_{iy} - N_{iy} \tag{9.5}$$

$$E_{iy} = \sum_{t} \frac{\big(w_{it} - e_{it}\big)}{2}\big(p^{PPA} + p_{it}^{DNO}\big) + \frac{e_{it}}{EC}p^h \tag{9.6}$$

$$N_{iy} = \sum_{t} \frac{w_{it}}{2}\big(p^{PPA} + p_{it}^{DNO}\big) \tag{9.7}$$

### 9.2.4 Optimisation input data

Wind speed data is available from the Met Office (the UK's national weather office) [285]. It is measured at weather stations across the UK, using a cup anemometer atop a 10m mast. Wind speed data measurements are carried out every 1/4 second to produce 1 minute average values, that are used to produce 10 minute and hourly mean values. Wind speed data is available for 158 weather stations in the UK in 2019. This work only considers sites that lie within GB's DNO regions, since site specific DNO Use-of-System charges are necessary for the optimisation model. Sites lying outside of these regions, including Northern Ireland, are excluded, leaving 144 remaining weather stations. Of these weather stations, only 7 have a year's worth of data. However, 50 stations have half a year (4380 hours) of data. For the sake of examining a greater number of locations, the optimisation model is run over half a year using wind data from the 50 stations.

In [287], the authors plot the long-term average monthly capacity factors for wind power in the UK. They find that it is highest in the winter and lowest in the summer. Equations 9.5, 9.6 and 9.7 are therefore determined over half a year (8760 half-hour time periods) and then doubled to estimate income over a full year. It is assumed that wind generation in the second half of the year is approximately equal to wind generation in the first half of the year. Therefore, by considering January to June we model maximum wind speed through to minimum wind speed. However, it is possible that total generation is lower in the second half of the year (July - December), than the first half, due to having two summer months (July and August) and one winter month (December). This may lead to a slight overestimation of results.

The wind speed recorded, $v_a$, is scaled up from anemometer height (10m), $z_a$, to wind turbine height, $z_{hub}$, using the following equation:

$$v_{hub} = v_a \frac{ln\left(\frac{z_{hub}}{z_0}\right)}{ln\left(\frac{z_a}{z_0}\right)} \tag{9.8}$$

where $z_0$ is the roughness length (the height at which wind speed theoretically becomes 0) which varies across Earth's surface; data for this at each of the sites was obtained from Global Wind Atlas [288].

In order to decide which turbine(s) to model, data from the RPD is analysed to determine the average turbine capacity and number of turbines for wind projects in the UK that are: operational, planning approved or under construction [25]. These values were found to be $\approx$ 2 MW and $\approx$ 7 turbines, respectively. Hence, we model 7 Vestas v90 2 MW turbines; the power curve for this design is obtained from Wind Turbine Models [289]. We use this power curve along with the wind speed data, scaled up to the hub height, to determine the hourly wind power profile for each site. This is then sub-sampled into half-hourly resolution, assuming that mean wind speed is constant throughout each hour.

Other input data required for the model includes: Distribution Use-of-System (DUoS) charges, PPA price, hydrogen price and electrolyser parameters. DUoS charges can be found on GB's DNO websites [250]–[255]. Generators receive negative charges (i.e. payments) for exporting power to the distribution networks. These payments vary with time and follow a red, amber and green charging structure (where red is at peak demand hours, amber during the day and green at night). At weekends there are no red time bands. The daily and weekend charging profiles are amalgamated to form half-yearly time-varying price profiles for each DNO. Each of the wind stations are matched with their corresponding DNO and hence DUoS prices, $p_{it}^{DNO}$, depending on their location.

Information concerning specific PPAs is confidential, therefore we look at a range that is reflective of real contracts (£0.03/kWh, £0.04/kWh, £0.05/kWh)[290]. We also look at a range of hydrogen prices (£3/kg, £3.50/kg, £4/kg) since green hydrogen is not an established market but prices are estimates to be around a mid-point of £3.50 [291].

Electrolyser parameters have been studied by The Fuel Cells and Hydrogen Joint Undertaking (FCH JU) [292]. For PEM electrolysers, electricity consumption and CAPEX are estimated to be 55 kWh/kg (52 kWh/kg), and 756 £/kW (588 £/kW) for 2020 (and 2024); a conversion rate of 1 Euro = £0.84 was used, based upon the average exchange rate in 2022 up to August. We model electricity consumption and CAPEX as 54 kWh/kg and 672 £/kW, respectively, as these lie within the predicted range between 2020 and 2024 [292]. PEM lifetime has been estimated as 50,000 - 80,000 hours [291], therefore we model a lifetime of 9 years.

## 9.3 Results and discussion

In Figure 9.3 the locations and sizes of the industrial carbon emitters are presented. Those that can be decarbonised with hydrogen are shown in blue. This may represent locations of hydrogen demand as these industries decarbonise, in line with legally binding targets. It can be seen that much of the potential demand is clustered around the north of England, approximately in the region between Liverpool and Hull. There is also a demand cluster in the south of Wales, around Cardiff. Additionally, there are several potential demand clusters in England's midlands, and smaller dispersed points of demand such as can be seen in south-east England and east Scotland, near Edinburgh. The quantity of hydrogen required to decarbonise these industries can be estimated using the method outlined in [48], however, this requires knowledge of the process feedstocks which is not readily available for the industrial emitters mapped here. The National Atmospheric Emissions Inventory only contains information on carbon emissions and individually researching the feedstocks and processes at each point source is outside of the scope of this work. Nonetheless we are still able to identify large potential sources of demand for hydrogen. This is an important factor to consider when choosing production locations for green hydrogen, to minimise infrastructure costs, such as transport.

In order to map potential sites for green hydrogen production, the locations of existing and upcoming renewable sites are identified. This provides an indication of where renewable electrolysis could profitably occur, using existing infrastructure. The locations of renewable generation and their estimated yearly outputs in the UK are shown in Figure 9.4. This is done for both the currently operational renewable sites and future sites, which have either planning permission granted or are under construction. There is a clear geographic divide between wind and solar projects in the UK. Onshore wind sites are generally located in Scotland, Northern Ireland, Wales and northern England; solar sites are primarily located in the mid and south England and Wales. Offshore wind is distributed around the coast.

It can be seen that there are many more planned renewable sites in the pipeline. Operational installed capacity is 33.6 GW (87.4 TWh/yr), however, there is an additional planned 30.8 GW (97.9 TWh/yr) of solar and wind projects, that have either planning permission granted or are under construction. This will bring the UK's future installed capacity to 64.4 GW (185.3 TWh/yr). The planned expansion of solar, onshore wind and offshore wind is 5.6 GW (79.1 TWh/yr), 5.4 GW (13.2 TWh/yr) and 19.8 GW (5.5 TWh/yr), respectively. The latter will be primarily based on England and Scotland's west coast.

In Figure 9.5 the locations and sizes of the largest potential green hydrogen demand and production are shown. We show production sites with installed capacity of 50 MW or greater (for both current and future sites), and demand sites with yearly carbon emissions of 10 Mt or greater, that can be decarbonised with green hydrogen. As previously discussed, the largest potential sources of industrial demand are in mid to north England, whereas the largest potential production sites are onshore wind in Scotland, or offshore - primarily on the east coast. There is little overlap between the largest sites of production and demand, therefore transportation infrastructure should be in-place to link supply and demand.

As identified in [282], there is heavy curtailment of onshore wind farms in Scotland (up to 32%), and little curtailment of offshore wind. The data provided by the authors of [282] in the supplementary material is used to estimate the yearly curtailed wind generation from onshore wind farms; this is shown in Figure 9.6. It can be seen that there is a huge amount of annually curtailed wind, this is primarily due to managing grid congestion. This curtailed wind could otherwise be used to produce hydrogen, such as in the system proposed by [293]. In order to maximise usage of curtailed wind, it could be sensible to produce green hydrogen production onshore, rather than or as well as offshore, despite the much greater (current and future) installed

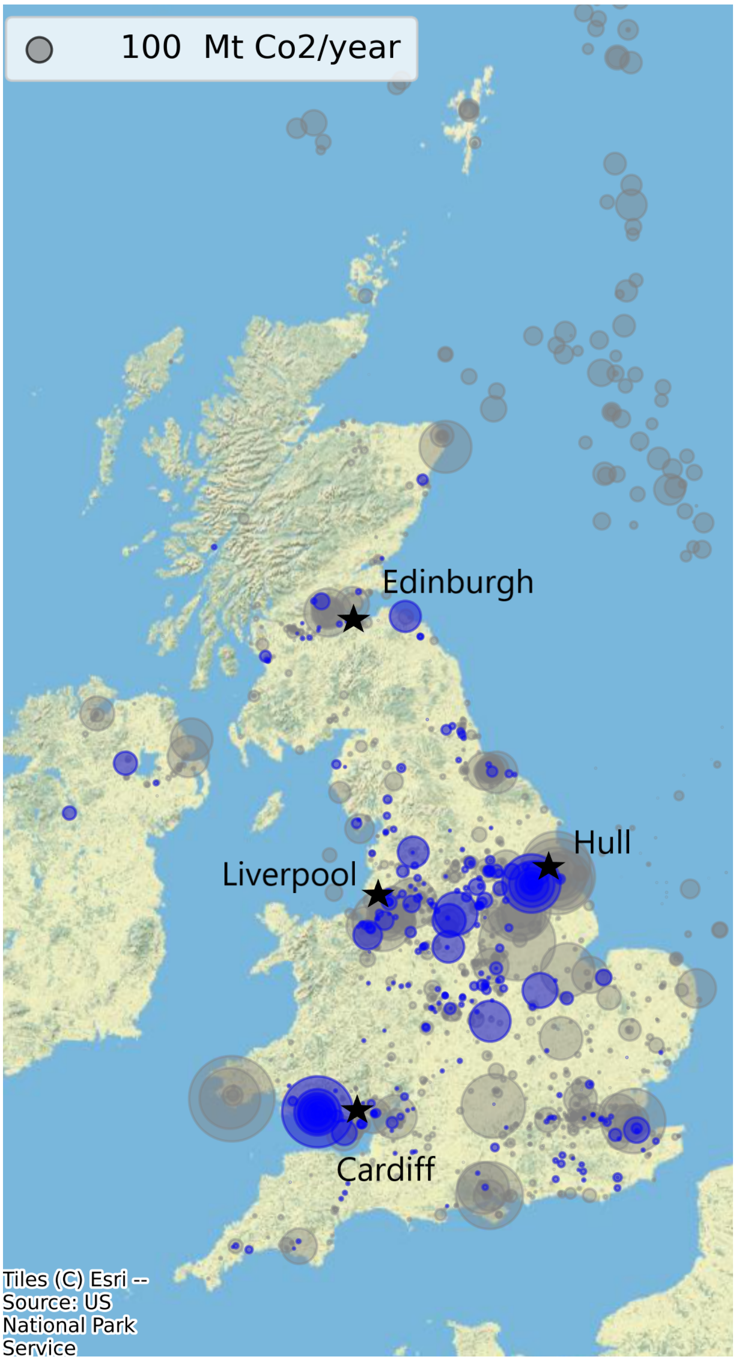
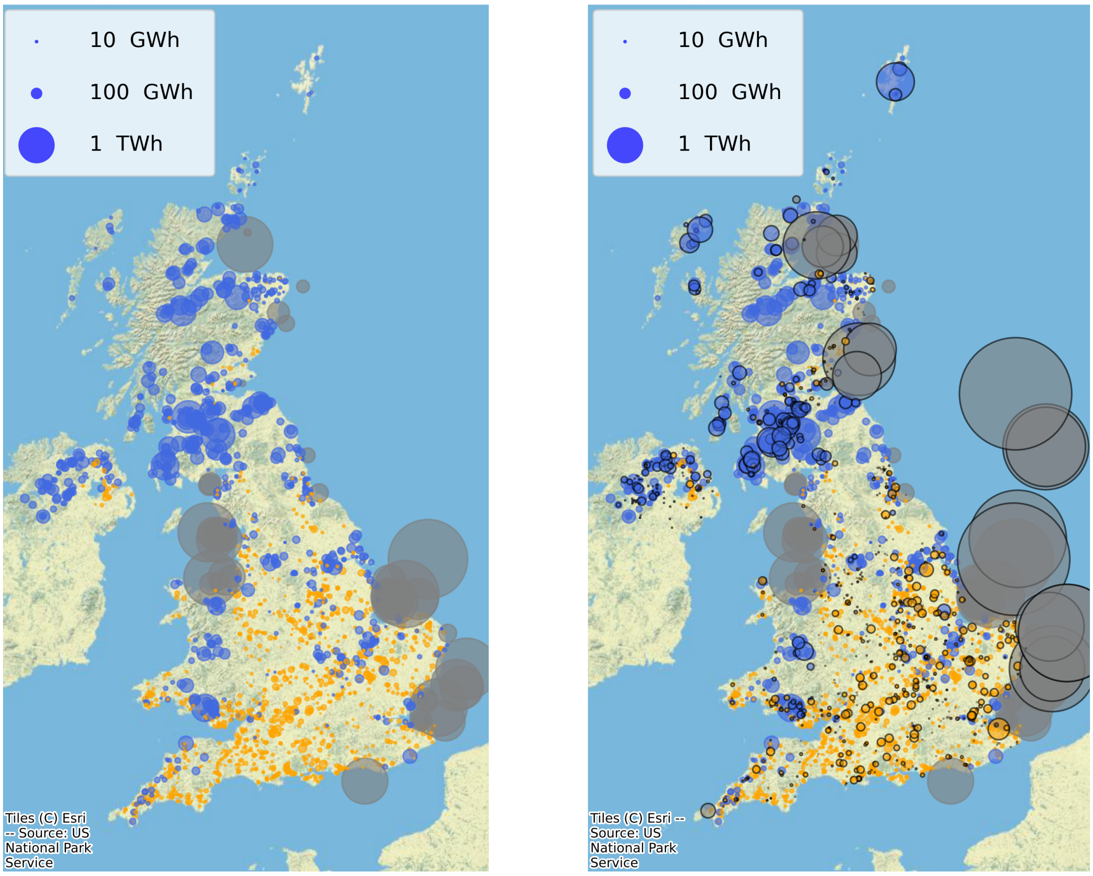



Figure 9.3: Location and size of industrial carbon emitters, those with hydrogen potential shown in blue. Data adapted from [283].




(a) Currently operational



(b) Future

Figure 9.4: Yearly renewable generation estimates in the UK. Blue = onshore wind; grey = offshore wind; orange = solar; black outline = planning permission granted or under construction. Data adapted from [25].

offshore capacity.

There should be infrastructure in place to transport hydrogen to the industrial end-users. In the UK, as in other countries, there are several projects exploring methods to transport hydrogen. HyDeploy are trialling blending hydrogen into the existing natural gas network [294]. Gas company Cadent are proposing pipelines to transport 100% hydrogen between industrial producers and end-users in north-west England, as part of the HyNet project [295]. HyNet, however, plans to use locally produced blue hydrogen, produced from natural gas and steam with carbon capture, rather than green hydrogen. Nonetheless the use of pipelines to transport hydrogen to demand sites is an option gaining traction. As discussed in [296], pipelines are the transport option with the lowest environmental impact. It could therefore be a promising option to link green hydrogen production in Scotland with industrial demand in north England. Although more transport studies should be conducted to examine the feasibility and economics of different hydrogen transport options.

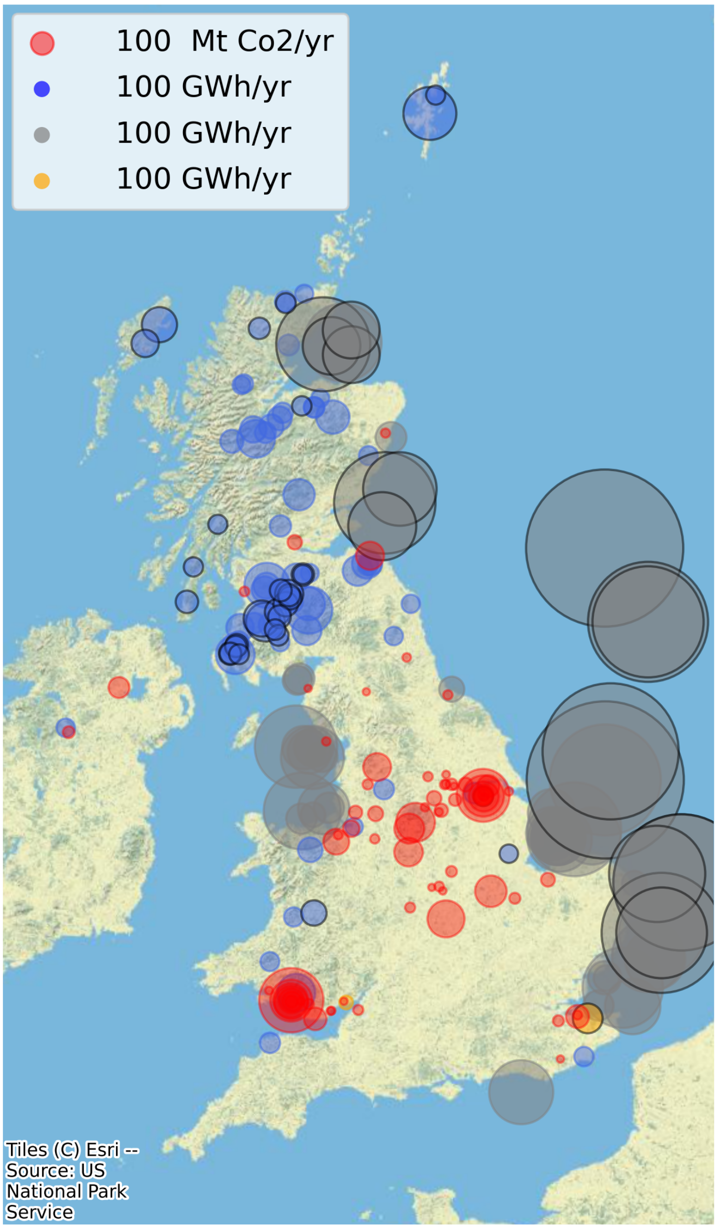



Figure 9.5: Locations of greatest green hydrogen potential demand (carbon emissions > 10 Mt) and production (installed capacity > 50 MW). Red = demand; blue = onshore wind; grey = offshore wind; orange = solar; black outline = planning permission granted or under construction. Data adapted from [283] and [25].

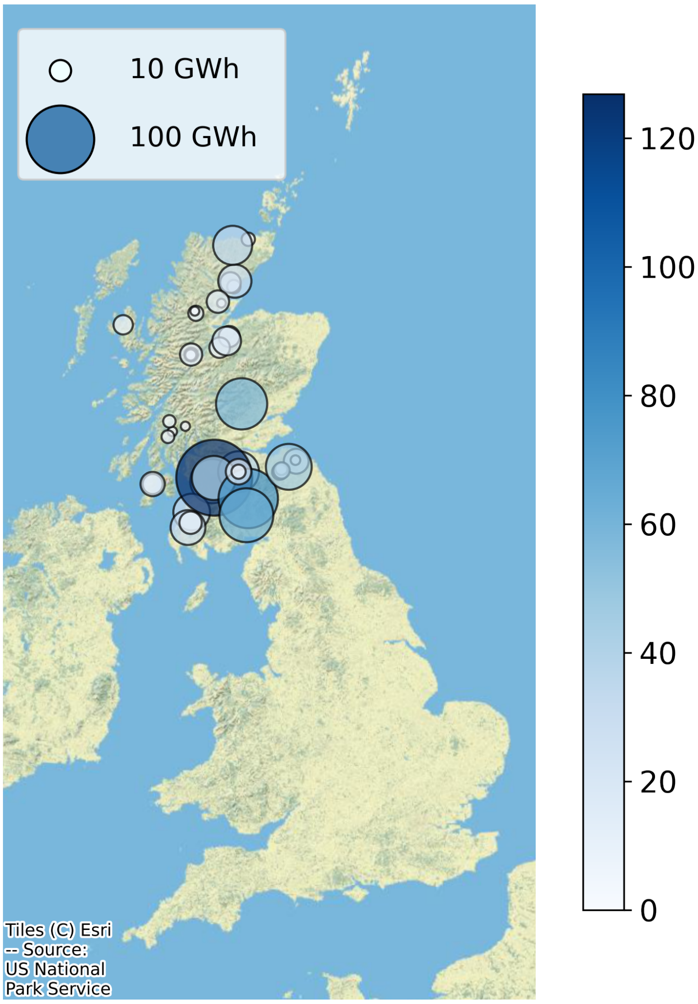
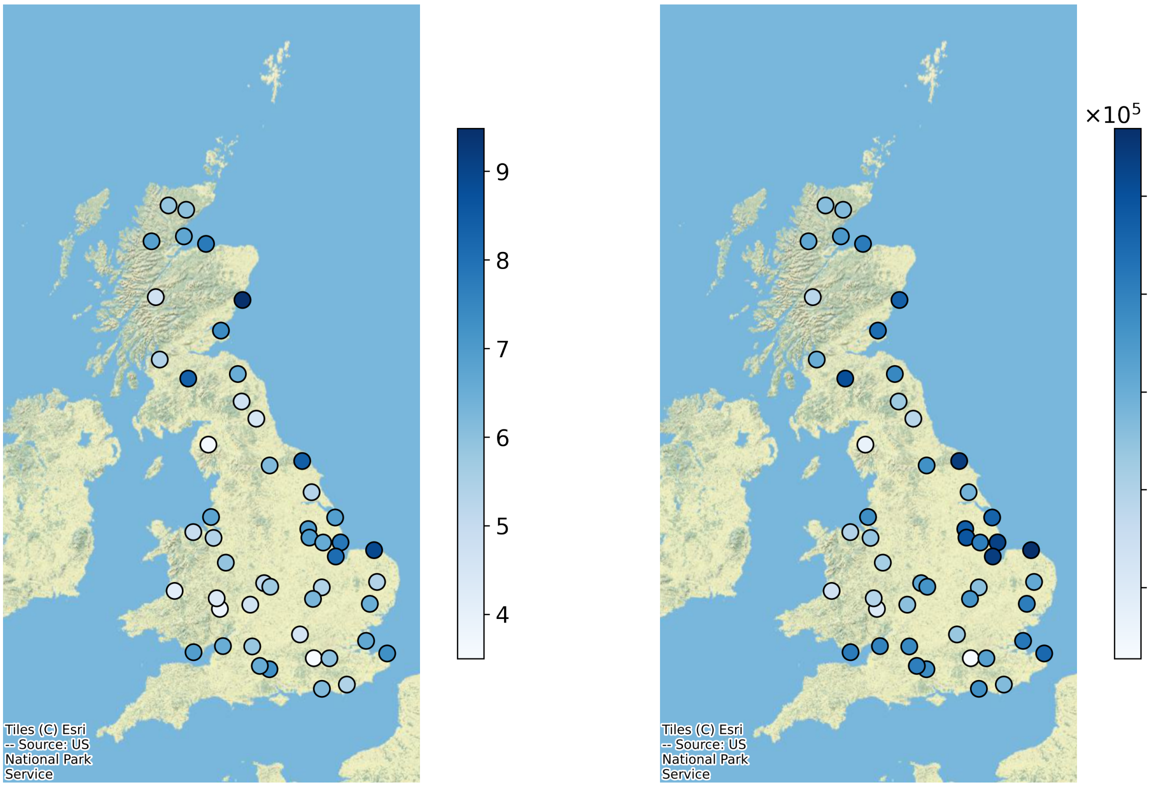



Figure 9.6: Yearly curtailed power (GWh) of onshore wind farms, estimated using data from [282].




(a) Mean wind speed (m/s)

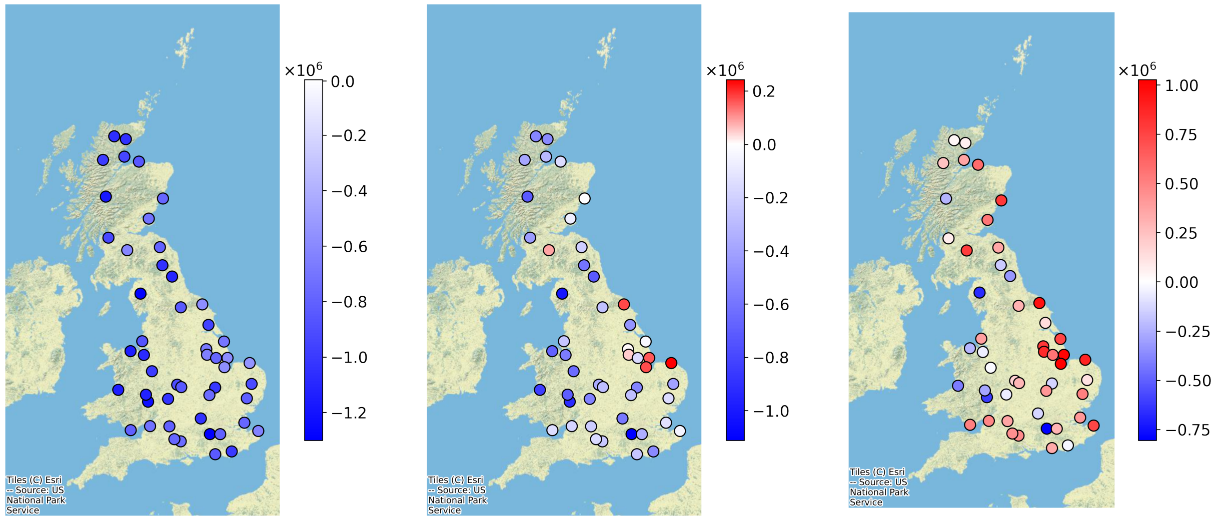
(b) Electrolyser profits (£)

Figure 9.7: Mean wind speed at 80m hub height and profits with electrolyser, relative to no electrolyser, over half year period.

The economics of producing green hydrogen at different onshore wind sites in the UK is assessed using the optimisation model developed here. It uses historic wind speed data and local DUoS charges. Figure 9.7 shows the mean wind speed at the 80m hub height and the profits with a 2000 kW PEM electrolyser, relative to no electrolyser, over the half year optimisation period. Some geographic variation can be observed, however, attention should be paid when drawing conclusions from this since there may be random factors relating to weather station location affecting wind speed. For instance, proximity to urban area, hills or elevation. The main observation is that, as expected, sites with a greater average wind speed are able to generate greater profits by adding an electrolyser, compared with sites with a lower average wind speed. Generally we find that sites that are able to generate the greatest profits are those on the east coast of England. Whereas sites situated on the west generally generate lower profits.

The Net Present Value (NPV) of adding an electrolyser in the different locations, with optimised scheduling, is shown in Figure 9.8 as hydrogen price is varied. At the mid-point of £3.50 there are a few locations where it is economically advantageous to add an electrolyser; these are mostly near the mid to north east of England and towards the south of Scotland. For a lower hydrogen price of £3/kg, it is not economical to add an electrolyser. However, for a higher hydrogen price of £4/kg it is economical in the majority of locations in GB, with a few exceptions in Wales.

In Figure 9.9 the NPV of adding an electrolyser is determined as PPA is varied. For a



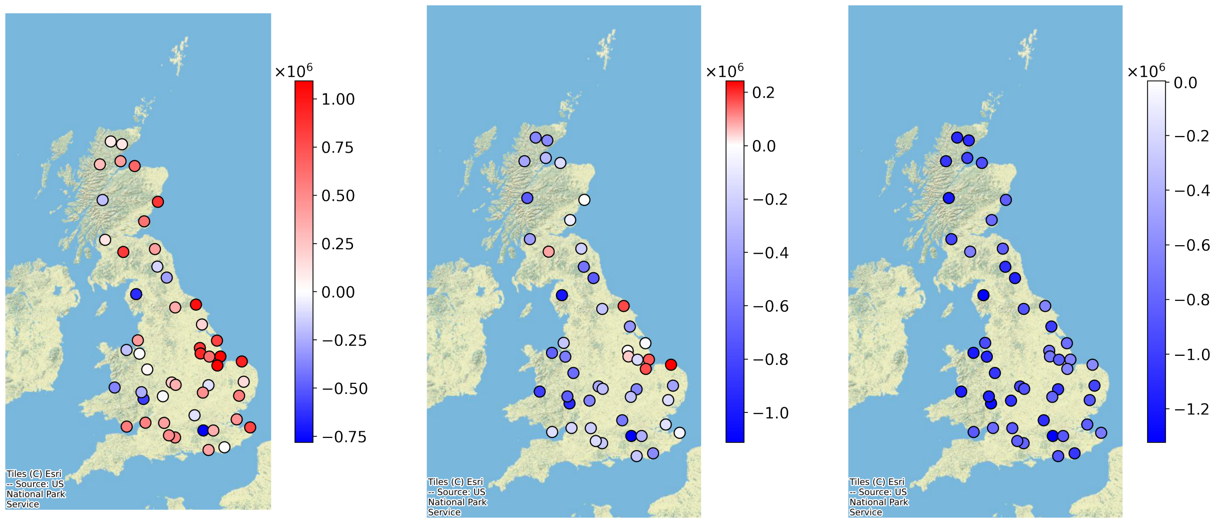

(a) Hydrogen price = £3/kg (b) Hydrogen price = £3.50/kg (c) Hydrogen price = £4/kg

Figure 9.8: NPV (£) of electrolyser in different locations. PPA = £0.04/kWh; 2000 MW electrolyser; energy consumption = 54 kWh/kg.

lower PPA of £0.03/kWh, it is more economical to add an electrolyser. However, for a higher PPA of £0.05/kWh, it is less economical. This is because the trade-off between directly selling electricity versus producing hydrogen favours selling electricity when PPA is high (£0.05/kWh). However, in a previous study, we found that even when PPA is £0.05/kWh, by waiting to invest in an electrolyser the expected value added decreases [2]. It can be seen in Figures 9.8 and 9.9 that the locations where electrolyser economics are most favourable correspond to locations with greater average wind speeds, as shown in Figure 9.7. Additionally, it should be noted that our optimisation model is based purely upon the recorded wind speed data and does not make any assumptions about curtailed wind. We can infer, therefore, that wind farms with greater capacity factors can improve their profits by adding an electrolyser to a greater extent than those with lower capacity factors. There does not appear to be any regional profit variations due to the different DUoS charges. However, given the regional variation in hydrogen demand and requirements for transport infrastructure, this could lead to location varying hydrogen prices.

Figure 9.10 compares the NPV of adding an electrolyser for the mid-point scenario (hydrogen price = £3.50/kg, PPA = £0.04/kWh, 2000 MW electrolyser, energy consumption = 54 kWh/kg), against the locations of existing and future (black outline) onshore wind sites and their yearly production. For this scenario it is economical to add an electrolyser in one location in Scotland that is located close to many current and future wind sites. This suggests that it could be economical to add electrolysers to these nearby sites. Additionally, as shown in Figure 9.6, there is a large amount of curtailed wind for sites in this region of Scotland. Therefore locating an electrolyser at these sites could be both economical and allow usage of curtailed wind, that would otherwise be wasted.

It is also economical to produce green hydrogen in locations in the mid-east of England (around Lincolnshire). There are some wind farms nearby where an electrolyser could be added. Producing green hydrogen in this region has the advantage that it is geographically close to industrial demand centres; these are primarily located in mid to north England, as shown in Figure 9.3. It should be noted that for scenarios with less favourable economics, such as lower




(a) PPA = £0.03/kWh (b) PPA = £0.04/kWh (c) PPA = £0.05/kWh

Figure 9.9: NPV (£) of electrolyser in different locations. Hydrogen price = £3.50/kg; 2000 MW electrolyser; energy consumption = 54 kWh/kg.

hydrogen price and/or higher PPA, it is not economical to add electrolysers to any onshore wind site. This suggests that if hydrogen price is not high enough then green hydrogen production could be hindered. Since green hydrogen has the potential to decarbonise so many industries, it should be highly valued to reflect this. For scenarios with more favourable economics, such as higher hydrogen price and/or lower PPA, it is economical to add electrolysers to the majority of onshore wind sites. Such conditions could most rapidly facilitate the transition to a low-carbon, hydrogen economy. Finally, the levelised cost of hydrogen (LCOH) was calculated for the sites considered as PPA was varied, using the equation presented in [297]. Mean LCOH, across all sites, was calculated to be £3.33/kg, £3.87/kg and £4.41/kg for PPA's of £0.03/kWh, £0.04/kWh and £0.05/kWh, respectively.

The results are summarised in Figure 9.11, which highlights the 2 regions where green hydrogen production was found to be economical. These regions are compared against the locations of onshore wind curtailment and potential industry demand (shown against the UK governemnt's Net Zero Industrial Clusters) to further justify why they are advantageous regions for hydrogen production. If the region in Scotland does become a production hub, then there could be infrastructure requirements to transport the hydrogen to the locations of industrial demand. This could be done either with pipeline(s) or transported by vehicles, such as trucks. Exploring optimum ways of transporting hydrogen between production and demand locations is an interesting research area for future work. Limitations of this work include: only considering a small number of weather stations, when more complete data sets are available this should be improved. Additionally, when there is more available data on hydrogen prices, this analysis can be repeated with these prices. Future work may also consider varying electrolyser size and energy consumption. Also, another interesting study would be to look at the economics of offshore green hydrogen production and transportation onshore.

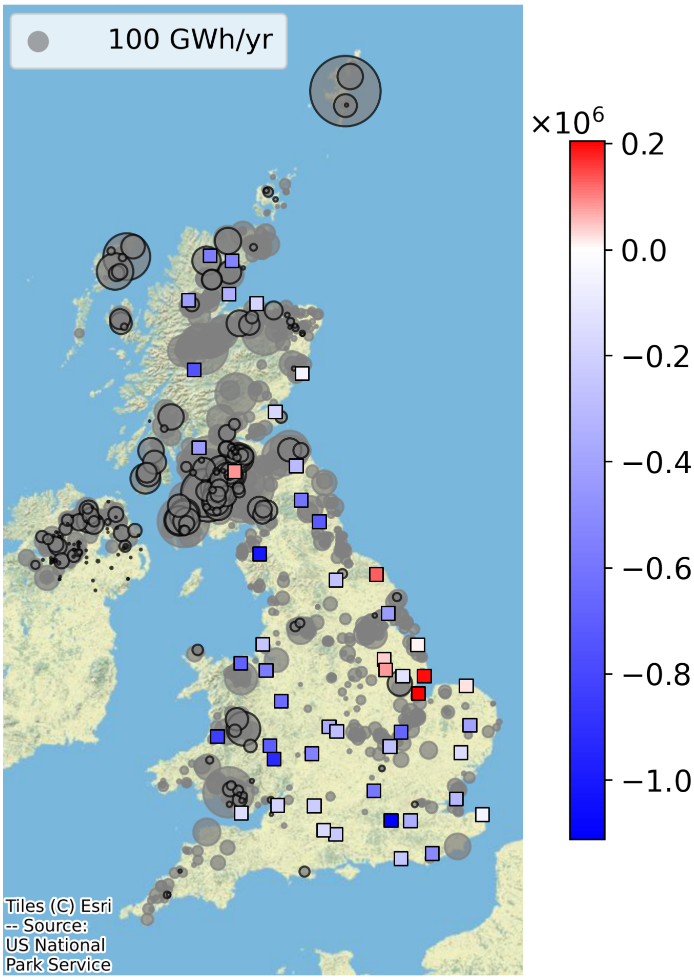



Figure 9.10: Current (no outline) and future (black outline) onshore wind yearly production, and optimised NPV (£) of electrolyser in different locations. Hydrogen price = £3.50/kg; PPA = £0.04/kWh; 2000 MW electrolyser; energy consumption = 54 kWh/kg.

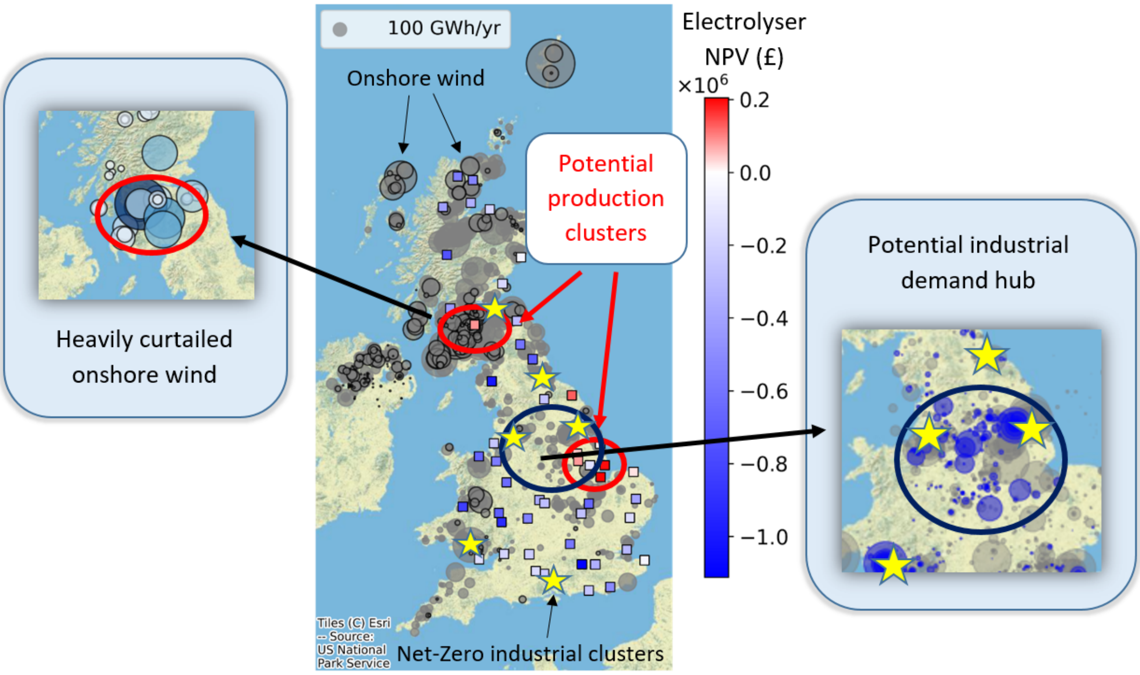



Figure 9.11: Summary of results, showing 2 identified potential green hydrogen production clusters with advantageous economics, and situated near heavily curtailed onshore wind and industrial demand, respectively.

## 9.4 Conclusion

This work seeks to support increased deployment of green hydrogen by optimising the profits (and minimising the costs) a wind farm owner, or investor, could make by adding an electrolyser. To do so, an optimisation model was developed and applied to different locations across Great Britain using real and openly available wind and DUoS price data. Additionally, we identified the most advantageous locations to deploy green hydrogen, using Great Britain as a case study. These are the locations with the best economics, that are also close to existing and future wind farm sites - in particular those that are heavily curtailed, and close to industrial demand hubs. Our methodology can be applied to other regions to examine the economics of adding an electrolyser to onshore wind sites.

It was found that, for the base case the Net Present Value of adding an electrolyser favoured 2 potential hydrogen production regions: southern Scotland (around Lanarkshire), and mid-east England (around Lincolnshire). The reader is referred to the map in Figure 11 where these locations are highlighted. These calculations were based upon actual recorded wind speed data and regional DUoS distribution system operator charges. There is a large number of existing and future wind farms in the Scottish region that could accomodate an electrolyser. Additionally, this region has the advantage of heavily curtailed wind farms, and the electrolyser could provide a useful pathway for curtailed power. However, significant infrastructure, such as pipelines or trucks, would be required to transport the green hydrogen to industrial end-users. This may then have an impact on the regional cost of hydrogen, given that the transition to hydrogen currently is vital to decarbonise industry. The region identified in mid-east England does not have as many existing or future wind farms as the region in Scotland, however it is located near to large potential industrial centres of green hydrogen demand. Therefore, less transport infrastructure would be required, lowering transport costs.

We find that for less economically favourable cost conditions, such as PPA $\geq$ £0.05/kWh or hydrogen price $\leq$ £3/kg, it is not profitable to add an electrolyser to wind farms in any region. Under these conditions, the deployment of green hydrogen is expected to be hindered. Therefore, the cost of green hydrogen should reflect its value in decarbonising many sectors. For the specific scenarios examined in this study, we suggest a hydrogen price of at least £3.50/kg, to encourage its increased deployment. For prices above this, it may be profitable to add an electrolyser to wind farms in the majority of regions in Great Britain. This analysis should be repeated once green hydrogen trading is more established and its price more accurately known. Future work should also quantify the economics of different transport options in order to link locations of production and demand.

# Chapter 10

# Green hydrogen investments: investigating the option to wait


## Abstract

Green hydrogen has the potential to play an important role in decarbonising energy systems globally, yet, its deployment remains low. In order to achieve greater roll-out of green hydrogen projects its value should be determined and used to advise industry and policy-makers. Real options (RO) analysis is an increasingly popular method for assessing the value of projects, particularly under uncertain conditions, since it allows for flexible decision making. This work applies an RO method to analyse the value of waiting before investing in a polymer electrolyte membrane (PEM) electrolyser for hydrogen generation at a wind farm. It is found that for wind power purchase agreements (PPAs) greater than £0.03/kWh, RO adds great value to the investment and reduces the chance of a negative investment compared with investing immediately. We explore a specific case study for a medium sized wind farm, with 20 turbines and a PPA of £0.055/kWh. It is found that by waiting to invest until hydrogen prices reach £4.40/kg, the expected value added by a 1000 kW PEM electrolyser increases from -£664,000 to £0. The average wait time is 17 months; however, if the turbine owner waits an average of 32 months, improvements in CAPEX and energy consumption reduce the required hydrogen price to £3.10/kg. This model is simple to use for wind turbine owners and can be adapted to different specifications and levels of risk-aversion. Furthermore, it is found to be robust to varying input parameters such as wind speed, resolution and electrolyser performance.



### Keywords

Green hydrogen, Real options, Investing under uncertainty, Renewable energy, PEM electrolysis


## 10.1 Introduction and literature review

### 10.1.1 Green hydrogen

Hydrogen has emerged as a key technology in enabling a low carbon energy transition. As outlined in a recent International Renewable Energy Agency (IRENA) report, it has the potential to decarbonise areas such as industry, shipping, aviation and heating which are traditionally harder to electrify [298]. The International Energy Agency (IEA) also believes that hydrogen's versatility and ability to work harmoniously alongside renewables will make it an integral part of our clean energy futures [273]. However, green hydrogen (produced by renewables) has historically contributed a negligible proportion of total hydrogen production; in 2018 green hydrogen made up 1% of the total [54]. In order to meet decarbonisation goals this proportion must be much greater [26]; for this to occur green hydrogen costs need to be more competitive.

Accordingly, there has been a surge in the literature studying the economics of green hydrogen projects, as highlighted by a recent review [299]. However, some of these papers are already outdated, given the rapidly advancing cost reductions. Hence, there is a need to understand how these reductions impact existing work. More recent papers on green hydrogen economics include [162], [300], [301]. Glenk and Reichelstein model the break-even price for green hydrogen in Texas and Germany and find that it is already cost competitive for niche applications [300]. For other applications it is expected to become competitive with fossil fuel hydrogen within a decade. Khan et al. present a detailed levelised cost framework to determine the costs of hydrogen, produced by renewable energies, and their sensitivity to different techno-economic parameters [301]. This is done for both near term (2020–2040) and long term (2030–2050) scenarios. Jiang et al. optimise the size of on-site hydrogen generation at a wind farm to maximise economics for different hydrogen prices [162]. The authors find that hydrogen price must be above 4.34 €/kg for it to be economical to include on-site generation.

There has also been a recent increase in green hydrogen optimisation models in the literature. Deng and Jiang optimise the size of wind-hydrogen systems to supply refuelling stations; they aim to increase utilisation of wind power whilst also matching demand [115]. Results show that when wind generation is low, power should be imported from the grid to avoid supply shortage. Carr et al. also optimise the scheduling of a wind-hydrogen refuelling station, with the aim of maximising profits and minimising demand shortfall [116]. They demonstrate performance benefits of their optimisation model, such as reducing wind curtailment. However, these benefits are dependent on there being sufficient hydrogen demand. Varela et al. present an optimisation model for alkaline water electrolysis (AEL), which takes into account its different modes of operation [114]. They optimise both the number of electrolysers and their scheduling to maximise profits. One flaw with all of the above studies, however, is that they do not consider uncertainties in wind generation and market prices. A few recent studies present scenario-based stochastic optimisation models which consider these uncertainties [153], [155]. However, they are limited in their scope as they only consider day-to-day profits rather than longer term investment decisions.

Another important issue affecting the economics of green hydrogen is degradation of the electrolyser stack. Some experimental studies have explored the mechanisms which cause this degradation [302]–[304]. They find that for polymer electrolyte membrane (PEM) electrolysers there is a link between degradation rate and current density. Chandesris et al. find that degradation rate is a maximum at low current density, however, the exact effect of current density is complicated [303]. Additionally, Feng et al. suggest that excess heat should be avoided to reduce thermal degradation [304]. They also suggest that operating PEM electrolysers alongside renewables may be detrimental to their performance and durability, due to aggressive operating conditions associated with rapid fluctuations. Modelling stack degradation is not within the scope of this work and will not be considered, however, the methodology is designed such that aggressive operating conditions due to wind fluctuations are limited.

One of the main flaws of the previously discussed studies is that they don't consider the flexibility of investors to make changes to projects part-way through. All decisions are taken at the start of project development and are independent of future events. This investment method does not allow for managerial flexibility, nor does it consider the dynamic nature of uncertainties inherent in hydrogen prices, electrolyser costs and parameters, such as energy consumption.

### 10.1.2 Real options

Real options is a useful approach for assessing the value of a project where there is inherent uncertainty and flexibility. The term real options refers to decisions, or *options*, made by an investor over a project's lifetime. Several of these are outlined in [173] and include, but are not limited to: invest, delay, expand, switch, suspend, contract or abandon. By analysing the real options at each step of a project, the risk of uncertainty can be managed by changing its course towards a more favourable direction.

Interest in the application of real options in the energy sector is rising due to the limitations of traditional techniques [174]. In particular, there are a number of studies relating specifically to energy storage, as outlined in [175]. However, only 2 of these have been identified as relating to hydrogen storage [176], [177]. Kroniger and Madlener use a real options approach to analyse the decision to run a wind-hydrogen system with or without a fuel cell to convert the hydrogen back to electricity [176]. Converting the hydrogen is found to be unprofitable; it is preferable to directly produce hydrogen. This study could be developed by considering a wider range of hydrogen prices, and electrolyser parameters with their predicted future evolution. Schmitz and Madlener consider the options associated with using kite-based wind energy to generate hydrogen. The authors use a binomial lattice approach to evaluate options and Monte Carlo simulation for uncertainties (compressed air price, hydrogen price and storage cost) [177]. It is found that for the three case studies considered their values are improved by considering a real options approach. This is an interesting case study, however, it is lacking in technical details particularly regarding the electrolysis unit and its operation.

Li et al. use real options to assess the optimal building strategy of hydrogen refuelling stations [178]. They find that the interaction between speed of infrastructure availability and adoption needs to be considered to avoid sub-optimal decisions. This is an interesting study, however, we are more concerned with the production of hydrogen than its use here. Secondly, Franzen and Madlener assess the option to expand a wind-hydrogen system by a 5 MW module at each time step [179]. They use a cascaded binomial tree to model the decision steps and Monte Carlo simulation for uncertainties in revenue (due to the stochastic nature of wind). By considering real options the valuation of the system significantly improves compared with a classical net present value calculation. Whilst this is a valuable contribution to the literature, there are several points which need addressing. Firstly, the sensitivity of the revenue to hydrogen prices should be analysed. Secondly, it is expected that advancements in PEM electrolyser technology will decrease their CAPEX and improve their energy consumption which will affect their future value and should be accounted for.

Overall our literature review has revealed that real options analysis has great potential to improve the value of investments by considering flexible decision making. Although there has been increased interest in the application of real options in the energy sector, there are still few studies looking specifically at investments in hydrogen production. Since hydrogen has been identified as a crucial part of our clean energy future, it is important to accurately assess it's value for both potential investors and policy makers. It is with this in mind that our paper aims to address the following existing shortcomings:

1. We apply a simple to use and easy to understand method (presented in [181] by Locatelli et al.) for assessing the options: *to invest, to wait, and to abandon*, for a wind farm looking to add a PEM electrolyser to maximise their revenue. This method has the advantage that it is easier for industry and policy makers to understand, and can easily be scaled up for multiple decision variables.

2. Future hydrogen price evolution and uncertainties are taken into account by stochastic

simulation of many possible price trajectories. This allows us to determine the expected mean value across these and the risk associated with the worst case scenario(s).

3. Evolution of electrolyser CAPEX and energy consumption are also considered using predicted values in the literature and simulating pessimistic and optimistic trajectories around these. By considering a range of future values for these we address the exogenous uncertainties they impose on hydrogen economics.

4. We explore how investment decision and the value of our project vary as we wait for threshold conditions on: hydrogen price alone, hydrogen price and CAPEX or energy consumption, hydrogen price and CAPEX and energy consumption, to be satisfied. This allows us to advise potential investors: wait until condition X is satisfied to maximise potential revenue.

The rest of this paper is organised in the following way: Section 2 presents our methodology; it discusses firstly how the wind farm and PEM electrolyser were modelled. Secondly, it outlines methods for determining cash flow, real options analysis and modelling hydrogen prices. Section 3 presents our results and discussion, in which we study the effects of varying PPA price, CAPEX and energy consumption thresholds, electrolyser size and perform a sensitivity analysis. Finally, Section 4 presents the concluding remarks.

# 10.2 Methodology

## 10.2.1 Wind turbine power

Wind speed data from [305] is used, since it has a resolution of 10 minutes and also includes the direction of the wind given as an angle. It should be noted that these speeds and angles are the average values over 10 minutes. A power curve is generated using data collected from a 225 kW community owned wind turbine in Holmfirth [306]. Each data point gives the current value of wind speed and output power of the turbine; by plotting all of these points we generate a curve of output power as a function of wind speed. This is used to convert wind speed to wind power by interpolating values from our curve.

It is unrealistic to assume that wind speed, and hence turbine power output, are constant over 10 minutes. In reality wind speed fluctuates rapidly causing a varying power output. Whilst some inertia may be provided by the turbines themselves, observations of the community turbine suggest that significant power fluctuations can occur on a second-by-second basis. For this reason we generate a power output profile with a time resolution of seconds; this is done by randomly adding noise to the 10 minute average power, $\hat{p}_t$, from a Gaussian distribution centred around $\hat{p}_t$ with a standard deviation of $0.15 \times \hat{p}_t$. The absolute value of these is taken to avoid any negative powers being generated.

In our simulations we consider a wind farm consisting of 20 such turbines, which is representative of an onshore wind farm in the UK [307]; these are distributed in a rectangular 4 by 5 layout. Since the time resolution being used is so small, the time taken for wind to travel between turbines needs to be considered. This is calculated using the 10 minute average wind speed, $\hat{v}_t$, direction, $\mathbf{\hat{n}_t}$, and direction vector to each turbine, $\mathbf{r^i}$:

$$t_t^i = \frac{\mathbf{r^i} \cdot \mathbf{\hat{n}_t}}{\hat{v}_t} \tag{10.1}$$

Our output power profile with seconds resolution is then shifted for each turbine, $i$, with respect to one another according to the time taken, $t_t^i$. Total power output of the wind farm is found by summing all of the individually shifted power profiles. This procedure is repeated every 10 minutes as average wind speed and direction changes. In reality, this model is not a perfect representation of wind behaviour since gusts may overtake each other and arrive at the same turbine at the same time. However, in [308] they find that gusts can be reasonably considered to travel at the 10 minute wind speed average. The model therefore gives a reasonable approximation whilst avoiding the computational complexities of fluid dynamics.

### 10.2.2 Electrolyser control strategy

PEM electrolysers can operate in 2 different modes:

1. Production - when input power is equal to or between the electrolyser's maximum and minimum loads and hydrogen production occurs
2. Idle - when input power is below the electrolyser's minimum load it is unable to operate and no hydrogen is produced

Preliminary work has found that directly using wind power to operate an electrolyser caused it to rapidly switch between these two modes causing accelerated degradation; this is due to wind fluctuations on a second-by-second basis. Consequently, smoothing must be provided by an external power source. This could be provided by a battery, however, preliminary simulations have found that the large capital costs of batteries outweighed the advantage of greater self-sufficiency through not needing to import power [46]. Therefore, it is assumed that power is imported whenever wind generation goes below the electrolyser's minimum load to keep it in production mode. On the other hand, when wind generation goes above the electrolyser's maximum load, the electrolyser runs at its maximum power and excess generation is sold to the grid. For generation between these maximum and minimum limits we assume that all power goes to the electrolyser.

Since the electrolyser stays in production mode (importing power when there is insufficient wind), we do not need to consider the transient phases due to switching between idle and production modes, known as cold starts. There is a ramp rate associated with cold starts, as discussed in [309], which means that during the transition period, the output of the electrolyser is reduced. Furthermore, there is some suggestion in the literature that repeated cold starts can affect electrolyser stack lifetime and should be avoided, although the full impact of this is currently unknown [310], [311]. For these reasons we limit our electrolyser to production mode only, to avoid transition periods which may reduce output and also electrolyser lifetime.

### 10.2.3 Cash flow valuation

Having established the power going to the electrolyser and/or from the grid on a second by second basis, the total energy to/from these over a period of time is calculated. From this we determine the total profits (and losses) from selling hydrogen and exporting (or importing) energy. Renewable generators typically have a contract known as a Power Purchasing Agreement, PPA, whereby they sell exported energy, $E_{t,exp}$ (kWh), at time $t$, at a fixed price, $P_{PPA}$ (£/kWh) [312]. The energy going to the electrolyser, $E_{t,e}$ (kWh), at time $t$, is used to determine the mass of hydrogen produced by dividing by energy consumption, $EC_t$ (kWh/kg). This value is a function of time since future electrolysers are predicted to have a lower energy consumption, hence cost calculations for future investments must take this change into account. The price at which hydrogen can be sold at, $P_h$ (£/kg), is uncertain and will be discussed in greater detail in Section 2.5. As previously mentioned, at times when wind generation is lower than the electrolyser's minimum power, power is imported from the grid, $E_{t,imp}$, at a UK non-domestic rate of $P_{imp}$. Net revenue is then calculated as:

$$R_t = E_{t,exp}P_{PPA} + \frac{E_{t,e}}{EC_t}P_{t,h} - E_{t,imp}P_{imp} \tag{10.2}$$

where $t$ indicates the time period over which this has been calculated; it is assumed that $P_{PPA}$ and $P_{imp}$ stay constant.

By considering the revenue obtained over the electrolyser's lifetime, along with its CAPEX and OPEX, calculations of its Net Present Value, NPV, are performed. These are useful to determine whether or not the project is a good investment. For an electrolyser investment starting in time period $j$, its NPV is determined using Equation 10.3, where DR is the discount rate and R is net revenue calculated in Equation 2. CAPEX has a subscript, $j$, as it changes with time due to technological improvements predicted in [292]: this is discussed later in this section and is shown in Figure 1. Hence, for an investment starting in time period $j$, we need to use the corresponding value of CAPEX; likewise, OPEX also changes with time, and is $4\%$ of CAPEX. Note that we keep things general and consider the possibilities of a) CAPEX and OPEX changing with time, and b) investing sometime in the future rather than immediately; in our real options analysis we assume that we have the flexibility to wait to invest.

$$NPV = \frac{-CAPEX_j}{(1+DR)^j} + \sum_{t=1}^{lifetime} \frac{R_{j+t} - OPEX_{j+t}}{(1+DR)^{j+t}} \tag{10.3}$$

For our NPV calculations we make the following assumptions:

- Our PEM electrolyser has a nominal power of 1000 kW. In [313] a minimum power of 5% of nominal power is found in 2017 and is predicted to be 0% in 2025; we have chosen 2%, 20 kW, as a reasonable assumption for our simulations starting in January 2022. These electrolysers may also output up to 200% of their nominal power for up to 10 minutes, therefore over 1 hour they can output a maximum of 1167 kWh.

- Since a PEM electrolyser has a lifetime of 50,000 - 80,000 hours [314], we evaluate the cash flow over time periods, $T$, each of 5,000 hours. In the case studies presented here we take lifetime to be the average of these values - 65,000 hours or $13T$.

- We model the wind farm output and electrolyser operation over 5,000 hours, and assume that the wind farm output in future time periods are the same (e.g. $E_{exp}, E_e, E_{imp}, E_{ne} =$ constant with T). This is to reduce computational time since we are using a time resolution of 1 second. Long term changes in wind speed and degradation of turbines are outside of the scope of this work.

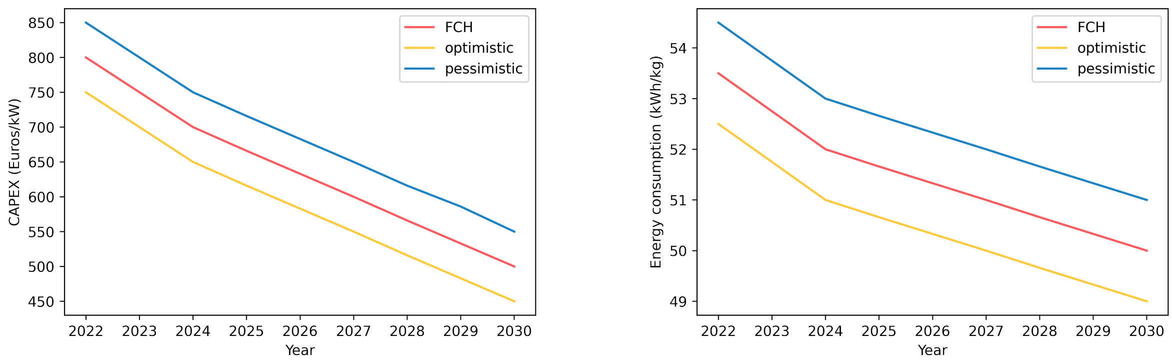
- The commissioning of the electrolyser-battery system is assumed to take 5,000 hours $\approx$ 7 months (e.g. 1 time period), such that revenue is generated from the second time period onwards, but not before.

- A discount rate of 8$\%$ is used since it is used in the latest IRENA report [314], additionally it is similar to renewable energy hurdle rates in the UK [315]. This annual discount rate is converted into discounted rate of 1 time period, using the method outlined in [316], to be 4.5$\%$.

- Electricity is imported when wind generation is not sufficient to maintain the electrolyser's minimum power. The electricity import price will be £0.126/kWh; this is based upon the

Table 10.1: Summary of parameters.

| Parameter | Value |
|---|---|
| PEM Nominal power (kW) | 1000 |
| PEM Max power (10 minute duration) (kW) | 2000 |
| PEM Max energy (over 1 hour) (kWh) | 1167 |
| PEM Min power (kW) | 20 |
| PEM Lifetime (hours) | 50,000-80,000 |
| T (1 time interval) (hours) | 5,000 |
| Commisioning time (hours) | 5,000 |
| Periodic discount rate (%) | 4.5 |
| Electricity import price (£/kWh) | 0.126 |




(a) CAPEX

(b) Energy consumption

Figure 10.1: Predicted values of PEM electrolyser CAPEX and energy consumption taken from the Fuel Cells and Hydrogen Joint Undertaking (FCH) [292] and optimistic and pessimistic simulations around these.

UK government's non-domestic energy prices [317] and is found to be the average price across Q3 2020 [318].

- Electrolyser CAPEX and energy consumption are predicted in [292] for 2020, 2024 and 2030. In our model we take into account the future variation of these in our calculations - an electrolyser bought in 2022 will cost more and be less efficient that one bought in 2028. We use Fuel Cells and Hydrogen Joint Undertaking (FCH) values for CAPEX and energy consumption predictions for our base case and examine the effects of more optimistic and pessimistic predictions, these can be seen in Figure 10.1.

The equivalent value of the wind farm with no electrolyser, $NPV_{ne}$, is calculated over the same time period using Equation 10.4, where $E_{ne}$ is the power going to the grid when there is no electrolyser. Then the added value due to investing in the electrolyser is determined by calculating $NPV - NPV_{ne}$. A positive value means that an electrolyser brings additional value, whereas a negative value means that it is not worth investing in.

$$NPV_{ne} = \sum_{t=1}^{lifetime} \frac{E_{ne} P_{PPA}}{(1 + DR)^{j+t}} \tag{10.4}$$

### 10.2.4 Real options analysis

In this work we consider the real options of a wind farm owner considering investing in a PEM electrolyser for hydrogen production, these are: invest, abandon, wait to make a decision. To do this we apply the method presented in [181] that uses "exercise thresholds". Whereby an exercise threshold is a particular value, which when reached by an uncertain cost variable triggers the option to invest. For multiple uncertain variables, multiple thresholds must be met to trigger the investment.

In this case study there are several cost variables that could affect NPV. These are: PPA, discount rate, electrolyser energy consumption, CAPEX, electrolyser lifetime and hydrogen sell price. All of these inputs except for hydrogen prices stay constant during the development of a wind-electrolysis project. The PPA is a long-term contract, already agreed upon, and the discount rate, electrolyser size, energy consumption, CAPEX and lifetime are decided at the start of the project. There is greatest uncertainty around hydrogen price (since current electrolyser parameters are known, and future trends can be predicted as in Figure 10.1), therefore, this is our principle uncertain cost variable, with threshold value $P_h^*$. However, we also explore the cases of combining this with threshold values for energy consumption, $EC^*$, and CAPEX, $CAPEX^*$. In Algorithm 3 we show the process to decide which real option to take: invest, abandon, and wait until time $j$ to make a decision. This depends on the current hydrogen price, learned in each new time period, and can be extended to also include electrolyser energy consumption and CAPEX. The maximum number of time periods for which we wait to make a decision is T = 10 (=50,000 hours ≈ 5.7 years); this was chosen because by this point the hydrogen market should be much more established with better methods of predicting prices, and hence newer models should be developed.

**Algorithm 3** Exercise threshold algorithm for hydrogen price with option of including energy consumption and CAPEX

**Result:** Decision to invest or abandon made in time period $j$ and value of project

j $= 0$ **while** $j \leq T$ **do**
  obtain current values of hydrogen price P$_{j,h},\ EC_j\ and\ CAPEX_j$
  **if** P$_{j,h} \geq P_h^*$ $(\&\ optional:\ EC_j \leq EC^*,\ CAPEX_j \leq CAPEX^*)$ **then**
    *invest* calculate NPV and NPV$_{ne}$
    **return** NPV, NPV$_{ne}, j$
  **else**
    **if** $j$ = $T$ **then**
      *abandon*
      NPV, NPV$_{ne} = 0$
      **return** NPV, NPV$_{ne}, j$
    **else**
      *wait to make decision*
    **end**
  **end**
  j $+ 1$ **end**

### 10.2.5 Modelling Hydrogen Prices

As previously mentioned, the price at which hydrogen can be sold is uncertain depending on market conditions. Since the green hydrogen market is very new there is very little existing data on it. Prices are estimated to be in the range £1.92-£4.96/kg [314]. In this model, we generate 50 random price paths to simulate possible price trajectories. We model these as a 1-d Wiener

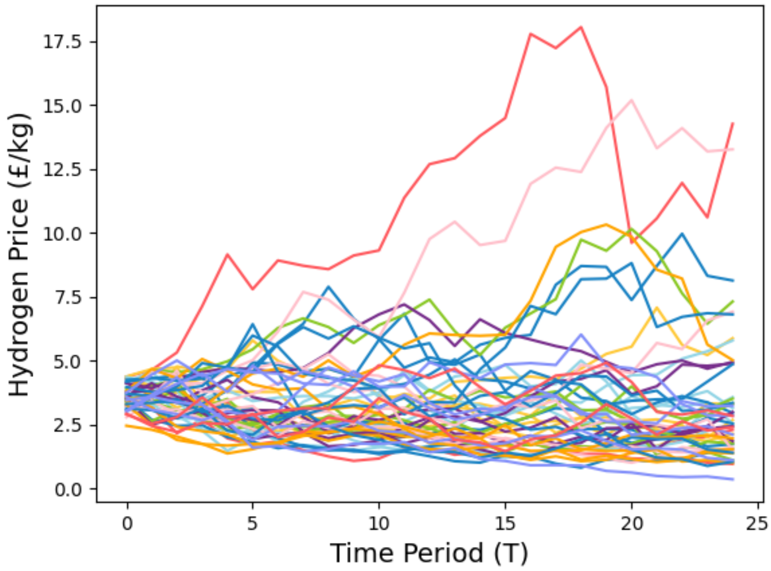



Figure 10.2: Generation of 50 possible hydrogen price trajectories.

process, or Brownian motion, which is used in the literature to model stock prices [319], [320]. This method is chosen since very little is known about green hydrogen markets, it is quick and easy to implement and extreme cases are a minority. We choose the midpoint £3.44/kg to be our starting price and for each time step, T (=5,000 hours), the price is updated as:

$$P_T = |P_{T-1} + P_{T-1}N(0, \sigma)| \tag{10.5}$$

where $N(0, \sigma)$ is the Gaussian distribution centered around 0 with standard deviation $\sigma$, and the absolute value is taken to prevent getting any negative prices. We choose $\sigma = (4.96 - 1.92)/20$ such that the majority of prices over the first 10 time periods are within the range £1.92-£4.96/kg as shown in Figure 10.2.

We optimise threshold value by cycling through a range. For each threshold value and each price trajectory the NPV of investing in hydrogen electrolysis is calculated. The investment only takes place if, and when, the price trajectory goes above the threshold price. If this condition is not met then the investment does not take place and the NPV is 0. If the investment takes place, $NPV_{ne}$ is also calculated over the same time period and the improvement due to adding the electrolyser is determined. A summary of the modelling procedure is shown in Figure 10.3; this procedure is implemented in Python with functions developed to 1. determine the electrolyser operation based upon user wind farm and electrolyser inputs, and 2. implement the real options algorithm based upon electrolyser operation and input cost parameters.

In the following section we present the results of implementing this methodology: firstly, in Section 3.1 we explore how investment decisions are affected by PPA price. Secondly, in Section 3.2 we set different thresholds on CAPEX and energy consumption and examine how this alters investment timings. In Section 3.3 we repeat this for different sized electrolysers. Finally, in Section 3.4 we present a sensitivity analysis of our model as we vary its input parameters and a discussion of the model's advantages and limitations.

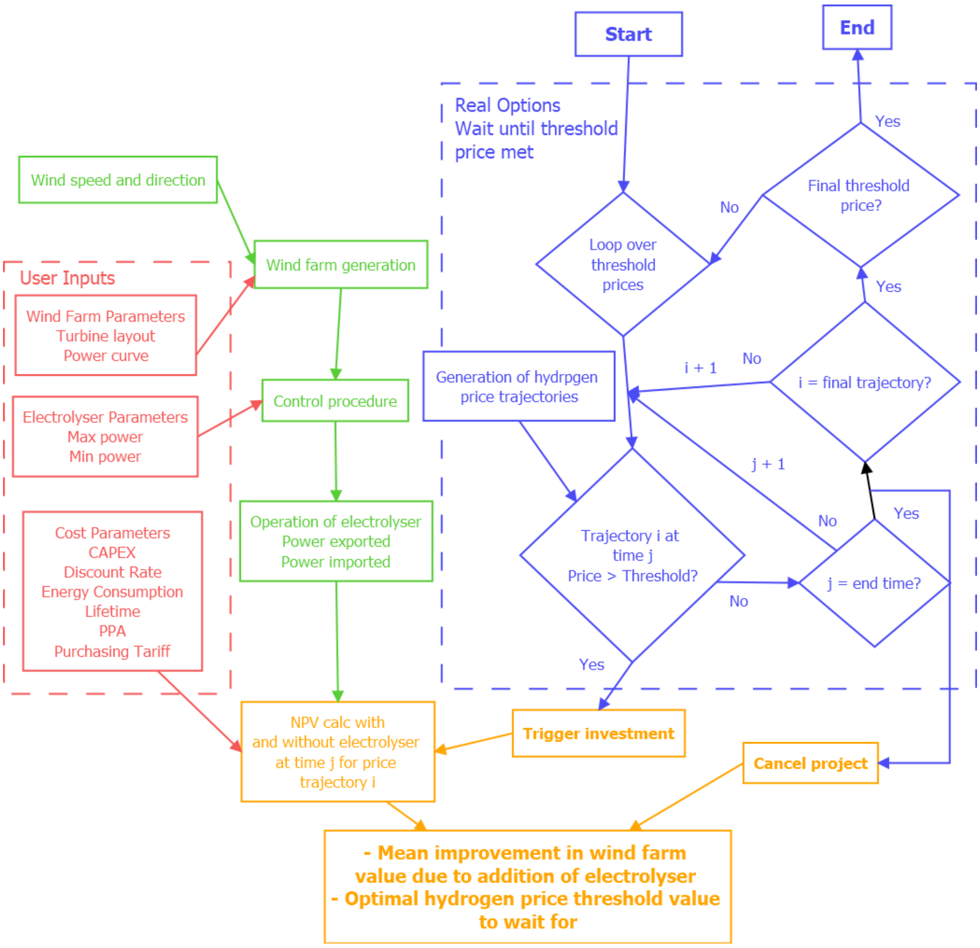
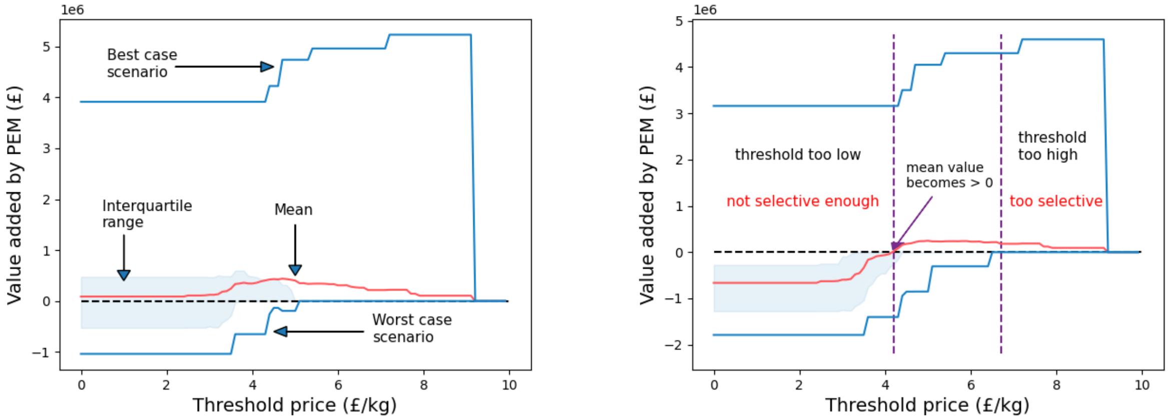



Figure 10.3: Flow chart showing modelling procedure.




(a) £0.035/kWh (b) £0.055/kWh

Figure 10.4: Value added by PEM electrolyser against threshold price for two different PPAs. Blue lines show best and worst case scenarios, and red lines the mean (across 50 generated price trajectories), the shaded region is the intequartile range.

## 10.3 Results and discussion

### 10.3.1 Varying PPA price

Firstly, we examine the effects of the PPA price (the price at which wind generation can be directly sold), on the value added by a PEM electrolyser. We determine whether to wait, invest or abandon at each hydrogen threshold price over a range, and for 50 different hydrogen price trajectories. For each time period and each hydrogen price trajectory we loop over the hydrogen threshold prices $P_h^* = \{0, 0.10, 0.20, ...., 9.80, 9.90, 10.00\}$ with units £/kg. The value added in each case is calculated. We do not consider threshold values for CAPEX or energy consumption at this stage and assume that they follow the FCH predicted values.

In Figure 10.4 we compare value added at different threshold prices for two PPA prices: £0.035/kWh and £0.055/kWh. The mean value added (across the 50 price trajectories) is seen to improve with threshold price up to a maximum point. When the threshold is low the investment is triggered for all price trajectories regardless of whether they are advantageous or not. Hence, mean value added is low. It is worse for the case with higher PPA since more revenue can be generated through directly selling wind; there is no economic advantage to be had by converting wind to hydrogen unless hydrogen sell price is high (threshold $>$ £4/kg).

As threshold price increases the choice to invest is more selective: fewer price trajectories are meeting the threshold level. Consequently, investments are made only for the most advantageous price trajectories, which are fewer in number as threshold increases. When the investment is made the value added is large, but otherwise it is zero (no investment). Beyond a point (threshold $>$ £5-7/kg) the mean value added decreases since the small number of high value scenarios are outweighed by the large number of zero value ones. Hence, it is not recommended to set the threshold price too high. The interquartile range decreases with threshold price, down to zero. This means that the range of value added, which can be used as a measure of risk, decreases with threshold. It must be noted, however, that when threshold is high there are fewer instances where investment occurs; hence there are fewer instances to base the statistics on.

Figure 10.5 shows the threshold prices where mean value added becomes greater than zero for different PPAs. Additionally, this is shown when values of CAPEX and energy consumption both follow FCH, pessimistic and optimistic predictions. As previously discussed, the lower the

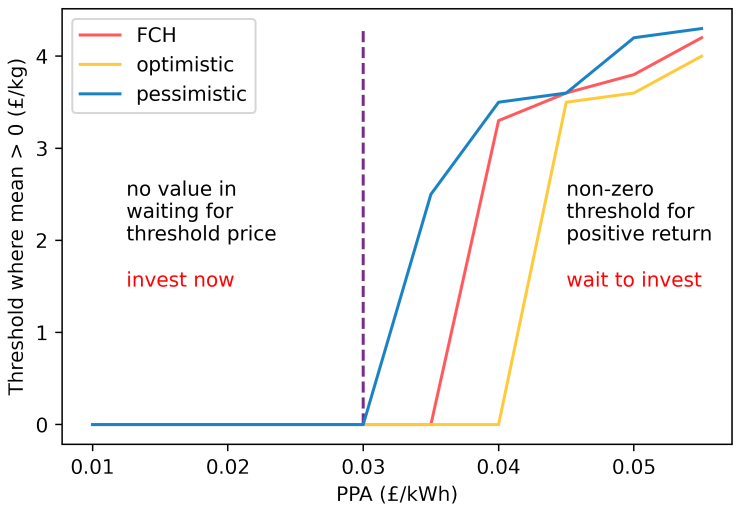



Figure 10.5: Threshold where mean value added becomes greater than zero for different PPAs. Shown when values of CAPEX and energy consumption both follow FCH, pessimistic and optimistic predictions.

PPA, the lower the threshold where the mean value added is above zero. When the electrolyser's CAPEX and energy consumption follow the pessimistic predictions greater thresholds are required provide a positive mean to counter these. For optimistic predictions, lower thresholds are required.

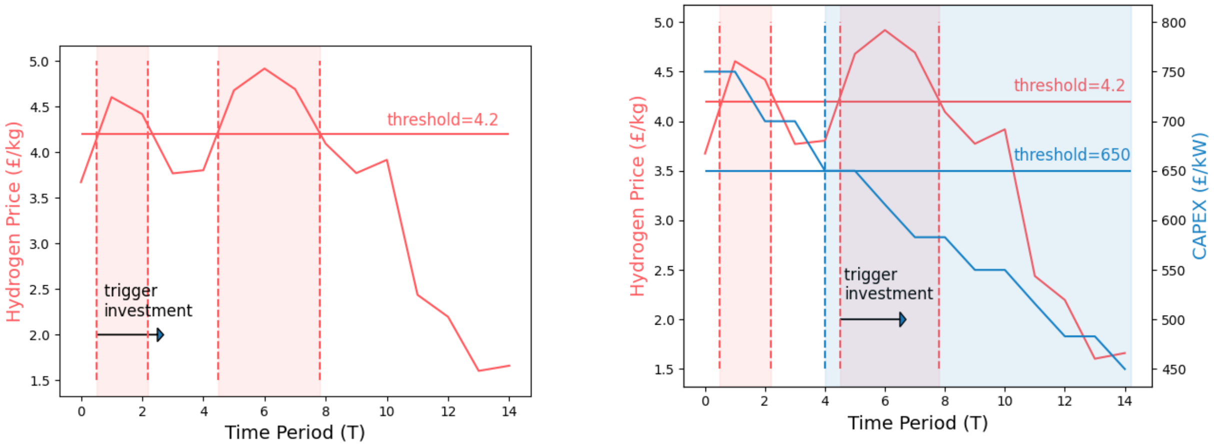
These results show that for certain PPAs (which will already be established between wind generator and a third party, such as a supplier), it may not be necessary to consider the real option *to wait* before deciding to invest or abandon. For PPAs of £0.03/kWh or lower, even for pessimistic CAPEX and energy consumption scenarios, the mean value added by a 1000 kW PEM electrolyser is positive for all thresholds. In these cases it is recommended to invest immediately. However, for PPAs above £0.03/kWh it is recommended to wait before investing.

### 10.3.2 CAPEX and energy consumption

We now examine the effects of waiting to invest until threshold prices for hydrogen price *and* CAPEX or energy consumption are met. Figure 10.6 shows the point at which an investment is triggered, for a particular hydrogen price and CAPEX trajectory with respective thresholds. By including a threshold for CAPEX, as well as hydrogen price, the investment is delayed since it takes longer for both conditions to be simultaneously satisfied.

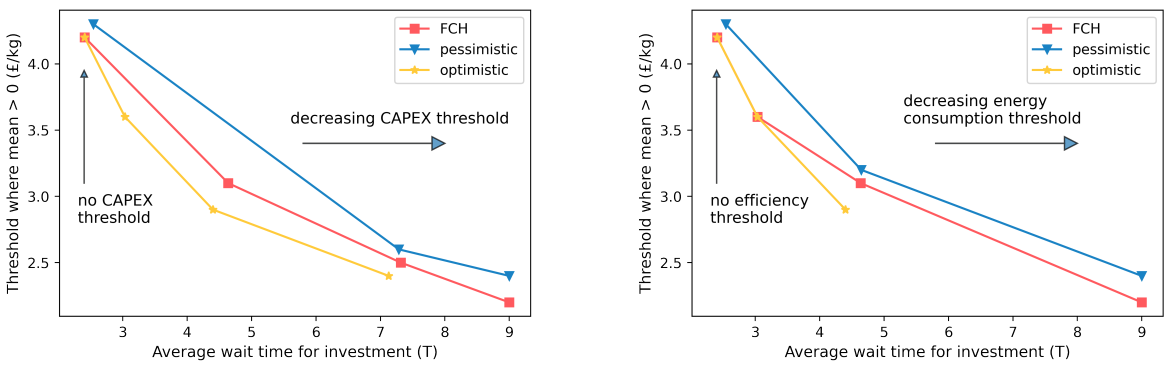
Simulations done here loop over hydrogen threshold prices and price trajectories (the same 50 randomly generated ones are used throughout), as well as CAPEX thresholds (No threshold, £700/kW, £650/kW, and £600/kW) and CAPEX trajectories (FCH, optimistic and pessimistic). Each time we determine whether to wait, invest or abandon, depending on whether both thresholds are simultaneously met. We do this for a PPA of £0.055/kWh since real options analysis was found to add greater value when PPA is higher. This analysis is repeated using energy consumption thresholds of 53, 52 and 51 kWh/kg and different energy consumption trajectories (FCH, optimistic and pessimistic). Whilst CAPEX threshold and trajectories are varied the energy consumption trajectory is kept constant using FCH values and vice versa.

The values of hydrogen price threshold that give a positive mean value are determined for each CAPEX and energy consumption threshold and trajectory. We then determine the average time period of investment at these particular thresholds. The results of this are shown in Figure




(a) Hydrogen price threshold (b) Hydrogen price and CAPEX threshold

Figure 10.6: Decision to invest is triggered once the threshold criteria are met - for multiple criteria they must both be met. Shown for randomly picked hydrogen price trajectory and optimistic CAPEX predictions.




(a) CAPEX (b) Energy consumption

Figure 10.7: Hydrogen threshold prices where mean value becomes greater than zero against average time period of investment. Determined by imposing thresholds on a) CAPEX and b) energy consumption and considering their respective possible future values.

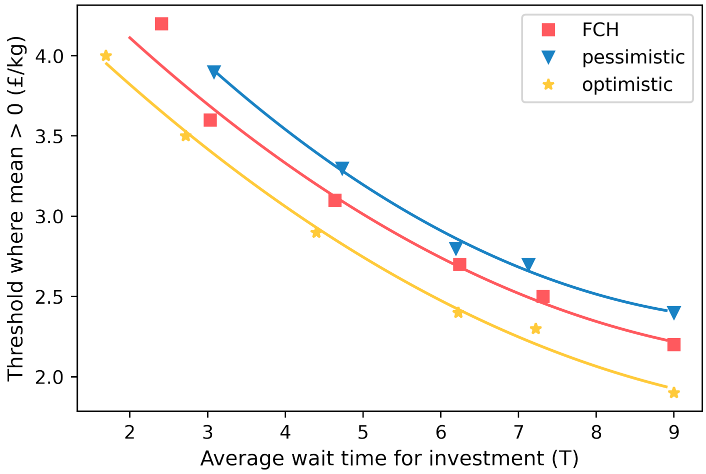
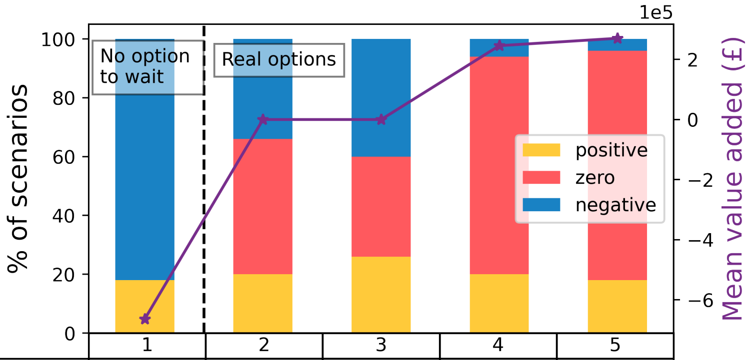



Figure 10.8: Distribution of hydrogen threshold prices giving a positive mean value as a function of average investment wait time. Shown for different levels of optimism regarding electrolyser CAPEX and energy consumption with second order regression curves fitted.

10.7 where we plot the distribution of thresholds against investment time. By imposing a stronger threshold on CAPEX or energy consumption (requiring lower values) we increase the wait time before investment and also decrease the hydrogen price threshold required for a positive mean. This makes sense, as if we wait for a cheaper or more efficient electrolyser, the income required to break-even is lower. For more optimistic future values of CAPEX and energy consumption the wait time is shorter and required threshold lower. It can be seen that there is a distribution of hydrogen price thresholds (giving a positive mean value across the price and CAPEX/energy consumption scenarios) as a function of average investment time period. This distribution is approximately centred around the FCH predicted values and gives a range of threshold values where an investment may be fruitful for different investment wait times.

To explore this in more detail we do a similar analysis imposing thresholds on hydrogen price, CAPEX and energy consumption, looping over thresholds of $P_h^* = [0....10, 0.10]$, $CAPEX^* = [560.....820, 20]$, $EC^* = [50.....55, 0.5]$ for 50 hydrogen price scenarios and for CAPEX-energy consumption scenarios where both follow pessimistic, FCH and optimistic trajectories. The hydrogen threshold at which mean value becomes positive is plotted against average time period of investment in Figure 10.8. Each point represents a particular pair of CAPEX-energy consumption thresholds; it should be noted that due to the discrete number of investment time steps many of these points lie on top of one another. Second order regression curves of the type $y = ax^2 + bx + c$ have been fitted to the points and represent the distribution of thresholds as a function of wait time for the different scenarios.

By considering different levels of optimism regarding CAPEX and energy consumption we incorporate exogenous price uncertainties into our analysis. Hence, rather than suggesting to a potential investor wait until a particular threshold is met at a particular time, we propose a range of suitable thresholds. A more risk averse investor would be advised to wait until the threshold corresponding to the pessimistic scenario is met. For an investor with a greater risk appetite they may choose to invest at the optimistic threshold.




| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| CAPEX | None | None | 700 | None | 700 |
| EC | None | None | 53 | None | 53 |
| Price | None | 0 mean | 0 mean | Max mean | Max mean |
| Wait time | 0 | 2.4 | 4.6 | 5.2 | 5.9 |

Figure 10.9: Percentage of scenarios where the investment adds positive, zero or negative value, and mean value added, for different threshold levels for a 1000 kW PEM electrolyser.

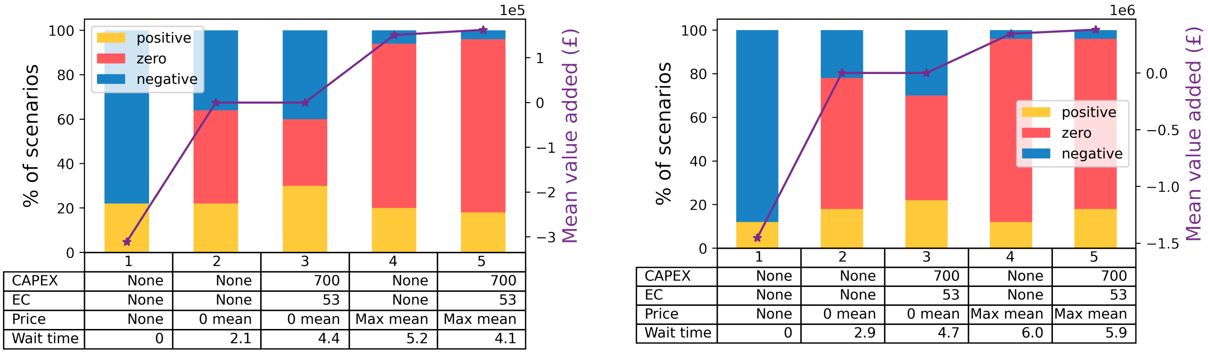
### 10.3.3 Improvement with real options and electrolyser sizing

In Figure 10.9 we show the percentage of possible hydrogen price scenarios for which investing in a 1000 kW PEM electrolyser adds positive, zero or negative value for the wind farm. This is shown for a PPA of £0.055/kWh and when CAPEX and energy consumption (EC) follow the FCH predicted values. We also show the mean value added to the wind farm. We do this for a number of different cases: firstly when the real option to wait is not considered and the investment occurs now; for cases 2 and 3 the investment occurs at the point when mean value becomes positive with and without thresholds imposed on CAPEX and energy consumption; for cases 4 and 5 the investment occurs when mean value is maximum with and without thresholds imposed on CAPEX and energy consumption.

It can be seen that by considering the option to wait, the number of cases where investment gives positive returns increases and decreases for negative returns. By waiting for a longer amount of time (until mean value added is maximum) the number of negative scenarios is very small. At this point hydrogen threshold price is sufficiently high that investment only occurs for the most advantageous scenarios, but not too high that the number of investments occurring drops off. At the point where mean value becomes positive there are a greater number of positive investments, however, also more negative investments, since this point is less selective. Importantly, even at this point fewer than 50% of investments turn out to be negative compared to $\approx 80\%$ when the option to wait is not considered.

For case 2, the hydrogen price threshold that yields a mean value $\geq 0$ is £4.40/kg and the average wait time to invest is 2.4 T $\approx$ 17 months. By imposing this threshold condition and waiting to invest, the mean value added for a 1000 kW electrolyser increases from -£664,000 to £0. Case 3 shows the same improvement in mean value. However, for this case our wait time is longer $\approx$ 32 months, due to waiting for CAPEX and energy consumption to decrease. Although, the hydrogen price threshold required is lower at £3.10/kg.

In practical terms, a wind turbine owner should be advised to initially wait for hydrogen prices to reach £4.40/kg before investing. If this price point is not achieved after 17 months, then they should be advised to wait for CAPEX and energy consumption to reduce to £700/kW and 53 kWh/kg, respectively. Once these improvements have occurred then they can invest as soon as hydrogen prices reach £3.10. The expected wait time for this to happen is 32 months. If




(a) 500 kW

(b) 2000 kW

Figure 10.10: Percentage of scenarios where the investment adds positive, zero or negative value, and mean value added, for different threshold levels for a) 500 and b) 2000 kW PEM electrolysers.

the wind turbine owner is risk averse, and wishes to minimise negative investments, then they should be advised according to cases 4 and 5. The risk averse turbine owner should wait until hydrogen price reaches £5.00/kg with an anticipated wait time (based upon Wiener process price progression) of 36-41 months.

In Figure 10.10 we show the same analysis for 500 and 2000 kW electrolysers. Mean value added for the 500 kW electrolyser is higher when there is no option to wait, however, when real options are considered the mean value added is lower. For the 2000 kW electrolyser, the converse is true. In particular, when real options are not considered the mean value is much more strongly negative than for the smaller electrolysers as the CAPEX is higher. Therefore real options are more valuable for a larger electrolyser because they allow consideration of lifetime risks, which increase with electrolyser size. For the smaller electrolysers the percentage of scenarios with positive value is higher and wait time is lower.

### 10.3.4 Sensitivity analysis and discussion

In this section we present a sensitivity analysis in order to verify that our methodology is reliable and address some of our assumptions. We also discuss some advantages and limitations of our methodology. Table 2 shows the results of running our model as we vary the following input parameters: maximum energy electrolyser can accept over 1 hour, standard deviation of the wind distribution, the time resolution considered, and the type of wind distribution used. Each of these are compared against our base case, where we consider a 1000 kW electrolyser, with thresholds of £700/kW and 53 kWh/kg for CAPEX and energy consumption imposed, and with CAPEX and energy consumption following the FCH predicted values.

It can be seen that when the maximum energy the electrolyser can accept over 1 hour is reduced (Cases 1 and 2) the threshold price required and wait time increase. This is due to the electrolyser's reducded capacity to produce hydrogen. However, the increases in threshold price (£3.10-3.30) and wait time (4.64-4.73 T $\approx$ 32-33 months) are not significant. This suggests that if our assumption that the electrolyser can output up to 200% of their nominal power for up to 10 minutes each hour (based upon [313]) does not hold in practise, then our results and conclusions are still valid.

Next we look at altering some of the assumptions which we made about the wind speed. In Cases 3 and 4 we changed the standard deviation of the wind speed distribution, in Cases 5-8

Table 10.2: Hydrogen price threshold where mean value becomes positive, wait time, and percentage of positive, zero and negative scenarios as input parameters are varied.

| Case | Electrolyser max energy (kWh) | Wind distribution | Time res (s) | Price threshold (£) value $>= 0$ | Wait time (T) | Pos (%) | Zero (%) | Neg (%) |
|---|---|---|---|---|---|---|---|---|
| Base | 1167 | Gaussian std $= 0.15 \times \hat{p}_t$ | 1 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |
| 1 | 1083.5 | Gaussian std $= 0.15 \times \hat{p}_t$ | 1 | 3.2 | 4.645161 | 0.24 | 0.38 | 0.38 |
| 2 | 1000 | Gaussian std $= 0.15 \times \hat{p}_t$ | 1 | 3.3 | 4.730769 | 0.24 | 0.48 | 0.28 |
| 3 | 1167 | Gaussian std $= 0.3 \times \hat{p}_t$ | 1 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |
| 4 | 1167 | Gaussian std $= 0.5 \times \hat{p}_t$ | 1 | 3 | 4.441176 | 0.26 | 0.32 | 0.42 |
| 5 | 1167 | Gaussian std $= 0.15 \times \hat{p}_t$ | 2 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |
| 6 | 1167 | Gaussian std $= 0.15 \times \hat{p}_t$ | 3 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |
| 7 | 1167 | Gaussian $0.15 \times \hat{p}_t$ | 5 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |
| 8 | 1167 | Gaussian std $= 0.15 \times \hat{p}_t$ | 10 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |
| 9 | 1167 | Gamma $0.15 \times \hat{p}_t$ | 1 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |
| 10 | 1167 | Gamma std $= 0.15 \times \hat{p}_t$ | 10 | 3.1 | 4.636364 | 0.26 | 0.34 | 0.4 |

we changed the time resolution it was modelled over, and in Cases 9 and 10 we modelled wind speed using a Gamma distribution rather than using the absolute values of a Gaussian. With the exception of Case 4 (the highest standard deviation) the results show no deviation from the base case which suggests that our model is robust to different wind speed distributions.

One of the main strengths of this methodology is that it is easy to use: a wind turbine owner simply has to input the layout and power specification of their turbines, the power of their intended electrolyser and their PPA and import tariffs. The model then outputs a hydrogen price threshold at which the mean expected value of their project is positive and an expected wait time for this; the owner is advised to make the investment when hydrogen price is equal to or greater than this threshold. Another advantage is that it takes into account future improvements in CAPEX and energy consumption of PEM electrolysers which will affect investment decisions.

One shortcoming of this methodology is the generation of hydrogen prices. Since there is little data available at the moment, price trajectories are generated using a Wiener process, based upon an estimated range of prices. In reality, supply and demand, and indeed the number of investors will affect these prices. Hence, future work should model the investor as a price-maker rather than a price-taker, and should be based upon actual market data once it becomes available. It is also possible that import tariff, PPA price and discount rate might change in the future as there is increased renewable penetration in electricity grids. However, the values of these are specific to each individual investor and vary regionally, as such they are left as user inputs. An interesting future addition to the model could be a method to predict how these prices might evolve and input them as time-varying parameters. Furthermore, although we have only considered PEM electrolysers, this model can easily be adapted for other types of electrolyser by altering input values of max/min power, CAPEX and energy consumption.

## 10.4 Conclusion

In this work we apply a simple to use method evaluating the option to wait for a wind farm looking to invest in a PEM electrolyser. This method is an improvement upon traditional cash flow analysis techniques since it allows flexible decision making under uncertain conditions, which are inherent in such a new market as green hydrogen. We account for future hydrogen price evolution and its uncertainties by stochastically simulating many possible trajectories. Also we consider future evolution of electrolyser CAPEX and energy consumption at different levels of optimism and analyse how investment time and value is affected by these exogenous uncertainties.

It is found that considering the option to wait can both improve the expected mean value of the electrolyser investment and reduce the scenarios where the returns are negative. However, we find that this is only the case for wind farms with power purchase agreements (PPAs) greater than £0.03/kWh; for wind farms with PPAs equal to or below this the best option is to invest immediately since market conditions are already favourable. It is only for higher PPAs and larger electrolysers when real options analysis adds significant value.

We present a specific case study for a medium sized wind farm, with 20 turbines and a PPA of £0.055/kWh. It is found that by waiting to invest until hydrogen prices reach £4.40/kg, the expected value added by a 1000 kW PEM electrolyser increases from -£664,000 to £0. The average wait time is 17 months; however, if the turbine owner waits an average of 32 months, improvements in CAPEX and energy consumption reduce the required hydrogen price to £3.10/kg. A more risk averse turbine owner should expect to wait 36-41 months and for hydrogen prices of £5.00/kg before investing in order to minimise the chance of a negative investment. This model is simple to use for and can be adapted to different specifications and levels of risk-aversion. Additionally, it is found to be robust to varying input parameters such as wind speed, resolution and electrolyser performance.

This work may be developed by considering other types of real options. For example, an interesting consideration for future work would be applying a similar methodology to [179], which considers the option to expand, with the added sensitivity analysis and up-to-date cost variables presented here. Additionally, as more information comes to light about hydrogen markets the hydrogen price predictions can be improved upon, along with prediction methods for import tariff and future PPA prices.

# Chapter 11

# Optimising a wind farm with energy storage considering curtailment and uncertainties


## Abstract

In this work, we present a scenario-based stochastic optimisation (SBSO) model to schedule a wind farm with battery storage (BS) and a hydrogen electrolyser (HE) considering curtailment and uncertainties in generation and market prices. We compare cases with BS only, HE only, and a combination of the two. We apply Markov Chain (MC) and Gaussian Process (GP) techniques to generate wind curtailment and electricity price scenarios, respectively, capturing their inherent uncertainties. The model then assesses the economic benefits of incorporating BS and/or HE alongside wind generation and their scheduling as a function of curtailed and non-curtailed wind. The results can be used to determine the suitability of such systems for the purposes of maximising profits and making optimal use of curtailed generation. Results show that HE increases mean income and curtailed wind utilisation significantly more than BS. However, by combining the two, wind curtailment can be reduced by 95%.



### Keywords

Wind farm; Battery storage; Hydrogen electrolysis; Curtailment; Stochastic optimisation.


## 11.1 Introduction

Energy storage technologies (EST) can facilitate the decarbonisation of energy systems and lead to more sustainable futures. Battery storage (BS) has been found to improve power quality in electrical grids [321] – particularly with high renewable energy penetration – and hydrogen storage (HS) can also replace fossil fuels in heating, industry and shipping [298]. Operating these technologies alongside renewables allows for the adoption of variable electricity sources [238] and a means to use otherwise curtailed generation. However, in order to do so optimially, the scheduling of these ESTs must further take into account uncertainties relating to renewable generation, curtailment and market prices due to their unpredictable nature.

There are a number of recent studies optimising the scheduling of renewable energy - energy storage systems under uncertainties, specifically wind-hydrogen systems. [153] consider uncertainties in wind generation and electricity price and present a scenario-based stochastic optimisation (SBSO) model which evaluates financial risk. They find that a hydrogen electroyser (HE) can increase the value of a wind system, the extent of which depends on hydrogen price. [155] and [156] present SBSO models which minimise operation costs of a system with wind generation and HS, the latter study also considers demand response (DR). Both of these papers consider uncertainties in wind generation, whilst [155] also considers uncertainties in demand. The efficacy of these models at reducing the risk of uncertainties is demonstrated. Finally, [157] present a SBSO model to minimise operation costs of an intelligent parking lot with HS and renewable generation. They present a Pareto set of solutions for different levels of risk aversion. These studies highlight the value of SBSO models for scheduling wind-hydrogen systems under uncertainties. However, they do not consider curtailed wind, which is an important issue as renewable penetration increases, nor do they consider other forms of energy storage, such as BS.

Several studies address using curtailed wind for an HE. For example, [160] explore different approaches for handling curtailed wind. They find that investing in an HE is both a profitable and environmentally friendly approach. However, they do not consider uncertainties in wind power or electricity price. [161] present a machine learning model to predict curtailed power which is used for an HE and BS. However, they optimise from a system operator point of view rather than that of an investor. On the other hand, [162] present a chance-constrained model that optimises the size of a wind-hydrogen system from an investor's perspective. Their methodology allows flexibility for the decision variables to not satisfy the constraints at a given probability level; thus adverse conditions can be accounted for. However, they do not model different curtailment or electricity price scenarios nor do they incorporate BS.

In this work we consider an investor's point of view, and present an SBSO which schedules a wind farm with HE and BS. We optimise their usage to maximise income, considering curtailment and uncertainties in wind generation, curtailment and electricity price. We compare case studies with HE and BS, HE only, BS only and no storage (NS). From this we determine the optimal choice for a wind farm owner to maximise income and utilise the maximum amount of curtailed wind.

## 11.2 Model Description

Wind curtailment occurs when generation exceeds demand, and generators are instructed to reduce, or sometimes halt, power export. At time $t$, in scenario, $i$, total wind generation can be divided into two categories: curtailed wind, $w^c_{t,i}$, which cannot be exported, and non-curtailed wind, $w^n_{t,i}$, which is available to export. The electrolyser can be powered using curtailed, $e^c_{t,i}$, or non-curtailed wind, $e^n_{t,i}$. Likewise the battery can be charged using curtailed, $c^c_{t,i}$, or non-curtailed wind $c^n_{t,i}$. The discharged power from the battery can be exported to the grid $d^n_{t,i}$ or curtailed $d^c_{t,i}$. It is assumed that at times when wind generation is not curtailed, $w^c_{t,i} = 0$, discharged battery is also not curtailed, $d^c_{t,i} = 0$. However where there is wind curtailment, it is assumed that discharged power cannot be exported to the grid, $d^n_{t,i} = 0$, and is also curtailed.

The objective function is given in Equation 11.1 and maximises revenue due to selling non-curtailed power in the day-ahead market (first term), selling hydrogen (second term) and minimises losses due to using curtailed wind (third term). The day-ahead price at time, $t$, and scenario, $i$, is $p^{da}_{t,i}$, $p^h$ is hydrogen price and $\eta^c$ is electrolyser hydrogen conversion efficiency. The cost of using curtailed wind, $p^c$, is neglected in most models, which assume that curtailed wind is free. This assumption is overly simplistic and not realistic, hence we consider $p^c$ here.

$$max \sum_{t,i=0}^{T,I} (w_{t,i}^n + d_{t,i}^n - c_{t,i}^n - e_{t,i}^n) p_{t,i}^{da} + (e_{t,i}^n + e_{t,i}^c) \frac{p^h}{\eta^e} - (e_{t,i}^c + c_{t,i}^c) p^c \tag{11.1}$$

The constraints are given in Equations 2-10. Equation 2 sets the lower limits on the battery charging and discharging powers and the power going to the electrolyser, where $\underline{e}$ represents the minimum power required for hydrogen production. Equations 3 and 4 set the upper limits; the upper bound on $d_{t,i}^n$ is set such that discharged power can only be exported when there is no wind curtailed. Equation 5 prevents the sum of curtailed and non-curtailed powers exceeding the maximum limits.

$$c_{t,i}^n, c_{t,i}^c, d_{t,i}^n, d_{t,i}^c \geq 0, \qquad e_{t,i}^n, e_{t,i}^c \geq \underline{e} \qquad \forall\ t, i \tag{11.2}$$
$$c_{t,i}^n, c_{t,i}^c \leq \bar{c}, \qquad d_{t,i}^c \leq \bar{d}, \qquad e_{t,i}^n, e_{t,i}^c \leq \bar{e} \qquad \forall\ t, i \tag{11.3}$$
$$if\ w_{t,i}^c = 0 :\ d_{t,i}^n \leq \bar{d}, \quad else :\ d_{t,i}^n \leq 0 \qquad \forall\ t, i \tag{11.4}$$
$$c_{t,i}^n + c_{t,i}^c \leq \bar{c}, \qquad d_{t,i}^n + d_{t,i}^c \leq \bar{d}, \qquad e_{t,i}^n + e_{t,i}^c \leq \bar{e} \qquad \forall\ t, i \tag{11.5}$$

Equations 6 and 7 set limits on the battery's capacity, $x_{t,i}$, and ensure that it is equal to the capacity at the previous time period plus any charging/discharging in the current time period, respectively. The charging and discharging efficiencies are $\eta^c$ and $\eta^c$, respectively, and are equal to 90%.

$$\underline{x} \leq x_{t,i} \leq \bar{x} \qquad \forall\ t, i \tag{11.6}$$
$$x_{t,i} = x_{t-1,i} + (c_{t,i}^n + c_{t,i}^c)\eta^c - \frac{d_{t,i}^n + d_{t,i}^c}{\eta^d} \qquad \forall\ t, i \tag{11.7}$$

Equation 8 prevents the battery from being simultaneously charged and discharged. In Equation 9 the curtailed generation and discharge is greater than or equal to the curtailed power used for charging and powering the electrolyser. Equation 10 ensures that when there is no wind curtailed there is also no curtailment of discharged battery. $M$ is a very large positive co-efficient which allows curtailed discharge to take on any value, satisfying previous constraints, when there is non-zero curtailed wind.

$$(c_{t,i}^n + c_{t,i}^c)(d_{t,i}^n + d_{t,i}^c) = 0 \qquad \forall\ t, i \tag{11.8}$$
$$w_{t,i}^c + d_{t,i}^c \geq c_{t,i}^c + e_{t,i}^c \qquad \forall\ t, i \tag{11.9}$$
$$Mw_{t,i}^c - d_{t,i}^c \geq 0 \qquad \forall\ t, i \tag{11.10}$$

## 11.3 Scenario Generation

A range of scenarios are generated to represent possible outcomes of the uncertain parameters, in this case wind generation, curtailment and electricity price. Three wind power profiles are randomly generated from [322], by adding noise from a Gaussian centred around each data point with a mean equal to that point and a standard deviation 0.25 * data point. This wind data is scaled such that the farm has a maximum output of 20 MW. Five curtailment profiles are then generated using a MC with probabilities of moving between states 'curtailed' and 'not-curtailed' determined using historic data, and initial state 'not-curtailed'. When the state is 'curtailed', the

Table 11.1: Input storage parameters for each case considered.

| | $\underline{e}$ (MW) | $\bar{e}$ (MW) | $\bar{c}$, $\bar{d}$ (MW) | $\underline{x}$ (MWh) | $\bar{x}$ (MWh) |
|---|---|---|---|---|---|
| HE + BS | 0.04 | 2 | 2 | 1.6 | 8 |
| HE | 0.04 | 2 | 0 | 0 | 0 |
| BS | 0 | 0 | 2 | 1.6 | 8 |
| NS | 0 | 0 | 0 | 0 | 0 |

percentage of wind power curtailed is determined by randomly selecting from historic data. The 'not-curtailed' wind profile is the difference between this and the original wind profile. Three price profiles are created using Gaussian Process (GP) techniques as described in [323]; the first profile is an ordinary GP, and the other two are created using a novel hybridisation method which combines Gaussian Processes with K-means clustering and hierarchical cluster.

A summary of the scenario generation procedure is shown in Figure 11.1. Each of these scenarios is input into our SBSO model which optimises the scheduling our of energy storage for cases with HE and BS, HE only, BS only, and no storage (NS). The input parameters for the storage for each of these cases is shown in Table 11.1. Finally, it is assumed that hydrogen can be sold at a price of £3.50/kg and the cost of curtailed wind is £0.01/kWh.

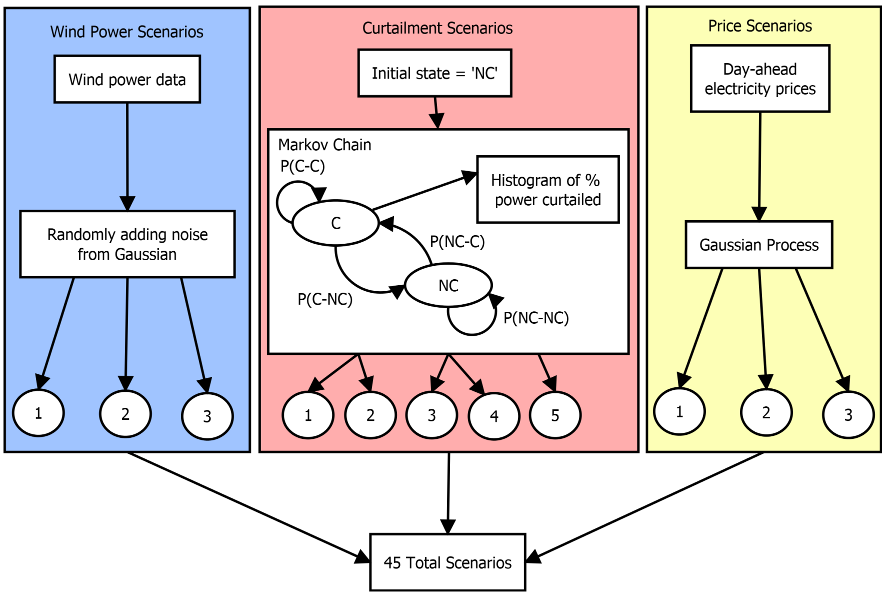



Figure 11.1: Scenario generation diagram

## 11.4 Results and Discussion

In Table 11.2 the mean income and percent of curtailed wind utilisation, across all scenarios, are shown for the different case studies, along with their standard deviations. It can be seen that the inclusion of storage increases both the mean expected income and curtailed wind utilisation. In particular, the HE is able to increase the values of these more than the BS. However, the combination of both is the most effective of the case studies presented here. Additionally, the inclusion of storage reduces the standard deviation of mean expected income. This is since storage adds flexibility; for instance, when wind generation is low and curtailment is high, additional revenue can still be achieved due to selling hydrogen and discharged power from the BS.

Figure 11.2 shows the optimised daily power profiles for each case study for Scenario 6. This

Table 11.2: Mean and standard deviation of daily income and percentage of curtailed wind utilised across all scenarios for each case study.

| | Mean income (£) | Standard deviation (£) | Curtailed wind usage (%) | Standard deviation (%) |
|---|---|---|---|---|
| HE + BS | 4989 | 222 | 0.949 | 0.029 |
| HE | 4870 | 300 | 0.679 | 0.034 |
| BS | 4311 | 629 | 0.165 | 0.037 |
| NS | 4208 | 689 | 0.0 | 0.0 |

scenario was chosen because there is a large amount of wind curtailment, occurring between 4:00 and 14:00 (8 and 28 in Figure 2), and shows how the scheduling of the storage responds to this. Wind generation is indicated by the red lines; wind power that is directly imported or curtailed is shown by a solid area, power used for the HE: a dashed area, and power used for or discharged by the BS: a dotted area. Non-curtailed wind may be exported, along with non-curtailed discharge from the BS (indicated by a dark blue area); alternatively, it may be consumed by the storage (green area). Curtailed wind (and BS discharge) is used to power the HE and/or BS (although the BS cannot simultaneously charge and discharge) and is indicated by a white area.

In the case of NS, we can seen that all curtailed wind is wasted. By adding BS, we are able to use some of the curtailed wind, however, once the BS is fully charged we cannot use it anymore. The BS also allows a greater amount of power to be exported in the evening when electricity prices are typically higher (34 - 38 in Figure 2). By adding HE we are able to use a greater proportion of the curtailed wind. Furthermore, under the conditions specified here, it is economical to self-consume and import power for the HE. By combining BS and HE we are able to utilise the most curtailed wind and maximise power used for the HE; at 10:30 and 12:00 (21 and 24 in Figure 2), there are two peaks above the red line which indicate curtailed BS discharge powering the HE. As shown in Table 11.2 this case generates the highest mean income across the different scenarios. Hence we conclude that of the cases explored here, a combination of BS and HE is optimal for both maximising income and utilising the maximum curtailed wind.

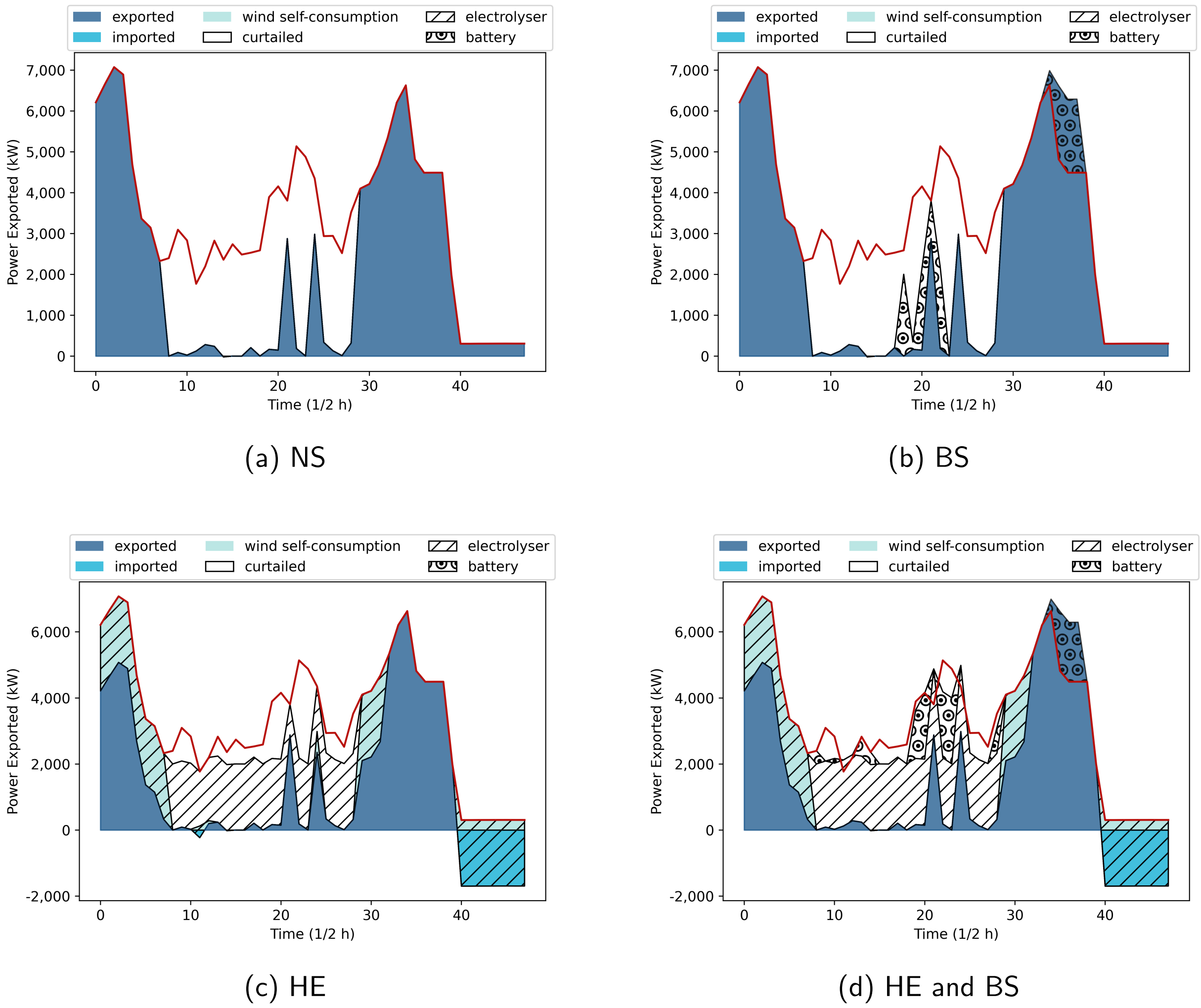



Figure 11.2: Daily power profile for Scenario 6, for each case study. Red line indicates total wind generation.

## 11.5 Conclusion

A scenario-based stochastic optimisation (SBSO) model is presented to schedule a wind farm with battery storage (BS) and a hydrogen electrolyser (HE) under uncertain conditions and considering curtailment. We generate wind curtailment and electricity price scenarios using Markov Chain (MC) and Gaussian Process (GP) techniques, respectively, to model a range of possible outcomes. We compare daily mean predicted income and utilisation of curtailed wind with BS only, HE only, both BS and HE, and no storage (NS).

We find that HE increases mean income and curtailed wind utilisation significantly more than BS. However, by combining HE and BS curtailed wind utilisation increases from 68% to 95%, compared with HE alone. At times when curtailed wind is greater than the HE maximum power, it can also be used to charge the BS; then at times when curtailed wind is lower than this maximum power, it can be additionally powered by discharging the BS. Future work will consider capital and operational costs of these technologies, as well as varying their sizes, ratios and hydrogen price.

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