School of Engineering

Viability and value of behind-the-meter battery storage

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Abstract

Behind-the-meter (BTM) battery storage is a distributed, flexible technology that can support the integration of renewable generation in low-carbon power systems. This research addresses three main challenges related to the integration of BTM battery storage systems: their financial viability from the local perspective, identifying a suitable approach to account for BTM battery storage systems as autonomous decision makers in the power system and quantifying the value of BTM battery storage within low-carbon power systems.

The viability of BTM battery storage was investigated from the local perspective, stacking up to three revenue streams simultaneously and accounting for battery degradation. The results indicate that single applications of BTM battery storage are unlikely to be an attractive investment but stacking more than one revenue stream improves investment viability and battery lifetime.

Two approaches were compared for their suitability to account for BTM battery storage as autonomous decision makers in the power system. Additionally, the impact of retail contracts on the value of BTM battery storage to the power system was investigated. The result identifies and justifies the most suitable approach and provides insights into which retail contracts are the most beneficial from the power system perspective.

The interactions between the power system and autonomous BTM batteries were studied in detail, to assess the value of BTM battery storage from the power system perspective. The results reveal BTM battery storage can have a positive or negative impact on the power system. Therefore, contract design and market structures are crucial to ensure the adoption of this technology benefits the power system.

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List of Abbreviations

Abbreviation	Description
BTM	Behind-the-meter
CCGT	Combined cycle gas turbine
DC	Dynamic Containment
DUoS	Distribution use of system
FFR	Firm Frequency Response
GB	Great Britain
GHG	Greenhouse gas
LES	Local energy system
NPV	Net present value
OCGT	Open cycle gas turbine
PV	Photovoltaic
UK	United Kingdom

Chapter 1

Introduction

1.1 Changes in the electricity generation mix

Electricity generation was responsible for approximately 30% of global greenhouse gas (GHG) emissions in 2021 [1], [2]. Global electricity demand is projected to triple by 2050 as electrification of heat and transport increases [3], intensifying the challenge to meet demand with net zero emissions. Traditionally, electricity is generated by fossil fuel power plants such as coal and natural gas, supplying 67.3% of global electricity in 2010 [4]. Fossil fuel power plants use combustion of fossil fuels to generate electricity, releasing harmful GHG emissions into the atmosphere. To achieve global targets of net zero GHG emissions, the use of fossil fuels to generate electricity must be ended.

The United Kingdom (UK) has seen a significant increase in the amount of electricity generated by renewable technologies, in a bid to reduce GHG emissions from the power sector. Figure 1.1 shows the UK's electricity generation by fuel, since 2010 [5]. In this time, renewable generation from wind and solar has increased from approximately 3% in 2010 to 25% in 2021. Initially, wind and solar displaced high emitting technologies such as coal. Where electricity generation from coal fell from 39.6% in 2012 to 2.1% in 2021. However, natural gas still supplies 40.3% of electricity generation, demonstrating more low-carbon generation is required. To achieve the UK's target of net zero electricity by 2035 [6], natural gas generation must also be significantly reduced. Coal and natural gas generation must be replaced by low-carbon alternatives such as wind, solar and nuclear. Wind and solar are expected to generate between 78% and 88% of the UK's annual electricity demand by 2050 [7].

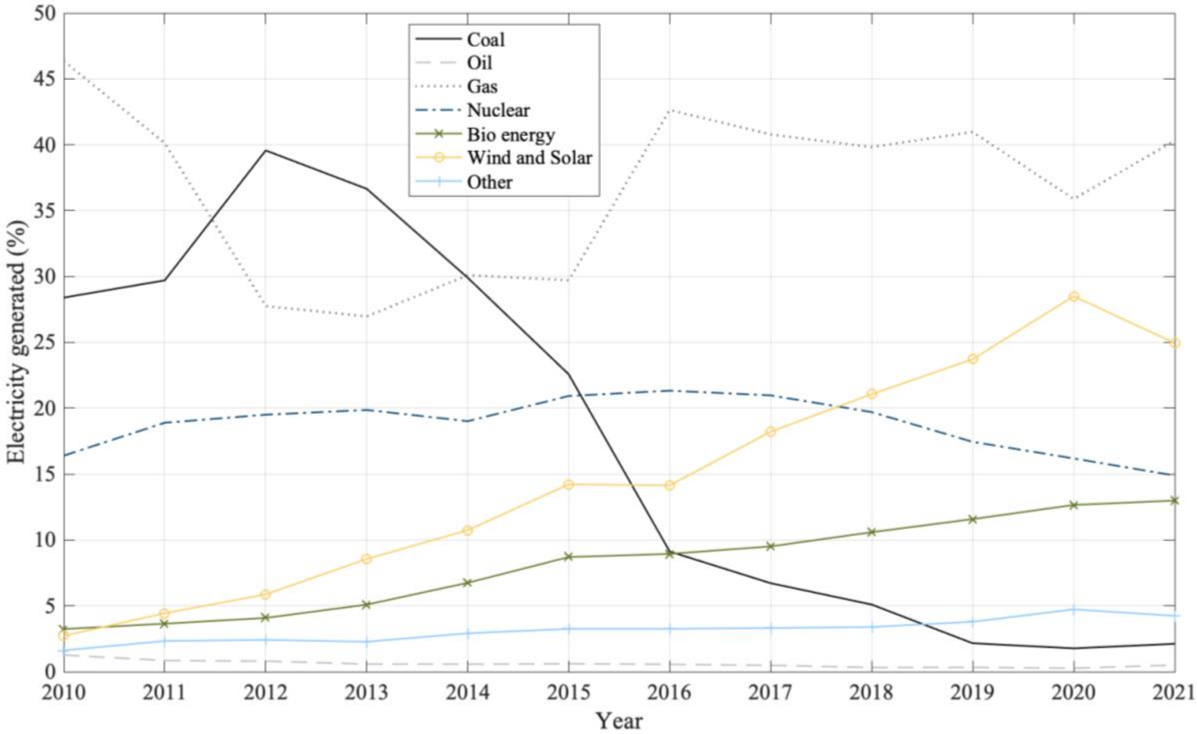

Figure 1.1 UK electricity generation by fuel from 2010 to 2021 [5].

Conventionally, a small number of fossil fuel power plants have generated electricity in large quantities. The electricity was then transported in one direction to medium and small scale consumers. This is called a '*centralised*' power system. Renewable technologies are smaller than fossil fuel power plants. Therefore, more renewable generation requires a transition to many smaller generators spread around the power system. This is called a '*decentralised*' power system. The difference between a fossil fuel based, centralised power system and a low-carbon, decentralised power system is demonstrated in Figure 1.2. Since 2010, electricity generated by large power plants has fallen by 26.6%, whereas electricity generated by small power plants has increased by 64.5% [8]. This change demonstrates the transition from a centralised to a decentralised power system.

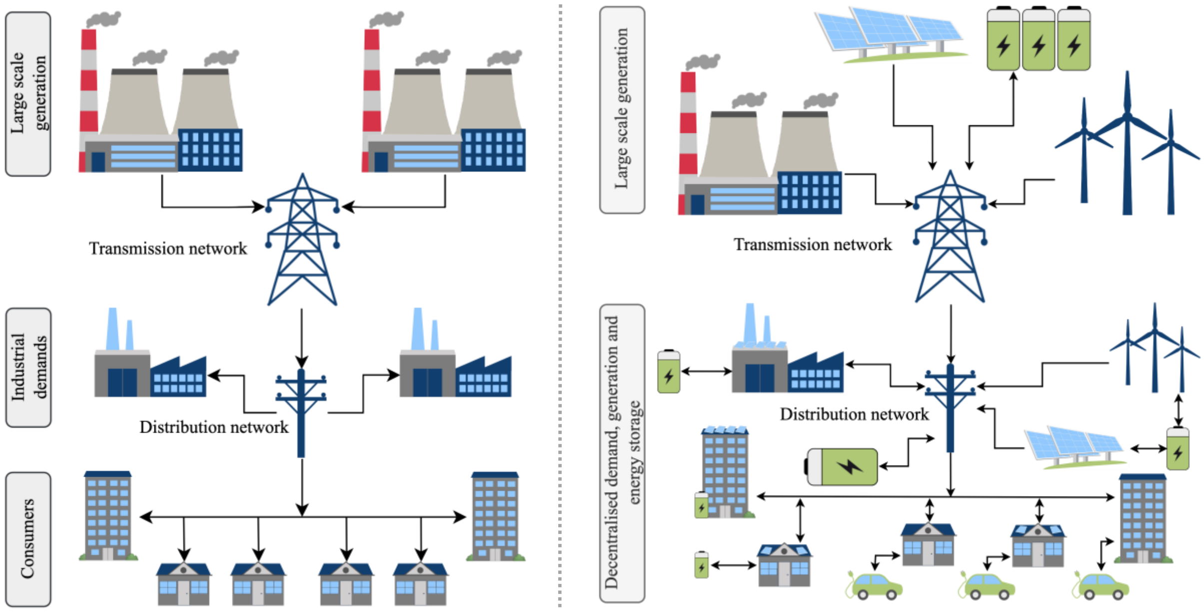

Figure 1.2 Power flow diagram of a fossil fuel based, centralised (left) power system and a low-carbon, decentralised (right) power system.

One of the key characteristics of decentralisation is the ability for small and localised energy systems to generate and control their own electricity. The use of technologies such as wind turbines and solar photovoltaic (PV) panels, to generate electricity at building and community level, is becoming more common. Local generation can also be paired with energy storage devices (battery storage, thermal storage tanks, hydrogen storage, etc.) to enable their operators to control their electricity demand. The combination of local electricity generation, storage and demand can be referred to as a '*local energy system*'. Delta-EE defined local energy systems (LESs) as any system "seeking to match local energy resources with local demand within a bounded, small energy system" [9]. However, the definition of a LES is ambiguous, as there are variations in their configuration and implementation [10]. They can vary in types of energy vector (electricity, heat, gas), types of technology (generation, storage and demand), geographical boundaries and the actors involved [11]. In this thesis, LESs are defined as a collection of local energy resources that are operated collectively to benefit local stakeholders.

1.2 The need for flexibility

Power system flexibility is the ability to increase or decrease electricity generation or consumption in response to an external signal. Power system flexibility is necessary to ensure electricity supply is always balanced with electricity demand. Traditionally, there has been very little flexibility in electricity consumption. Therefore, flexibility from electricity generation has been employed to reliably balance supply with demand, called '*supply side flexibility*'. With notice, fossil fuel power plants can increase or decrease their electricity generation, offering significant supply side flexibility. Fossil fuel power plants offer additional forms of flexibility (such as inertia to support frequency and reactive power to support network voltages) that help to support the stable operation of the electricity grid.

Renewables generate electricity when their resource is available. For example, when the wind is blowing or the sun is shining. The intermittency of their energy resources (wind and sunshine) means these technologies do not provide the same supply side flexibility or stability support as fossil fuel generation. As renewable generation replaces traditional fossil fuel generation, supply side flexibility decreases, making it harder to balance supply with demand and ensure the stable operation of the electricity grid. Adequately compensating for decreasing supply side flexibility is a key challenge in the transition to low-carbon power systems. There is an increasing need for alternative sources of flexibility in power systems [12], to compensate for diminishing supply side flexibility [13]. The UK's Carbon Trust has indicated that Great Britain (GB) could make net savings of between £9.6bn/year and £16.7bn/year by 2050, through investing in flexibility [14].

In power systems, energy storage systems utilise surplus generation by storing it and using it when there is a shortfall in generation. Therefore, energy storage systems provide on demand flexibility by charging and discharging. The charging process increases demand (equivalent of reducing generation) and the discharging process increases generation (equivalent of reducing demand). There are many types of energy storage with varying characteristics such as size, efficiency, cost and lifetime. One energy storage technology that has shown promise in recent years is battery storage. With falling prices [15], fast response and scalability, batteries are expected to grow significantly in scale across the UK [7] and globally [16].

1.3 Behind-the-meter battery storage

Small scale battery storage systems that are connected directly to consumers are known as '*behind-the-meter'* battery storage. Figure 1.3 shows the position of behind-the-meter (BTM) battery storage within an energy system.

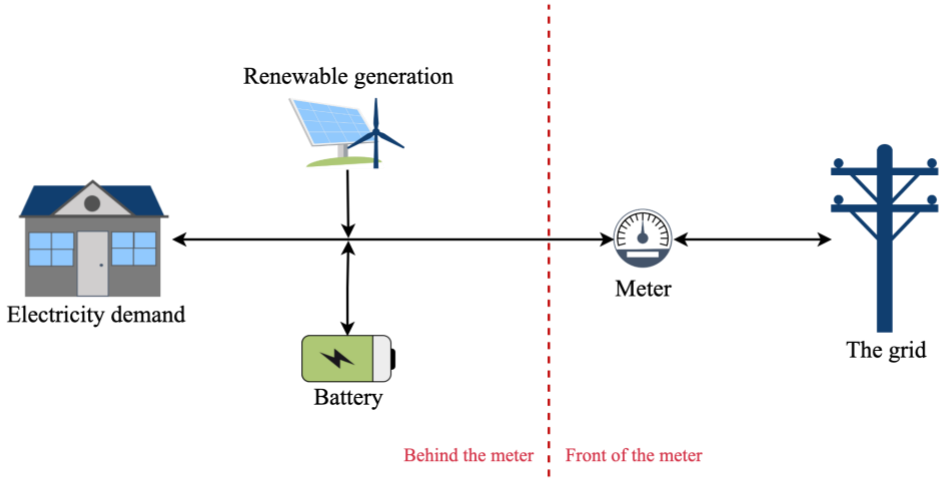

Figure 1.3 Power flow schematic of behind-the-meter battery storage within an energy system.

BTM battery storage systems can provide power to meet onsite demand, without passing electricity through the grid [17], [18]. The scale of BTM battery storage systems varies but includes those connected to commercial, industrial and domestic demands. Battery storage systems that must pass electricity through the grid to service demands are called '*in-front of the meter*' [18]. Figure 1.4 shows the decentralised distribution network with meters. In-front of the meter is shown with dashed blue arrows and BTM is shown with solid black arrows. The BTM battery storage systems are highlighted in red boxes.

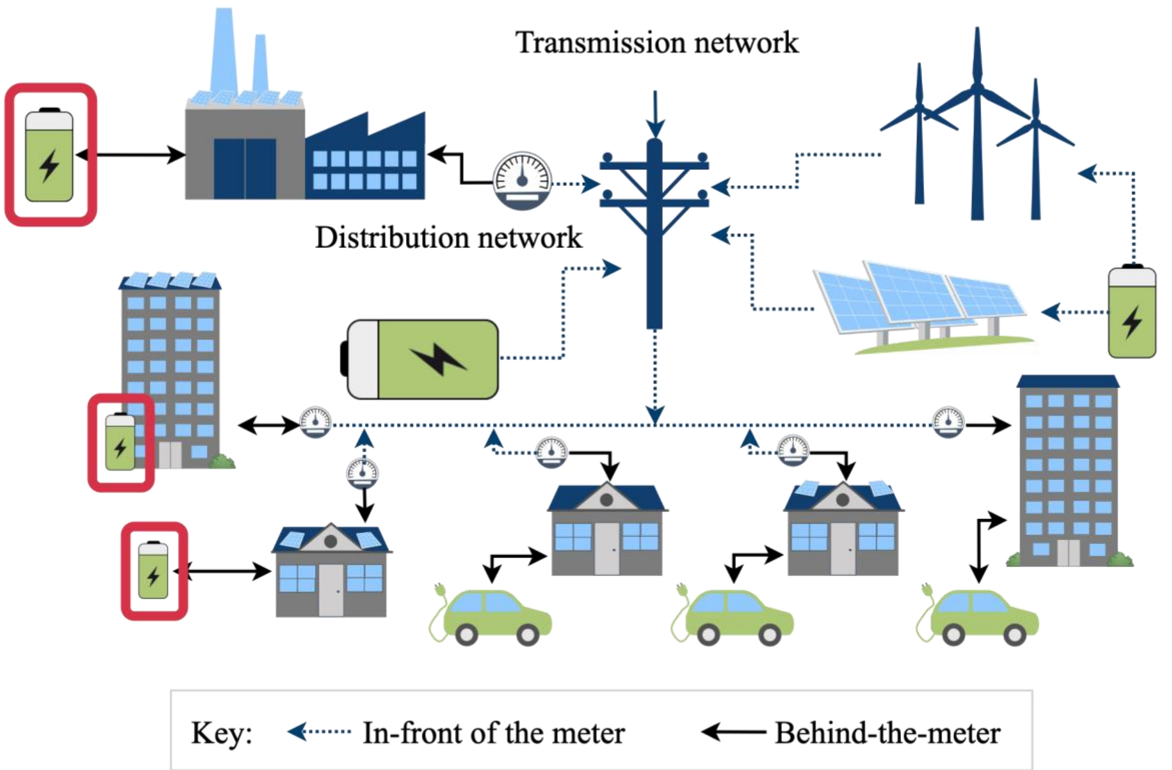

Figure 1.4 Decentralised distribution network including meters. Behind-the-meter batteries are highlighted in red.

Owing to the fall in battery prices driven by the growing electric vehicle market, there has been an increased deployment of BTM battery storage systems around the world [19]. There are several benefits of locally focused decarbonisation solutions such as BTM battery storage. These include a lower cost to achieve decarbonisation, quicker decarbonisation and better outcomes for consumers [20]. BTM battery storage achieves this by providing flexibility close to where electricity is consumed, also known as ‘*demand-side flexibility*’. Increasing demand side flexibility helps to compensate for decreasing supply side flexibility.

BTM battery storage systems can be used for several applications. One well-known application is called ‘*self-consumption*’, where the battery is used to minimise an energy systems reliance on the grid. The battery will charge when there is excess onsite generation and discharge to meet onsite demand to minimise energy purchased from the grid. This application saves the battery operator money by reducing electricity purchased from the grid. Another common application is called ‘*price arbitrage*’, where the battery is used to take advantage of variations in electricity price. For example, by charging when the price is low (increasing purchased electricity or reducing electricity sold to the grid) and discharging when the price is high (reducing purchased electricity or increasing electricity sold to the grid). This application creates income from the variation in electricity price. Other applications can generally be categorised as providing '*ancillary services*'. There is a range of different support services that ensure the stable operation of electricity grids. Ancillary services remunerate participants for providing services with specific technical requirements. These applications offer differing financial benefits to the battery operator. By participating in ancillary services, BTM battery storage supports the power system by compensating for reduced supply side flexibility. The applications chosen and how they influence battery operation are fundamental to unlocking the full potential of BTM battery storage.

1.4 Challenges of integrating behind-the-meter battery storage

Although there are many advantages to BTM battery storage, their integration into the power system brings challenges. Some of the key challenges are described in this section.

- Increasing numbers of BTM battery storage systems, aiming to minimise their operating cost and maximise battery revenue in numerous markets, will lead to complex operating strategies and unpredictable variations in power system demand.
- Battery storage systems must present an attractive investment to accelerate their adoption. However, the maximisation of remuneration from batteries is complicated by the variety of operating strategies and numerous markets available to participate in. The identity and development of methodologies suitable for planning the charging and discharging schedule of battery storage is crucial. Furthermore, methodologies must be generalised to ensure applicability with many operating strategies and market structures, as well as the influence of battery degradation.

- The interactions between many autonomous BTM battery storage systems and the power system influence the value of BTM battery storage. Their independent objectives prove challenging to account for within a whole power system operational structure.
- Integrating high numbers of BTM battery storage systems will increase system wide flexibility. However, it would also significantly increase the complexity of operating the power system. Understanding the impact that operating behaviour has on the value of BTM battery storage is key to unlocking its potential. If not coordinated appropriately, BTM battery storage may increase complexity without providing sufficient flexibility to support the power system.

1.5 Research objectives

This research aims to develop methods for assessing the investment viability of BTM battery storage systems and their value to their owners and the wider power system.

The research objectives of this thesis are:

1. To identify applications of BTM battery storage and review approaches for optimising local and power system operating objectives simultaneously.
2. To maximise the revenue of a battery storage system participating in multiple markets and evaluate its value from the owner's perspective.
3. To develop an approach that accounts for the independent decision making of BTM battery storage systems within a whole power system operational optimisation.
4. To analyse the whole-system value of BTM battery storage considering a range of operational objectives.

1.6 Structure of Thesis

Chapter 1 is an introduction. Chapter 2 is a review of literature relating to BTM battery storage systems. This critical analysis looks at the benefits of integrating BTM battery storage and the methods used by researchers to schedule battery storage, participate in multiple market to increase financial benefits and account for multiple actors in the power system.

In Chapter 3, the financial impacts of battery storage participating in multiple markets are investigated. This chapter identifies markets that are suitable for battery storage systems and determines those that can be stacked to increase revenue. A case study was used to make a comparison of operating strategies for BTM battery storage and determine the viability of their investment.

In Chapter 4, a comparison of optimisation approaches was carried out to determine their suitability for capturing independent battery storage objectives within a whole power system operational optimisation. The impact of battery storage operation on the national power system operating cost was analysed for a range of retail contracts. Fixed, time-of-use and dynamic retail contracts were compared to demonstrate the importance of retail contracts in coordinating battery operation with national power system objectives.

In Chapter 5, the methodology was developed to account for BTM battery storage systems as price makers, scheduling their flexibility in the wholesale electricity market and frequency response markets. The impact of increasing BTM battery storage system capacity on the power system was investigated and compared to equivalent grid-scale, centralised battery storage. In addition, the impact of BTM battery storage system operating strategy was investigated from the local and power system perspectives.

Chapter 6 summarises the work carried out in this thesis, concludes the key findings and discusses directions for future work.

1.7 Summary of work and achievements

A summary of the main achievements of this work are given below.

1. A method for optimal participation of battery storage in multiple markets was developed and examined. The method is easily adapted to numerous energy and ancillary services markets, to allow battery storage system owners to manage battery operation and gain maximum revenue. The method also allows prospective investors to assess the investment viability accounting for battery degradation caused by cycling at different depths of discharge. The annual profitability, investment viability and battery lifetime were discussed in detail for five operating scenarios. The findings of this work were published as "*Revenue stacking for behind the meter battery storage in energy and ancillary services markets*" in the Electric Power Systems Research journal (DOI: https://doi.org/10.1016/j.epsr.2022.108292).

2. An approach that was able to account for both BTM battery storage objectives and the power system objectives simultaneously, was developed and tested. A comparison was done between this approach and the traditional approach of assuming centralised control over BTM battery storage. A case study was carried out to analyse both approaches and compare their outcomes. The bilevel and centralised approaches were discussed and how they impact the operating costs of the battery operator and power system. In addition, there was analysis of how retail contracts can coordinate battery operating behaviour to be in line with the power system objectives. The outcomes of this study were published as "*Quantifying the value of distributed battery storage to the operation of a low carbon power system*" in the journal Applied Energy (DOI: https://doi.org/10.1016/j.apenergy.2021.117684).

3. Bilevel optimisation makes it possible to consider BTM battery storage systems as price makers in power system electricity markets. Therefore, they could affect the electricity price to benefit themselves. A comparison was made between BTM battery storage systems and grid-scale, centralised battery storage, assessing the value to the power system. Furthermore, the operating

strategies of BTM battery storage systems were investigated for their impact on the local operating cost and power system operating characteristics such as operating cost, renewable curtailment and electricity price. This work will be submitted to a journal for peer review.

Chapter 2

Applications, benefits and optimisations of behind-the-meter battery storage systems

2.1 Introduction

This chapter provides insights into applications of BTM battery storage systems and their techno-economic benefits for power systems. Additionally, methods that account for BTM battery storage within power systems are identified and evaluated for suitability. Challenges and research gaps are identified and summarised at the end of this chapter.

In the remainder of this thesis, BTM battery storage systems are considered as one example of a technology that provides '*distributed flexibility*'. Distributed flexibility is a general term for flexibility provided by any technology that is connected to power system distribution networks [21].

2.2 Applications and benefits of behind-the-meter battery storage systems

Battery storage systems enable the control of demand and generation, which can deliver technical, economic and social value of various scales in power systems. BTM battery storage systems are of relatively small scale and are not visible to power system operators. Therefore, they are not under the control of central power system operators. This gives BTM battery storage the freedom to operate in ways that create value for a variety of stakeholders. The following sections will discuss the applications and benefits of BTM battery storage from a consumer and power system perspective. A detailed discussion of all services that BTM battery storage systems can provide, is presented in [22].

2.2.1 Consumer perspective

This section discusses consumer motivations for investing in BTM battery storage systems. An appraisal of literature identified several applications and their techno-economic advantages from the consumers perspective. Table 2.I summarise these findings.

Table 2.I BTM battery storage applications and benefits from the consumer perspective

Application	Description	Benefits
Backup power [19], [22], [23]	An emergency power supply that meets demand when the primary source is unavailable [24].	• Improved reliability and quality of power supply [25], [26] • Lower emissions of backup power
Self-consumption [19], [22], [23]	The renewable electricity generation that is consumed onsite and not exported to the grid [27].	• Increase the use of onsite renewable generation • Emission reduction of meeting electricity demand • Reduced cost of electricity
Energy time shifting [19], [23]	Moving power consumption to an alternative time to avoid or reduce punitive measures. Also known as '*demand charge reduction*'.	• Reduces electricity costs • Reduces the carbon intensity of consumed electricity
Price arbitrage [22], [23]	Altering power exchange with the grid in response to price fluctuations in electricity markets.	• Reduces electricity costs • Creates revenue
Grid support services [19], [22]	Services procured by the power system operator to maintain security of electricity supply.	• Creates revenue

2.2.1.1 Backup power

A backup power system is designed to supply electricity when the primary source fails [24]. In a typical energy system, the primary source of electricity is the power grid. Figure 2.1 shows an industrial demand being met by its primary source of electricity (the grid) and the supply of electricity from the backup BTM battery storage system when the primary source of electricity fails.

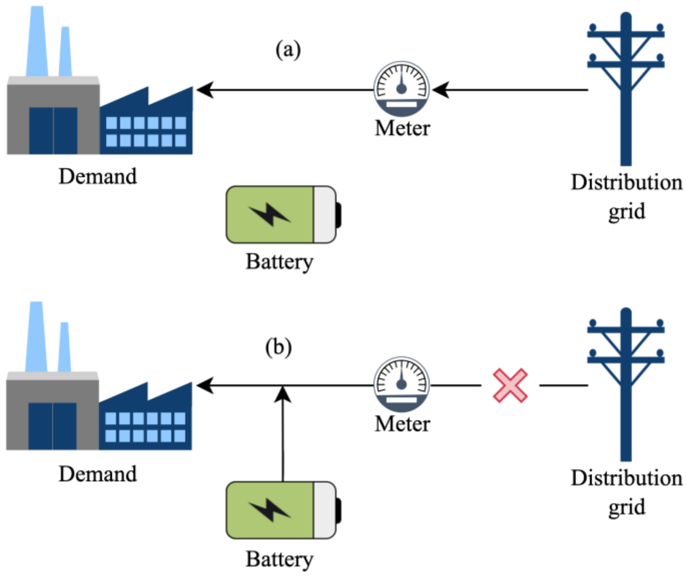

Figure 2.1 (a) industrial electricity demand being supplied by the grid, as the primary source, (b) primary source of electricity fails, therefore industrial demand is supplied by backup behind-the-meter battery storage.

Backup power is valuable where power supply is critical, especially where power outages and fluctuations in power supply are commonplace [28]. Critical power demands require robust electrical infrastructure to ensure an uninterruptible power supply. Outages of critical power demand can result in catastrophic economic, technical and/or social consequences, such as loss of potential revenue, expensive equipment repairs, and deterioration of public health. Examples of such critical loads include medical facilities, life support systems, security systems, emergency equipment, industry processes [28], military facilities [23], data centres [29] and telecommunications [30].

The initial proposition for BTM batteries was for backup power to improve security of electricity supply during power outages [19]. The rapid response capabilities of battery storage alleviate the transition from grid power supply to backup power supply with negligible impact on critical demands. Experimental research has demonstrated the capability of BTM battery storage systems to provide backup power within 50 milliseconds of grid failure [26].

BTM battery storage appointed as backup generation will improve the reliability and quality of electricity supply [26]. The negligible delay between grid failure and delivery of battery power supply ensures critical demands are continually satisfied, with minimal disturbance. Additionally, displacing non-renewable backup generation, such as diesel generators, reduces the GHG emissions. However, with a relatively reliable grid supply, backup battery storage systems remain mostly idle and unproductive. Therefore, the cost of a backup battery storage system is high, with relatively low utilisation [30]. Furthermore, battery storage systems cannot supply power indefinitely. Therefore, additional backup supplies, such as diesel generators, may be necessary for longer power outages. Finally, with low utilisation for backup power supply, the true potential of BTM battery storage is not realised for this application alone.

2.2.1.2 *Self-consumption*

Self-consumption is the electricity generated by renewable technologies that is not injected to the power grid but is consumed onsite, without passing through the meter [27]. Figure 2.2 shows domestic demand and PV generation profiles, highlighting area (c) as self-consumption of PV generation.

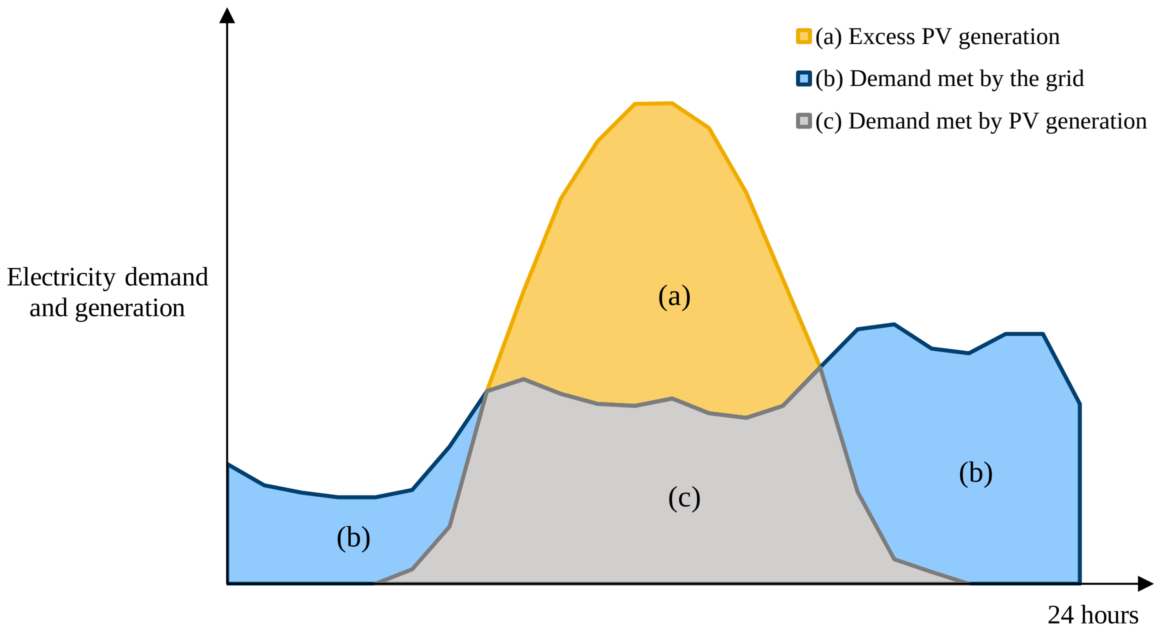

Figure 2.2 Illustrative domestic demand and PV generation profiles.

When the price for importing electricity is higher than the price for exporting electricity (typically the case due to transmission and distribution charges), maximising self-consumption will reduce costs for the consumer, as one unit of energy not purchased from the grid is worth more than one unit of energy sold to the grid. Increasing self-consumption of renewable generation can benefit consumers in several ways:

- lowering electricity bills by reducing electricity purchased from the grid,
- reducing emissions by utilising onsite, zero emission electricity instead of GHG emitting electricity from the grid, and
- reducing reliance on the grid to improving self-sufficiency.

Standalone PV arrays cannot alter generation to increase self-consumption. Though this can be achieved with a BTM battery storage system. BTM battery storage systems can store excess PV generation (area (a) in Figure 2.2) for later use, to displace electricity imported from the grid (area (b) in Figure 2.2). Figure 2.3 shows how battery storage can reshape the demand and PV generation characteristics shown in Figure 2.2. In Figure 2.3, the arrow indicates the battery displacing imported electricity with excess PV generation.

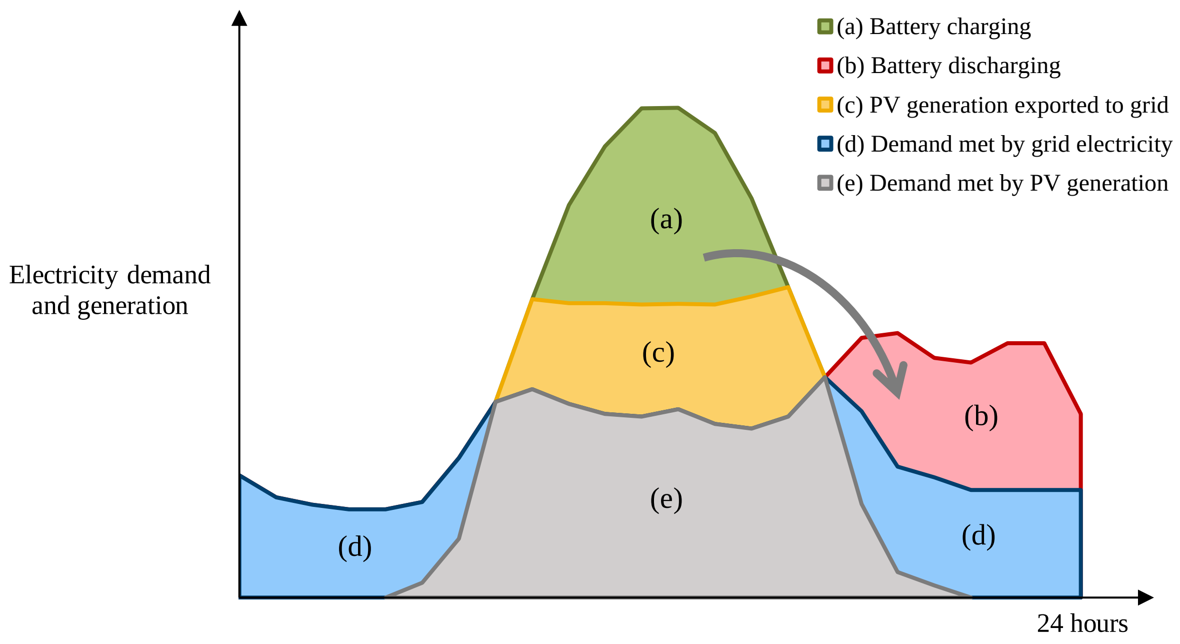

Figure 2.3 Illustrative domestic demand, PV generation and battery operating profiles.

The high efficiency, modularity and falling prices of BTM battery storage systems make them well suited to the application of self-consumption. In addition to reducing electricity bills, storing excess PV generation to replace electricity imported from the grid can reduce emissions. While many countries are transitioning to net zero power grids, as of January 2020, country specific grid emission factors are not close to net zero. With the exception of Iceland, which has a grid emissions factor of 0.00013 kgCO2e/kWh [31]. Therefore, almost all self-consumption of renewable generation will reduce GHG emissions by reducing electricity generated by electricity grids. Finally, those who invest in renewable generation are inclined to use that generation themselves. Therefore, increasing self-consumption of renewable generation can provide social benefits through increased self-sufficiency.

Despite battery prices falling significantly [32] and the rising cost of electricity [33], the cost of BTM battery storage remains high and the return on investment for self-consumption is too low [34]. Experimental research focused on BTM batteries in Poland concluded that self-consumption only was not profitable [35]. In addition, adding BTM battery storage to renewable generation can increase system complexity and maintenance requirements [36].

2.2.1.3 Demand charge reduction

During peak electricity demand, the cost of electricity increases in the wholesale electricity market. During times of peak demand, older and less efficiency generation technologies are called upon to satisfy demand. These technologies are costly to start-up and run, which increases electricity prices. Additionally, transporting high peak power demands puts strain on transmission and distribution networks.

Demand charges target peak demand periods by allocating additional charges to those who contribute to peak demand. Charges are allocated according to power requirement, in kW, rather than typical electricity charges that use energy, in kWh. Demand charges are common for industrial and commercial consumers, contributing between 30% and 70% of commercial electricity bills in the United States [37]. Although demand charges are common within the United States, the UK is set to remove demand charges by April 2023 [38].

Consumers that have BTM battery storage systems can perform peak shaving to avoid demand charges, reducing cost of electricity for the consumer. Figure 2.4 shows how a BTM battery storage system can be charged during times of low demand and discharged during times of peak demand, reducing demand charges.

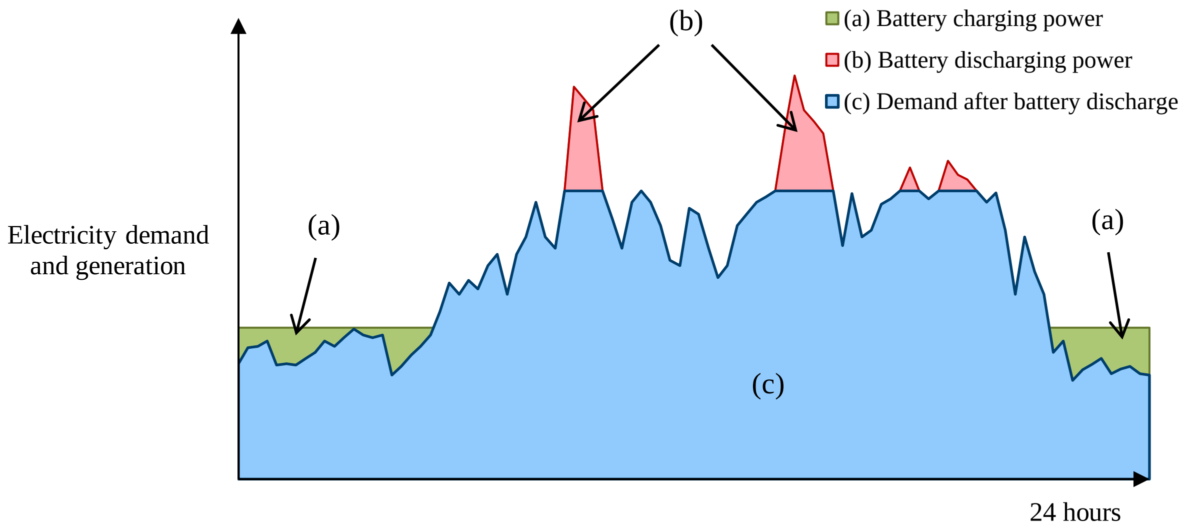

Figure 2.4 Demand and battery operation for an industrial consumer avoiding demand charges.

Introducing demand charges favours PV generation paired with energy storage systems, due to the lack of flexibility in PV generation alone [39]. Therefore, PV and storage enhances demand charge reduction compared to standalone PV [40]. Overall, this reduces the electricity bill for commercial and industrial consumers that are subject to peak demand charges.

In 2017, the biggest driver for BTM battery installations was for demand charge reduction, revealed by commercial investments from Morgan Stanley and Walmart [41]. Although commercial and industrial consumers often operate battery storage for a single application such as demand charge reduction [42], [43], this leads to low utilisation and limited financial remuneration from the battery [44]. In [45], demand charge reduction is combined with other applications to realise economic feasibility for a battery storage system.

2.2.1.4 Price arbitrage

Price arbitrage is the process of altering power exchange with the grid in response to variations in electricity price. For example, storing energy (charging) when the price is low (to increase purchased electricity or reduce electricity sold to the grid) and using the stored energy (discharging) when the price is high (to reduce purchased electricity or increase electricity sold to the grid) [46], [47]. Figure 2.5 shows the charge and discharge behaviour of an energy storage system operating for price arbitrage. Where the top figure shows electricity price varying over 24-hours and the bottom figure shows the energy storage system state of charge, with charge and discharge periods highlighted.

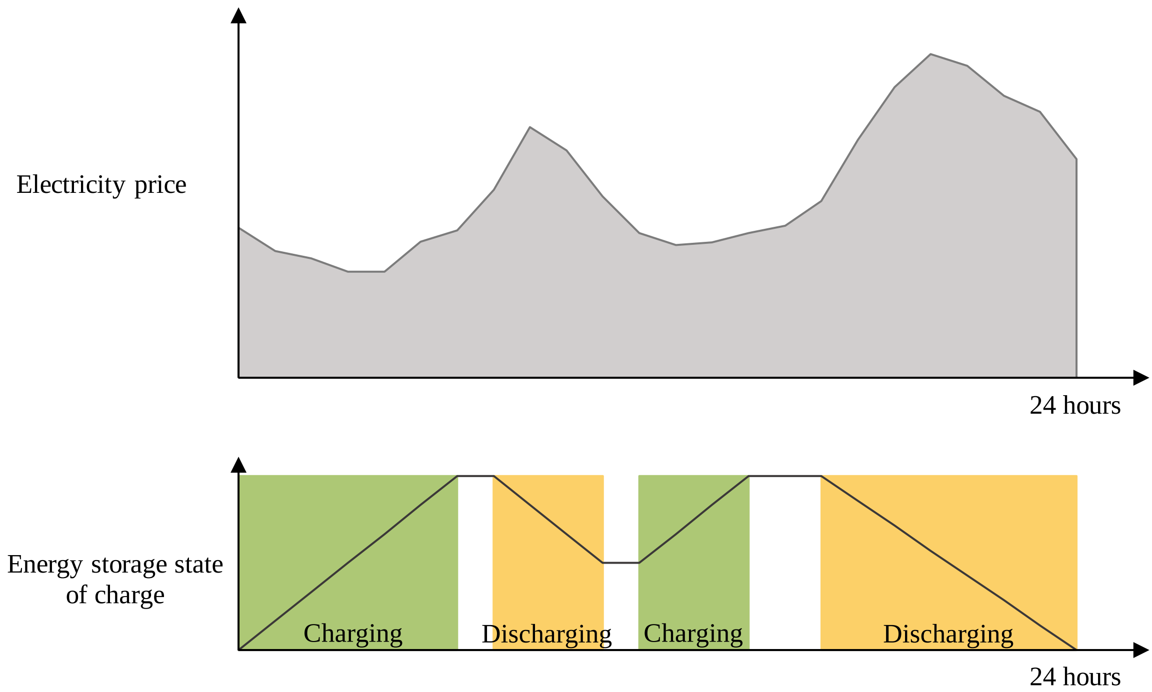

Figure 2.5 Operation of an energy storage system in relation to varying electricity price.

Price arbitrage is a process that can be employed to make cost savings or to gain revenue from flexible technologies. Energy systems with flexibility can perform price arbitrage in any energy market with time varying prices. Some of the suitable markets in GB are identified below.

- Wholesale day-ahead electricity market
- Wholesale intraday electricity market
- Balancing market
- Retail electricity markets with time-of-use tariffs.

BTM battery storage systems are an example of an energy storage system that can effectively perform price arbitrage at any scale. Their fast response and scalability allow them to be installed within any energy system and work alongside generation and demand to exploit variations in electricity price.

Many detailed studies have focused on the operation of battery storage for price arbitrage. In [48], price arbitrage is performed using three energy storage technologies, pumped hydro storage, compressed air energy storage and lithium-ion batteries. The benefits of price arbitrage are explored in [47], for a battery storage system participating in the wholesale day-ahead and real-time electricity markets with wind and solar generation uncertainty. These studies show that battery storage can provide revenue when performing price arbitrage.

Previous studies have analysed battery storage performing price arbitrage, demonstrating that this application can provide cost savings, when purchasing electricity, and revenue, when selling electricity back to the grid [47], [48]. Additionally, a study of real virtual power plants with BTM battery storage in Australia has shown the value of price arbitrage, reducing consumer bills, creating revenues for aggregators and increasing the number of viable projects [49]. Notwithstanding this, many studies indicate that the high price and relatively short lifetime of batteries results in an unattractive investment opportunity for the application of price arbitrage alone [48], [50]–[53].

2.2.1.5 Grid support services

Grid support services are procured by national power system and distribution system operators to manage the secure supply of electricity. Grid support services target specific characteristics of the power system to ensure safe and reliable supply of electricity to all consumers. Table 2.II summarises common grid support services and their requirements from the provider’s perspective.

Table 2.II Summary of grid support service categories, from the provider's perspective [19], [23].

Grid support service categories	Description	Remuneration	Response	Duration
Active power supply [54]	Slow response dispatch of power capacity in response to notification from the market operator.	Availability (£/MW/h) and/or energy delivered (£/MWh)	Minutes – hours	Minutes – hours
Reactive power supply [55], [56]	The absorption or injection of reactive power into the grid, in response to instructions from the market operator. The provider absorbs reactive power to decrease voltage and injects reactive power to increase voltage.	Utilisation and dispatch (£/MVArh)	Minutes	Minutes – hours
Frequency response [57]	Automatic fast response dispatch of power capacity in response to power system frequency going outside of predetermined ranges.	Availability (£/MW/h) and/or energy delivered (£/MWh)	Seconds	Seconds – minutes
Power generating capacity [58], [59]	Power capacity kept available for dispatch when required by the power system. Monthly payments are made to providers for committing power capacity one and four years ahead.	Monthly capacity payments (£/MW)	Hours	Hours
Congestion management [60]	Restrictions on or dispatch of power or energy according to ahead of time contracts.	Energy utilisation (£/MWh) and/or fixed fees (£/settlement period)	Minutes – hours	Minutes – hours
Restoration [61]	Delivery of power capacity when electricity from the grid is unavailable. Provision of this service by distributed flexibility is limited to generation and storage devices that can export without the support of power system frequency.	Availability (£/settlement period) and/or contribution to investment cost	Minutes – hours	Minutes – hours

Participants in grid support services receive remuneration for participating in these markets and providing the services. The income provided by grid support services is either the primary source of income for an asset [62], [63], or more commonly, an additional source of income to boost overall revenue from an asset [64]. Battery storage systems are well suited to providing these services due to their fast response capabilities, scalability and controllability.

Participating in grid support services offers battery storage systems an assortment of additional revenue streams to improve their economic feasibility. Acquiring additional revenue streams offers an opportunity to utilise periods where the battery is idle. Nonetheless, the technical requirements can be strict and the testing process rigorous. For example, minimum capacity requirements are common, limiting the participation of distributed and BTM battery storage systems. In this case, aggregators are necessary to combine their capacities to meet the requirements. Consequently, some revenue will be lost to compensate the aggregator.

2.2.1.6 Frequency response

Batteries are particularly well suited to providing frequency response [34], [65], which requires exceptionally fast and automated responses to changes in power system frequency. Figure 2.6 depicts an example response requirement for a frequency response service. The example in Figure 2.6 is a symmetric frequency response service, as equivalent dispatch requirements are given for high and low frequency events. Furthermore, this represents an automatic dispatch of staggered and proportional increases in response power.

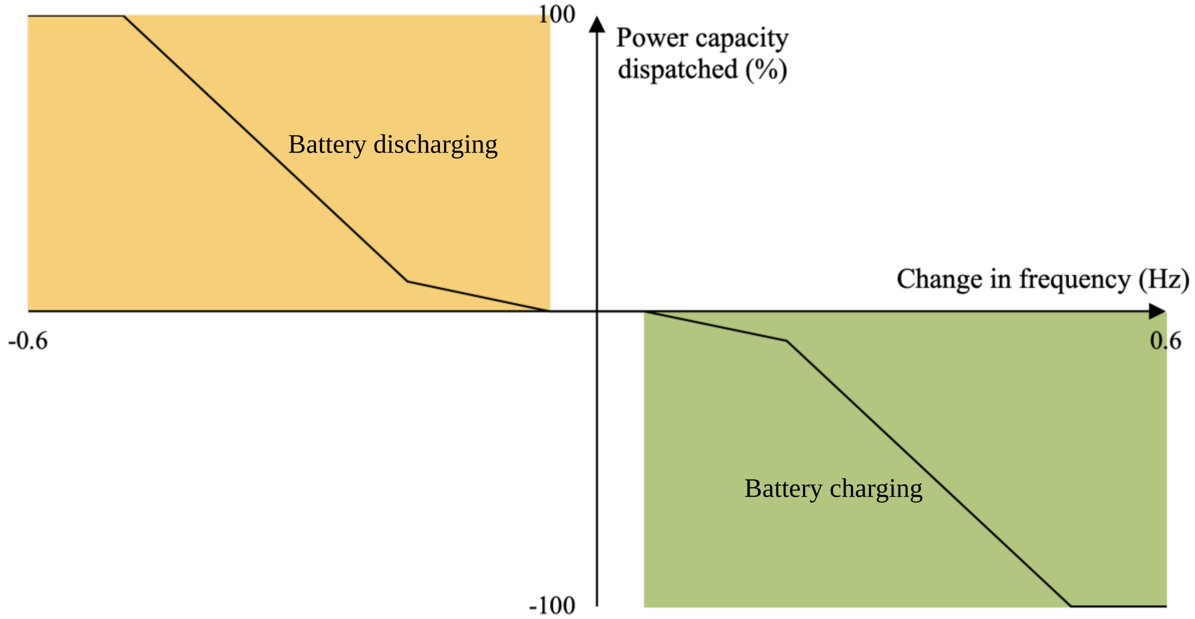

Figure 2.6 Schematic power dispatch requirements for a frequency response service.

In Figure 2.6, the service requires automated power dispatch with staggered intensity, when power system frequency falls below the specified level. A battery would respond by discharging in accordance with the requirements. Additionally, the service requires automated power consumption with staggered intensity when power system frequency climbs above the specified level. A battery would respond by charging in accordance with the requirements.

In [45], a control algorithm is presented to manage battery charge and discharge power in frequency response markets, while further reducing costs through price arbitrage. The study demonstrates perfect delivery of frequency response commitments without any market penalisations. The efficacy of battery storage systems for providing frequency response is analysed in [45]. The results suggest frequency response is appropriate for battery storage systems, with high profitability and performance.

2.2.2 Power system perspective

The role of power system operators is to maintain the stable operation of the electricity transmission system, from second-by-second balancing of supply and demand to ensuring sufficient long-term generating capacity [66].

To achieve this, power system operators develop markets to:

- ensure sufficient generation to meet demand;
- maintain power system frequency;
- maintain power system voltages;
- operate within the technical limits of the power network;
- encourage suitable generation and network investments.

Traditionally, large, centralised power plants have participated in these markets to reliably manage power system operation at low cost. However, as intermittent renewable generation replaces dispatchable fossil fuel generation, supply side flexibility is declining. Therefore, alternative sources of flexibility are necessary to replace supply flexibility and support the integration of renewable generation. Distributed flexibility is an emerging group of technologies that have the potential to offer flexibility to support the power system [67]. Therefore, power system operators are key stakeholders in distributed flexibility [68]. They have power to create opportunities that increase the value of distributed flexibility from the power systems perspective.

This section discusses the applications and benefits of BTM battery storage systems as a distributed flexibility technology, from the power system perspective. An appraisal of research and commercial literature identified several applications and their value from the power systems perspective. Table 2.III identifies BTM battery storage system applications and their benefits to the power system.

Table 2.III BTM battery storage applications and benefits from the power system perspective

Application	Description	Benefits
Ancillary services	Markets designed to maintain the reliability, stability, integrity and power quality of the power system [69].	• Efficient and safe supply of electricity for consumers
Real-time power balancing	Trading in markets designed to manage power imbalances close to real-time, after spot markets have closed [70].	• Balance of supply and demand through trading very close to delivery [71] • Reduce the need for activation of ancillary services
Network congestion management [72]	Altering power supply and consumption according to geographical limitations in transmission and distributed network operating characteristics [73].	• Reduce bottlenecks in power transportation [74] • Improve efficiency of grid operation, utilising existing infrastructure [75] • Delays or mitigates costly grid upgrade investments [75]
Spot market trading	Trading of electrical energy ahead of time to balance supply and demand.	• Reducing demand (providing extra supply) during times with high electricity prices • Utilisation of low cost and zero-emission electricity

2.2.2.1 Ancillary services

In the previous section, grid support services were identified as an additional revenue source for BTM battery storage systems. Transmission level grid support services procured by the power system operator are often referred to as '*ancillary services*'. Ancillary services are procured by power system operators to maintain and manage technical characteristics of the transmission network, to ensure safe and reliable supply of electricity. Table 2.IV presents grid support services from the power system's perspective, detailing types of ancillary services and how they contribute to maintaining electricity supply.

Table 2.IV Grid support service categories from the power system's perspective [19], [23].

Grid support service category	**Description**	**Specific contribution to power system operation**
Active power supply [23], [54]	When demand is greater than the forecast demand or renewable generation is lower than forecast, action must be taken to ensure supply and demand are balanced. Active power is procured via increasing generation or reducing consumption.	Ensures sufficient active power is available to satisfy demand.
Reactive power supply or Voltage regulation [22], [23], [55], [56]	Voltage levels in electricity networks must remain within a given range. Procurement of reactive power services ensures providers are prepared to inject or absorb reactive power when required.	Maintains voltage levels within the power network, ensuring the safe operation of electricity transportation equipment.
Frequency response [19], [23], [57]	Power system frequency must remain as close to the design frequency as possible, fluctuating within a safe operating range. Active power capacity is procured to be available for dispatch in response to changes in frequency second-by-second.	Maintaining frequency levels within a safe operating range avoids damage to electrical equipment.
Power generating capacity [58]	Active power capacity is procured, years in advance, to ensure enough power capacity is available to meet future peak demands.	Ensures sufficient power capacity is built to secure reliability of electricity supply in the future.
Congestion management [22], [23], [60]	Where power generation or consumption approaches the limitations of the infrastructure connecting it to the grid, congestion management ensures the limits are adhered to. Procurement of this service is done via predetermined maximum generation or consumption contracts. This service can take many forms, which are discussed in detail in [60].	Ensures electricity transportation infrastructure operates within its technical specifications, reducing the risk of outages and damage to equipment. Additionally, managing congestion can prolong the use of existing equipment, avoiding expensive infrastructure investment.
Restoration [61]	In the event of total or partial shutdown, the power system must have the capability to energise the network from scratch. The power system procures backup power capacity that can energise without needing electricity from the grid.	Ensures the power system can be energised and restored to full power from a complete blackout. Reducing delays after significant failures. This improves the resilience of the power system.

Ancillary services target specific power system technical characteristics such as the power balance, voltage and frequency. From the power systems perspective, these services contribute to safe, reliable and resilient power system operation.

2.2.2.2 Real-time power balancing

Real-time power balancing refers to energy trading markets that balance supply and demand at real-time, after the ahead-of-time spot markets have closed. In GB, this market is called the '*balancing* *mechanism*' [76]. In the balancing mechanism, participants submit bids, to consume electrical energy, and offers, to sell electrical energy 60 to 90 minutes prior to delivery [77]. Bids and offers are matched by the power system operator to effectively balance power supply with demand at the lowest cost.

BTM battery storage systems have the technical capability to participate in these markets but lack the scale to meet entry requirements. However, BTM battery storage can be aggregated to meet entry requirements and contribute to the balancing mechanism. The more market participants submitting bids and offers, the more competition there is in the market, pushing down prices. Therefore, BTM battery storage systems can contribute to markets, such as the balancing mechanism, to balance supply and demand at the lowest cost possible to the power system.

2.2.2.3 Network congestion management

The transportation of electricity is limited by the power capacity ratings of the equipment in transmission and distribution grids. Congestion in power lines occurs when one or more line constraints, limits the supply of electricity [73]. When power networks experience congestion, action must be taken to avoid cascading outages [78] or overloading system components [79]. Conventional approaches for congestion management can be categorised as technical and non-technical [80]. Where non-technical solutions are further split into market- and non-market based solutions. However, as the decentralisation of power systems accelerates, distributed and independently operated assets are available to provide services such as congestion management.

BTM battery storage technologies are a source of distributed flexibility that can be utilised to alleviate congestion in power systems. BTM battery storage provision of congestion management is classified in two main groups: incentive and price based methods [80]. Where incentive based methods focus on market design and direct control contracts and price based methods focus on time-of-use or peak pricing programmes.

BTM battery storage can deliver benefits to the power system through congestion management by supplying load where buses are close to or over their limits [73]. Also called peak load shaving, this can reduce the transfer of electricity through the overloaded buses, alleviating pressure on transmission and distribution components. This can not only avoid damage and accelerated wear of components but delay the need for costly infrastructure upgrades, also known as '*network reinforcement deferral*' [18], [81], [82]. Providing power during peak hours reduces stress and congestion levels on the network [83].

2.2.2.4 Spot market energy trading

Spot markets facilitate the trading of electrical energy ahead of physical delivery [84]. Through aggregation, BTM battery storage systems can be utilised to participate in spot markets to gain revenue. Two examples of spot markets in GB are the day-ahead electricity market and the intraday electricity market [85], [86]. Both are energy markets that trade between 90 minutes and 48 hours prior to delivery of electricity.

BTM batteries can participate in these markets to reduce their cost of electricity or make money by performing price arbitrage. By performing price arbitrage, BTM battery storage systems avoid purchasing electricity when the price is high [87]. Avoiding purchasing electricity when the price is high, reduces demand when the marginal cost of generation is high. Therefore, reducing the output of expensive centralised generation.

It is clear from literature that flexibility from BTM battery storage has a multitude of applications from both the consumer and power system perspective, with the potential to add value in many ways. Conclusions in [23] suggest that BTM battery storage can benefit consumers and improve the overall power system performance and identifies BTM energy storage systems as capable of supporting safe and smooth operation of the power system.

2.3 Approaches for optimising behind-the-meter battery storage operation

Distributed flexibility can be optimised from several perspectives. This study considers the local perspective and the power system perspective. The local perspective focuses on the operator of the

BTM battery storage system, with no consideration for other actors in the power system. The power system perspective focuses on the operation of the whole power system including centralised generation and storage, as well as meeting transmission system demand.

Many studies have investigated the operation of distributed generation and flexibility technologies via a virtual power plant or aggregator structure. The research in [88]–[90] are examples of studies that investigated the operation of BTM battery storage within virtual power plants. Although this is a common representation of distributed flexibility and one that reflects its typical implementation, being part of a virtual power plant introduces motivations of another actor with potentially additional sources of flexibility. This detracts from the decision making of BTM battery owners. Therefore, this study focuses on the immediate owner and operator of the BTM battery storage system.

Optimising the operation of BTM battery storage systems can be compared to that of other distributed flexibility technologies that perform similar roles such as thermal energy storage systems and demand flexibility. Therefore, this section will analyse approaches that are applied to a wide range of distributed flexibility technologies.

2.3.1 Local perspective

Research studies that focus on distributed flexibility from the local perspective neglect the operation of other actors in the energy system. Research presented in [91] takes a local perspective of BTM battery storage using optimal dispatch, valuation and sizing, in a commercial setting. The results show that the method can find suitable power ratings and energy capacities for their case study energy systems, while providing battery dispatch schedules that lead to higher net present values. In [92], the dispatch of a BTM energy storage system is investigated considering uncertainty in forecasting of generation and demand. The results show the proposed methodology can schedule the BTM energy storage system to maximise operational benefits within multiple BTM service markets. These studies provide insights into some of the key challenges surrounding BTM battery storage operation by neglecting interactions with other actors in the power system. The focus is the LES perspective, assuming all interaction with other actors in the energy systems are feasible.

2.3.1.1 Approaches for modelling BTM battery storage

The variety of BTM energy storage system topics covered by literature is diverse. Some focus on design, sizing [93], reliability [94] and control mechanism [95] studies and others investigate stochastic characteristics, such as electricity price [96], renewable generation [97] and demand [98]. However, this literature review focuses on the operation of BTM battery storage and their deterministic optimal dispatch in various markets. The aim is to maximise the utilisation of battery storage, increasing local benefits. Operational studies allow LESs with distrusted flexibility to understand how to improve their operation and provide the basis for many other studies such as optimal sizing investigations.

2.3.1.2 Operational optimisation of BTM battery storage

Battery storage systems can provide flexibility to improve the operation of LESs. This has motivated researchers to carry out techno-economic analysis of their profitability and investment viability. Despite a 89% fall in battery capital cost since 2010 [99], the upfront cost remains the main barrier to rapid and wide-spread adoption of BTM battery storage systems [100]. In [50], the power flow operation of an energy park connected to the grid was investigated. A BTM battery was added to a renewable energy generation park to perform price arbitrage under a constrained grid connection. The study concluded that adding battery storage was not viable at current capital costs and electricity prices. The optimal technology configuration for a LES with PV was studied in [101]. Among other technologies, batteries were integrated with the PV energy system for an economic assessment. The results show that including BTM battery storage becomes more attractive at much lower capital costs.

With the cost of lithium-ion battery storage (the fastest growing BTM battery storage technology) no longer falling and possibly increasing in 2022 [102], investors cannot rely on falling capital costs to improve investment viability. Alternatively, investors can improve the utilisation of batteries to increase their revenue. By increasing their revenue, investors can improve the investment viability without relying on falling battery prices. Battery storage systems are commonly used to perform price arbitrage in retail or wholesale electricity markets, which was applied in [50], [101], [103]. However, these studies reveal that battery storage systems are not an attractive investment at current capital costs and electricity prices for a single application, such as price arbitrage.

2.3.1.3 BTM battery storage investment viability

The lack of investment viability at current battery capital costs has led researchers to study maximising the operational revenue from battery storage systems. Battery technologies were reviewed in [104], concentrating on performance factors, system design and their operation for a variety of applications. Although the study mostly focused on single applications, it was suggested that combining applications had potential for increasing battery revenue.

Net present value (NPV) was used to assess the investment viability of several battery applications in [105]. The applications included self-consumption, price arbitrage, investment deferral, frequency response and reserve. The study began by evaluating single applications, which demonstrated, in both 2015 and 2020, none of the single applications were likely to be an attractive investment, without policy support. The paper went on to study combined applications, such as price arbitrage and grid support services, as a way of increasing revenue from batteries to improve the NPV. Combining price arbitrage as the primary application with secondary applications handsomely increased profits, resulting in improved investment viability in all cases and led to profitable investments for some cases.

Battery storage systems, as part of virtual power plants and as stand-alone systems, were considered in [88]. The study combined price arbitrage in an intraday energy market with frequency restoration reserve for three virtual power plant configurations. Despite combining price arbitrage and frequency services, the study found none of the virtual power plant configurations were economically feasible at current battery capital costs. However, lower battery capital costs, higher volatility in intraday markets or higher frequency service prices could change the outcome.

These studies addressed challenge related to maximising revenue from battery storage systems and the importance of cost benefit analysis is determining their investment viability. However, they all indicate that without subsidies or lower capital costs, investment in battery storage for a single application is not cost-effective. Their results emphasise that high capital costs are still hindering the investment viability of battery storage systems. Furthermore, these studies show how combining applications simultaneously can improve the investment prospect and, in some cases, lead to positive NPVs.

2.3.1.4 Stacking multiple BTM battery revenue streams

In [100], the NPV was calculated for a selection of battery storage applications, grouped into operating strategies with a single application and operating strategies with up to three applications. The applications were peak shaving, frequency containment reserve and price arbitrage. The outcomes of the study show higher investment viability for stacked applications, than single applications with the operating strategy with the highest investment viability being peak shaving, frequency containment reserve and price arbitrage. The optimal operating strategy for a battery storage system, stacking ancillary services is presented in [106]. The participation in ancillary services was incentivised through varying prices, remuneration or penalties. The results reveal that stacking ancillary services can improve investment viability and contribute to power system flexibility, reliability, safety and quality of the power network.

Research conducted in these studies provide valuable insights into battery storage system operating behaviour, both for single applications and combined applications. Combinations of applications include self-consumption, price arbitrage or peak shaving with grid support services including frequency response. However, a detailed generalised method for optimal dispatch of LES battery storage simultaneously in combined applications is required. Furthermore, a detailed breakdown of revenue from ancillary services must be given to identify the revenue streams to prioritise. Finally, although battery degradation has been considered for revenue stacking in previous research [100], the impacts of simultaneously participating in more than one application need further investigation.

2.3.1.5 Summary of local perspective

One of the key assumptions in all local perspective studies, is that any power exchanged with the power system can be met. Therefore, that the grid can absorb or provide the necessary power the LES requires, at any time. Furthermore, this formulation assumes the LES is a price taker, making decisions based on deterministic or stochastic electricity prices. The next section evaluates optimisations that address these limitations by including distributed flexibility in a power system optimisation and look at distributed flexibility from a whole system perspective.

2.3.2 Power system perspective

Four approaches for scheduling the operation of multiple actors in power systems are agent based modelling, sequential optimisation, centralised optimisation and bilevel optimisation. One study utilised an agent based model to account for BTM batteries and their interactions with aggregators who participate in ancillary services [107]. This agent based model considered each actor as an autonomous decision maker. However, in this decision making structure, actors make independent decisions based on fixed inputs or inputs from other actors. Any single actor cannot anticipate the decision making of another and manage their operation accordingly. Sequential optimisation is also limited by the interaction between actors, where neither actor can manage their impact on the other. The following sections discuss the centralised and bilevel optimisation approaches and draw comparisons between their decision making structures.

2.3.2.1 Centralised optimisation approach

The operating strategy of distributed flexibility influences their power exchange with the grid. Hence, their operation can impact other actors in the power system. One method of ensuring distributed flexibility is operated to benefit the power system is through direct control contracts. Direct control contracts are a common way of maximising the benefit of distributed flexibility, such as interruptible loads [108]. They allow utilities, aggregators and electricity retailers to take action to reduce demand during peak times to limit the electricity price and/or their operating costs. Research suggests the aggregation of distributed flexibility technologies through direct control contracts can help support the integration of renewable generation in power systems [109].

Several research studies have used direct control contracts to simplify the optimisation of distributed flexibility. Reference [110] suggests that these methodologies are categorised as a centralised optimisation approach because a direct control contract allows central control of distributed flexibility by a centralised operator. Reference [111] identifies the centralised approach as focusing on one participant that aims to optimise their objective. In this context, the centralised optimisation approach considers only the power system perspective, assuming centralised control over all distributed flexibility.

The structure of the centralised optimisation is shown in Figure 2.7. Where, the central operator shown in Figure 2.7 represents any organisation that has control of multiple assets in the power system, e.g., power system operators, electricity suppliers, aggregators and cooperatives. Typically formulated as dispatch models, centralised optimisations optimise the power output and exchange of conventional power plants, renewable generators and energy storage systems.

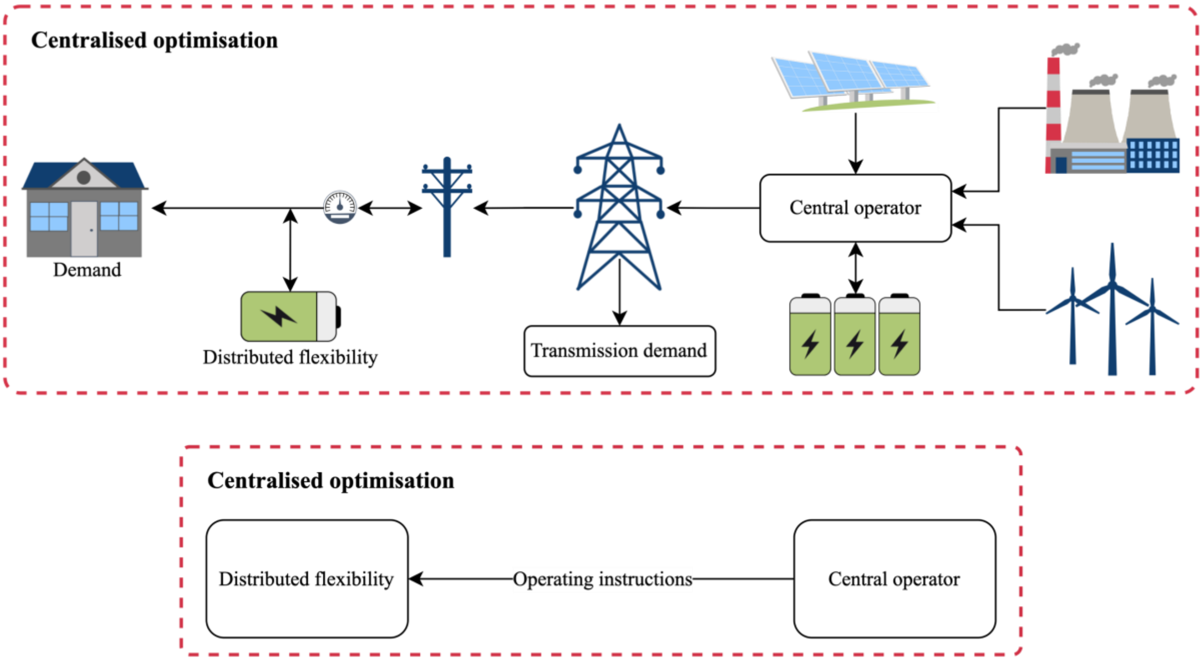

Figure 2.7 power flow (top) and communication (bottom) diagrams for the centralised optimisation.

The earliest examples of these focused on elastic demand [112]. More recently, varying penetration of electrical load shifting via thermal energy storage has been modelled to assess its impact on wind curtailment [113]. This study focused on detailed thermal dynamic models of buildings to accurately represent thermal flexibility in the power system. The thermal model and end-user constraints were integrated into a power system economic dispatch model. The results demonstrate the flexibility potential of the thermal electric space heater and hot water storage tank for load shifting and price arbitrage. Furthermore, the use of thermal flexibility results in decreased wind curtailment, indicating better utilisation of central renewable energy generation.

Thermal distributed flexibility was also analysed in [114] to assess the value of active demand response in an electric power system with high intermittent renewable generation. The study integrated thermal electric heating models within an electric power system model. The results of this study compare different approaches for optimising the operation of thermal flexibility in the power system, including price-elasticity-based models, virtual generator models and merit order models. The results suggest that the integrated approach results in the most accurate assessment of the value of distributed flexibility. However, the computational time is prohibitive, particularly for time horizons as long as a year.

In [115], a unit commitment model is presented for the Illinois power system with wind power generation and distributed flexibility (electric vehicles and demand response). The simulation simplified the representation of distributed flexibility by assuming centralised control by the system operator, hence a centralised approach. The results show that centrally dispatched distributed flexibility can significantly reduce the power system operating cost.

These studies show the contribution that distributed flexibility can make in supporting high levels of renewable generation in power systems. Additionally, their results demonstrate that integrated power system optimisations allow the impact of distributed flexibility technologies to be assessed within a power system optimisation.

Centralised optimisations help tackle challenges faced by the power system, such as network congestion and achieving the balance between supply and demand [116]. Furthermore, they allow for a simplified assessment of distributed flexibility within a power system. However, the centralised optimisation simplifies power system operation and neglects the autonomous decision making of distributed flexibility owners. Moreover, consumers are generally unwilling to relinquish their end-use electrical consumption in exchange for remuneration [114]. The result is low adoption of direct control contracts, limiting the practicality of using the centralised optimisation approach to account for the independent decision making of distributed flexibility.

2.3.2.2 *Bilevel optimisation approach*

Subsequent research studies have addressed the drawbacks of the centralised optimisation approach by accounting for the individual objectives of the system operator, retailer and/or consumer behaviour. A common approach has been to apply a hierarchical optimisation approach called '*bilevel optimisation'*.

Bilevel optimisations are mathematical programs with two levels, where one level is nested within the other. The outside level is called the leader or '*upper level*' and the nested level is known as the follower or '*lower level*'. The two levels are formulated in a non-symmetric, hierarchical structure, where the follower optimisation(s) constrains the leader optimisation. Each optimisation has its own objective function, set of variables and set of constraints. This formulation enables the optimisation of decision-making structures where the leader's decision is directly affected by the response of the followers, who optimise their own objectives. The complex nature of power system operation means the decisions made by one entity are likely to impact others. For example, the operation of energy assets in power systems is often related to the electricity price, which is the outcome of bids and offers made by other market participants. Therefore, the operation of energy assets (leader) is affected by the outcomes of the electricity market (follower). A detailed description of bilevel optimisation is given in Appendix A.

2.3.2.2.1 Comparison of centralised and bilevel approaches

Some studies have compared a bilevel optimisation approach for scheduling distributed flexibility in power systems with the traditional centralised approach. In [117], a hierarchical decision-making framework was created using a bilevel optimisation approach, to study the interactions between several microgrids and an electricity supplier. The microgrids coordinate the operation of distributed generation, load curtailment and battery storage to achieve the effect of distributed flexibility. The results show the efficacy of the bilevel optimisation approach and the influence of microgrid technology configuration on electricity prices.

The analysis in [118] considers distributed flexibility from aggregated thermal energy storage systems participating in the day-ahead electricity market. Three mid-flat archetypes were tested with different heating and heat inertia characteristics, with approximately 70,000 flats being aggregated in total. These results suggest that maximising the profit of distributed flexibility leads to a deviation from the optimal performance for the whole power system, compared to the centrally operated distributed flexibility.

The study in [118] was subsequently advanced in [110] by separating the aggregator decision making from the distributed flexibility decision making. The result was an approach that considered the independent decision making of the system operator, an aggregator and the distributed flexibility operators. The approach includes detailed state space models of the thermal distributed flexibility to ensure the accuracy of available flexibility in relation to comfort constraints. The results of this study indicate the bilevel optimisation approach is necessary to account for market participants as '*autonomous decision makers*'. In this context, autonomous decision makers are actors that make their own decisions, without influence from external decision makers such as the power system. Retail contract design is also an important consideration when aiming to maximise the value of distributed flexibility for the wider power system.

The bilevel optimisation approaches presented in [117], [118] and [110] are compared with their equivalent conventional centralised optimisation approach. They compare the performance of bilevel optimisation and centralised optimisation approaches for considering multiple actors in an energy system. These results show that where distributed flexibility was operated centrally, the whole system performance was maximised. However, this result is an optimistic solution. When distributed flexibility operators were autonomous decision makers in the market, aiming to maximise their own objective, the whole system performance worsened. The studies conclude that centralised optimisation approaches tend to overvalue distributed flexibility from the whole power system perspective.

2.3.2.2.2 Bilevel optimisation approach for a variety of actors in power systems

Bilevel optimisation can consider a variety of energy system participants. From the power system operator to retailers and microgrids to flexible consumers. Electric heating and energy storage was used in [119] and [120], to evaluate the interactions between flexible customers and their retailers. Whereas, in [117], [121] and [122] the focus was on microgrids with multiple sources of flexibility interacting with retailers. Although understanding the interactions between retailers and their flexible customers is valuable, the wholesale electricity price is exogenous and therefore neglects the interaction with the national power system and wholesale market.

2.3.2.2.3 Using bilevel optimisation to explicitly account for power system operation

Other researchers have focused on explicitly considering the objectives of the power system operator or wholesale market operator by calculating the electricity price endogenously. The transition of suppliers and aggregators from price takers to price makers is identified in [123], attributed to increasing distributed generation and penetration of distributed flexibility. The authors account for the autonomous decision-making authority of suppliers and aggregators using bilevel optimisation with an endogenous wholesale electricity price. The methodology was applied to a case study with generation companies and retailers participating in wholesale energy and reserve markets. The results show the efficacy of the approach for allowing the retailers and suppliers to act as autonomous decision makers in the market. At times this caused decreases in the wholesale electricity price and at other times increases in the wholesale electricity price.

The bidding strategy of a virtual power plant was studied in [89], operating distributed energy resources including wind generation, battery storage and consumer demand. The virtual power plant participated in the day-ahead wholesale electricity market by utilising flexibility from its distributed flexibility resources. There was also a focus on uncertainty from the distributed energy resources production and the demand consumption. To account for this, a stochastic bilevel optimisation was presented, considering the virtual power plant as the leader and the day-ahead electricity market as the follower. The methodology was applied to the Greek power system to assess its effectiveness and applicability. The results show that with this bilevel optimisation approach, the virtual power plants were able to manage their distributed energy resources to prioritise their own objectives.

Similarly, [90] considers the participation of a virtual power plant in energy and reserve markets using a bilevel optimisation approach. Therefore, the virtual power plant was considered as a price maker, making autonomous decisions that influence the electricity price to benefit themselves. The technologies included in the virtual power plant were conventional and renewable generation, flexible demands and energy storage. The virtual power plant was the leader in the bilevel formulation and the clearing of energy and reserve markets was the follower. Considering the virtual power plant as a price maker resulted in higher profits, when compared to the price taker scenario.

The optimal bidding of a flexibility aggregator is presented in [124]. The aggregator coordinated the operation of distributed energy storage, electric vehicles and flexible thermal load to provide flexibility. The flexibility was harnessed to participate in energy and reserve markets, maximising the profits of the aggregator. The flexibility aggregator was the leader in a bilevel optimisation, interacting, through bids and offers, with the independent system operator, formulated as the follower. The bilevel formulation was applied to a modified PJM-5bus power system to demonstrate the effectiveness of the framework. One key result from this study showed that enabling the flexibility aggregator to be an autonomous decision maker in the markets increased their profit. Additionally, the flexibility aggregator can reduce the energy and reserve prices.

In [118], an aggregator of demand response flexibility aimed to maximise their profits in the wholesale day-ahead electricity market, as a price maker. The authors proposed a bilevel optimisation approach that considered the aggregator as the leader and the wholesale day-ahead electricity market as the follower. The demand response technology was electric heating and thermal energy storage. The results from this work focus on the drawbacks of exogenous pricing and benefits of having the feedback of endogenous pricing. The results also highlight the non-optimal outcome for the whole power system, while the aggregator was a price maker. Instead, the aggregator experiences high profits, while effecting negative impacts on the wider power system.

In a development of their previous work presented in [118], the authors explicitly included the operation of individual demand flexibility operators in [110]. Therefore, a three actor bilevel optimisation structure was developed, including: the system operator, a retailer and the demand flexibility operators. Each actor was able to make operating decisions that benefit themselves, while interacting with each other. The retailer was the leader and the system operator and demand flexibility operator were the followers. Not only does this configuration include three autonomous decision makers but also two endogenously calculated electricity prices. Firstly, the wholesale electricity price, which is the price the retailer pays for electricity from the system operator. Secondly, the retail price, which is the price the demand flexibility operator pays the retailer to purchase electricity. The result of this study provides a holistic view of distributed flexibility in power systems, capturing the autonomous behaviour of wholesale and retail market operators. Additionally, the study concludes that higher levels of distributed flexibility can decrease retailer profits and reduce the value of distributed flexibility to their owners, also known as '*self-cannibalisation*'.

These studies provide valuable insights into methodologies that account for autonomous decision making of actors in the power system, particularly distributed flexibility. They demonstrate the value of participating in energy markets as price makers, allowing distributed flexibility to reduce their operating cost. They also reveal the adverse effects of autonomous decision makers from the power system perspective, increasing the whole power system cost. Therefore, these studies demonstrate the suitability of the bilevel optimisation approach with endogenous pricing for representing the subtle differences between price taker and price maker decision makers in the power system.

2.3.2.3 Impact of retail contract design

The results presented in [118], [110], [119] and [125] also indicate the significance of contract design in maximising the value of distributed flexibility to the power system. Trading contracts and market design play an important role in encouraging cooperative operation that benefits the whole power system.

2.3.3 Summary of power system perspective

Although these studies provide significant contributions to the research field of distributed flexibility, they assume a single operating strategy for all distributed flexibility. Therefore, these studies neglect the variety of applications available to distributed flexibility operators, such as backup, self-consumption, demand charge reduction, price arbitrage and grid support services. Additionally, further study is required to understand the impact of varying penetrations of distributed flexibility.

2.4 Summary of challenges and research gaps

The role of distributed flexibility in supporting low-carbon power systems is still not thoroughly understood. As such, there are still many challenges related to maximising the benefits of distributed sources of flexibility. This section summarises some key challenges identified from the literature.

2.4.1 Challenges

1. High capital cost of BTM battery storage systems

Notwithstanding the 89% fall in price [99], the capital cost of battery storage is still the main barrier to mass adoption BTM. Although this cost is expected to continue falling [102], there is no guarantee and investors cannot rely on uncertain projections. This is made evident by a probable increase in battery prices in 2022 [102], due to increased raw material cost.

An alternative approach to combat high capital costs is to increase the annual revenue of the battery. Achieving this requires suitable revenue opportunities being identified by navigating complex market structures and barriers to entry. Numerous markets are available to flexibility providers in power systems but understanding which ones to participate in, when to participate in them and whether simultaneous participation is permissible, is a challenge. This challenge is exacerbated by technical requirements, which restrict access to markets. Therefore, navigating complex operation, accessibility to markets and changing prices is a key obstacle to the widespread adoption of BTM battery storage.

2. Integrating BTM battery storage as autonomous decision makers in the power system

BTM battery storage offers unconventional flexibility to the power system. Conventionally, flexibility has been delivered by large, centralised power plants that either automatically respond to changes in power system operating characteristics or respond to instructions from the centralised system operator. Therefore, the centralised system operator had authority over the operation of flexibility, facilitating second-by-second power system balancing. However, BTM battery storage systems are controlled by their local operators, who have independent objectives that are not influenced by external decision makers, such as the power system operator.

Developing an approach to account for the realistic operation of BTM battery storage systems as autonomous decision makers in the power system and determine how to influence their operation, to cooperate with power system operator objectives, are key challenges for maximising the value of BTM battery storage systems.

3. **BTM battery storage growth and operating strategy**

National Grid ESO publish future scenarios for the growth of BTM battery storage systems in GB. The scenarios range from 8.8 GW to 19.2 GW in 2050 [126], implying a wide range of possible future capacities for BTM battery storage. Furthermore, market developments are continuously underway, creating new energy markets and grid support services that change the way BTM battery storage interacts with the power system.

The future capacity of BTM battery storage is unknown and the operating strategies that BTM batteries will employ are unpredictable. However, both factors will influence the way that BTM battery storage interacts with the power system and how well they will support low-carbon power systems. Therefore, the value of BTM battery storage is subject to two main factors: growth in capacity and their operating strategies. Understanding the importance of each of these and how BTM battery storage systems can be influenced to operate in line with power system objectives, are key challenges for unlocking maximum value from BTM battery storage.

2.4.2 Research gaps

1. **Identification of applications suitable for BTM battery storage**

Although studies have discussed the operation of BTM battery storage and often choose specific revenue streams to consider, few provide a clear summary of the revenue options available. Specifically, research must identify those applications that are most suited to BTM battery storage and how they can benefit their operator. Additionally, analysis of applications has typically focused on either the BTM perspective or the power system perspective. A compendium of BTM battery storage applications from the local and power system perspectives is necessary to support their growth.

2. **Generalised methods for scheduling BTM battery storage in existing electricity and grid support service markets**

To overcome the high capital cost of battery storage and present a viable investment, operators must maximise the revenue from BTM battery storage systems. Previous studies select specific services to optimise. However, operators require a generalised method that can be adapted to various market frameworks, to coordinate the scheduling of BTM battery storage in existing and future markets. In addition, the method must be capable of scheduling participation in more than one market simultaneously, making compromises between markets and revenue streams.

3. **A narrative for stacking participation in multiple markets and the impact on degradation**

Many studies indicate that stacking more than one revenue stream would increase the investment viability of BTM battery storage systems. However, few consider the intricacies of stacking specific grid support services or investigate the direct impact of revenue stacking on battery degradation. The impact of specific revenue streams and combinations of revenue streams on battery degradation has not been thoroughly studied. The cause of differing degradation from various revenue streams must be better understood.

4. **Suitable methodology for accounting for the decision making of distributed flexibility operators.**

Conventional approaches integrate distributed flexibility into the power system decision making structure. This approach assumes centralised control of all flexibility, which is a limitation of this approach. Research has developed methods that account for more than one actor in power systems, using a bilevel optimisation approach. However, a suitable methodology to account for the autonomous behaviour of BTM battery storage systems, as part of LESs, participating in the wholesale electricity market is unobserved. Furthermore, a detailed comparison of the bilevel BTM battery approach and the centralised approach is necessary.

5. **Clear conclusions on the capability of retail contracts to unlock the value of distributed flexibility.**

Notwithstanding the conclusions of some studies, the influence of retail contract design on the behaviour of BTM battery storage systems is not well understood. Furthermore, retail contract designs that encourage BTM battery storage systems to operate cooperatively with the power system must be identified and their value quantified.

6. **A method to account for the feedback of distributed flexibility operation into electricity prices**

Some studies have presented optimisations that calculate an endogenous wholesale electricity price. Therefore, the distributed flexibility considered in these studies are price makers and can actively influence prices using bids and offers. However, the impact that price maker BTM battery storage systems can have on wholesale electricity prices and the centralised generating cost has not been studied in detail.

7. **Conclusions on the value of BTM battery storage to the power system**

The value of distributed flexibility has been studied for specific technologies such as electric heating, thermal energy storage and demand flexibility. These studies indicate distributed flexibility can add value to the power system but do not provide detailed analysis of BTM battery storage systems. The contribution that BTM battery storage systems can make must be further investigated, particularly its contribution to lowering centralised generating cost, reducing central renewable curtailment and lowering power system GHG emissions.

Chapter 3

Maximising customer revenue from behind-the-meter battery storage

This chapter presents a method for maximising the revenue of a battery storage system in wholesale day-ahead electricity and frequency response markets simultaneously. A case study based on a school in Cardiff with a PV array and storage was used to demonstrate the efficacy of the methodology. Several scenarios were evaluated to determine the optimal combination of participation in electricity and frequency response markets.

3.1 Introduction

Battery storage systems are capable of trading energy and power capacity. Therefore, batteries can participate in numerous energy and ancillary services markets to gain revenue. An overview of markets available in GB is given Figure B.1 in Appendix B. Battery storage systems are particularly well suited to frequency response services due to the requirement for rapid response to changes in frequency with relatively short duration of response.

Participating in two or more applications to gain additional revenue is called '*revenue stacking*'. Revenue stacking is emerging as a way of increasing the utilisation of battery storage systems to increase their revenue and offer a more attractive investment prospect. Revenue stacking presents a challenge to battery storage system operators, from economic and technical perspectives.

Committing power and energy capacity in more than one market simultaneously adds complexity to battery operation. Battery storage system operators must optimise the revenue of batteries simultaneously in multiple markets, with different technical requirements and varying prices. Additionally, the added value of increased utilisation must outweigh any consequential acceleration of battery degradation. Therefore, operational optimisation and degradation quantification are key to understanding the viability of BTM batteries to a consumer.

Research studies in literature have investigated the value of revenue stacking for battery storage systems using operational optimisation. These studies are discussed in detail in Section 2.3.1 in Chapter 2. One key study focuses on the comparison between single applications of battery storage systems and revenue stacking with two or more applications [105]. Another study compares the investment prospect of battery storage with different application combinations, accounting for the impact on battery degradation over the lifetime of the battery [100].

3.2 Local energy system methodology

A general LES structure is shown in Figure 3.1.

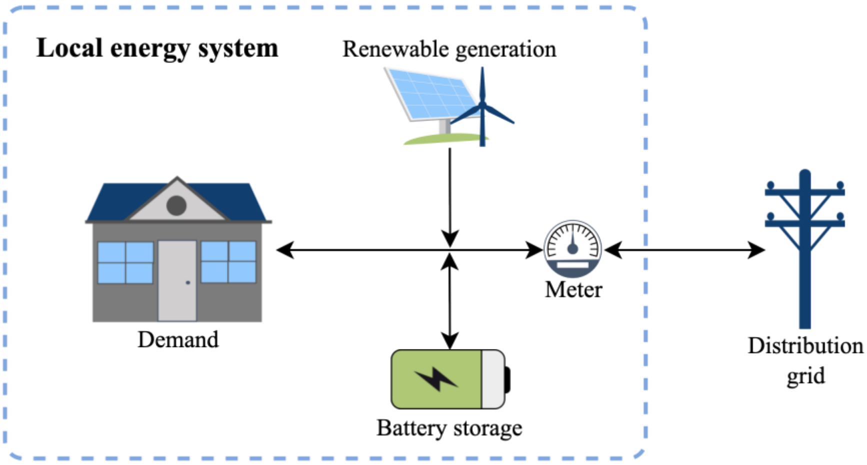

Figure 3.1 General local energy system power flow diagram with grid connection.

The LES participates in an electricity market and frequency response markets. The electricity market is the trading of electrical energy in £/MWh, such as the wholesale day-ahead market. The frequency response markets trade power capacity for rapid dispatch in response to changes in power system frequency, such as Firm Frequency Response, Enhanced Frequency Response or Dynamic Containment. The remuneration for frequency response is an '*availability fee*' paid in £/MW per hour and a '*response energy payment'* paid in £/MWh. In this thesis, revenue gained from an availability fee will be referred to as '*availability income*' and revenue gained from a response energy payment will be referred to as '*dispatch income*'.

Most wholesale electricity and frequency response markets have minimum capacity entry requirements. However, smaller assets can be aggregated to meet entry requirements. This study assumes that the LES directly participates in wholesale electricity and frequency response markets. This is justified as their participation in the market is possible through an aggregator.

The method is shown in Figure 3.2. The method was split into several stages, with four main formulation stages (highlighted with bold outlines in Figure 3.2): operational optimisation, frequency response energy dispatch, battery degradation and calculation of NPV.

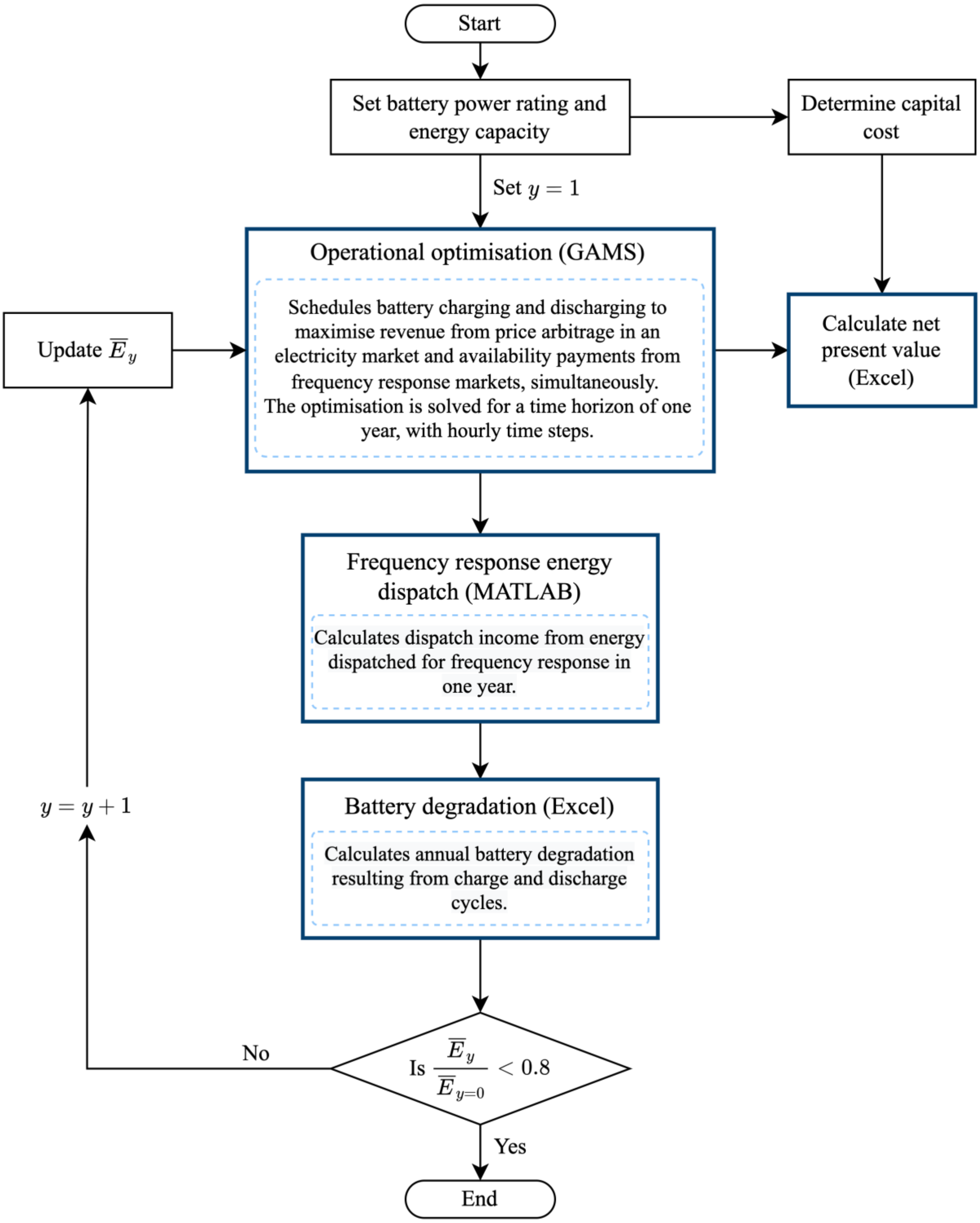

Figure 3.2 Flow chart of the method and the interacts between each stage.

In Figure 3.2, the four main stages are performed in succession for each year of the battery's lifetime. These are the:

1. Operational optimisation (labelled ‘Operational optimisation (GAMS)’ in Figure 3.2)
2. Frequency response energy dispatch calculation (labelled ‘Frequency response energy dispatch (MATLAB)’ in Figure 3.2)
3. Battery degradation model (labelled ‘Battery degradation (Excel)’ in Figure 3.2)
4. NPV calculation (labelled ‘Calculate net present value (Excel)’ in Figure 3.2).

The operational optimisation schedules battery charging and discharging to maximise revenue from price arbitrage in an electricity market and availability payments from frequency response markets, simultaneously. The frequency response energy dispatch calculation uses the power committed to frequency response from the operational optimisation to calculate the dispatch income from dispatching energy for frequency response. The battery degradation model uses the battery state of charge to calculate the annual battery degradation, corresponding to the battery charge and discharge cycles. The NPV calculation uses the capital cost and annual operating costs to calculate the NPV in each year of battery lifetime. Each major stage is described in detail in the following subsections.

The method starts by setting the battery power rating and energy capacity as fixed inputs for the duration of the method. Then, the term y is set as 1 to represent the first year of battery operation. Next, the operational optimisation, frequency response energy dispatch and battery degradation models are performed in succession, for one year of operation, feeding data from one stage to the next.

After each year of LES operation, the annual battery degradation (calculated in the battery degradation stage) is applied to the battery energy capacity. Therefore, the decrease in battery energy capacity each year corresponds to battery operation. All other input data is consistent for each year of battery operation.

If the battery capacity is more than 80% of its original capacity, the remaining battery energy capacity is updated, the year counter is updated ($y = y + 1$) and the process is repeated from the operational optimisation. After each year, if the battery capacity is less than 80% of its original capacity, the battery has reached its end-of-life and the process stops. After each operational optimisation, the NPV is calculated, where the battery power rating and energy capacity determine the capital cost.

All terms in the methodology are defined in the nomenclature in Appendix B.2.

3.2.1 Operational optimisation

The operational optimisation is the first main step in the method, shown as the 'Operational Optimisation (GAMS)' block in Figure 3.2. The operational optimisation schedules the LES's battery storage to minimise the annual LES operating cost, neglecting response energy payments from frequency response and battery degradation cost. The LES reduces its operating cost through price arbitrage in an electricity market and/or by gaining availability income from committing power capacity to frequency response markets for an availability fee. The LES is assumed to be a price taker in the electricity and the frequency response markets with exogenous prices. The required power exchange with the grid is assumed to be feasible, with no consideration for power system operation. The optimisation structure and interaction with electricity and frequency response markets are shown in Figure 3.3.

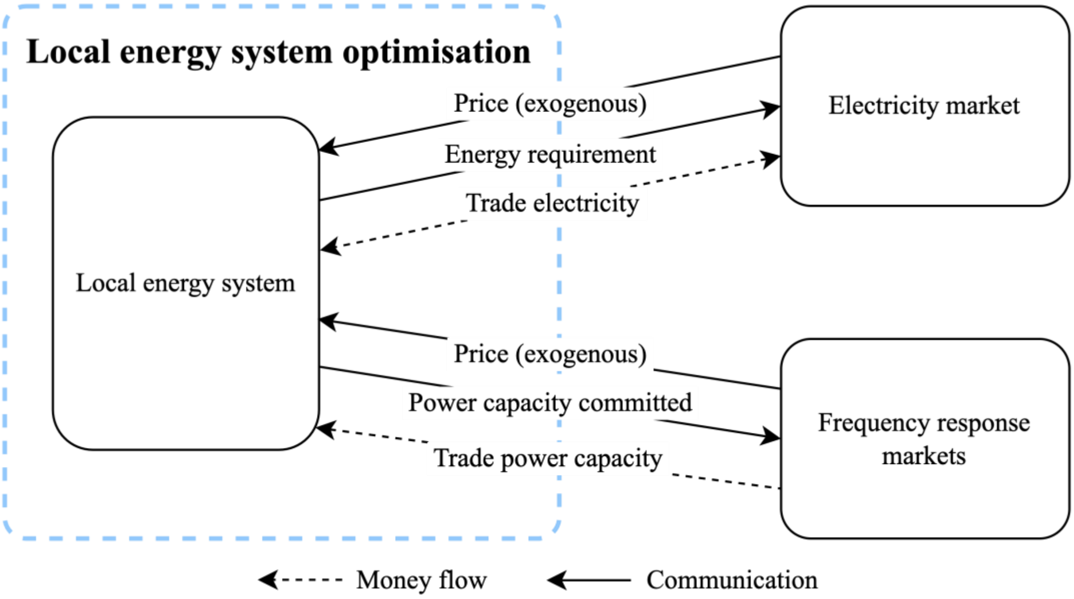

Figure 3.3 Interactions between the local energy system and the electricity and frequency response markets.

The deterministic optimisation assumes perfect foresight of renewable generation, demand and electricity prices. Therefore, the optimisation is solved once, with hourly time intervals, for the full year of operation. The decision to participate in frequency response markets is based on availability income only. Therefore, the LES does not consider the dispatch income from response energy payments. The impact of dispatch income is addressed using the methodology described in Section 3.2.2. Details of the optimisation structure are given in Figure 3.4, defining the aim of the objective function and decision variables.

Local energy system

Objective function: minimise operating cost.

Decision variables: import power ($P_{b,t}^{im}$), export power ($P_{b,t}^{ex}$), power committed to frequency response ($P_{b,n}^{FR,h}$,$P_{b,m}^{FR,l}$), battery charging ($P_{b,t}^{ch}$) and discharging ($P_{b,t}^{dis}$) power, energy stored in the battery ($E_{b,t}$).

Figure 3.4 Concise structure of optimisation, defining objective function and decision variables.

The objective function of the operational optimisation is as follows.

$$
\begin{aligned}
Min \quad \Pi = \sum_{b=1}^{Bn}\sum_{t=1}^{Tn} \tau\left(K_{b,t}^{E}\left(P_{b,t}^{im} - P_{b,t}^{ex}\right) + K_{b,t}^{DUoS} P_{b,t}^{im}\right) \\
- \sum_{b=1}^{Bn}\left(\sum_{n=1}^{Nn}\left(K_{b,n}^{FR,h} P_{b,n}^{FR,h}\right) + \sum_{m=1}^{Mn}\left(K_{b,m}^{FR,l} P_{b,m}^{FR,l}\right)\right)
\end{aligned}
\tag{3.1}
$$

The objective function minimises the LES operating cost. The first term in the objective function represents trading in the electricity market, where $\tau K_{b,t}^{E} P_{b,t}^{im}$ is the electricity import cost, $\tau K_{b,t}^{E} P_{b,t}^{ex}$ is the income from exporting electricity and $K_{b,t}^{DUoS} P_{b,t}^{im}$ is the distribution use of system (DUoS) cost.

The second term in the objective function defines the income from frequency response services. Where $K_{b,n}^{FR,h} P_{b,n}^{FR,h}$ is availability income from committing to high frequency response and $K_{b,m}^{FR,l} P_{b,m}^{FR,l}$ is the availability income from committing to low frequency response. n represents the set of high frequency response services the LES participates in and m represents the set of low frequency response services the LES participates in.

Frequency response services are typically procured for specific time slots throughout the day. These are included by splitting the time horizon into a set of blocks, labelled b. Each block is split into a set of time steps, which indicates the set of electricity market settlement periods, labelled t. These tend to be 60-minute, 30-minute or 15-minute time steps, but are specific to each electricity market. Together, b and t represent the time horizon of the optimisation. The constant τ represents the time interval between each time step (e.g., 1 hour, 0.5 hours or 0.25 hours). Multiplying by τ converts the power values to energy.

The objective function is subject to several constraints, including the power balance.

$$P_{b,t}^{im} + P_{b,t}^{Ren} + P_{b,t}^{dis} = P_{b,t}^{ch} + P_{b,t}^{D} + P_{b,t}^{ex} \tag{3.2}$$

The power balance equation ensures all power flows are equal. Therefore, the renewable generation ($P_{b,t}^{Ren}$), imported power ($P_{b,t}^{im}$) and battery discharge ($P_{b,t}^{dis}$) satisfy the local demand ($P_{b,t}^{D}$), with any excess power charging the battery ($P_{b,t}^{ch}$) or exported to the grid ($P_{b,t}^{ex}$). The following equations constrain the battery operation.

$$E_{b,t} = E^{ini}\Big|_{b=1,t=1} + E_{b-1,Tn}\Big|_{b>1,t=1} + E_{b,t-1}\Big|_{t>1} + \tau\left(\eta^{ch} P_{b,t}^{ch} - \frac{P_{b,t}^{dis}}{\eta^{dis}}\right) \tag{3.3}$$

$$0 + \sum_{m=1}^{Mn}\left(P_{b,m}^{FR,l} T_{m}^{FR,l}\right) \leq E_{b,t} \leq \overline{E} - \sum_{n=1}^{Nn}\left(P_{b,n}^{FR,h} T_{n}^{FR,h}\right) \tag{3.4}$$

$$0 \leq P_{b,t}^{ch} + \sum_{n=1}^{Nn}\left(P_{b,n}^{FR,h}\right) \leq \overline{P}^{bat} \tag{3.5}$$

$$0 \leq P_{b,t}^{dis} + \sum_{m=1}^{Mn}\left(P_{b,m}^{FR,l}\right) \leq \overline{P}^{bat} \tag{3.6}$$

The battery energy balance equation is shown in (3.3), where the energy in the battery ($E_{b,t}$) is equal to the energy in the previous time step plus/minus energy from charging/discharging power ($\tau\eta^{ch} P_{b,t}^{ch}$ /

$\tau\eta^{dis}P_{b,t}^{dis}$). Three separate terms define the battery energy in the previous time step. The first term defines the initial battery energy ($E^{ini}\big|_{b=1,t=1}$) for the first time step. The second term ensures continuity from the previous blocks final time step ($E_{b-1,T}\big|_{b>1,t=1}$). The third term defines the energy in the previous time step, within each block ($E_{b,t-1}\big|_{t>1}$). Equation (3.4) constrains the energy stored in the battery. The battery energy is limited to the maximum capacity of the battery ($\overline{E}$) minus the energy capacity required to deliver high frequency response services ($P_{b,n}^{FR,h}T_n^{FR,h}$). Additionally, sufficient energy is guaranteed to deliver low frequency response services ($P_{b,m}^{FR,l}T_m^{FR,l}$). Multiplying by the dispatch duration of frequency response services ($T_m^{FR,l}$, $T_n^{FR,h}$) converts the power values to energy. Equations (3.5) and (3.6) ensure the power committed to frequency response services ($P_{b,n}^{FR,h}$, $P_{b,m}^{FR,l}$) and the charging/discharging power is within the battery power rating ($\overline{P}^{bat}$). No power capacity limitations are considered for the LESs connection to the grid, therefore, $P_{b,t}^{im}$ and $P_{b,t}^{ex}$ have no upper limit. The final optimisation is a linear programming problem, which was formulated in GAMS and solved with the Gurobi commercial solver.

3.2.2 Energy dispatch of frequency response services

The frequency response energy dispatch calculation is the second main stage in the method, labelled ‘Frequency response energy dispatch (MATLAB)’ in Figure 3.2. This stage determines the energy injected to the grid in each time step and the dispatch income from receiving response energy payments. The key inputs for this section are the power system frequency, dispatch requirements for the frequency response service and the power committed to frequency response in each time step. Illustrative dispatch requirements for a symmetrical frequency response service are shown in Figure 3.5.

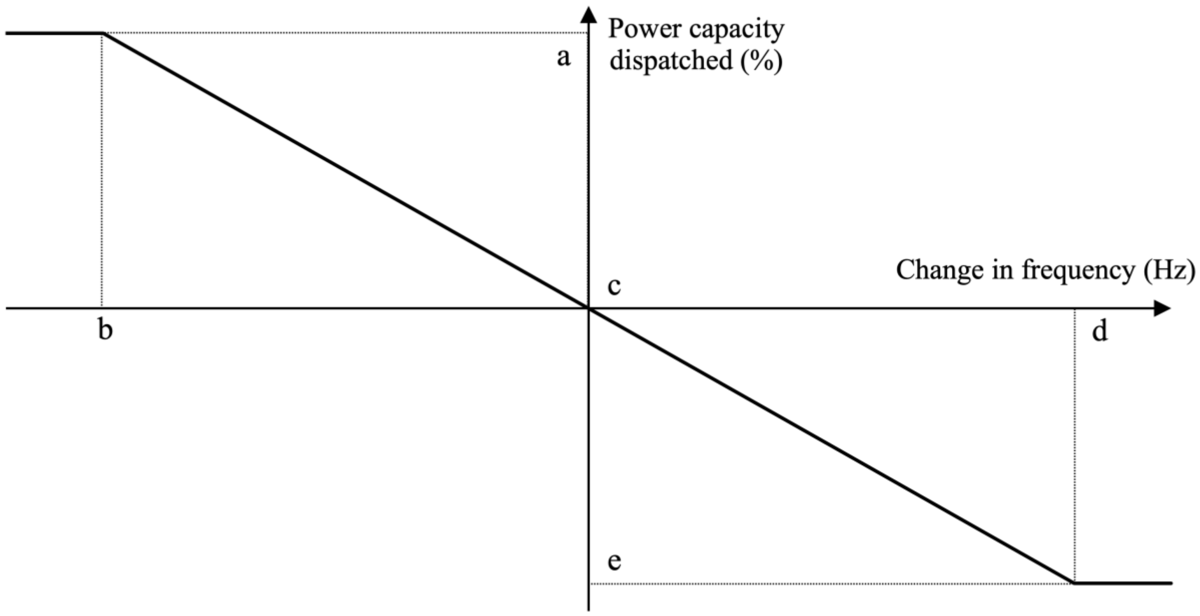

Figure 3.5 Power dispatch requirements for a symmetrical frequency response service.

Figure 3.5 shows the percentage committed power capacity that is dispatched, in response to changes in frequency. During low frequency, power is injected to the grid. During high frequency, power is imported from the grid. The dispatch requirements are written as the following constraints.

$$P_{b,t,s}^{SFR,\%} = \begin{cases} a, & \Delta f_s \leq b \\ {}^{a}/_{b}\,\Delta f_s, & b < \Delta f_s < c \\ {}^{e}/_{d}\,\Delta f_s, & c \leq \Delta f_s < d \\ e, & d \leq \Delta f_s \end{cases} \tag{3.7}$$

Where the subscript s represents the seconds within each time step and the superscript 'SFR' represents the symmetrical frequency response service. Equation (3.8) calculates the total energy dispatched in each time step.

$$E_{b,t}^{SFR,disp} = P_b^{SFR} \sum_{s=1}^{Sn} \left({P_{b,t,s}^{SFR,\%}}/{3600} \right) \tag{3.8}$$

In (3.8), the percentage dispatched power capacity ($P_{b,t,s}^{SFR,\%}$) is divided by 3600 (60^2, the number of seconds in an hour) to give energy dispatched per unit power, in each second. Each second is summed to convert to the time step duration and multiplied by the power committed to the service (P_b^{SFR}), which was determined by the operational optimisation. The output is the total energy dispatched in each time step, for each service.

Equation (3.9) gives the formulation for calculating the dispatch income.

$$\varphi^{SFR,disp} = \sum_{b=1}^{Bn} \sum_{t=1}^{Tn} \left(K_{b,t}^{REP} E_{b,t}^{SFR,disp} \right) \tag{3.9}$$

Where, $K_{b,t}^{REP}$ is the response energy payment (the price paid for power exchange with the grid), in £/MWh. The frequency response energy dispatch calculation was formulated outside of the operational optimisation to calculate the dispatch income from frequency response services. These results do not influence the power commitment decision making in the operational optimisation.

3.2.3 Battery degradation

Battery degradation is complex to model, as it is affected by numerous factors. These include the cell chemistry, the total energy throughput and operating stresses such as deep discharges, high or low temperatures and charging/discharging voltages [127]. Typically, battery degradation is split into calendar and cycle aging [128], [129]. Both calendar and cycle aging result in a loss of usable energy capacity. Calendar aging occurs regardless of charge/discharge cycles, whereas cycle aging is a consequence of charging/discharging and is influenced by depth of discharge. The typical end-of-life of a lithium-ion battery is 70-80% of its original capacity [130], [131].

In the following equations, the block index (b) has been removed and the time index (t) represents every hour of the full time horizon.

3.2.3.1 Calendar aging

The calendar aging model is a linear reduction in energy capacity over the 20-year shelf-life of a battery. In [132], the battery is assumed to reach end-of-life at 80% of its original energy capacity, after 20 years with no charge/discharge cycles. Equation (3.10) describes this process and provides a percentage capacity degradation per day (δ_{day}^{cal}).

$$\delta_{day}^{cal} = \frac{capacity\ reduction}{days * years} = \frac{20\%}{365 * 20} = 0.00274\%. \tag{3.10}$$

3.2.3.2 Cyclic aging

For lithium-ion batteries, larger depth of discharge causes higher battery degradation. This characteristic is commonly described using the relationship between the number of cycles until end-of-life and the depth of discharge of those cycles. Figure 3.6 shows this relationship for a lithium-ion battery with an end-of-life capacity of 80% [133]. The characteristic shown in Figure 3.6 was found experimentally by repeating charge/discharge cycles to the same depth of discharge, until the battery reached end-of-life.

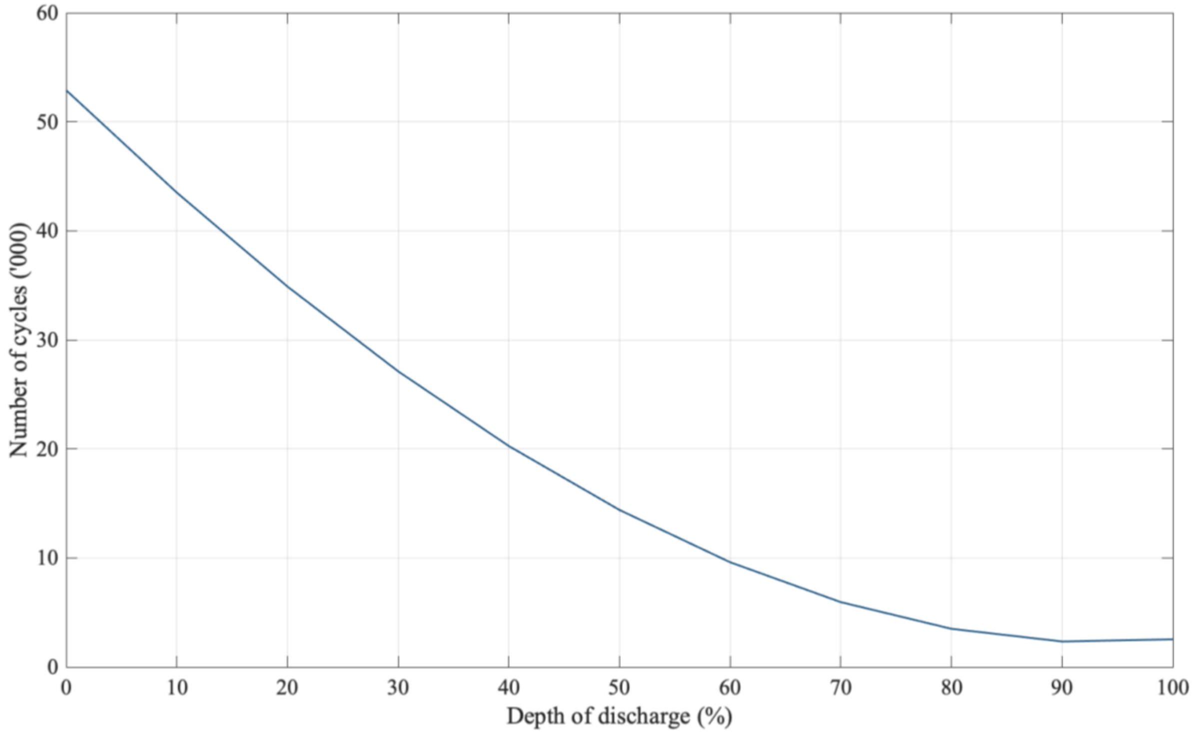

Figure 3.6 Maximum number of cycles until end-of-life against depth of discharge cycles.

Figure 3.6 shows a non-linear relationship, where deep discharge cycles reduce the number of cycles to end-of-life. The cycle aging model accounts for the number of cycles and their depth of discharge. In [132], the cycle aging model uses the characteristic in Figure 3.6 to determine battery aging for irregular charge/discharge cycles. Firstly, the cycle degradation in each time step is found.

$$\delta_t^{cyc} = 0.5\left|\frac{1}{N_t^{cyc}} - \frac{1}{N_{t-1}^{cyc}}\right| \tag{3.11}$$

Where,

$$N_t^{cyc} = 12198DOD_t^3 + \ 34954DOD_t^2 - 97517DOD_t + 52895 \tag{3.12}$$

$DOD_t = \left(\overline{E} - E_t\right)/\overline{E}$ and N_t^{cyc} is the number of cycles for a specific depth of discharge, defined by the characteristic in Figure 3.6. The inverse of N_t^{cyc} represents the percentage battery degradation of one cycle at a specific depth of discharge. Equation (3.11) calculates the battery degradation between the current and previous time steps by finding the difference between degradation at different depth of discharges. The magnitude of this difference is multiplied by 0.5 to recognise that the charge/discharge between two time steps is only half of a cycle. The sum of cycle aging over 24 time steps gives the capacity degradation in each day, shown in (3.13).

$$\delta_{day}^{cyc} = \sum_{t=1}^{24} \delta_t^{cyc} \tag{3.13}$$

3.2.3.3 Total aging

Once calendar and cycle aging are defined, the total battery aging must be calculated. Several methodologies exist in literature for combining calendar and cycle aging [127]. Some model a superposition of calendar and cycle aging [128], [134]. While others model them as independent processes, where cycle aging is used when the battery is operating and calendar aging is used when the battery is idle [135], [136]. However, the approach applied in this model uses the larger of the two 24-hour degradation values [132], [137], as shown in (3.14).

$$\delta_{day}^{total} = max\left\{\delta_{day}^{cal}, \delta_{day}^{cyc}\right\} \tag{3.14}$$

The degradation over each day is summed to give the total battery degradation over the time horizon of a year, shown in (3.15).

$$\delta^{PA} = \sum_{day=1}^{365} \delta_{day}^{total} \tag{3.15}$$

Where, δ^{PA} is the annual battery degradation caused by operation for price arbitrage. The degradation from frequency response energy dispatch is not included in δ^{PA}. The proportion of frequency response energy dispatch degradation was assumed to be equal to the proportion of energy throughput for frequency response dispatch, compared with energy throughput for price arbitrage. Therefore,

$$\delta^{Total} = \delta^{PA}\left(1 + \frac{Energy\ throughput\ from\ service\ delivery}{Energy\ throughput\ from\ price\ arbitrage}\right). \tag{3.16}$$

Where, $Energy\ throughput\ from\ service\ delivery$ is the output of the frequency response energy dispatch model and $Energy\ throughput\ from\ price\ arbitrage$ is an output of the operational optimisation. Equation (3.16) calculates the total battery degradation for the year, including price arbitrage degradation and frequency response energy dispatch degradation.

3.2.4 Net present value

The NPV was performed each year until the battery reached end-of-life, as shown in Figure 3.2. Equation (3.17) was used to find the NPV after each year.

$$NPV = -I + \sum_{y=1}^{Yn}\left(\frac{OCS_y}{(1+i)^y}\right) \tag{3.17}$$

Where, I is the initial investment cost, OCS_y is the operational cost savings, y is the year ($y = 1, \dots, Y$) and i is the discount rate. OCS_y is the difference between the operating cost without the battery storage system and the operating cost with the battery storage system. Each year, the operating cost with a battery storage system was calculated, with the useable battery energy capacity ($\overline{E}$) updated to account for battery degradation. As Figure 3.2 shows, the process was repeated until the battery reached 80% of its original energy capacity.

3.3 Case study definition

Figure 3.7 shows the case study LES of a school in Cardiff with local demand, 50 kW of PV solar panels and a prospective battery with 10 kW power rating and 20 kWh energy capacity. A battery round-trip efficiency of 90% [26] was applied to the charging and discharging process as the square root of round trip efficiency, 94.87%. The initial state of charge of the battery was defined as 50% of its usable energy capacity. The final state of charge was set equal to or larger than the initial state of charge. The battery storage system was allowed to operate from 0%-100% of its available energy capacity, no limitations were applied to reduce battery degradation.

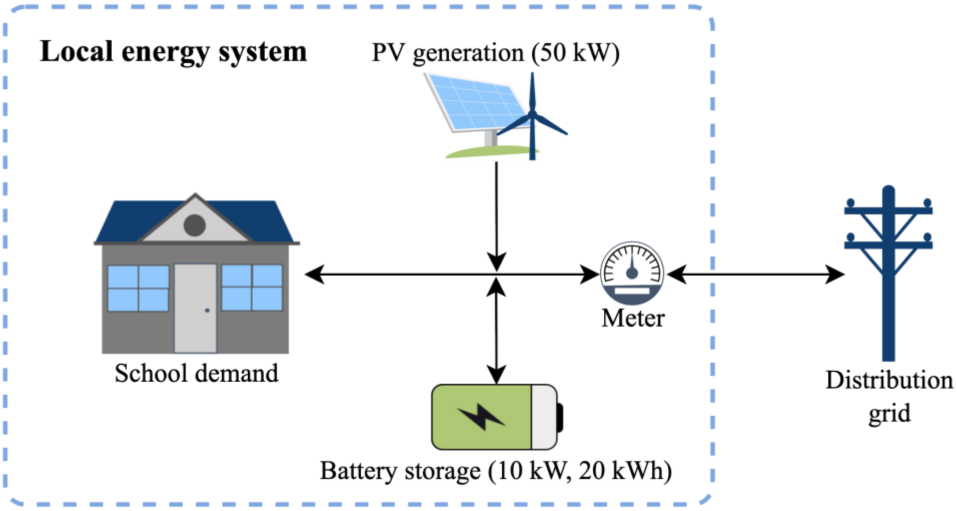

Figure 3.7 Case study local energy system with real data from a school in Cardiff.

Hourly time intervals were used for the case study ($\tau = 1$), for a one year time horizon. The local demand and PV generation data was from 2019, shown in Figure 3.8 and Figure 3.9.

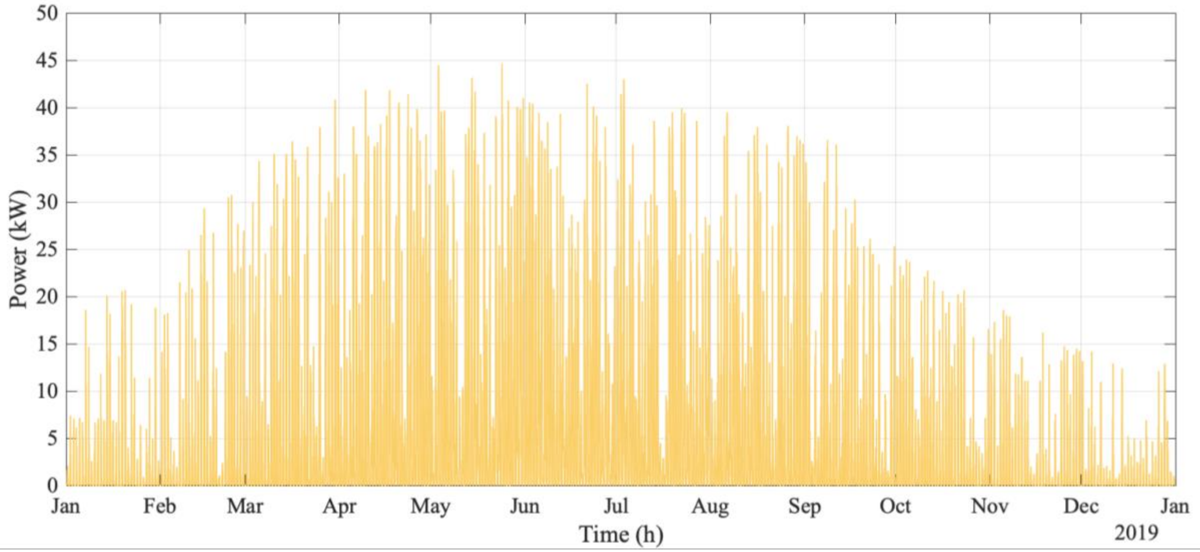

Figure 3.8 Hourly PV power generation for the one year time horizon.

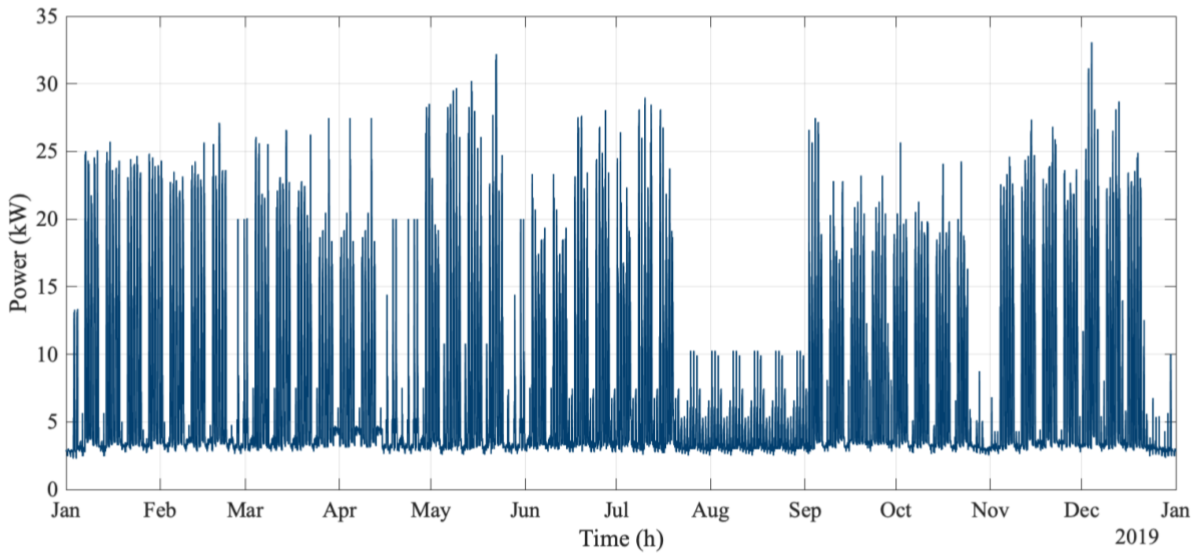

Figure 3.9 Hourly total power demand for the one year time horizon.

The electricity market considered in this study was the GB wholesale day-ahead electricity market, with hourly prices shown in Figure 3.10. In reality, the LES cannot participate in wholesale electricity markets, due to the minimum capacity entry requirements. However, aggregators combine small scale energy systems to meet the markets minimum capacity requirements [138], [139].

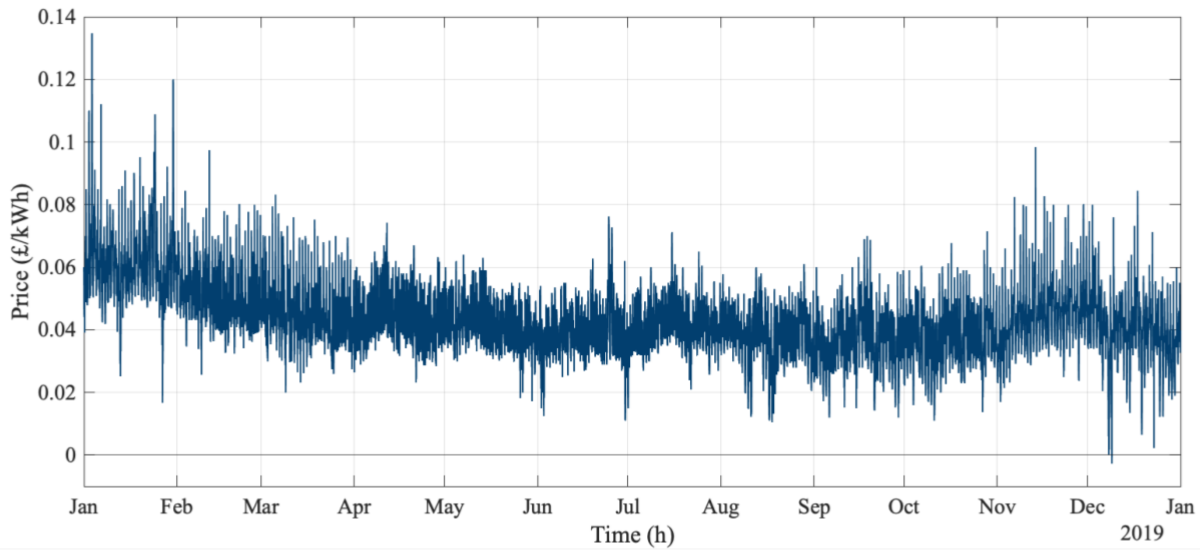

Figure 3.10 Hourly GB wholesale electricity price in 2019.

Figure 3.11 shows the DUoS charges that were applied to import power.

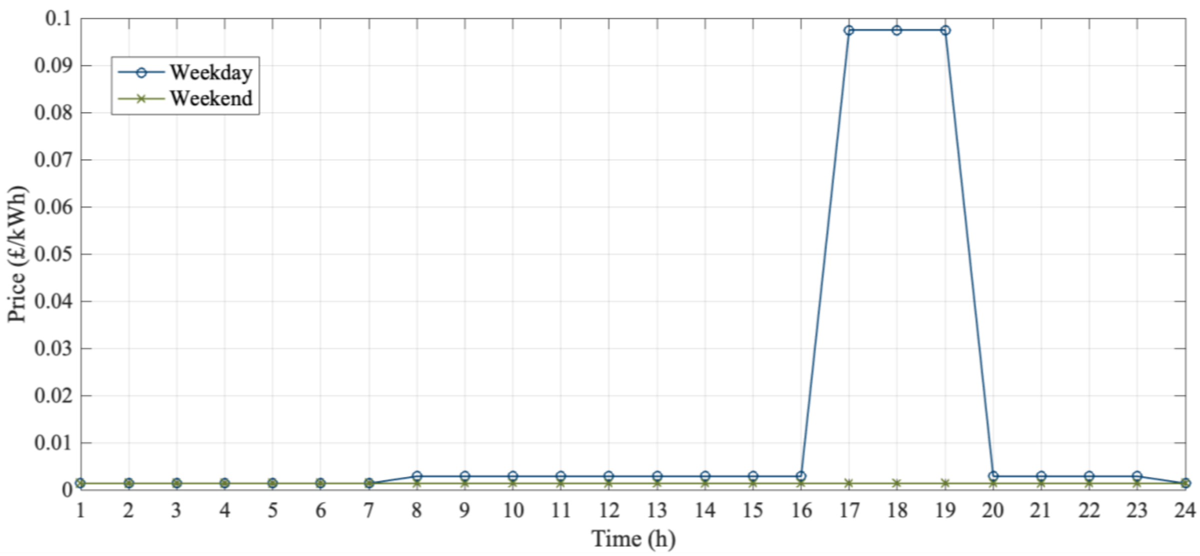

Figure 3.11 Distribution use of system charges for weekday and weekends.

3.3.1 Frequency response markets

In GB, frequency response services are organised by National Grid ESO to ensure security of electricity supply at a frequency of 50 Hz. Three frequency response services offered by National Grid ESO were considered in this study.

1. Dynamic Containment low (DCL)

2. Firm Frequency Response high (FFRH)

3. Firm Frequency Response low (FFRL)

The technical requirements of these services align well with battery capabilities and battery storage systems typically provide these services in the real market. At the time of investigation, National Grid ESO were procuring DC for low frequency only. Therefore, DC low was considered, without DC high. Dynamic FFRH and FFRL, as well as DCL, respond automatically and proportionally to changes in frequency. As the change in frequency increases, so does the proportion of power dispatch. Figure 3.12 shows the dynamic dispatch requirements.

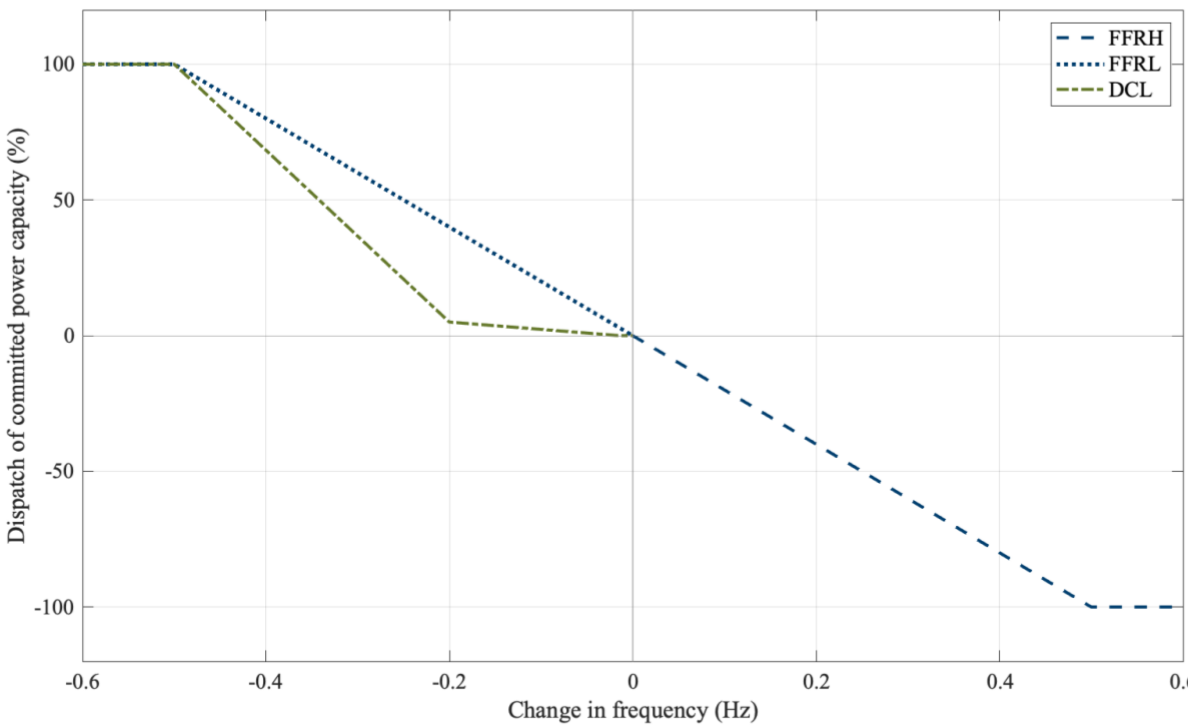

Figure 3.12 DCL, FFRL and FFRH dispatch requirements.

Figure 3.12 shows that FFRH consumes power from the grid during high frequency events (positive change in frequency), whereas DCL and FFRL inject power to the grid during low frequency events (negative change in frequency). Where, the target power system frequency is 50 Hz. According to

Figure 3.12, the dispatch requirements in (3.7) were defined for DCL, FFRH and FFRL, shown in (3.18)-(3.20).

$$P_{b,t,s}^{DCL,\%} = \begin{cases} 100, & \Delta f_s \leq -0.5 \\ -316.7\Delta f_s - 58.3, & -0.5 < \Delta f_s \leq -0.2 \\ -27.0\Delta f_s - 0.4, & -0.2 < \Delta f_s \leq -0.015 \\ 0, & \Delta f_s > -0.015 \end{cases} \tag{3.18}$$

$$P_{b,t,s}^{FFRL,\%} = \begin{cases} 100, & \Delta f_s \leq -0.5 \\ -200\Delta f_s, & -0.5 < \Delta f_s < 0 \end{cases} \tag{3.19}$$

$$P_{b,t,s}^{FFRH,\%} = \begin{cases} -200\Delta f_s, & 0 < \Delta f_s < 0.5 \\ -100, & \Delta f_s \geq 0.5 \end{cases} \tag{3.20}$$

Table 3.I describes the characteristics of DCL, FFRL and FFRH.

Table 3.I Frequency response characteristics [140], [141]

Characteristic	**DCL**	**FFRL**	**FFRH**
Respond when frequency is:	low	low	high
Minimum power capacity (MW)	1	1	1
Block duration (h)	24	4	4
Dispatch duration, T^{FR} (h)	0.25	0.5	0.5
Response time (s)	1	2	2

The LES is assumed to be aggregated to comply with the minimum power capacity of 1 MW. At the time of investigation, each DCL block was 24-hours (a full day). Whereas, for FFRH and FFRL, there were six 4-hour blocks throughout the day [142]. Therefore, the operational optimisation for DCL was run separately to FFRH and FFRL with different sets for t ($t = 1,2,\dots,T$) and b ($b = 1,2,\dots,B$). The size of each block is shown in Table 3.II. There are 2190 4-hour blocks and 365 24-hour blocks in a year.

Table 3.II Size of t and b sets within the operational optimisation

Service	T	B
FFRH & FFRL	4	2190
DCL	24	365

The dispatch duration of DCL is 15 minutes at full committed power. This is shown in Table 3.I as a dispatch duration of 0.25 hours. For FFRH and FFRL, the dispatch duration was 30 minutes at full committed power, shown as 0.5 hours in Table 3.I. When delivering at less than 100% of committed power, the dispatch duration is longer. Finally, DCL must respond within 1 second of frequency change, whereas FFRH and FFRL must respond within 2 seconds.

The DCL availability price was 1.7p/kW/h, which was the typical availability price for DCL in auctions [143]. The price for FFR varies between blocks and throughout the year. Prices for a week within each month of 2019 were acquired and repeated to give FFR availability prices for the year. The FFRH and FFRL availability prices were assumed to be identical and are shown in Figure 3.13.

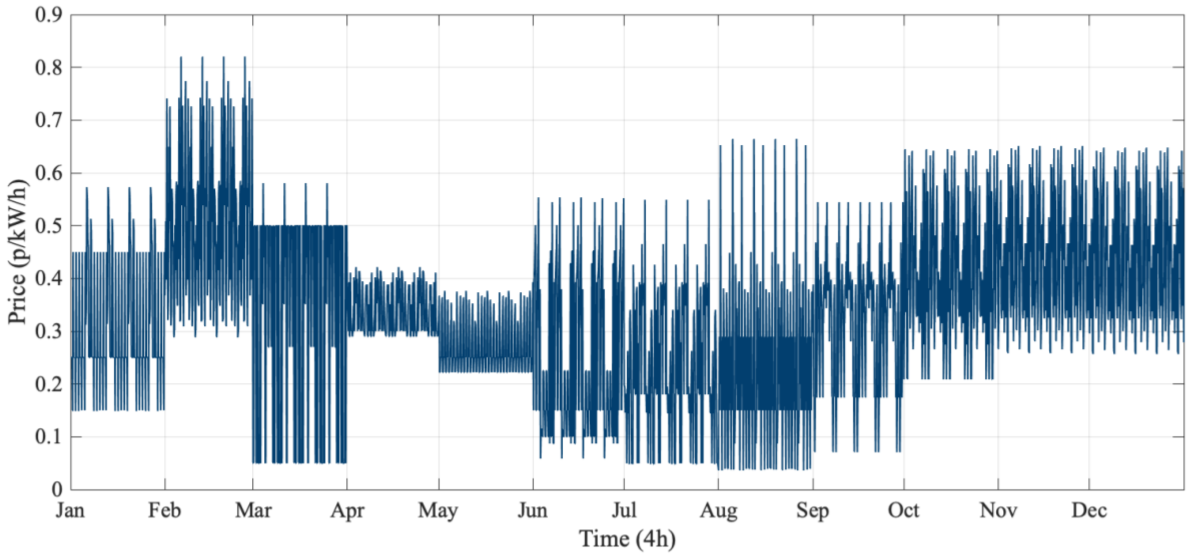

Figure 3.13 FFRH and FFRL availability prices estimated for each block of 2019.

There is no response energy payment for DCL, therefore the price paid for energy delivered to the grid is equal to zero ($K_{b,t}^{REP,DCL} = 0$). Whereas, the response energy payment for FFRH and FFRL is related to the balancing price ($K_{b,t}^{bal}$) [144].

$$K_{b,t}^{REP,FFR} = \begin{cases} -0.75K_{b,t}^{bal}, & E_{b,t}^{FFR,disp} < 0 \\ 1.25K_{b,t}^{bal}, & 0 < E_{b,t}^{FFR,disp} \end{cases} \tag{3.21}$$

When exporting energy in response to low frequency, 125% of the balancing price is received by the LES. Whereas, when importing energy in response to high frequency, 75% of the balancing price is paid by the LES. Therefore, the measurable advantage is a 25% increase/decrease in balancing price when responding to low/high frequency. The following equation gives the dispatch income for FFRH and FFRL.

$$\varphi^{FFR,disp} = \sum_{b=1}^{B}\sum_{t=1}^{T}\left(0.25K_{b,t}^{bal}E_{b,t}^{FFR,disp}\right) \tag{3.22}$$

The dispatch income for FFRH and FFRL was the energy dispatched multiplied by the balancing price and 0.25, summed over all time steps and blocks. The dispatch income was calculated outside the operational optimisation. Therefore, this income has no influence over the power committed to each service.

3.3.2 Scenarios

FFRH and FFRL can be stacked together, however, regulation prevents them being stacked with DCL. Therefore, five scenarios were defined.

1. Price arbitrage only (PA)
2. Price arbitrage and FFRH (PA & FFRH)
3. Price arbitrage and FFRL (PA & FFRL)
4. Price arbitrage, FFRL and FFRH (PA & FFRHL)
5. Price arbitrage and DCL (PA & DCL)

The first scenario is price arbitrage with no frequency response participation. The next three scenarios include FFRH and FFRL with price arbitrage. Finally, scenario 5 considers price arbitrage stacked with DCL. The operational optimisation problem was solved once for each year of the battery operation, as shown in Figure 3.2.

3.4 Results and discussion

3.4.1 Economic analysis

The financial value of revenue stacking for LESs was evaluated in three ways: the operating cost, the investment viability through NPV and the income received when responding to changes in frequency.

3.4.1.1 Local energy system operating cost

The total operating cost of the LES was a direct output of the operational optimisation. The operating cost savings from price arbitrage and revenue from frequency response are shown in Figure 3.14. For each scenario, there is a waterfall plot, relative to the operating cost of a base case scenario with no battery storage system. The operating cost for the base case, with no battery storage system, was £1,279.94.

Figure 3.14 shows the LES operating cost was reduced for all operating strategy scenarios. However, the magnitude of cost savings varied between scenarios. Scenario 1, the typical operating strategy using price arbitrage only, saw a 33.7% reduction in operating cost. This was the smallest cost saving across all scenarios. Stacking either FFRH or FFRL with price arbitrage further reduced the operating cost. However, stacking FFRH and FFRL with price arbitrage was the best combination of FFR services with a total operating cost saving of 65.2%. The largest cost saving was made with price arbitrage and DCL. The price arbitrage income and availability income from DCL was larger than the base case operating cost, leading to net profit for the year. This is shown as a negative value in the "PA & DCL" bar in Figure 3.14. The LES's operating cost saving made by price arbitrage and DCL was 118.2%.

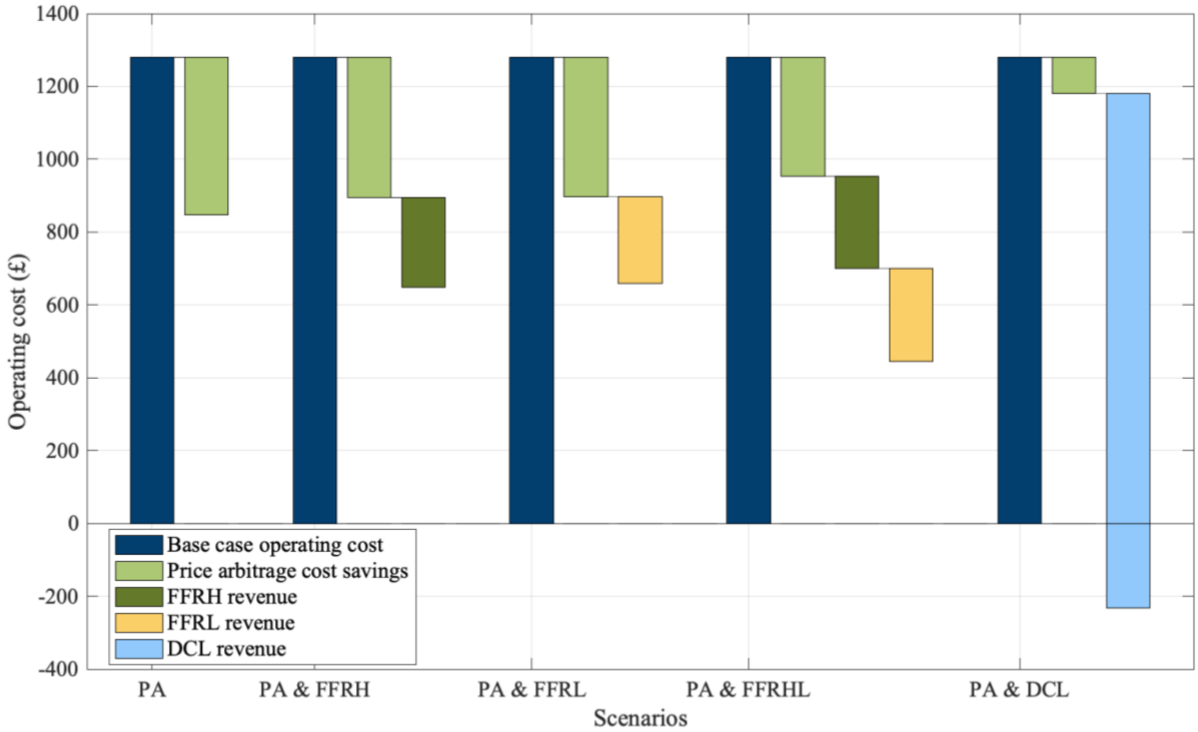

Figure 3.14 Individual waterfall plots for each scenarios' operating cost savings from price arbitrage and revenue from frequency response, relative to a base case with no battery storage.

The results in Figure 3.14 show that adding a battery storage system reduces the operating cost of the LES. However, the magnitude of operating cost reduction is related to the chosen operating strategy. Stacking revenue streams from electricity and frequency response markets increases the utilisation of a battery storage system to increase revenue. The following section discusses whether the operating cost savings made by the battery storage system justify the investment cost.

3.4.1.2 Investment viability

NPV with a discount rate of 10% was used to assess the battery investment viability for each scenario. The capital cost was assumed to be £128/kWh, the average price of stationary battery storage in 2020 [6]. The NPV at each year of the battery's lifetime is shown in Figure 3.15. The final NPV was calculated when the battery reached the end of its life at 80% of its original energy capacity. All scenarios show increasing NPV each year, as their operational cost savings payback the investment cost. Furthermore, all scenarios show curved lines due to the reduction in operational cost savings caused by battery degradation.

Scenario 1, with price arbitrage only, resulted in the lowest NPV over the battery's lifetime. Scenario's 1, 2 and 3 were inviable investments as they had a negative NPV when the battery reached end-of-life. Whereas Scenarios 4 and 5 were viable investments as they had positive NPVs when the battery reached end-of-life. Scenario 5, with price arbitrage and DCL had the largest NPV (£7,255.42) and longest lifetime (11 years).

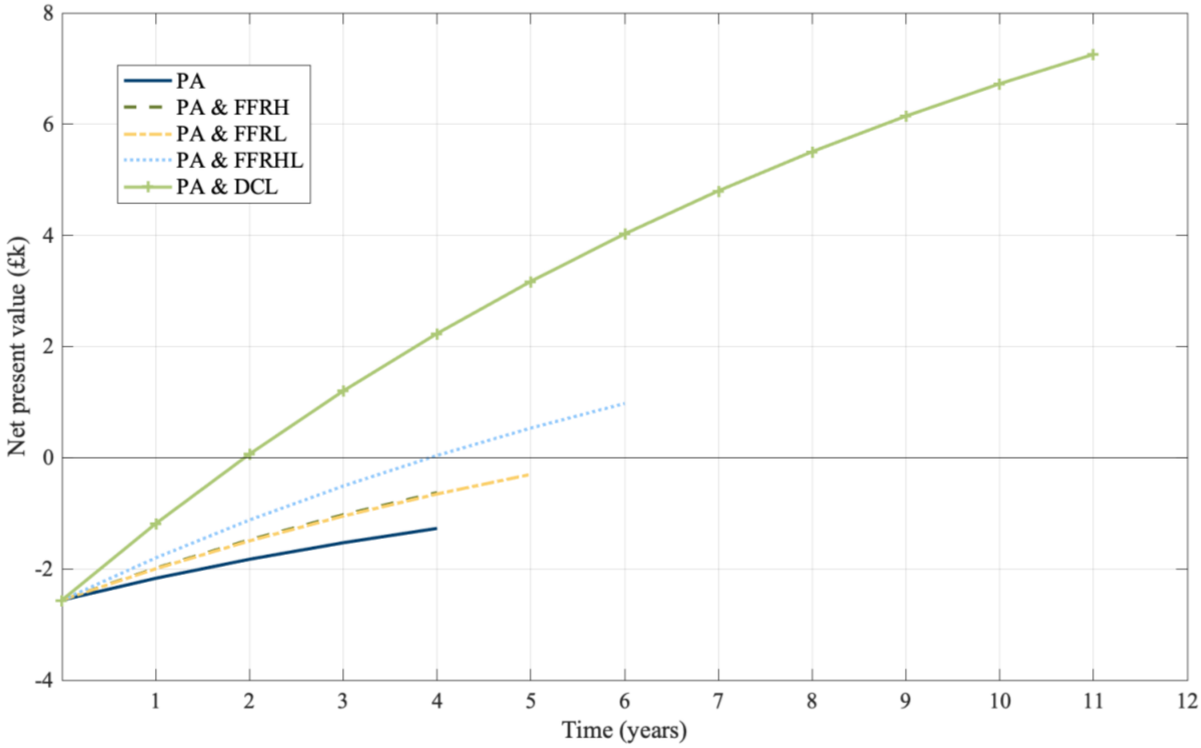

Figure 3.15 Net present value for local energy system operating strategy scenarios.

The NPV results show that revenue stacking increases the investment viability by increasing the overall income from the same battery storage system. The result also shows that participating in frequency response services increases battery lifetime.

Grid scale stationary battery storage systems are too large for the LES used in this case study. The prices for smaller scale, domestic battery storage systems are higher, ranging between £445/kWh and £1,315/kWh [31]. With the investment cost this high, only Scenario 5, with price arbitrage and DCL, was a viable investment, with a positive NPV. However, the maximum battery price to achieve a positive NPV was approx. £490/kWh. Analysis of small-scale battery storage systems shows that revenue stacking improves investment viability, but lower battery prices are required to create attractive opportunities for investors.

3.4.1.3 Frequency response energy dispatch revenue

The balance of availability income and dispatch income for the frequency response services are shown in Figure 3.16. The income for frequency response is shown for the first year of battery operation. No dispatch income is received for DCL. Therefore, all DCL revenue was availability income. Moreover, the availability income made up the majority of FFRH and FFRL revenue. Where, approximately 9% of total FFRH and FFRL revenue was dispatch income.

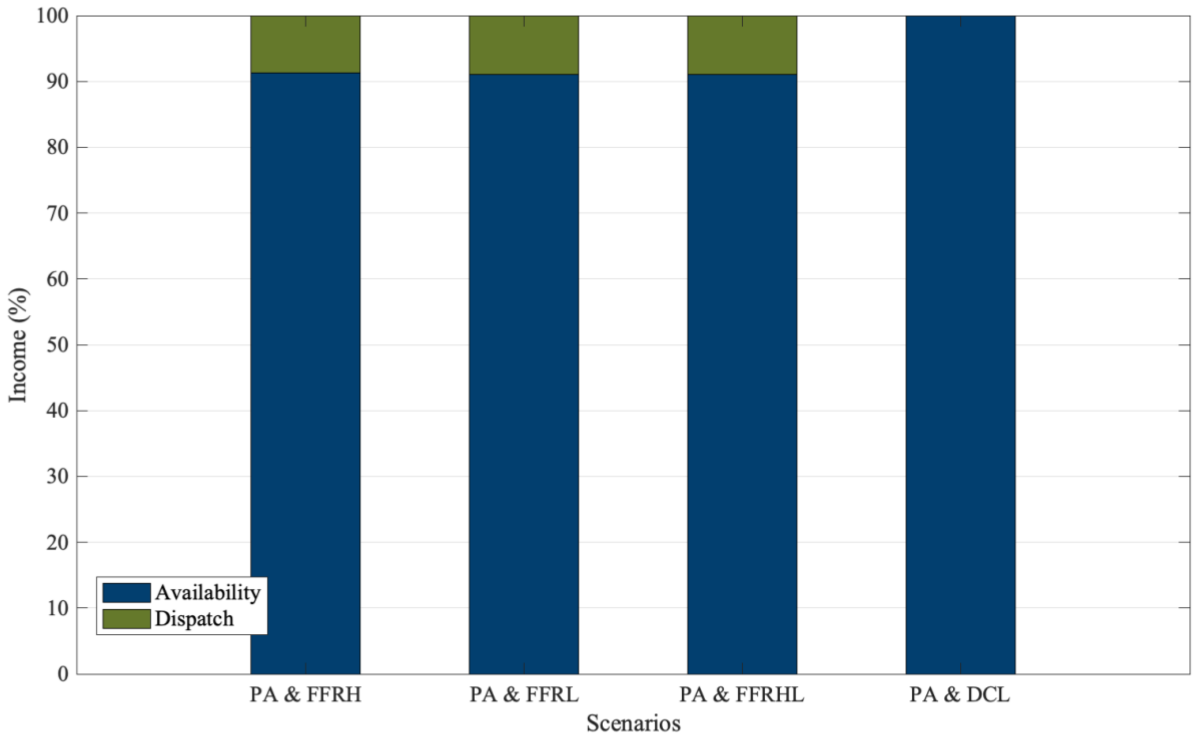

Figure 3.16 Frequency response revenue split into (navy) availability and (green) dispatch income.

This result demonstrates the limited significance of frequency response dispatch income and justifies the exclusion of dispatch income in the operational optimisation. With dispatch income contributing such a small proportion of frequency response income, battery operators are likely to make decisions on participation based on the availability income only. Additionally, forecasting of dispatch income is complex due to the uncertainty of power system frequency and balancing market prices.

3.4.1 Battery operation

3.4.1.1 State of charge

In Figure 3.17, the battery state of charge was averaged in each hour of the day, for every day of the year. The result is a representation of battery state of charge for an average 24-hours.

In Figure 3.17, price arbitrage only shows the highest variation in average battery state of charge. Price arbitrage only has a low average state of charge at midday and throughout the night and a high average state of charge during the early morning and early evening. The result was an average of two large charge/discharge cycles per day. Stacking FFRH and FFRL with price arbitrage reduced this large cycling characteristic, decreasing either/both the maximum and/or minimum average state of charge. However, Scenarios 2, 3 and 4, with FFRH, FFRL and FFRHL, all went through an average of two cycles per day. Scenario 5, with price arbitrage and DCL, showed the least variation in average state of charge over 24-hours. The result was an average of one small charge/discharge cycle per day.

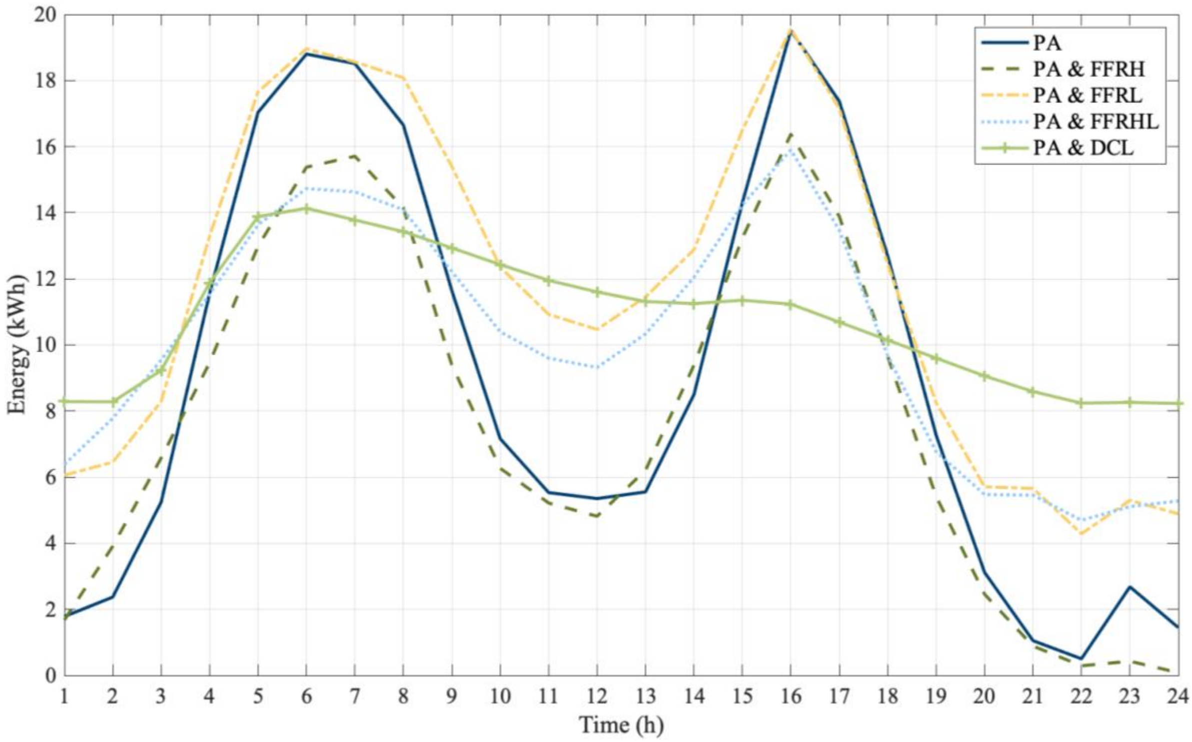

Figure 3.17 Energy stored in the battery averaged in each hour of the day over the full year of operation.

The result in Figure 3.17 shows frequency response services reduce the average depth of charge and discharge cycles. Furthermore, DCL reduced the average number of cycles per day from 2 cycles to 1 cycle. This result demonstrates stacking frequency response services with price arbitrage reduces the energy throughput, severity of charge and discharge cycles and operational stress on the battery.

3.4.1.2 Degradation

Battery degradation is key to understanding the value of revenue stacking for battery storage systems. Section 3.2.3 describes the model used to calculate battery degradation. Total battery degradation is shown in Figure 3.18, for the first year of battery operation. The results show battery degradation caused by price arbitrage in blue and energy dispatched for frequency response in green.

Price arbitrage was responsible for the majority of battery degradation across all scenarios. The highest total degradation was in Scenario 1 with price arbitrage only. In all other scenarios, where frequency response services are included, the total battery degradation was reduced. Scenario 5, with price arbitrage and DCL, had the lowest battery degradation with less than 2% per year.

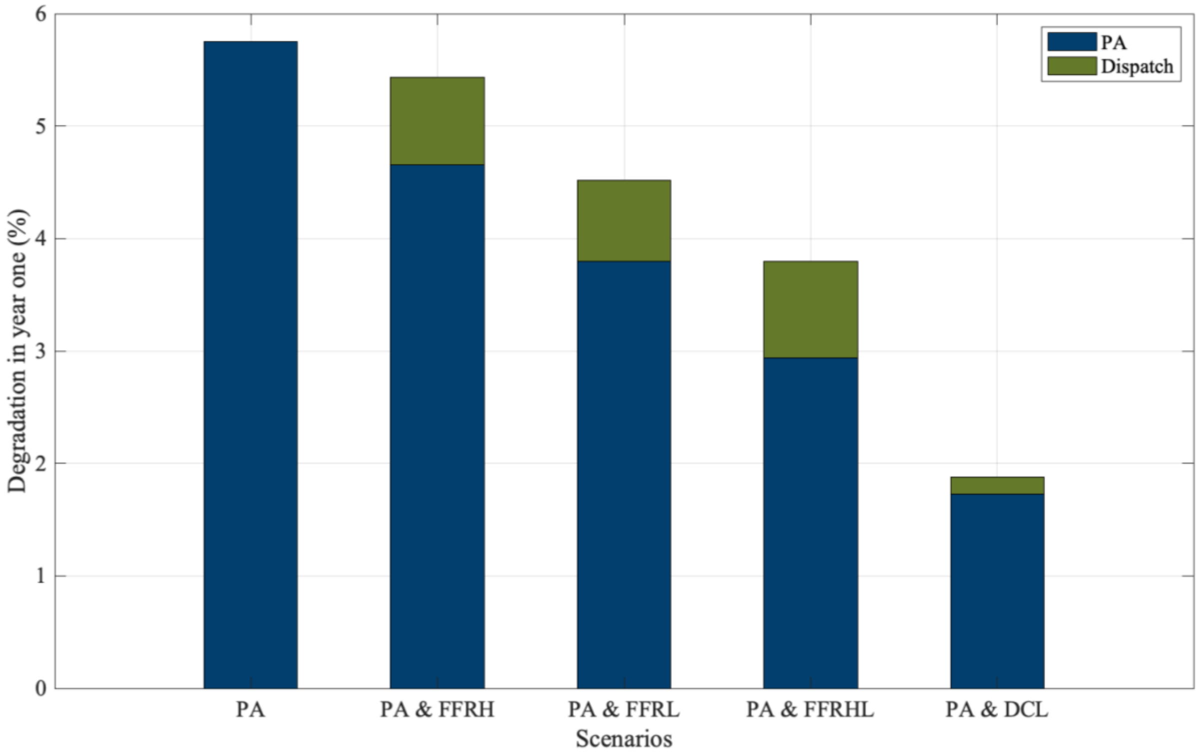

Figure 3.18 Battery degradation resulting from (navy) price arbitrage and (green) energy delivered.

Figure 3.18 shows that stacking frequency response services with price arbitrage lowers battery degradation, extending the battery lifetime. The advantage of frequency response is that the payments are relative to power capacity and time rather than energy exchanged. To gain revenue through price arbitrage, energy must be exchanged for a payment in £/kWh. Therefore, charge/discharge cycles are required to gain revenue. In contrast, the majority of revenue gained from frequency response services is based on available power capacity and time, paid in £/kW per h. Therefore, revenue is gained regardless of battery charge/discharge cycles. Hence, a battery storage system gains revenue with a lower requirement for energy throughput, reducing battery degradation.

Including battery degradation as part of the NPV calculation has shown that participating in frequency response services will increase battery lifetime. Scenario 5, with price arbitrage and DCL, resulted in the highest NPV and the longest battery lifetime, as shown in Figure 3.15. This is because of the high price of DCL and the low energy dispatch requirement.

The severity of battery degradation is subject to numerous operating and environmental conditions. A major influence is the battery chemistry. The manufacturer is also significant, with some offering a warranty for a period of time, and others limiting the number of cycles [145]. The accurate modelling of battery degradation is highly sensitive to these and other factors discussed in Section 3.2.3. Therefore, the accuracy of the number of cycles vs depth of discharge characteristic, shown in Figure 3.6, has significant influence on the accuracy of the degradation model.

3.5 Chapter summary

This study investigated a local energy system participating in the GB wholesale day-ahead electricity market and frequency response markets. A linear programming problem was formulated to minimise the local energy system operating cost by scheduling the charging and discharging of a battery storage system. The linear programming problem was formulated in GAMS and solved using the Gurobi simplex solver. The operating cost savings were used to assess the battery investment viability using net present value. The energy dispatched for frequency response was found using the power system frequency. Including the energy dispatched in the service enabled the comparison of revenue from availability income and dispatch income. Finally, a detailed assessment of battery degradation was carried out, considering the number and depth of battery charge and discharge cycles. The degradation occurring from energy dispatched for frequency response was accounted for. The energy dispatch income and battery degradation contributed to the net present value calculation.

The benefits of stacking frequency response services with price arbitrage were demonstrated in the operation and net present value results. Stacking revenue streams reduced the local energy system operating cost. Accordingly, the battery net present value was higher while participating in frequency response services alongside price arbitrage. In both the operational and investment analysis, stacking price arbitrage and Dynamic Containment gave the highest profits. Revenue gained from frequency response is mostly from availability income, shown to be approximately 90% for Firm Frequency Response and 100% for Dynamic Containment. The battery degradation modelling showed that participating in frequency response services extends the battery lifetime by reducing the need to gain revenue by trading energy in the wholesale day-ahead electricity market. This further improved the investment viability of the battery storage system.

The study demonstrates the value that revenue stacking adds to battery storage system operating costs and investment viability. Furthermore, the results highlight the need for stackable markets that will accelerate the adoption of battery storage. The results also show the importance of accounting for battery degradation when analysing operating cost and investment viability of battery storage systems.

Chapter 4

Optimising the operation of behind-the-meter battery storage from the consumer and power system perspectives

The focus of this chapter is the consumer and power system perspectives of BTM battery storage systems. This chapter presents the method to explicitly account for BTM battery storage decision making, within a whole power system optimisation. The BTM battery storage system minimises its operating cost, while exchanging power with the grid. The power system simultaneously minimises its own operating cost, while ensuring all power demand (including all BTM battery storage systems demand) is satisfied.

The suitability of this method was verified using a LES case study based on a school in Cardiff with an existing PV array. The LES performs price arbitrage with retail time-of-use electricity tariffs to reduce operating costs. The power system performs an economic dispatch of generation, reducing operating costs by prioritising the dispatch of low-cost generation. The method is compared to a conventional approach that accounts for distributed flexibility within a power system optimisation.

4.1 Introduction

Growing penetration of BTM battery storage systems will increase overall power system flexibility. However, at present, BTM battery decision making is independent from the power system operator and aims to optimise their own objectives with little regard for the wider power system. While minimising their operating costs, BTM batteries exchange power with the grid. The power system must satisfy the power exchange required by the BTM battery storage systems, even if doing so increases their own operating cost. Without coordination of BTM batteries, their contribution to system wide flexibility may be sub-optimal from a whole power system perspective, leading to an increase in power system operating costs.

Although there is value in battery storage systems for their owners, their contribution to power system flexibility is challenging to quantify. Traditionally, BTM battery storage system and power system operation are optimised independently or within a single decision maker representation. However, this can result in unrealistic outcomes for the value assessment of BTM battery storage. To inform new BTM battery development, regulation and incentives, their value to the power system (as autonomous decision makers) must be understood. Not only to ensure investment in assets is well placed but to inform developments of market structures and incentives to encourage their decision making to align with power system objectives. Therefore, understanding the interaction between BTM battery storage systems and the power system can help create cooperative operation, unlocking their potential contributions to whole power system flexibility.

Early studies acknowledged the increasing significance of distributed flexibility in supporting low-carbon power systems with high proportions of renewable generation [112]–[115]. This research shows the value of distributed flexibility to power systems, offering cost savings in comparison to lower levels of distributed flexibility. However, these studies assume centralised control of the distributed flexibility.

This assumption removes the autonomy of distributed flexibility, making it operate to benefit the power system. Although these integrated optimisations account for power system and distributed flexibility operation, they neglect the autonomy of distributed flexibility decision makers.

Several researchers suggest bilevel optimisation as a suitable approach for explicitly accounting for distributed flexibility decision makers and other actors in the power system [110], [117]–[122]. Bilevel optimisation is an approach used to explicitly account for multiple decision makers, without compromising on their decision making autonomy. The bilevel optimisation approach has been developed and applied to combinations of distributed flexibility, retailers, aggregators and power system operators. The suitability of this approach has been evaluated using case studies with a range of technologies including load flexibility, electric heating, thermal energy storage and electric vehicles.

This chapter presents the bilevel optimisation approach that accounts for BTM battery storage system decision makers and power system operators simultaneously. The BTM battery storage system is part of a LES structure. The LES optimisation and power system optimisation are individually defined and their bilevel structure described. The bilevel optimisation is solved by reformulating the power system optimisation using Karush-Kuhn-Tucker (KKT) conditions and applying them to the LES optimisation. The school case study and the power system case study are described with all input data provided. The optimisation is formulated in GAMS and solved using the Gurobi branch and cut solver. The results are analysed and compared with a conventional approach to justify the use of bilevel optimisation.

4.2 Formulation of optimisations

All BTM battery storage in this methodology is considered as part of a LES. The LES structure includes onsite generation, local electricity demand, a bidirectional connection to the grid and a battery storage system. For the remainder of this chapter, BTM battery storage is contained within the term LES.

4.2.1 Centralised optimisation

In the centralised optimisation approach, the power system operator schedules the operation of central power plants and the operation of LESs. Figure 4.1 presents the power flow structure of the centralised approach.

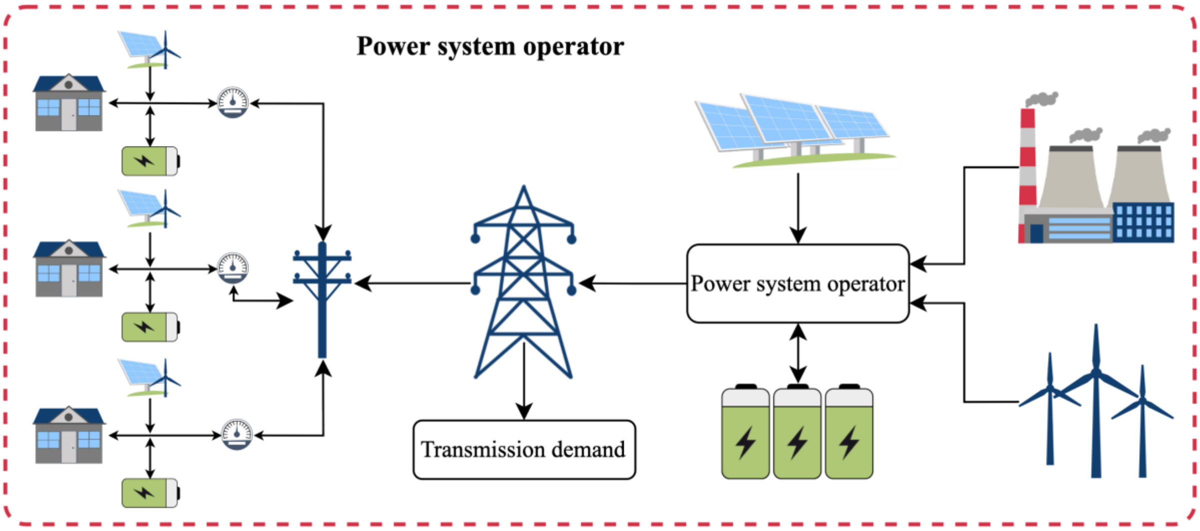

Figure 4.1 Centralised optimisation power flow diagram, where the power system is the only decision maker.

To compliment Figure 4.1, the centralised optimisation has been presented in Figure 4.2 to indicate the communication interactions between the LESs and power system operator.

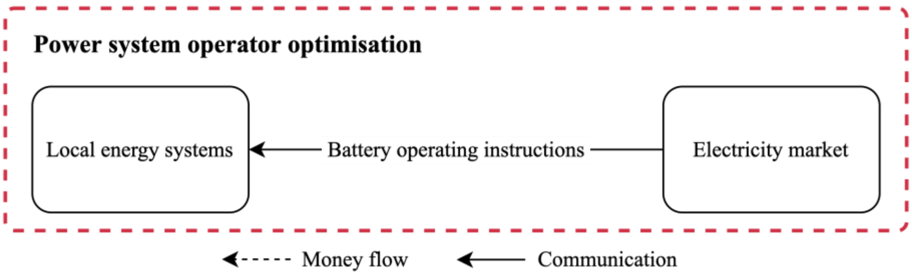

Figure 4.2 Centralised optimisation decision making, where the local energy systems are centrally controlled.

The centralised approach assumes all LESs are controlled centrally to benefit the power system operator. The centralised optimisation objective function aims to minimise the whole power system's operating cost of meeting demand. Figure 4.3 presents details of the centralised power system optimisation, including objective function and decision variables.

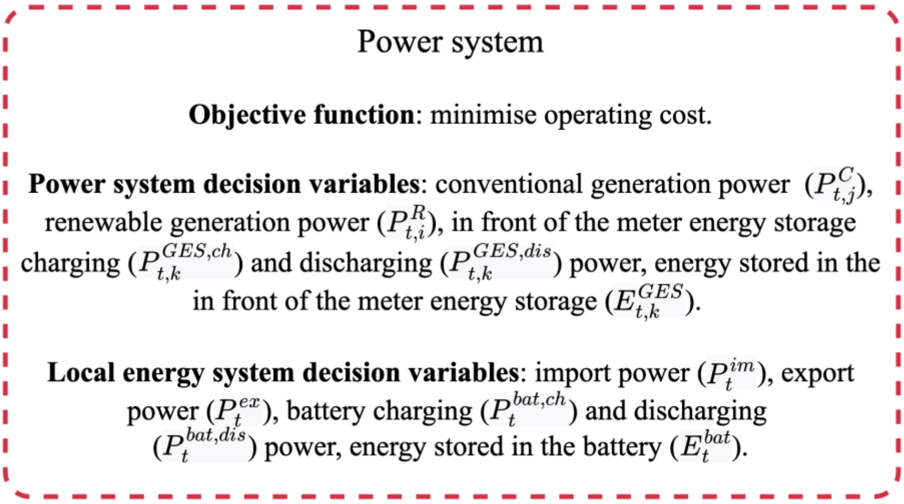

Figure 4.3 Centralised optimisation structure, defining the objective function and decision variables.

4.2.2 Bilevel optimisation

Bilevel optimisation separates the objectives of the LESs from those of the power system operator, where each optimisation has its own objective function, set of variables and set of constraints. Therefore, the optimisations are autonomous decision makers with potentially conflicting objectives [146]. In the bilevel optimisation, one optimisation is nested within another optimisation. The outside optimisation is called the leader and the nested optimisation is called the follower. The two optimisations have a hierarchical structure, where the leader can anticipate the reaction of the follower. A detailed description of bilevel optimisation theory is given in Appendix A.

The LESs are price takers in the retail electricity market (exogenous retail electricity prices), buying electricity through existing retail contracts. The power system operator schedules power plants to satisfy the overall electricity demand, including LES demand requirements. Therefore, the leading decision is made by the LESs (leader problem) and the following decision is made by the power system operator (follower problem). The objective of the LESs is to minimise the cost of meeting their own demand. The objective of the power system operator is to minimise the cost of meeting power system demand, specifically, the cost of meeting transmission level demand and the LESs demand. Figure 4.4 describes the bilevel optimisation and how the LESs and the power system operator interact.

In Figure 4.4, the LESs schedule their battery operation based on exogenous electricity prices. The LESs pass their optimal power exchange values to the power system operator as fixed parameters. Then, the power system schedules centralised generation to meet power system demand at the lowest cost. The power system optimisation constrains the LESs optimisation to ensure a feasible solution for the power system operator. Therefore, the LESs achieve optimality provided their solution is feasible for the power system and the power system achieves optimality, given the import and export power values the LESs choose.

Although the LES configuration in Figure 3.1 was used for this formulation, there are many alternative LES configurations. These may include alternative sources of generation (such as combined heat and power, and wind) or alternative sources of flexibility (such as thermal energy storage, electric heating, flexible demands or electric vehicles).

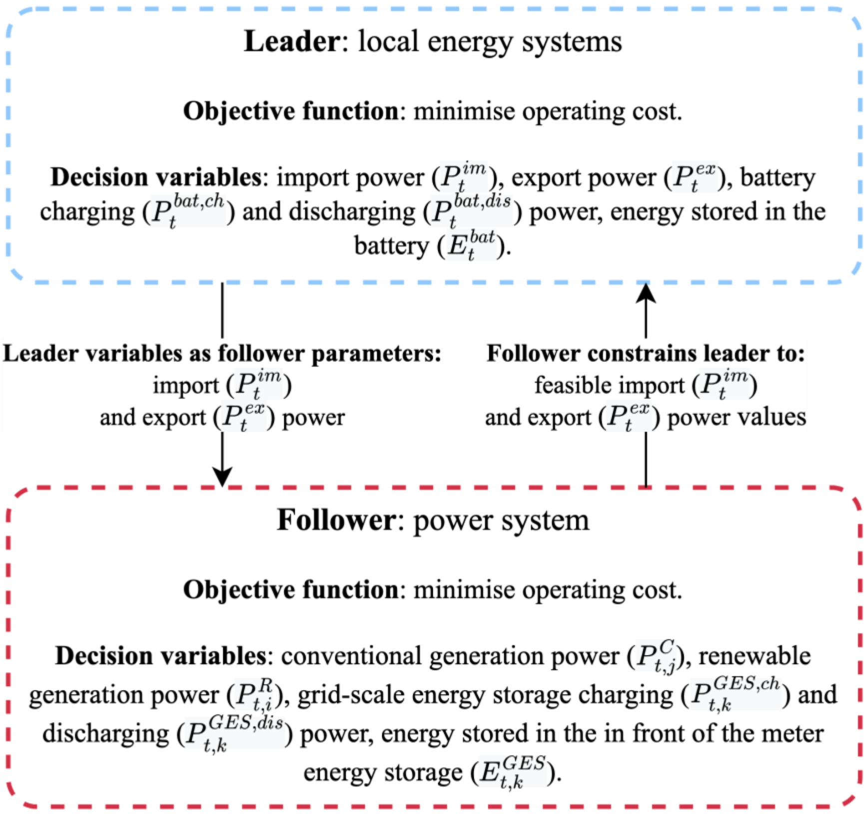

Figure 4.4 Bilevel optimisation structure with information exchange between the leader and follower.

The distributed LESs and the power system interact by exchanging power, where the LESs import/export power from/to the grid. Figure 4.5 presents the power flow diagram of the bilevel optimisation approach. The LESs and power system are autonomous decision makers that interact through power exchange.

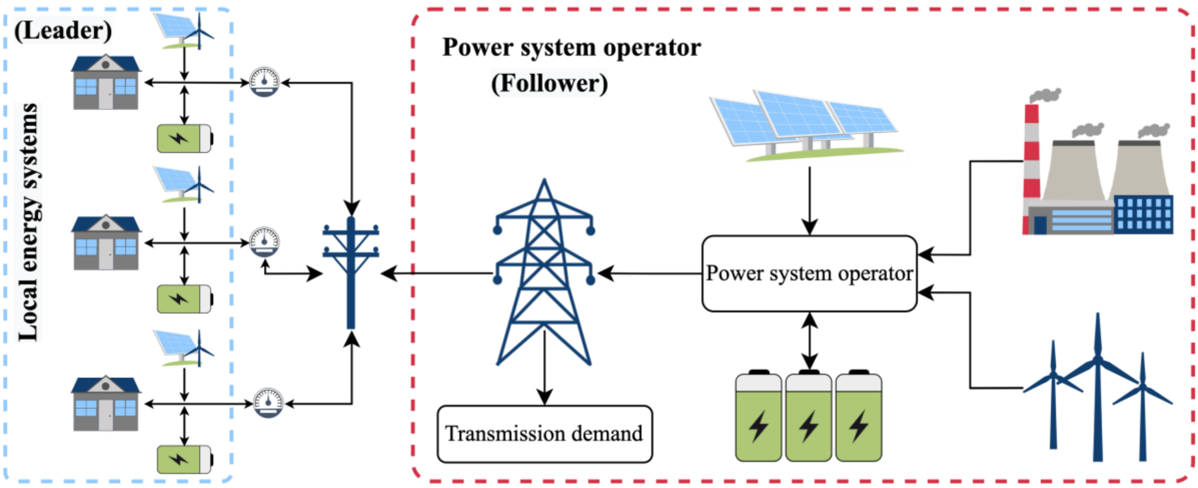

Figure 4.5 Bilevel optimisation power flow diagram.

To compliment Figure 4.5, the bilevel optimisation has been presented in Figure 4.6 to indicate the communication interactions between the LESs and the power system operator.

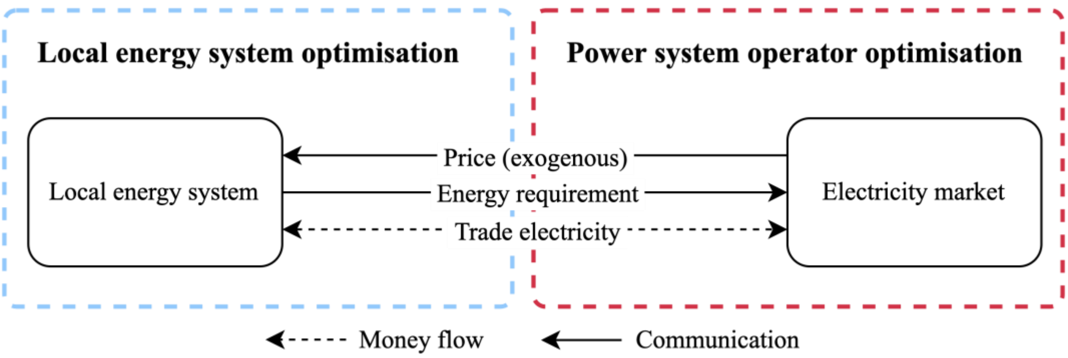

Figure 4.6 Bilevel optimisation interactions as autonomous decision makers.

Although the leader in this bilevel optimisation is the LES operator, alternative actors could be the leader. Virtual power plants, aggregators, retailers and coops are examples of real autonomous decision makers that aggregate and operate flexibility for the benefit of themselves and their flexibility providers.

In reality, participation in alternative markets is likely to be via one of these actors, due to market technical requirements and battery owner resource limitations. Any one of these could be the leader in this bilevel optimisation. However, neglecting these actors simplified the formulation as it removed their service charges, commission and/or other remuneration.

4.2.3 Leader optimisation: local energy system operating cost minimisation

This section describes the LESs operational optimisation. The LESs optimise their operating cost in response to exogenous retail electricity prices. The leading problem aims to minimise the operating cost of many aggregated LESs. The objective function is defined in (4.1). All terms are defined in the nomenclature in Appendix C.

$$\text{Min} \quad \Pi^L = \sum_{t=1}^{Tn} \tau (K_t^{im} P_t^{im} - K_t^{ex} P_t^{ex}) \tag{4.1}$$

The objective function minimises the LES's operating cost. Where operating cost is the difference between the cost of purchasing electricity and the revenue from selling electricity. The cost of purchasing electricity is defined as the import price multiplied by the imported power, $\tau K_t^{im} P_t^{im}$. The revenue from selling electricity is defined as the export price multiplied by the exported power, $\tau K_t^{ex} P_t^{ex}$. The power terms are multiplied by the time interval (τ) to convert power to energy. The minimisation of operating cost is achieved by scheduling the charging and discharging of the battery storage system. The following equations constrain the LES optimisation.

$$P_t^{LR} + P_t^{bat,dis} + P_t^{im} = P_t^{LD} + P_t^{bat,ch} + P_t^{ex} \tag{4.2}$$

$$0 \le P_t^{im} \le \overline{P}^{im} \tag{4.3}$$

$$0 \le P_t^{ex} \le \overline{P}^{ex} \tag{4.4}$$

Equation (4.2) is the power balance and ensures that onsite renewable generating power (P_t^{LR}), battery discharge power ($P_t^{bat,dis}$) and import power (P_t^{im}) are equal to local power demand (P_t^{LD}), battery charging power ($P_t^{bat,ch}$) and export power (P_t^{ex}), in every time step. Equations (4.3) and (4.4) limit the power exchange between the LESs and power grid. The battery storage system model is defined in (4.5)–(4.9).

$$0 \leq P_t^{bat,ch} \leq \overline{P}^{bat} \tag{4.5}$$

$$0 \leq P_t^{bat,dis} \leq \overline{P}^{bat} \tag{4.6}$$

$$\underline{E}^{bat} \leq E_t^{bat} \leq \overline{E}^{bat} \tag{4.7}$$

$$E_t^{bat} = E_{t-1}^{bat} + \tau\left(\eta^{bat,ch}P_t^{bat,ch} - \frac{P_t^{bat,dis}}{\eta^{bat,dis}}\right) \tag{4.8}$$

$$\sum_{t=1}^{Tn} \tau P_t^{bat,dis} \leq \frac{\tau Tn}{24} C^{bat} \tag{4.9}$$

The battery charging and discharging power is limited by the battery power rating ($\overline{P}^{bat}$) in (4.5) and (4.6). Equation (4.7) ensures the battery operates within its usable energy capacity ($\overline{E}^{bat}$). The battery energy balance is given in (4.8), which defines the energy stored in the battery during each time step (E_t^{bat}). The energy stored in the battery is determined by the stored energy in the previous time step and the charging and discharging behaviour in the current time step. To reduce battery degradation, (4.9) limits the battery to one full cycle per day by constraining the energy throughput over the time horizon.

This generalised formulation can be applied to numerous LES configurations by changing the inputs for renewable generation, demand and battery storage characteristics (power rating, energy capacity, efficiency and energy throughput limit).

4.2.4 Follower optimisation: power system operating cost minimisation

The follower optimisation is an economic dispatch model of a representative power system generation mix. The generation mix includes conventional generation, renewable generation and transmission connected or '*grid-scale*' energy storage. The economic dispatch is performed according to the marginal generating cost of each technology. Each grid-scale energy storage technology was assumed to be aggregated to give one power rating and energy capacity [118]. The power system optimisation aims to minimise the operating cost of meeting demand seen by the transmission system. The objective function is defined in (4.10).

$$\text{Min} \quad \Pi^F = \sum_{t=1}^{Tn} \tau \left(\sum_{j=1}^{Jn} \left(K_j^C P_{t,j}^C \right) + \sum_{i=1}^{In} \left(K_i^R P_{t,i}^R \right) + K_t^{ex} P_t^{ex} \right) \tag{4.10}$$

The objective function is comprised of three terms: the cost of electricity generation from conventional technologies, the cost of generation from renewable technologies and the cost of power purchased from the LESs. All terms are multiplied by the time interval (τ) to convert from power to energy. The following equations constrain the economic dispatch model. The corresponding dual variables are indicated for each constraint.

$$\sum_{j=1}^{Jn} P_{t,j}^C + \sum_{i=1}^{In} P_{t,i}^R + P_t^{ex} + \sum_{k=1}^{Kn} P_{t,k}^{GES,dis} = P_t^{im} + \sum_{k=1}^{Kn} P_{t,k}^{GES,ch} + P_t^{TD} \quad : \ \mu_t^1 \tag{4.11}$$

Equation (4.11) is the power balance and ensures all power sources are equal to all power demands, in every time step. The power sources are the conventional generation ($P_{t,j}^C$), renewable generation ($P_{t,i}^R$), LES export power (P_t^{ex}) and grid-scale energy storage discharge power ($P_{t,k}^{GES,dis}$). The power demands are the LES import power (P_t^{im}), grid-scale energy storage charging power ($P_{t,k}^{GES,ch}$) and transmission demand (P_t^{TD}). The demand seen by the transmission system is an inflexible input. The power operating limits of conventional and renewable generation are given in (4.12) and (4.13).

$$\underline{P}_j^C \leq P_{t,j}^C \leq \overline{P}_j^C \quad : \quad \lambda_{t,j}^1, \lambda_{t,j}^2 \tag{4.12}$$

$$\underline{P}_{t,i}^R \leq P_{t,i}^R \leq \overline{P}_{t,i}^R \quad : \quad \lambda_{t,i}^3, \lambda_{t,i}^4 \tag{4.13}$$

Conventional generation is limited by the capacity of the technology ($\overline{P}_j^C$). Whereas renewable generation is limited by a time series input of available renewable generation ($\overline{P}_{t,i}^R$). Any available renewable generation that is not used ($P_{t,i}^{R} < \overline{P}_{t,i}^{R}$), is assumed to be curtailed. The following equations constrain the operation of grid scale energy storage.

$$0 \leq P_{t,k}^{GES,ch} \leq \overline{P}_{k}^{GES} \quad : \quad \lambda_{t,k}^{5}, \lambda_{t,k}^{6} \tag{4.14}$$

$$0 \leq P_{t,k}^{GES,dis} \leq \overline{P}_{k}^{GES} \quad : \quad \lambda_{t,k}^{7}, \lambda_{t,k}^{8} \tag{4.15}$$

$$0 \leq E_{t,k}^{GES} \leq \overline{E}_{k}^{GES} \quad : \quad \lambda_{t,k}^{9}, \lambda_{t,k}^{10} \tag{4.16}$$

$$E_{t,k}^{GES} = E_{t-1,k}^{GES} + \tau\left(\eta_{k}^{GES} P_{t,k}^{GES,ch} - P_{t,k}^{GES,dis}\right) \quad : \quad \mu_{t,k}^{2} \tag{4.17}$$

The grid-scale energy storage charging and discharging powers are limited in (4.14) and (4.15). The energy stored is limited to the capacity of the grid-scale energy storage ($\overline{E}_{k}^{GES}$) in (4.16). The energy balance is given in (4.17), where the energy stored in the grid-scale energy storage ($E_{t,k}^{GES}$) is dependent on the energy stored in the previous time step, the charging power and the discharging power. The charging process is subject to a round-trip efficiency, implemented during the charging process.

The economic dispatch formulation can be applied to various power system configurations, by changing the collection of conventional generation, renewable generation and grid-scale energy storage technologies.

4.2.5 Solution methodology

The power system formulation described in Section 4.2.2 is a linear optimisation. Therefore, the bilevel optimisation was reformulated as a single level non-linear optimisation, using Karush-Kuhn-Tucker (KKT) conditions. The single-level optimisation was linearized using the Fortuny-Amat reformulation of the KKT conditions [147]. The final optimisation is a deterministic, single-level mixed-integer linear program. For a full description of the solution methodology and reformulation, refer to Appendix C. The reformulated bilevel optimisation was constructed in GAMS and solved with the Gurobi branch and cut solver.

4.3 Case study definition

A case study was defined to demonstrate the efficacy of the bilevel approach for studying the interaction between a low-carbon power system and the independent decision making of LESs with BTM battery storage. This section defines the LES configuration and the power system structure. One LES would have a negligible impact on the power system. Therefore, the optimisation considers many identical LESs that are aggregated within the power system.

The GB electricity market settlement period is 0.5 hours [148]. Therefore, time intervals of 30 minute were used, over an operational time horizon of 24-hours. A typical summer weekday during school holidays was used for the analysis.

The purpose of using a simplified case study was to showcase the application of the formulation. However, more complex and realistic case studies are possible. For examples, sets of LESs can be included with many size and technology configurations. This would better represent real development of LES configurations in power systems. Also, centralised generation can be broken down into individual power plants and assigned accurate marginal costs to improve the accuracy of the marginal cost curve. Furthermore, multiple aggregators or retailers can be included to represent a group of actors competing in electricity markets.

4.3.1 Local energy system configuration

A school in Cardiff was used as the LES case study. The onsite renewable generation was a 50 kW PV array and the battery had a 10 kW power rating and a 20 kWh energy capacity. The school has a variety of electricity demand requirements including lighting, computers and kitchen appliances (fridge, kettle, microwave, etc.). The school also has a bidirectional grid connection, where they import electricity to meet demand and export excess electricity.

50,000 identical schools were assumed to be aggregated. Power exchange with the grid was limited to 5 GW, to ensure no impact on the results of the investigation. The battery charging and discharging efficiencies were 98% and 96% [127]. At $t = 0$, the energy stored in the battery was assumed to be 50% of the battery's energy capacity. The energy stored in the battery in the final time step ($t = 48$) was set equal to or larger than 50% of the battery's energy capacity. The total energy throughput of the battery was limited to 20 kWh or one full cycle over the 24-hour time horizon. Figure 4.7 shows the fixed, time series local demand and PV generation inputs. The data in Figure 4.7 is given for a typical weekday during the school's summer holidays.

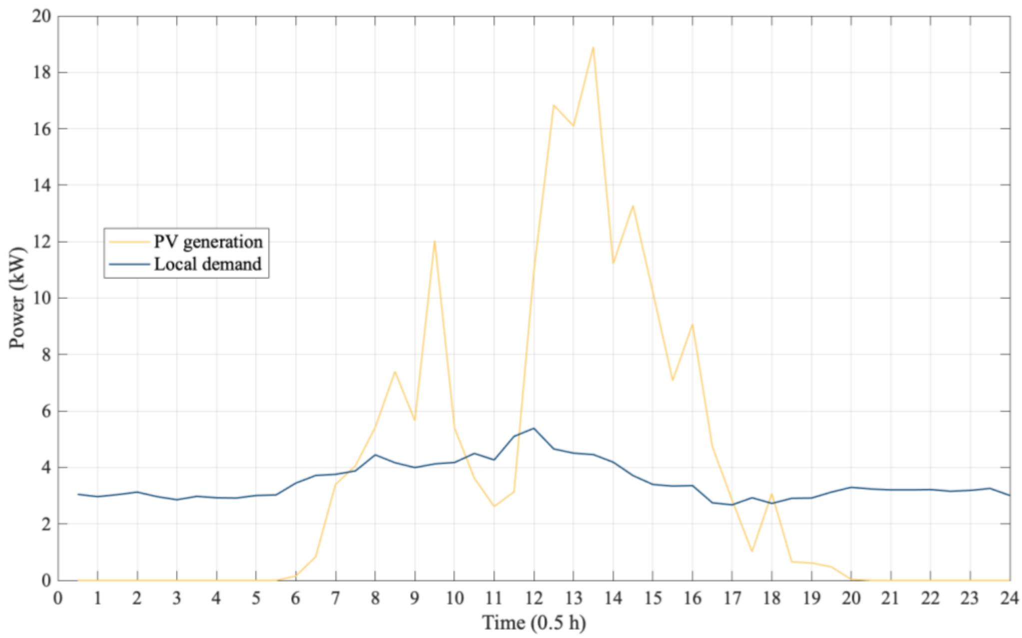

Figure 4.7 Local energy system demand and PV generation.

4.3.2 Power system configuration

A 2030 GB power system was used to create a scenario with high levels of renewable generation. Nuclear, combined cycle gas turbines (CCGTs) and open cycle gas turbines (OCGTs) were the conventional generation technologies. Maximum CCGT and OCGT power outputs were limited by their aggregated GB capacities. Whereas, nuclear generation was restricted to a small range, representing the technologies low variation over 24-hour periods. The range of nuclear generation was representative of a typical summer weekday during school holidays. The details of conventional generation are shown in Table 4.I. The ramp rates of conventional generation were neglected in this study. The resulting marginal cost curve is shown in Figure 4.8.

Table 4.I Input data for conventional generation technologies [149]–[152].

Technology	Maximum capacity (MW)	Minimum generation (MW)	Marginal cost (£/MWh)
CCGT	15,536	0	57
Nuclear	4,570	4,560	10.4
OCGT	1,126	0	83

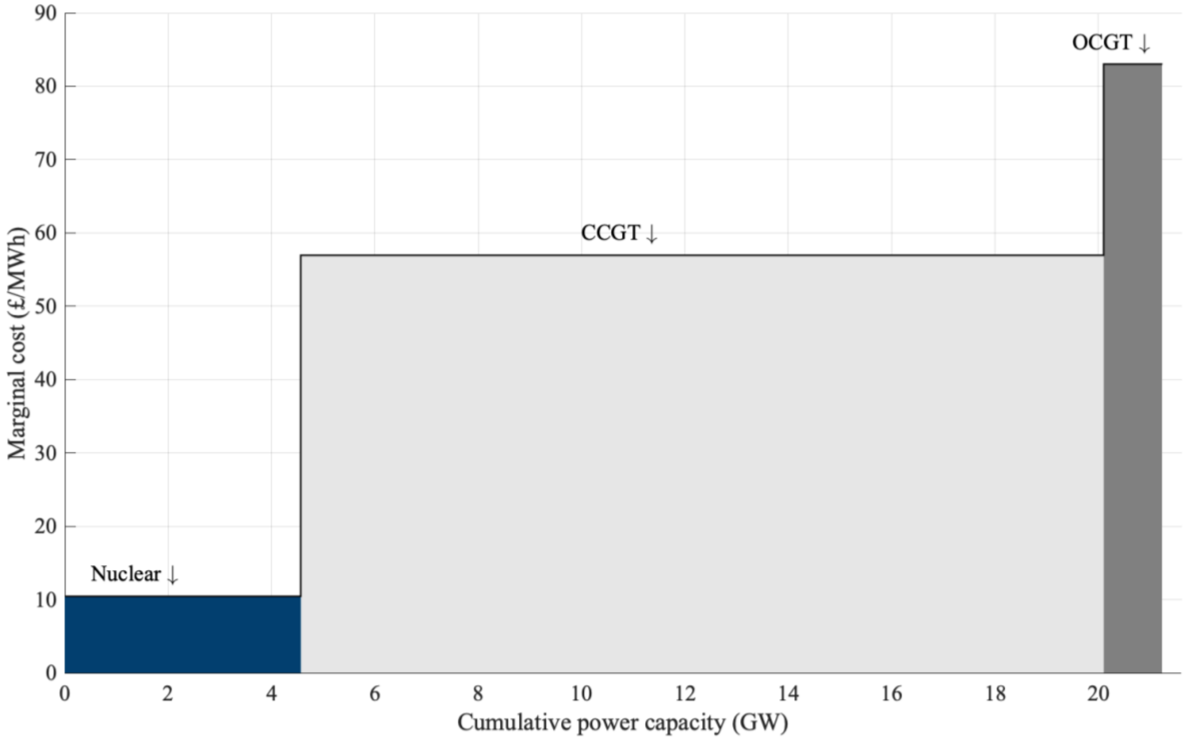

Figure 4.8 2030 GB power system marginal cost curve for conventional generation.

Wind, biomass and hydro were the renewable generation technologies. The maximum power capacity of the renewable technologies were real time series input data from a typical summer weekday during school holidays. The biomass and hydro power outputs were assumed to be related to external operating requirements and therefore could not be curtailed. This was implemented by applying identical time series inputs for minimum and maximum generation for each technology. In contrast, wind curtailment was possible and implemented by setting the minimum generation to 0 MW. The marginal costs of the renewable technologies were [151], [152]:

- Wind, £3/MWh
- Biomass, £41/MWh
- Hydro £6/MWh.

Wind, biomass and hydro time series data were acquired from [149], for the 31st July 2019, which was a weekday during summer school holiday. The time series inputs for wind, biomass and hydro generation were scaled in line with National Grid ESO's 2030 projections [153]. The available renewable generation and transmission demand inputs are shown in Figure 4.9, for a typical weekday during summer school holidays. The transmission level demand was a real time series input from a weekday during summer school holidays [154].

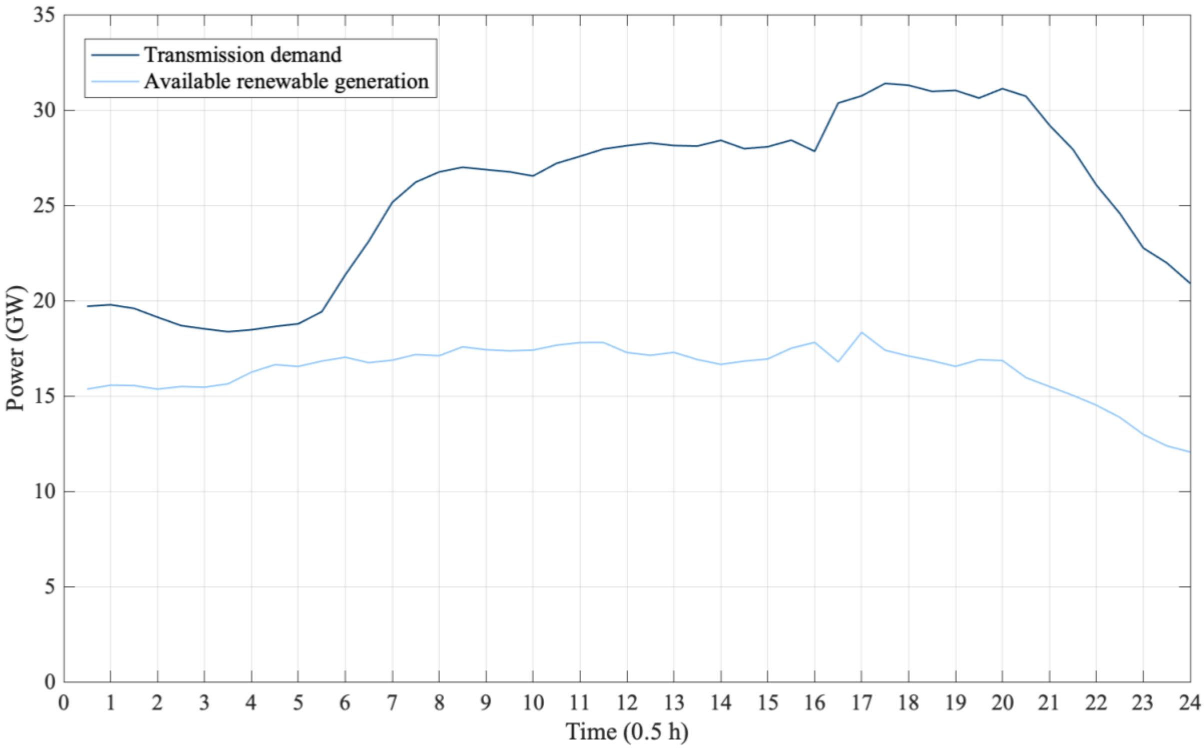

Figure 4.9 Transmission demand and available renewable generation.

Pumped storage was assumed to be the only grid-scale energy storage technology. Pumped storage had an aggregated power rating of 2,744 MW and an aggregated energy capacity of 38,450 MWh [153]. The energy stored in pumped storage at $t = 0$ was assumed to be 50% of the total energy capacity. In the final time step ($t = 48$), the energy stored in pumped storage was set equal to or larger than 50% of the total energy capacity.

4.3.3 Retail contracts

Several real electricity contracts offered by UK retailers were used to assess the impact of the LESs operation on the power system. The school's existing contract had a fixed day rate and a reduced night rate (00:00-07:00) for importing electricity but no contract for selling electricity back to the grid. The remaining contracts were:

- Fixed tariff – fixed import and export prices
- High peak tariff – fixed export price and increased import price during peak hours of the day
- Low off-peak tariff – reduced import price at night (00:00-04:00) and no export price
- Dynamic tariff – import and export prices are directly proportional to the wholesale electricity price.

To calculate the dynamic tariff, the wholesale electricity price was multiplied by a factor of 2.2 and an additional 12p/kWh added during peak hours (16:00-19:00). Finally, the price was capped at 35p/kWh. Customers receive prices the preceding evening of a 24-hour period. Therefore, customers were able to plan scheduling of battery operation for the upcoming 24-hours. For details of the dynamic tariff, refer to [155]. The fixed, high peak and low off-peak tariffs were predetermined time-of-use tariffs. Figure 4.10 and Figure 4.11 show the import and export retail contract prices over 24-hours.

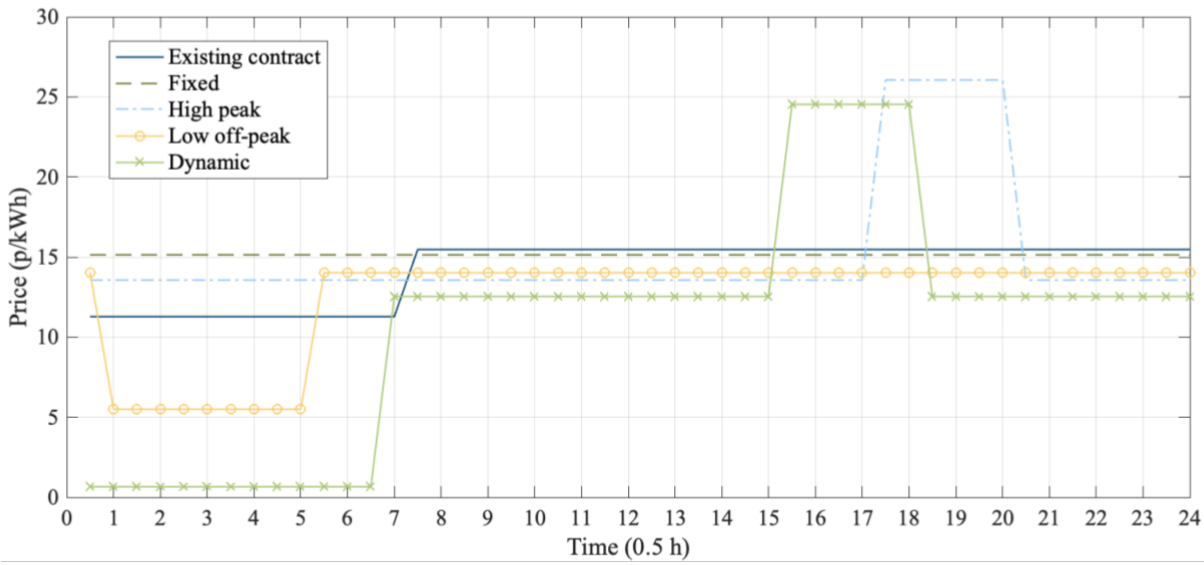

Figure 4.10 Retail electricity contracts, time-of-use import tariffs.

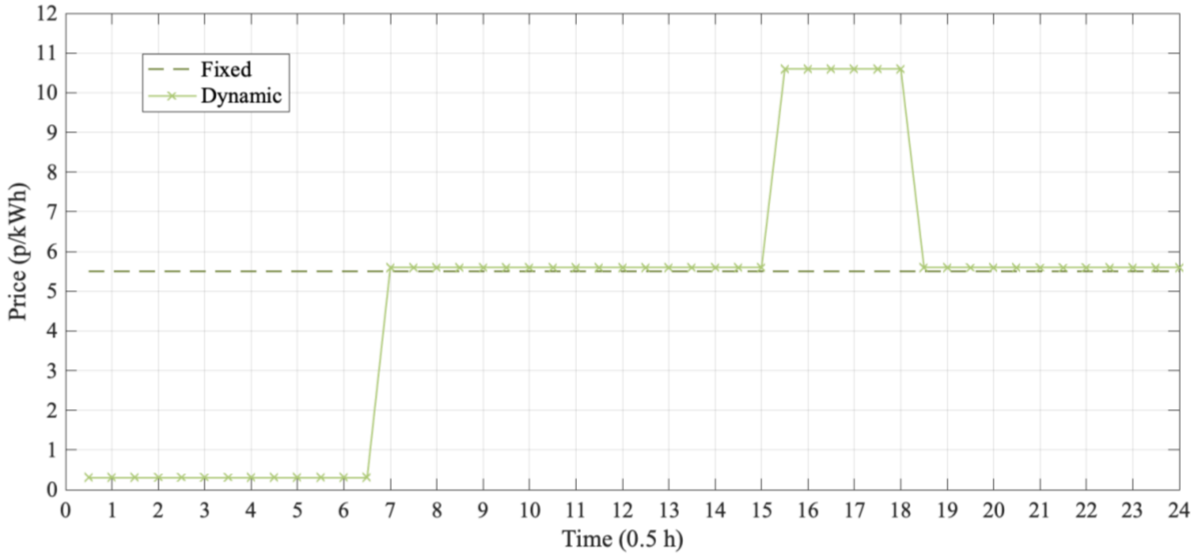

Figure 4.11 Retail electricity contracts, time-of-use export tariffs.

4.4 Results & discussion

To effectively compare the centralised and bilevel approaches, a benchmark scenario was defined with:

- no LES battery storage;
- the existing LES retail contract (fixed through the day, reduced night (00:00-07:00) price for importing and no contract for exporting).

The LESs and power system operating costs were minimised for the benchmark scenario, giving identical results for the centralised and bilevel approaches. This is justified, as the benchmark represents the operating cost when the LESs have no capability to change their power exchange with the grid.

The power system operating cost was the total cost of generation, required to meet demand. The benchmark power system operating cost was £7.54 million. The benchmark operating cost for the LESs was £275,011, equivalent to £5.50 per school.

4.4.1 Centralised vs bilevel approach

4.4.1.1 Operating cost

The battery storage system was included for the comparison of the centralised and bilevel approaches. The changes in LES and power system operating costs, relative to the benchmark case (with no battery storage), are shown in Figure 4.12. In the centralised approach, the power system operating cost decreases. The centralised optimisation did not consider the LES's operating cost. Therefore, the LES's operating cost was calculated outside of the centralised optimisation, by summing the cost of importing electricity and the revenue from exporting electricity. The output of this calculation was an increase in the LES's operating cost. In reality, the centralised operator would offer direct control contracts that guarantee the LESs would receive financial compensation for giving up control of their storage system. The results show that centrally operated BTM battery storage systems can provide cost savings to the power system. However, the LES's financial benefits are determined by the direct control contract.

The bilevel approach considers the LESs as autonomous decision makers that control the operation of their own battery storage systems. In the bilevel results shown in Figure 4.12, the LESs reduce their operating costs by 37%, when controlling the operation of their own battery. However, the operation of their battery storage systems resulted in an increase in operating cost for the power system.

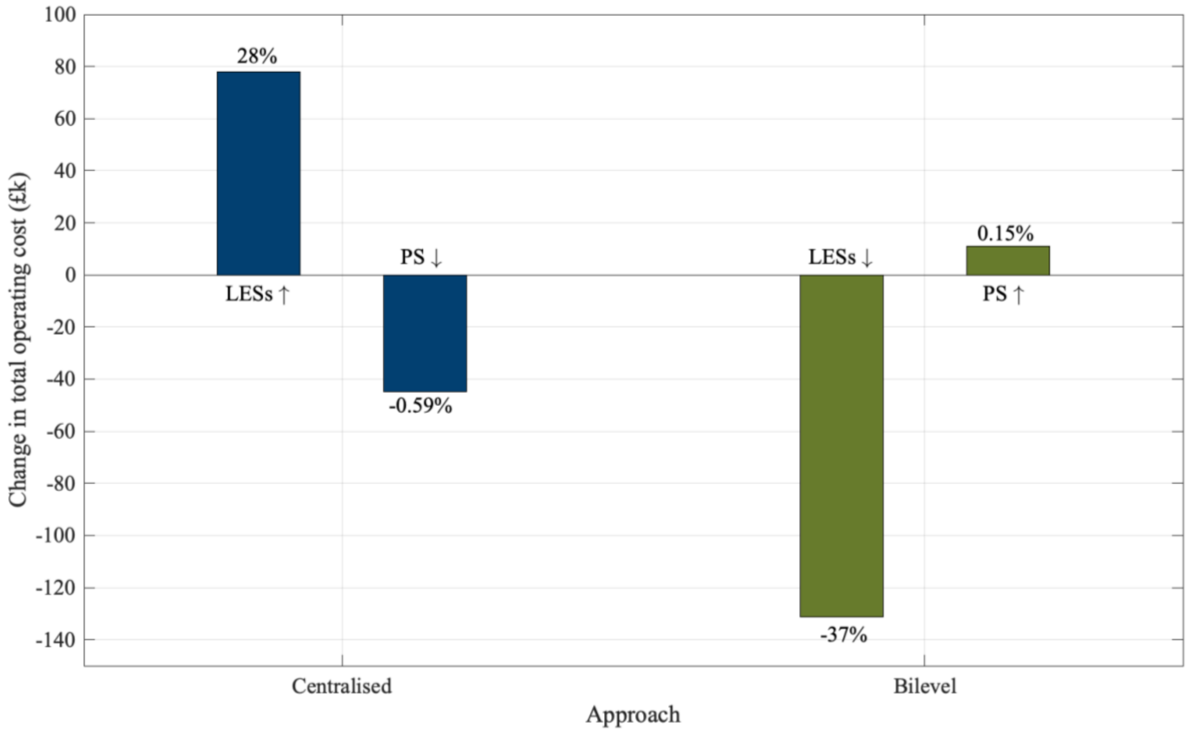

Figure 4.12 Changes in operating cost for the (left) centralised approach and (right) bilevel approach (with battery storage), relative to the benchmark case (with no battery storage).

The result in Figure 4.12 shows that autonomous BTM battery storage systems can negatively affect the power system. In addition, the bilevel approach can effectively account for the objectives of BTM battery storage operators within the power system. This result reflects previous findings of centralised and bilevel optimisation comparisons [110], [117], [118].

4.4.1.2 Renewable curtailment

Another key factor for a low-carbon power system is the utilisation of renewable generation. Figure 4.13 shows the change in renewable curtailment in comparison to the benchmark (with no battery storage). The existing retail contract was applied to produce this result. In the centralised approach, the centrally controlled battery storage systems reduced renewable curtailment by approximately 1,000 MWh. In contrast, the bilevel approach resulted in a 75 MWh increase in renewable curtailment.

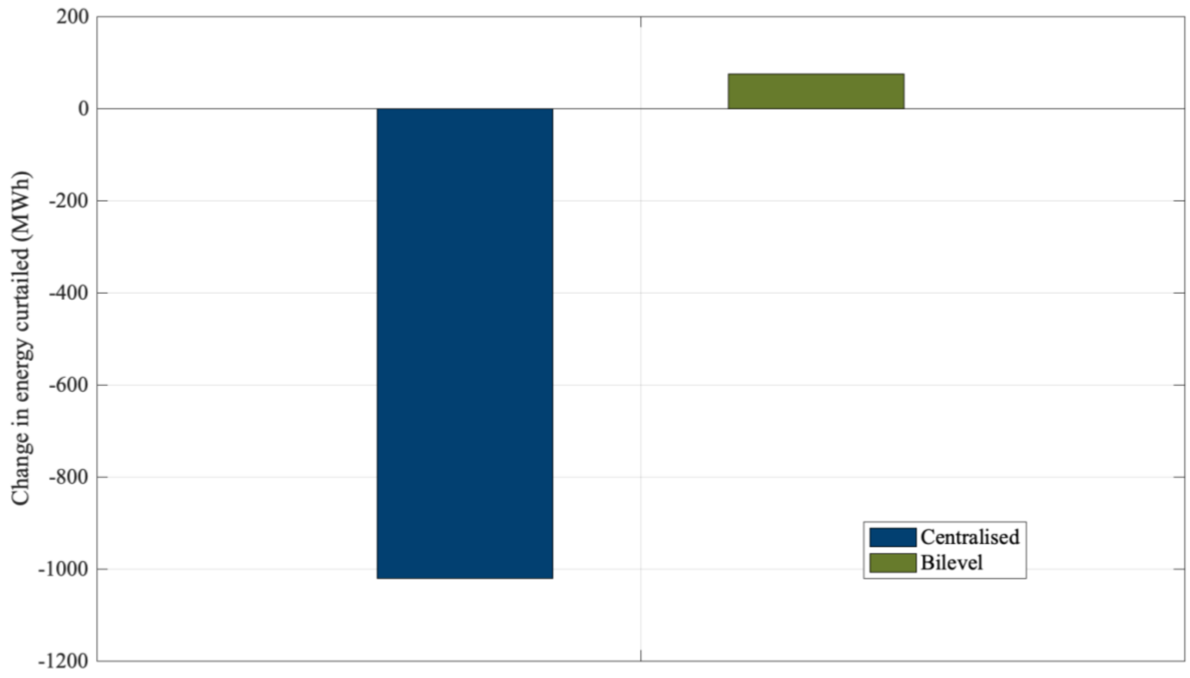

Figure 4.13 Change in curtailed wind generation, relative to the benchmark (with no battery storage).

The result in Figure 4.13 demonstrates the contrast between centralised and bilevel approaches. The centralised approach assumes all BTM battery storage systems are operated to benefit the power system. Whereas, in the bilevel approach, BTM battery storage systems are autonomous decision makers with their own objectives. The consequence is a lack of coordination with the power system that caused an increased renewable curtailment. In real power systems, BTM battery storage is typically invisible to the power system operator and are autonomous decision makers. Therefore, bilevel optimisation is necessary when analysing the value of BTM battery storage to the power system.

4.4.1.3 Operating behaviour

The operating behaviour of the LESs is key to understanding the difference between the centralised and bilevel approaches. Figure 4.14 presents the power exchange between the LESs and the grid, for the dynamic retail tariff. Power exported to the grid is positive and power imported to the LESs is negative. During 00:30-01:30 in the centralised approach, the LESs export power. Whereas, in the bilevel approach the LESs import power. Here, the centralised approach uses BTM battery storage to meet power system demand when the electricity price is low. Whereas in the bilevel approach, the LESs use the low prices to import power to meet demand and charge the battery. During 10:30-11:30 and 17:00-18:00 in the bilevel approach, the LESs have no power exchange with the grid. The LESs use their batteries to avoid importing electricity at high prices. Whereas in the centralised approach, the LESs import power to meet demand, irrespective of the high price. Finally, for 21:30-23:30 in the bilevel approach the LESs import less electricity than with the centralised approach. This is because they are prioritising reducing their own operating cost, not the power system operating cost.

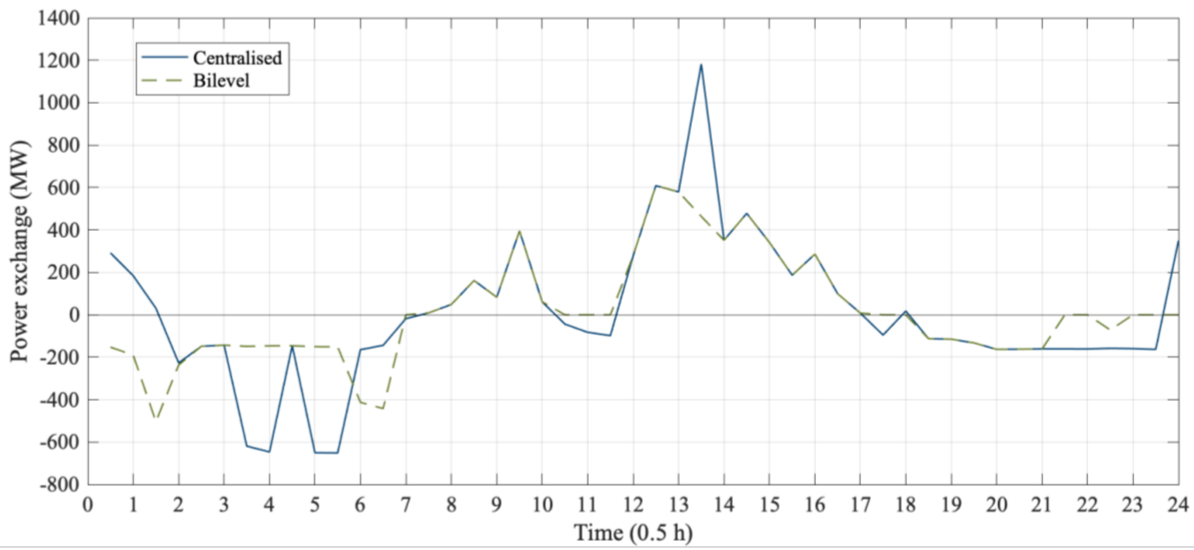

Figure 4.14 Power system and local energy systems power exchange, shown for the dynamic retail tariff. The power imported to the local energy systems is negative and power exported to the power system is positive.

The operating behaviour, shown in Figure 4.14, clearly distinguishes the difference between the operating objectives of the centrally controlled and autonomously controlled BTM battery storage systems. Bilevel optimisation enables the representation of autonomous decision makers like LESs within a power system optimisation.

To realistically analyse the value of BTM battery storage, their independent objectives cannot be neglected and must be explicitly considered. The centralised approach is focused on the whole power system perspective and neglects the BTM battery storage perspective. Therefore, the centralised approach does not accurately represent the decision making of BTM battery storage and can result in overestimations of their value to the power system. The bilevel outcome is sub-optimal from the whole power system perspective. However, it provides an improved representation of the value of BTM batteries, as autonomous decision makers.

4.4.2 Impact of retail contracts

BTM battery storage has potential to support power system operation [110], [156]. However, without cooperative operation, BTM battery storage can increase power system operating costs. A key influence on the value of BTM battery storage is retail contract design. This section evaluates the impact of retail contracts on the value of BTM batteries.

4.4.2.1 Local energy system operating cost

To understand the significance of coordinating BTM battery storage, the bilevel approach was used to analyse five retail contracts relative to the benchmark (with no battery storage and the existing retail contract). Figure 4.15 presents the change in LES operating cost for the five retail contracts. Notably, adding a battery storage system reduced the LES operating cost, regardless of the retail contract. However, the retail contact does impact the scale of operating cost savings for the LES. Installing the battery storage system without changing the existing retail contract resulted in the lowest operating cost savings. Whereas, the dynamic tariff, that is directly proportional to the wholesale electricity price, resulted in the biggest reduction in operating cost.

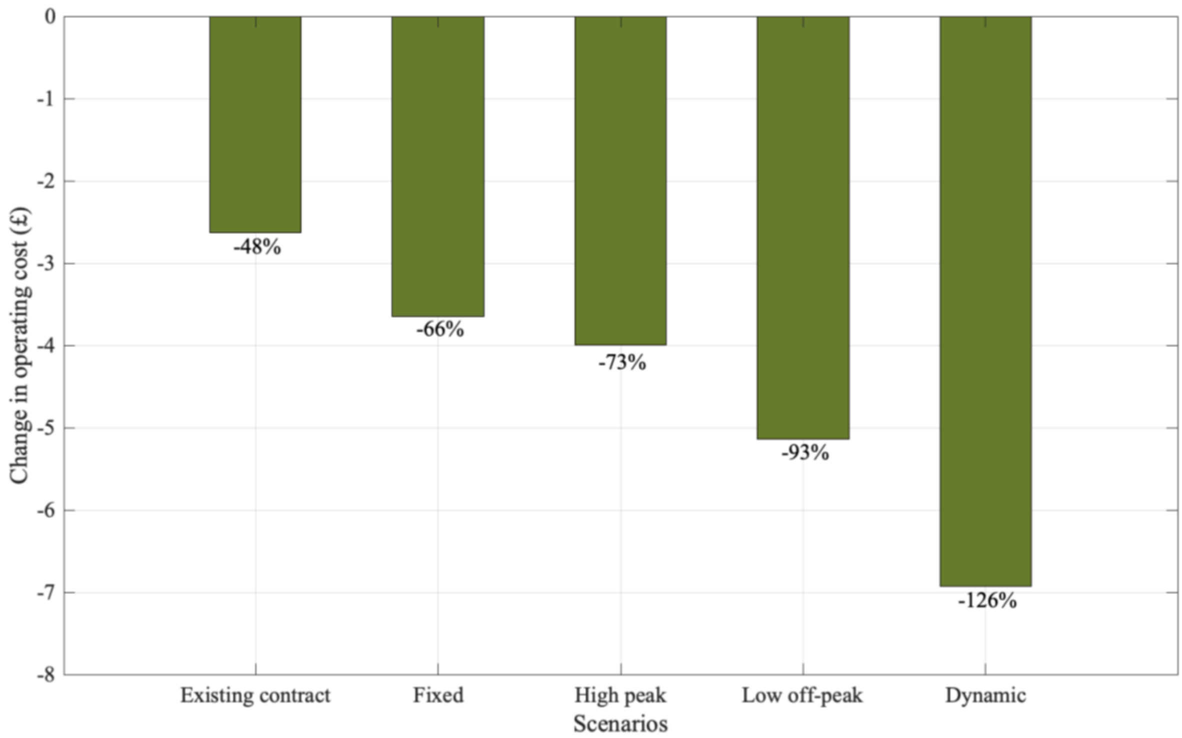

Figure 4.15 Changes in operating cost for one school.

The result in Figure 4.15 shows retail contracts have significant influence over the local value of BTM battery storage. Additionally, higher volatility in the electricity price increases opportunities for the LES to perform price arbitrage and increase revenue from BTM battery storage.

4.4.2.2 Power system operating cost

Retail contract design impacts LES decision making, changing the LESs power exchange with the grid. Therefore, retail contracts also impact the operation of a power system with high penetrations of BTM battery storage. The bilevel approach was used to find the power system operating cost relative to the benchmark. Figure 4.16 shows the change in power system operating cost in comparison to the benchmark (with no battery and the existing retail contract). The existing, fixed and high peak retail contracts increased the power system operating cost. Whereas the low off-peak and dynamic tariffs decreased the power system operating cost. The dynamic tariff, that is directly proportional to the wholesale electricity price, decreased the power system operating cost the most.

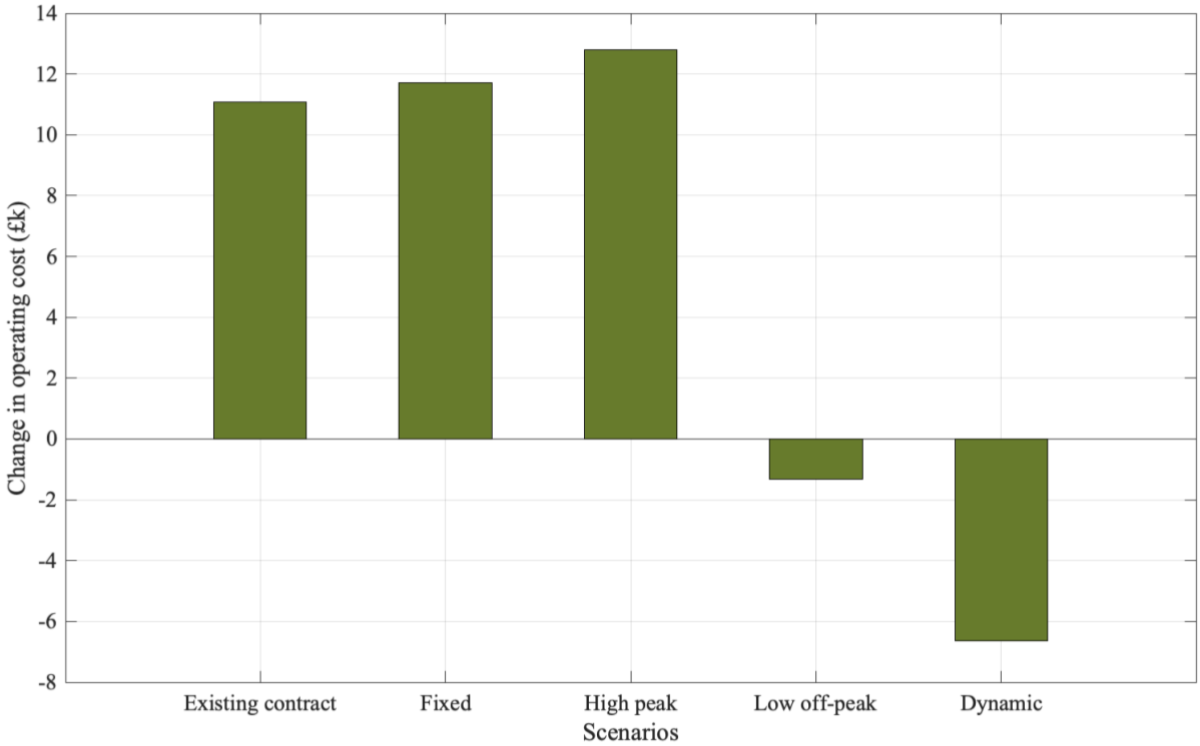

Figure 4.16 Change in power system operating cost.

The result in Figure 4.16 shows that retail contracts can influence the operating behaviour of BTM battery storage systems to either increase or decrease their value to the power system. Although the time-of-use tariffs encourage electricity consumption at typically off-peak times, they do not dynamically match the requirements of the power system. In contrast, the dynamic tariff reflects the market conditions and encourage demand shifting from high price times to lower price times, in response to the generation that is available in the power system. This influences BTM battery storage systems to operate in line with power system objectives, reducing the power system operating cost. Therefore, retail contract design is crucial when determining the value of BTM battery storage systems.

4.5 Chapter summary

This chapter presented two approaches for assessing the value of behind-the-meter battery storage systems. The approaches were compared to evaluate their efficacy for accounting for behind-the-meter battery storage in a power system optimisation. The centralised optimisation approach assumed all behind-the-meter battery storage was centrally controlled and operated for the benefit of the power system. The bilevel optimisation approach considered the behind-the-meter battery storage systems as autonomous decision makers with their own objectives.

Comparing the approaches showed the centralised optimisation tends to overestimate the value of behind-the-meter battery storage systems. In contrast, the bilevel optimisation approach led to a sub-optimal solution for the whole power system but was able to account for the autonomy of behind-the-meter battery storage systems. The results highlight the importance of accounting for independent objectives when quantifying the value of behind-the-meter battery storage systems.

The influence of retail contracts on the value of behind-the-meter battery storage systems was also investigated. Five retail contracts available from UK retailers were compared to a benchmark case (with no battery storage system and the existing retail contract), using the bilevel optimisation approach. The battery reduced the local energy system operating cost for all retail contracts. In contrast, three of the retail contracts increased the power system operating cost, while two reduced the power system operating cost. The retail contract that reflected the wholesale electricity price resulted in the largest reduction in power system operating cost. This result shows retail contracts influence the behaviour of behind-the-meter battery storage. Retail contacts must encourage BTM battery storage to add value to the power system, rather than increase power system operating costs.

This study demonstrates the suitability of bilevel optimisation for accounting for the decision making of behind-the-meter battery storage systems within a power system optimisation. Furthermore, the study shows that retail contracts have significant influence over the value of behind-the-meter battery storage from both the local energy system perspective and the power system perspective.

The limitations identified in this chapter are as follows. Assuming 50,000 identical local energy systems is unrealistic. In reality, local energy systems with behind-the-meter battery storage are likely to have different configurations with various types and sizes of generation and storage technologies. However, the design of a suitably diverse local energy system portfolio was not the focus of this work and would not have affected the conclusions. To address this limitation, a suitable portfolio of local energy system configurations can be created and included as a set. The selection of power system generation technologies is simplified, which reduces price variations for the power system. However, the scope of this study did not extend to the definition of a detailed 2030 economic dispatch portfolio with high granularity.

Chapter 5

Quantifying the value of behind-the-meter battery storage

This chapter presents a methodology for analysing the impact of BTM battery revenue stacking on low-carbon power systems. The BTM battery minimises its operating cost while participating in the wholesale electricity market and frequency response markets simultaneously. The power system minimises the cost of meeting electricity demand using an economic dispatch optimisation. A case study was carried out to address two key challenges:

- Uncertain penetration of BTM battery storage and the effect on low-carbon power systems
- BTM battery operating strategies and their influence on the value of BTM batteries in low-carbon power systems.

5.1 Introduction

Small-scale battery storage systems are increasingly being deployed in power systems around the world. In Germany, approximately 40% of consumer PV systems are coupled with BTM battery storage systems [157]. Australia has over 21,000 consumer battery storage systems and aims to have 1 million by 2025 [158]. Figure 5.1 shows the Consumer Transformation scenario, from National Grid ESO's Future Energy Scenarios, for BTM battery storage power and energy capacity in GB.

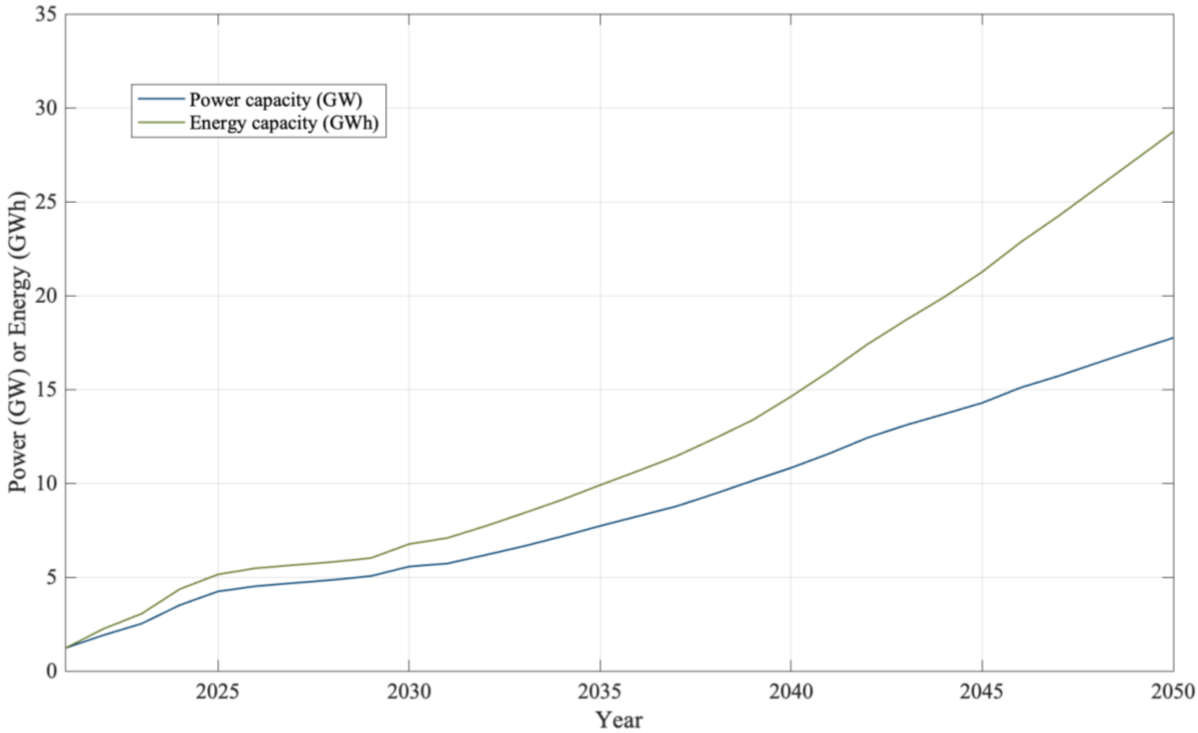

Figure 5.1 Decentralised battery storage capacity from 2021 to 2050 in GB [126].

Rising penetration of BTM battery storage systems will increase overall power system storage capacity. However, the value of extra storage capacity may not be seen by the power system. Understanding the impacts of BTM battery operating strategies is vital to quantifying the value of BTM battery storage to the power system. Furthermore, facilitating the highest possible value of BTM battery storage systems requires an in depth understanding of their operating strategies and their influence on power system operation and electricity prices. The aggregated operation of distributed flexibility, is studied in [118], [124]. These studies demonstrate the value of participating in energy markets as price makers.

5.2 Methodology

All BTM battery storage systems are assumed to be part of a LES. A single LES would have a negligible effect on the operation of the power system. Therefore, the method considers many identical LESs that are aggregated and operated as a single entity. The power flow diagram of the bilevel optimisation is given in Figure 5.2, where the LESs and the power system are autonomous decision makers. In Figure 5.2, the LESs control their renewable generation and battery storage and the power system operator controls all transmission connected generation and energy storage.

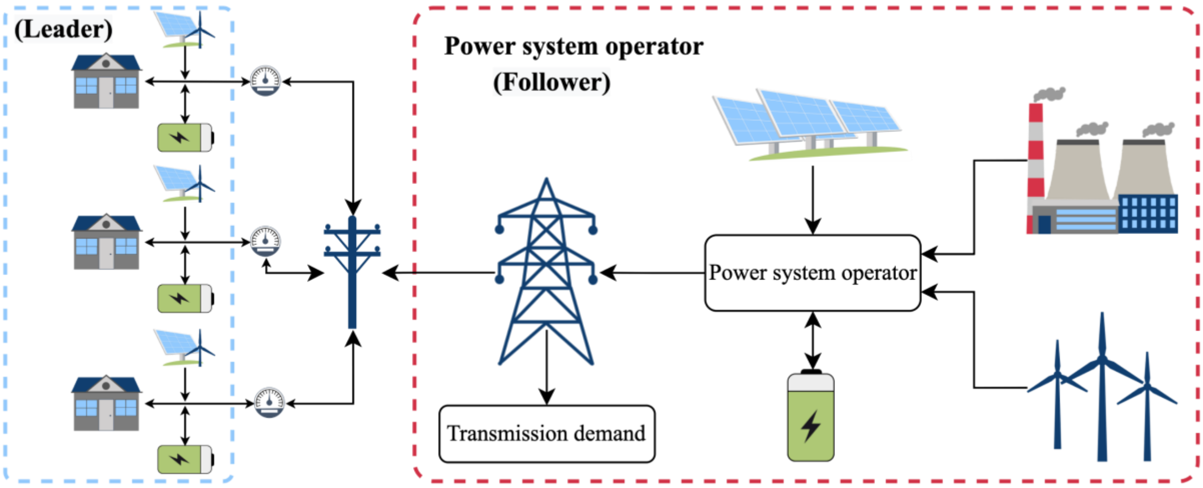

Figure 5.2 Power flow diagram of the bilevel optimisation.

The communication structure of the LESs and power system in the bilevel optimisation is presented in Figure 5.3. Figure 5.3 shows the LES and power system operator's interactions are limited to the electricity market. The two decision makers communicate prices and energy requirements, to facilitate trading in the electricity market. In contrast, the frequency response markets are separate from the power system operator. The LESs receive exogenous frequency response market prices and commit power capacity without involving the power system operator. Figure 5.3 clarifies that the frequency response market has no influence on the power system optimisation.

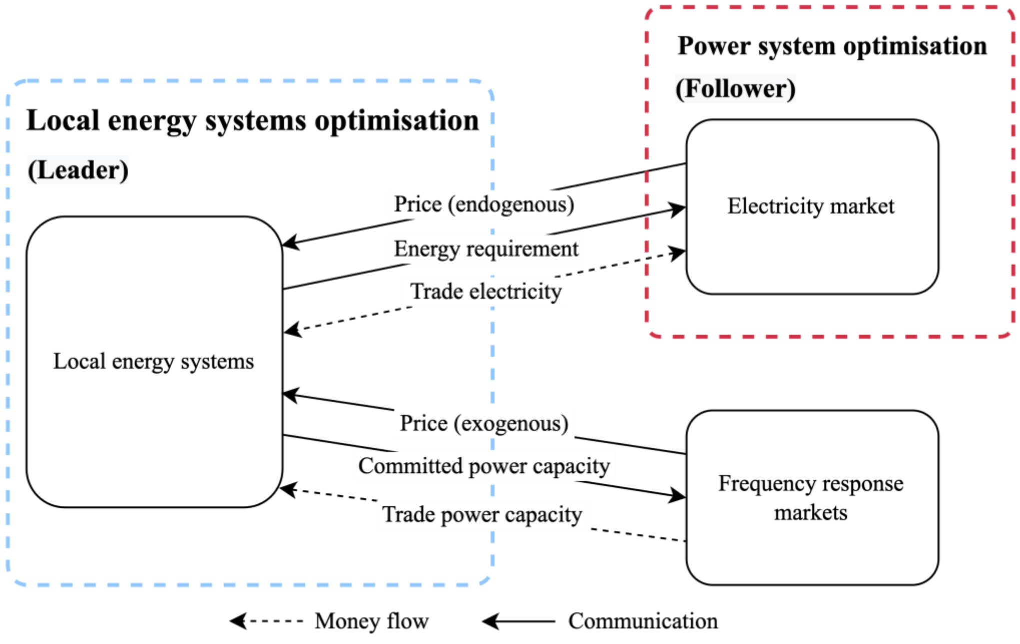

Figure 5.3 Bilevel optimisation communication and money flows.

5.2.1 Bilevel optimisation structure

The LESs are price makers, influencing wholesale electricity prices. The power system operator schedules power plants to satisfy overall demand, including LES demand requirements. Therefore, the LESs make the first decision (leader problem) and the power system operator makes the following decision (follower problem). The LESs minimise the cost of meeting their demand and the power system operator minimises the cost of meeting power system demand, including centralised generation cost and the cost of power exchange with the LESs. Figure 5.4 describes the bilevel optimisation and how the LESs and power system operator interact.

In Figure 5.4, the LESs schedule their battery operation to satisfy their demand and trade endogenous wholesale electricity prices and exogenous frequency response prices. The frequency response participation has no interaction with the power system optimisation. The LESs pass their wholesale electricity price bids/offers and power exchange values to the power system operator as fixed parameters. Then, the power system operator schedules centralised generation to meet power system demand at the lowest cost. The endogenous wholesale electricity price is the dual variable of the follower power balance constraint. The power system optimisation provides the wholesale electricity price to the LESs and constrains the LESs to ensure a feasible solution for the power system operator. Therefore, the LESs achieve optimality by managing their import and export power to influence the wholesale electricity price to benefit themselves, provided their solution is feasible for the power system. The power system achieves optimality, given the import and export power values the LESs choose.

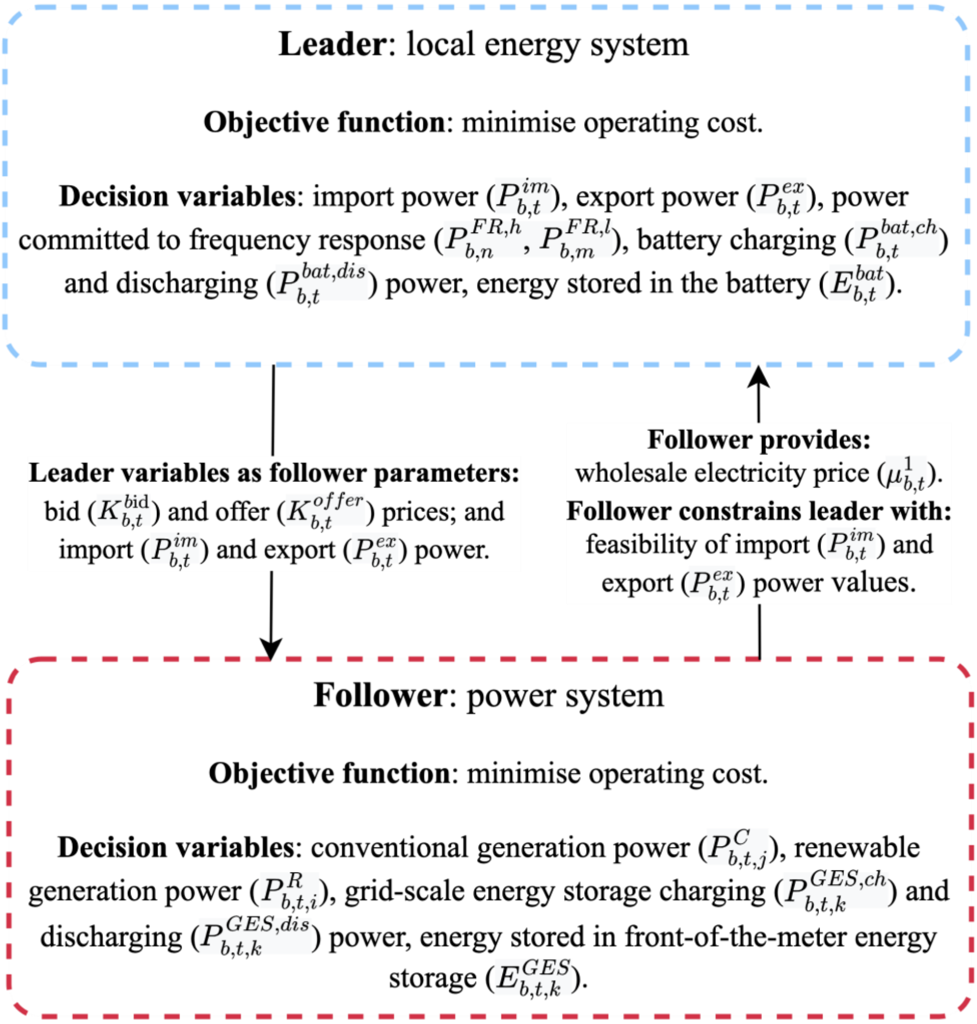

Figure 5.4 Bilevel optimisation, defining objective functions, decision variables and interactions.

In Figure 5.4, the frequency response market is represented by the $P_{b,n}^{FR,h}$ and $P_{b,m}^{FR,l}$ decision variables in the Leader optimisation box. $P_{b,n}^{FR,h}$ and $P_{b,m}^{FR,l}$ are power commitments that are decided by the LESs without interaction with the power system.

5.2.2 Leader optimisation – local energy system operating cost minimisation

The LESs gain revenue by performing price arbitrage in a wholesale electricity market and trading power capacity in frequency response markets. The bilevel formulation constraints can be applied to the technical requirements of various frequency response services.

The wholesale electricity price is endogenously calculated, determined by the LESs bids/offers and the marginal cost of generation in the power system. Whereas the frequency response service prices are exogenous, predetermined inputs that reflect real world market prices. Therefore, the LESs can affect the wholesale electricity price with bids/offers but cannot affect the frequency response prices.

The LES objective function is defined in (5.1).

$$\begin{aligned}\text{Min} \quad \Pi^{L} = &\sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\tau\left(\mu_{b,t}^{1}\left(P_{b,t}^{im}-P_{b,t}^{ex}\right)+K_{b,t}^{DUoS}P_{b,t}^{im}\right)\\ &-\sum_{b=1}^{Bn}\left(\sum_{n=1}^{Nn}\left(K_{b,n}^{FR,h}P_{b,n}^{FR,h}\right)+\sum_{m=1}^{Mn}\left(K_{b,m}^{FR,l}P_{b,m}^{FR,l}\right)\right)\end{aligned} \tag{5.1}$$

The objective function minimises the operating cost of the LESs, considering price arbitrage in the wholesale electricity market ($\tau\mu_{b,t}^{1}\left(P_{b,t}^{im}-P_{b,t}^{ex}\right)$), the cost of DUoS charges ($\tau K_{b,t}^{DUoS}P_{b,t}^{im}$) and revenue from frequency response markets ($K_{b,n}^{FR,h}P_{b,n}^{FR,h}$,$K_{b,m}^{FR,l}P_{b,m}^{FR,l}$). The endogenous wholesale electricity price is given by $\mu_{b,t}^{1}$, which is the shadow price of the follower optimisation power balance equation (5.10). Multiplying the first term of (5.1) by τ converts the power values to energy values.

Similar to Chapter 3, frequency response services are procured for blocks with specific duration. Set b represents the frequency response procurement blocks (where $b = 1,2,\dots,Bn$). Set t represents the time steps within each block (where $t = 1,2,\dots,Tn$). Energy trading in the wholesale electricity market is done for each time step, therefore, the first term in (5.1) must include both b and t sets. Frequency response commitments are made in blocks, therefore, the second term in (5.1) only includes set b.

The leader optimisation is subject to several constraints.

$$P_{b,t}^{LR} + P_{b,t}^{bat,dis} + P_{b,t}^{im} = P_{b,t}^{LD} + P_{b,t}^{bat,ch} + P_{b,t}^{ex} + P_{b,t}^{LR,curt} \tag{5.2}$$

Equation (5.2) defines the power balance, which ensures all generated power ($P_{b,t}^{LR}$, $P_{b,t}^{bat,dis}$, $P_{b,t}^{im}$), is equal to all power demands ($P_{b,t}^{LD}$, $P_{b,t}^{bat,ch}$, $P_{b,t}^{ex}$) and the curtailed PV power ($P_{b,t}^{LR,curt}$). The term $P_{b,t}^{LR,curt}$ is included to allow the LESs to curtail PV generation, when doing so improves the LES's optimal solution. Primarily, this was included to ensure no simultaneous charging and discharging of the batteries.

The following set of equations constrain the operation of the battery storage system.

$$0 \leq P_{b,t}^{bat,ch} \leq \overline{P}^{bat} - P_{b,n}^{FR,h} \tag{5.3}$$

$$0 \leq P_{b,t}^{bat,dis} \leq \overline{P}^{bat} - P_{b,m}^{FR,l} \tag{5.4}$$

$$0 + P_{b,m}^{FR,l} T_m^{FR,l} \leq E_{b,t}^{bat} \leq E_{b,t}^{bat,a} - P_{b,n}^{FR,h} T_n^{FR,h} \tag{5.5}$$

$$E_{b,t}^{bat} = E^{bat,ini}\Big|_{b=1,t=1} + E_{b,t-1}^{bat}\Big|_{t>1} + E_{b-1,Tn}^{bat}\Big|_{b>1,t=1} + \tau\left(\eta^{bat,ch} P_{b,t}^{bat,ch} - \frac{P_{b,t}^{bat,dis}}{\eta^{bat,dis}}\right) \tag{5.6}$$

$$E_{b,t}^{bat,a} = \overline{E}^{bat}\Big|_{b=1,t=1} + E_{b,t-1}^{bat,a}\Big|_{t>1} + E_{b-1,Tn}^{bat,a}\Big|_{b>1,t=1} - \overline{E}^{bat}\left(0.2\,\frac{\tau P_{b,t}^{bat,dis}}{E^{bat,TET}}\right) \tag{5.7}$$

$$E_{Bn,Tn}^{bat} \geq E^{bat,ini} \tag{5.8}$$

The charging and discharging powers are limited by the battery power rating ($\overline{P}^{bat}$) and the power committed to frequency response markets ($P_{b,n}^{FR,h}$, $P_{b,m}^{FR,l}$); these are shown in (5.3) and (5.4). In (5.5), the energy stored in the battery is limited by the available battery capacity ($E_{b,t}^{bat,a}$) and the energy required to deliver the frequency response service commitments ($P_{b,n}^{FR,h} T_n^{FR,h}$, $P_{b,m}^{FR,l} T_m^{FR,l}$).

In (5.6), the energy stored in the battery is determined by the energy in the previous time step and the charging and discharging power. The first three terms on the right side of (5.6) provide continuity through the procurement blocks. $E^{bat,ini}\big|_{b=1,t=1}$ defines the initial energy stored in the battery,

$E_{b,t-1}^{bat}\big|_{t>1}$ defines the energy stored in the previous time step within a block and $E_{b-1,T}^{bat}\big|_{b>1,t=1}$ defines the energy stored in the last time step of the previous block.

Equation (5.7) accounts for battery degradation assuming 2800 full cycles until end-of-life [130]. The number of full cycles translates to an energy throughput, which is a predetermined input to the optimisation ($E^{bat,TET}$). Dividing the energy dispatched from the battery ($\tau P_{b,t}^{bat,dis}$) by the total energy throughput until end-of-life gives the percentage of total degradation. Where total degradation is a 20% reduction in the battery operating capacity. Therefore, multiplying by 0.2 gives the percentage drop in total available battery capacity. Multiplying by the initial battery capacity gives the fall in total available battery capacity in MWh. The total fall in available energy capacity is subtracted from the available energy capacity in the previous time step. The available capacity in the previous time step consists of the initial battery capacity ($\overline{E}^{bat}\big|_{b=1,t=1}$), the available capacity in the previous time step within a block ($E_{b,t-1}^{bat,a}\big|_{t>1}$) and the available capacity in the last time step of the previous block ($E_{b-1,T}^{bat,a}\big|_{b>1,t=1}$).

In (5.8), the batteries' stored energy in the last time step was set to be larger than or equal to the initial stored energy.

5.2.3 Follower optimisation – low-carbon power system

The follower is the power system operator, scheduling the dispatch of conventional generation, renewable generation and grid-scale energy storage. Conventional and renewable generation are dispatched according to the merit order of their marginal generating costs. The amount of centralised generation required to meet power system demand determines the clearing price in the wholesale electricity market.

The power system objective function is shown in (5.9).

$$\text{Min} \quad \Pi^F = \sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\tau\left(\sum_{j=1}^{Jn}\left(K_j^C P_{b,t,j}^C\right) + \sum_{i=1}^{In}\left(K_i^R P_{b,t,i}^R\right) + K_{b,t}^{offer} P_{b,t}^{ex} - K_{b,t}^{bid} P_{b,t}^{im}\right) \tag{5.9}$$

The objective function, shown in (5.9), aims to minimise the operating cost of meeting power system demand. The first term ($K_j^C P_{b,t,j}^C$) accounts for the cost of dispatching conventional generation, the second term ($K_i^R P_{b,t,i}^R$) accounts for the cost of renewable generation and the third and fourth terms ($K_{b,t}^{offer} P_{b,t}^{ex}, K_{b,t}^{bid} P_{b,t}^{im}$) account for the bids/offers made by the LESs to buy/sell power. All power terms are multiplied by τ to convert from power to energy.

The follower optimisation is subject to several constraints, with corresponding dual variables indicated on the right.

$$\sum_{j=1}^{Jn} P_{b,t,j}^C + \sum_{i=1}^{In} P_{b,t,i}^R + P_{b,t}^{ex} + \sum_{k=1}^{Kn} P_{b,t,k}^{GES,dis} = P_{b,t}^{im} + \sum_{k=1}^{Kn} P_{b,t,k}^{GES,ch} + P_{b,t}^{TD} \quad : \ \mu_{b,t}^1 \tag{5.10}$$

Equation (5.10) defines the power balance of the power system. Where all power sources (conventional ($P_{b,t,j}^C$), renewable ($P_{b,t,i}^R$), LES export ($P_{b,t}^{ex}$) and grid-scale storage discharge ($P_{b,t,k}^{GES,dis}$)) are equal to all power demands (LESs import ($P_{b,t}^{im}$), grid-scale storage charging ($P_{b,t,k}^{GES,ch}$) and power system transmission demand ($P_{b,t}^{TD}$)). The power system transmission demand is an inflexible input.

The power output limits of the conventional and renewable generation are presented in (5.11) and (5.12).

$$\underline{P}_j^C \le P_{b,t,j}^C \le \overline{P}_j^C \quad : \ \lambda_{b,t,j}^1, \lambda_{b,t,j}^2 \tag{5.11}$$

$$\underline{P}_{b,t,i}^R \le P_{b,t,i}^R \le \overline{P}_{b,t,i}^R \quad : \ \lambda_{b,t,i}^3, \lambda_{b,t,i}^4 \tag{5.12}$$

Conventional generation is limited by the capacities defined in the marginal cost curve. Renewable power output is limited by the time series of available renewable generation. Any unused renewable generation (when $P_{b,t,i}^R < \overline{P}_{b,t,i}^R$) is assumed to be curtailed. The following equations limit the power exchange between the LESs and the power system.

$$0 \le P_{b,t}^{im} \le \overline{P}^{im} \quad : \ \lambda_{b,t}^5, \lambda_{b,t}^6 \tag{5.13}$$

$$0 \le P_{b,t}^{ex} \le \overline{P}^{ex} \quad : \ \lambda_{b,t}^7, \lambda_{b,t}^8 \tag{5.14}$$

Equations (5.13) and (5.14) ensure the power exchanged between the LESs and the power system does not exceed their grid connection capacity. The following constraints govern the operation of grid-scale energy storage.

$$0 \leq P_{b,t,k}^{GES,ch} \leq \overline{P}_{k}^{GES} \quad : \quad \lambda_{b,t,k}^{9}, \lambda_{b,t,k}^{10} \tag{5.15}$$

$$0 \leq P_{b,t,k}^{GES,dis} \leq \overline{P}_{k}^{GES} \quad : \quad \lambda_{b,t,k}^{11}, \lambda_{b,t,k}^{12} \tag{5.16}$$

$$0 \leq E_{b,t,k}^{GES} \leq \overline{E}_{k}^{GES} \quad : \quad \lambda_{b,t,k}^{13}, \lambda_{b,t,k}^{14} \tag{5.17}$$

$$\begin{aligned} E_{b,t,k}^{GES} = E_{k}^{GES,ini}\big|_{b=1,t=1} + E_{b,t-1,k}^{GES}\big|_{t>1} + E_{b-1,Tn,k}^{GES}\big|_{b>1,t=1} \\ + \tau\left(\eta^{GES} P_{b,t,k}^{GES,ch} - P_{b,t,k}^{GES,dis}\right) \quad : \; \mu_{b,t,k}^{2} \end{aligned} \tag{5.18}$$

$$E_{Bn,Tn,k}^{GES} \geq E_{k}^{GES,ini} \quad : \quad \lambda_{k}^{15} \tag{5.19}$$

In (5.15) and (5.16), the charging and discharging powers of the grid-scale energy storage are limited by the aggregated capacity of each technology. Each grid-scale energy storage technology has a limited energy capacity, applied in (5.17). Equation (5.18) is the energy balance and ensures the continuity throughout the blocks. The first three terms on the right side of equation (5.18) play the same role as in equation (5.6). Equation (5.19) ensures the grid-scale storage state of charge in the last time step is equal to or greater than the initial state of charge.

5.2.4 Solution methodology

The final formulation is a single leader, single follower bilevel optimisation. The follower optimisation is a linear programming problem. Therefore, the bilevel optimisation was solved by reformulating the follower optimisation into a set of KKT conditions, which were applied to the leader optimisation problem. The result was a single level non-linear programming problem.

There were two sources of non-linearity in the single level reformulation. The first was the complementary slackness conditions, where the variables were multiplied by the corresponding dual variables. The complementary slackness conditions were linearised using the Fortuny-Amat method

[147]. The second source of non-linearity was in the leader optimisation's objective function, where the wholesale electricity price is multiplied by the import and export power of the LESs. The leader's objective function was linearised by applying duality theory to create an equivalent set of terms to replace the non-linear terms in the objective function. A detailed description of the reformulation is presented in Appendix D. The result is a single level mixed integer linear programming problem that was formulated in GAMS and solved with the Gurobi branch and cut solver.

5.3 Case study definition

The value of BTM battery storage systems was assessed by applying the bilevel optimisation to a case study. Hourly time steps were used for a time horizon of one year. However, due to the large number of binary variables in the final mixed integer linear programming problem, solving the full year in one go proved impractical. Therefore, the time horizon was split into days, which were solved in a loop, called a '*rolling horizon optimisation*'. Each day was solved sequentially and the results of the preceding day used as inputs for the following day.

The bilevel optimisation inputs are based on projections for the 2030 GB power system.

5.3.1 Leader optimisation

5.3.1.1 Local energy system configuration

The LESs were configured with PV generation, local electricity demand, a battery storage system and a bidirectional connection to the grid. The LESs were assumed to have various PV generation and demand profiles and be distributed throughout GB. As such, the aggregated LESs PV generation profile was defined using the GB PV generation profile. The PV generation profile was scaled down to the 2030 capacity of decentralised PV generation in the Consumer Transformation scenario of National Grid ESO's Future Energy Scenarios. This capacity was 28,449 MW [159]. Similarly, GB's national demand was scaled down to represent the LES demand. This was scaled to the level where the total demand in MWh was equal to the total LESs PV generation in MWh. The LESs PV generation and demand profiles are shown in Figure 5.5 and Figure 5.6. Using national PV and demand profiles ensures the collection of LESs represents a diverse portfolio in different locations with different electricity demand requirements.

The DUoS charges applied to import power were identical to those used in Chapter 3, given in Figure 3.11

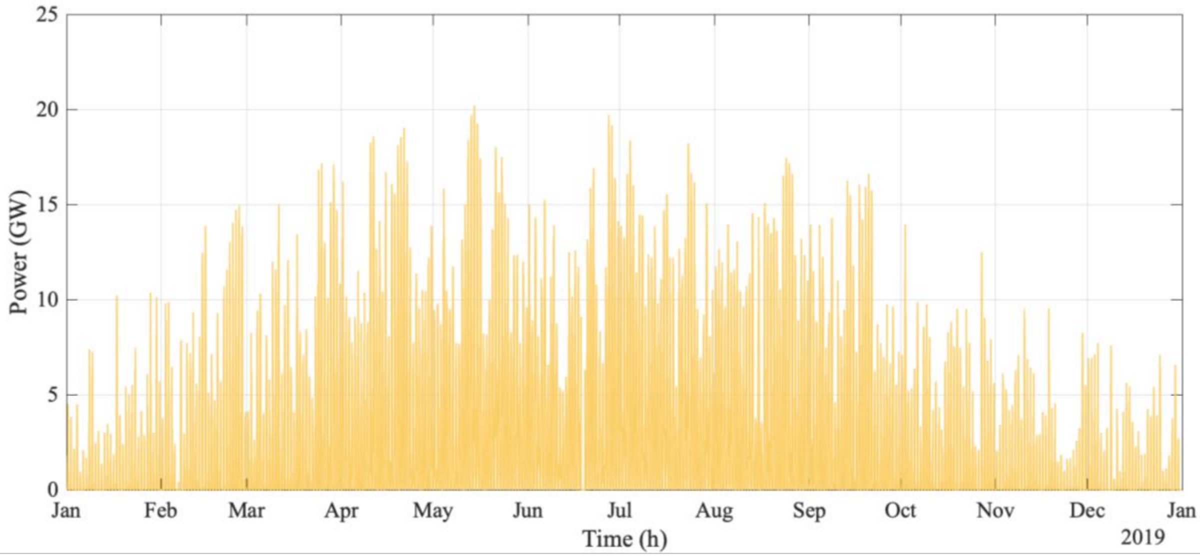

Figure 5.5 Aggregated local energy system PV generation.

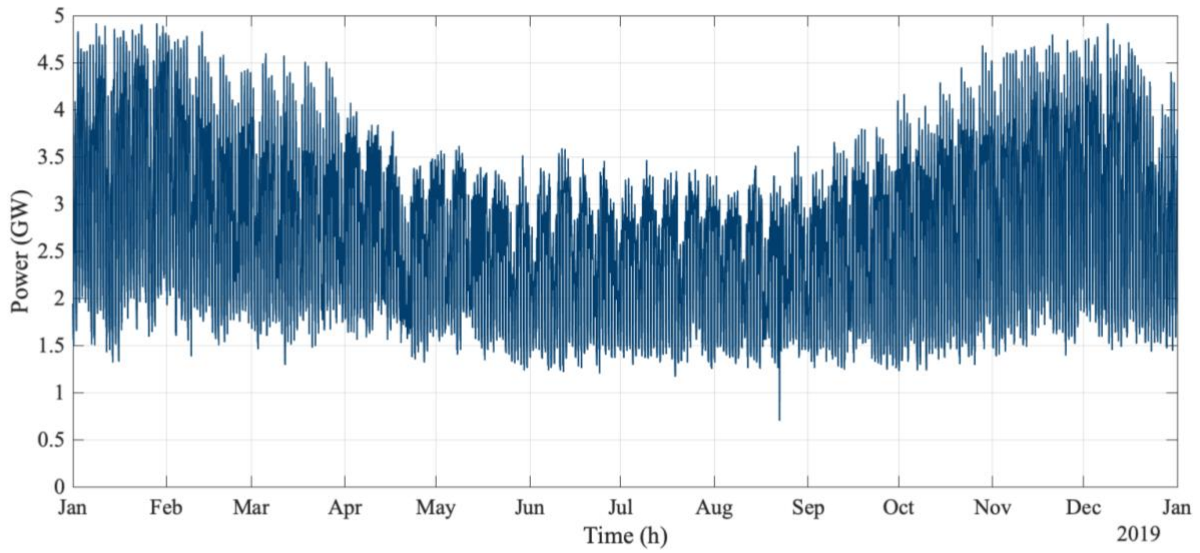

Figure 5.6 Aggregated local energy system demand.

5.3.1.2 *Local energy system battery storage characteristics*

The aggregated LES battery power rating and energy capacity were 5,555 MW and 6,754 MWh respectively [126], given by the Consumer Transformation decentralised battery capacity in 2030, in National Grid ESO's Future Energy Scenarios. The square-root of a 90% [26] round-trip efficiency (94.87%) was applied to charging and discharging and the initial battery state of charge ($E^{bat,ini}$) was 50% of the available energy capacity.

The Tesla Powerwall warranty covers the equivalent of 2,800 full cycles [130]. Therefore, the LES's battery energy throughput limit was $6{,}754\ \text{MWh} \times 2{,}800\ cycles = 18{,}911\ \text{GWh}$.

5.3.1.3 *Frequency response services*

The frequency response services chosen for this study were:

- Firm Frequency Response low
- Firm Frequency Response high
- Dynamic Containment low
- Dynamic Containment high,

which are procured by National Grid ESO in GB. Therefore,

$$\sum_{n=1}^{Nn} \left(P_{b,n}^{FR,h}\right) = P_b^{FFR,h} + P_b^{DC,h}, \tag{5.20}$$

$$\sum_{m=1}^{Mn} \left(P_{b,m}^{FR,l}\right) = P_b^{FFR,l} + P_b^{DC,l}. \tag{5.21}$$

DC and FFR were chosen because, in reality, they are typically delivered by battery storage systems. Additionally, procurement information (including price data) is published by National Grid ESO. At the time of writing, distribution network operator services were in the early stages of procurement and had no published price data. Therefore, they were discounted from this case study.

DC and FFR are services that require proportional and automated responses to changes in grid frequency. FFR and DC low, inject power to the grid when the grid frequency falls below 50 Hz. FFR and DC high, consume power from the grid when grid frequency rises above 50 Hz. The technical characteristics of each service are described in Table 5.I.

Table 5.I Technical requirements for frequency response services.

Characteristic	DC low and high	FFR low and high
Respond when frequency is:	low and high	low and high
Minimum power capacity (MW)	1	1
Block duration (h)	4	4
Dispatch duration ($T_n^{FR,h}$, $T_m^{FR,l}$) (h)	0.25	0.5
Response time (s)	1	2
Average availability price (£/MW/h)	13.28	7.53

The minimum capacity of 1 MW can be met by a single asset or multiple aggregated assets. At the time of investigation, the block duration for both services was 4 hours. Therefore, $t = 1,2,\dots,Tn$ and $b = 1,2,\dots,Bn$, where $Tn = 4$ and $Bn = 6$. The dispatch duration at full committed power was 15 minutes for DC and 30 minutes for FFR. The response time was 1 second for DC and 2 seconds for FFR. The average availability price was 13.28 £/MW/h for DC and 7.53 £/MW/h for FFR. These were the average availability prices for both frequency response markets in 2022 [160], [161]. The prices for low and high were assumed to be identical.

5.3.2 Follower optimisation

The low-carbon power system case study was a representation of the 2030 GB power system. The technologies available to the power system operator were identified and formulated into marginal cost curves.

5.3.2.1 Conventional generation technologies

The conventional generation technologies were able to vary between a maximum aggregated capacity and a minimum capacity. Most of the technologies were limited by their aggregated capacities. However, CCGT was split into individual power plants and given marginal prices based on the age of the power plant. The conventional technology power limitations are given in Table 5.II. The minimum generating capacity implemented nuclear as a baseload generating technology, removing the ability for nuclear to be turned off.

Table 5.II Conventional generation power limitations [159].

Conventional generation technology	Max power capacity (MW)	Min power capacity (MW)
Nuclear	5,200	2,600
BECCS	1,200	0
Biomass	4,340	0
CCGT	29,956	0
OCGT	2,404	0
Interconnectors	18,650	0

The aggregated CCGT capacity was split into individual power plants to account for increasing price with increasing age. One group was given the notation ‘E’, which represents existing CCGT plants that will be operational in 2030. CCGT plants more than 30 years old in 2030, were assumed to be decommissioned. The existing CCGT capacities were aggregated according to the power station age, assuming the same price for the same age of plant. The other group was given the notation ‘N’, which represents new CCGT developments. The new developments were estimated as an even distribution of capacity built over the decade from 2020 to 2030. The aggregated existing capacity that will be operational in 2030 was 19,172 MW. Therefore, 10,784 MW of CCGT was assumed to be built over 10 years, giving an annual build rate of 1,078.4 MW. The CCGT power limitations are given in Table D.I, in Appendix D. CCGT plant capacities were aggregated into age groups and assigned prices. The marginal cost curve is shown in Figure 5.7, presenting the prices allocated to each conventional power generating capacity.

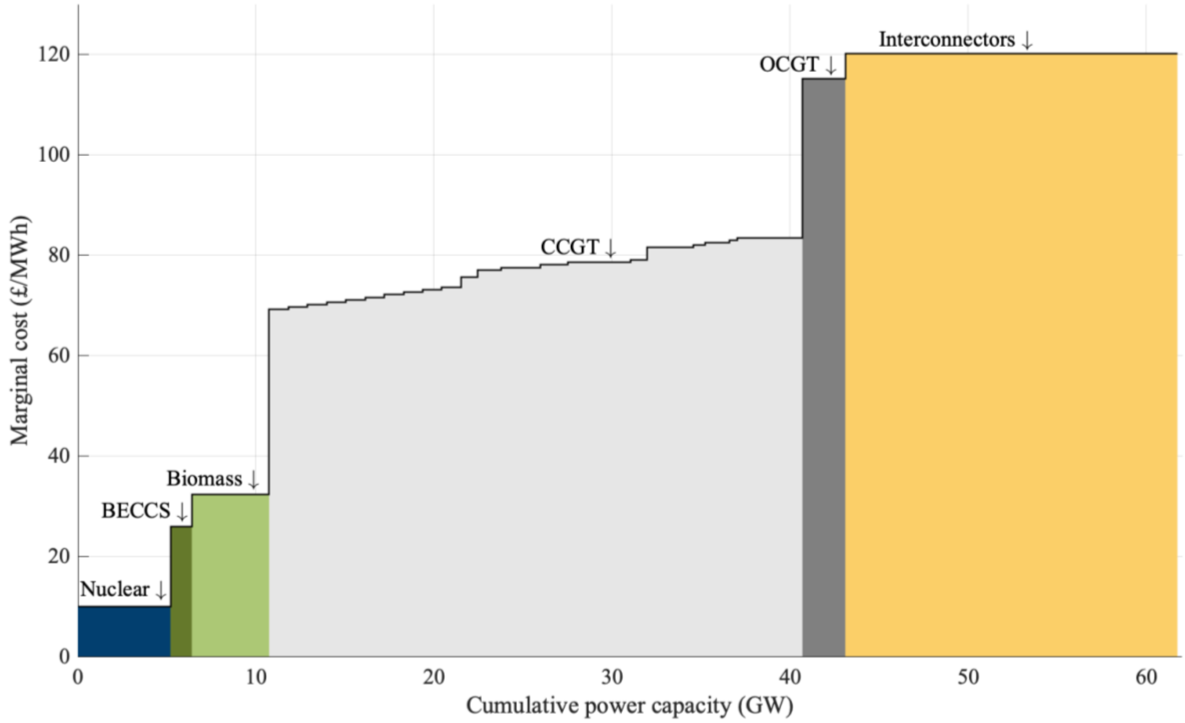

Figure 5.7 Conventional generation marginal cost curve.

The marginal cost curve defines the order in which generation technologies are scheduled to supply demand. Additionally, this determines the endogenous wholesale electricity price that the LESs pay for their electricity. The price of interconnectors was set as £120/MWh, making it the most expensive technology. This assumption ensures enough capacity is available to meet demand, while prioritising GB generation.

5.3.2.2 Renewable generation technologies

Grid-scale solar generation was included in the transmission power demand input data. Therefore, wind was the only technology in the renewable generation cost curve. The available wind generation input data is shown in Figure 5.8. The available wind generation was created by scaling historic GB wind generation data from 2019 [149] to the GB 2030 power capacity, using the National Grid ESOs Future Energy Scenarios Consumer Transformation scenario [159]. The marginal cost of wind generation was £3/MWh [152].

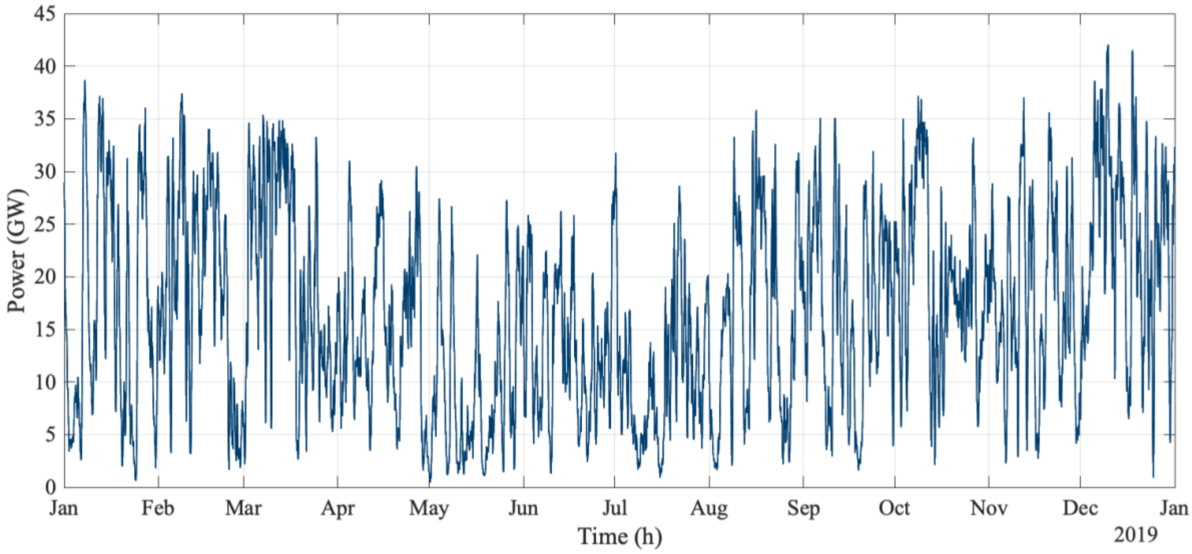

Figure 5.8 Available wind generation time series input data.

5.3.2.3 *Grid-scale energy storage*

The grid-scale energy storage technologies considered were pumped hydro and grid-scale battery storage. The power rating of pumped hydro storage was 3054 MW, with an energy capacity of 30,084 MWh [159]. Grid-scale battery storage was included to ensure a consistent capacity of total power system battery storage across all scenarios. Therefore, the capacity of grid-scale battery storage varied throughout the scenarios. The capacities will be discussed in the following section: 5.4 Scenarios.

The initial (when $t = 0$, $b = 0$) and final (when $t = 4$, $b = 6$) energy stored in the pumped hydro and grid-scale battery storage was assumed to be 50% of the energy capacity. Therefore, the energy storage technologies start each day with 50% state of charge, which ensures continuity for state of charge across the duration of the rolling horizon optimisation.

5.4 Scenarios

Scenarios were defined to assess two key aspects of BTM battery storage: the total capacity of battery storage systems and their operating strategy. The following sections describe the scenarios and define their input parameters.

5.4.1 Penetration of behind-the-meter battery storage

The BTM battery storage systems in this section were assumed to operate for price arbitrage only. Therefore, for both scenarios, the maximum frequency response capacity was set to zero ($\overline{P}_{b,n}^{FR,h} = 0$, $\overline{P}_{b,m}^{FR,l} = 0$).

Two scenarios were considered for the penetration of BTM battery storage:

A.1. Adding BTM battery storage, effectively increasing total power system storage capacity

A.2. Moving battery storage to BTM, effectively keeping total power system storage capacity constant.

In Scenario A.1, the penetration of BTM battery storage systems was increased by adding battery capacity to the LESs. Therefore, increasing the total battery storage capacity in the power system. This represents the transition from 2020 capacity to 2030 capacity of BTM battery storage. In Scenario A.2, the penetration of BTM battery storage systems was increased by moving grid-scale battery storage to BTM. Therefore, increasing the capacity of BTM battery storage systems but maintaining the total power system battery storage capacity. This represents the 2030 capacity only, however, with either BTM or grid-scale battery storage fulfilling the 2030 capacity projection.

The input data for Scenario A.1 was split with 25% intervals between 2020 and 2030. Therefore, the range was labelled “2020”, “25%”, “50%”, “75%”, “2030”. The input data for Scenario A.2 was split into a range from minimum to maximum capacity of BTM battery storage. The minimum BTM battery capacity was the decentralised capacity in 2020 and the maximum was the decentralised capacity in 2030 in the Consumer Transformation scenario, in National Grid ESO’s Future Energy Scenarios [126]. Consumer Transformation was chosen as it favours distributed technologies, resulting in a high level of BTM battery storage. For Scenario A.2, the incremental increases in battery capacity were 25% of the difference between the 2020 and 2030 battery capacities. Therefore, the range was labelled ‘Min’, ‘25%’, ‘50%’, ‘75%’ and ‘Max’.

The battery power ratings and energy capacities are presented in Figure 5.9 for Scenario A.1 (adding BTM battery storage) and Figure 5.10 for Scenario A.2 (moving battery storage to BTM). The input data for Figure 5.9 and Figure 5.10 are given in Table D.II in Appendix D.

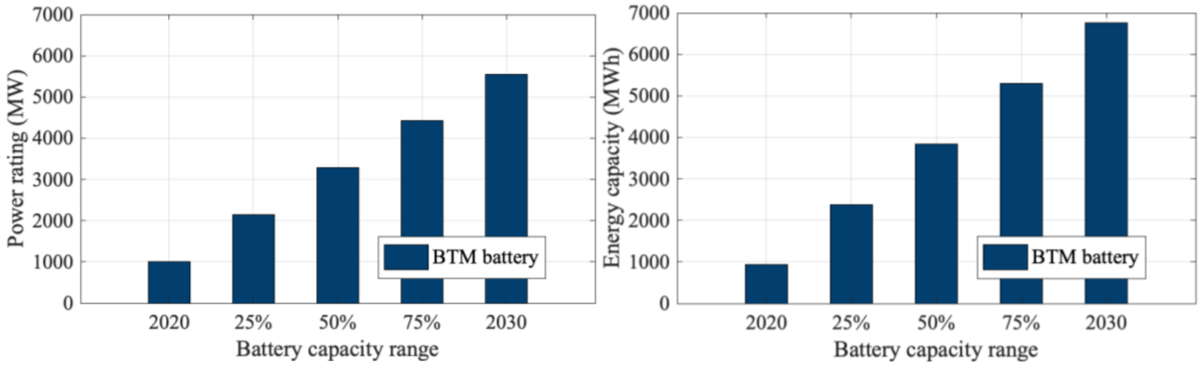

Figure 5.9 Scenario A.1, adding behind-the-meter battery storage (increasing total power system storage capacity).

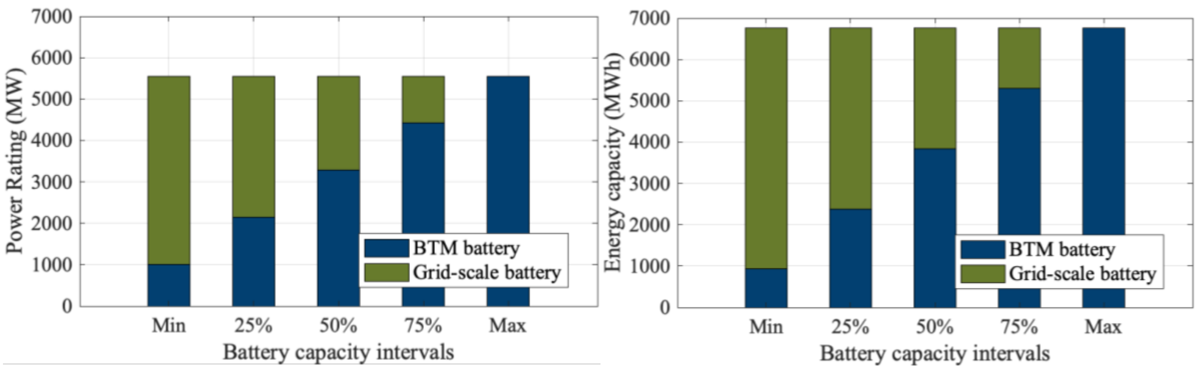

Figure 5.10 Scenario A.2, moving battery storage behind-the-meter (keeping total power system storage capacity constant).

5.4.2 Behind-the-meter battery storage system operating strategies

The BTM battery storage applications were:

- Self-consumption
- Price arbitrage
- Frequency response.

The applications were formulated into the following operating strategy scenarios.

B.1. Self-consumption only (SC)

B.2. Price arbitrage only (PA)

B.3. Price arbitrage and firm frequency response high and low (PA & FFR)

B.4. Price arbitrage and dynamic containment high and low (PA & DC)

B.5. Firm frequency response and dynamic containment (FFR & DC).

All scenarios assume the highest level of BTM battery storage (power capacity of 5555 MW, energy capacity of 6754 MWh). The BTM battery storage capacity is constant. Therefore, no grid-scale battery storage was included in the power system to compensate for changes in BTM battery storage capacity. The total battery storage capacity in the power system was constant across all scenarios.

To alter the LES's operating strategy, the optimisation formulation was altered. All updates to the formulation are discussed below.

5.4.2.1 Scenario B.1 – self-consumption

To operate for self-consumption, the leader optimisation objective function was updated. The import purchase price was an arbitrary value (£10/MWh) and the export sell price was set as a lower arbitrary value (£1/MWh). Because the import price was higher than the export price, the LESs operated to minimise imported electricity and maximise utilisation of onsite generation (also minimising export electricity). Therefore, the objective function was set to:

$$\text{Min} \quad \Pi^{UL} = \sum_{b=1}^{Bn} \sum_{t=1}^{Tn} \left(10 P_{b,t}^{im} - P_{b,t}^{ex}\right). \tag{5.22}$$

Additionally, the capability to participate in frequency response services was removed by limiting $P_{b,n}^{FR,h}$ and $P_{b,m}^{FR,l}$ to zero.

5.4.2.2 Scenario B.2 – price arbitrage

The first term in (5.1) was used to ensure the LESs only performed price arbitrage. Also, the capability to participate in frequency response services was removed by limiting $P_{b,n}^{FR,h}$ and $P_{b,m}^{FR,l}$ to zero.

5.4.2.3 *Scenario B.3 – price arbitrage and firm frequency response*

All terms in the objective function (5.1) were utilised for this scenario. However, the capability to participate in DC was removed by limiting the DC power variables $P_b^{DC,h}$ and $P_b^{DC,l}$ to zero.

5.4.2.4 *Scenario B.4 – price arbitrage and dynamic containment*

All terms in the objective function (5.1) were utilised for this scenario. However, the capability to participate in FFR was removed by limiting the FFR power variables $P_b^{FFR,h}$ and $P_b^{FFR,l}$ to zero.

5.4.2.5 *Scenario B.5 – firm frequency response and dynamic containment*

The optimisation was run with no limitations on the frequency response power commitment variables. Price arbitrage was neglected by removing the $\mu_{b,t}^{1}\left(P_{b,t}^{im} - P_{b,t}^{ex}\right)$ term in the objective function (5.1). Therefore, the only remaining costs considered in the objective function were the DUoS charges ($K_{b,t}^{DUoS} P_{b,t}^{im}$) and frequency response ($K_{b,n}^{FR,h} P_{b,n}^{FR,h}, K_{b,m}^{FR,l} P_{b,m}^{FR,l}$). This ensured no simultaneous importing and exporting to the grid and prioritised participation in frequency response services only.

For scenarios B1 and B5, the LES's operating cost was not given by the objective value. Therefore, the operating cost was calculated outside of the optimisation.

5.5 Results & discussion

5.5.1 Penetration of behind-the-meter battery storage

This section evaluates the impact of different capacities of BTM battery storage in low-carbon power systems. The impact is evaluated using power system operating cost and centralised wind curtailment.

5.5.1.1 *Power system operating cost*

The power system operating cost was calculated outside of the optimisation using the following equation.

$$\begin{aligned} &\textit{Power system operating cost} \\ &\quad = \textit{generating cost } + \textit{cost of power purchased from LESs} \\ &\quad - \textit{income from power sold to LESs} \end{aligned} \tag{5.23}$$

The '$generating\ cost$' is the cost of centralised electricity production, which is the sum of the marginal generating costs from each centralised generating technology multiplied by their electricity output in each time step. The '$cost\ of\ power\ purchased\ from\ LESs$' is the cost to the power system of buying electricity back from the LESs at wholesale electricity price. The '$income\ from\ power\ sold\ to\ LESs$' is the revenue the power system makes when selling electricity to the LESs at wholesale electricity price.

5.5.1.2 Scenario A.1 adding BTM battery storage, effectively increasing total power system storage capacity

The power system operating cost and centralised wind curtailment for Scenario A.1 are shown in Figure 5.11. The increases in BTM battery storage capacity are shown from 2020 capacity through to 2030 capacity with increments of 25%. Where, the 2020 capacity is shown on the left and 2030 capacity is shown on the right. Figure 5.11 shows that increasing BTM battery storage capacity increased power system operating cost. The increase in power system operating cost was small and non-linear, with the largest difference being between 2020 and 25%. In contrast, Figure 5.11 shows that increasing BTM battery storage capacity reduced centralised wind curtailment, showing a total reduction of 668 GWh.

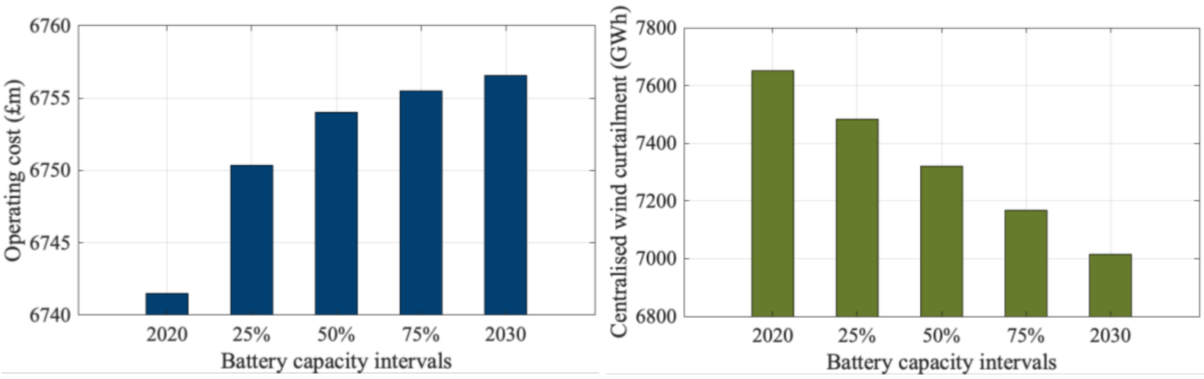

Figure 5.11 Results for Scenario A.1, showing power system operating cost on the left (navy) and centralised wind curtailment on the right (green).

The results in Figure 5.11 show that increasing the battery power and energy capacity in LESs, increased the power system operating cost slightly. As autonomous decision makers, the LESs worked to reduce their own operating cost, while adversely affecting the power system. In contrast, adding extra battery storage capacity as autonomous BTM decision makers benefited the power system by reducing wind curtailment. Therefore, increasing the efficiency of power system operation and reducing total power system GHG emissions.

5.5.1.3 Scenario A.2 moving battery storage to BTM, effectively keeping total power system storage capacity constant.

Results for power system operating cost and centralised wind curtailment for Scenario A.2 are shown in Figure 5.12. The results are shown for incremental increases in BTM battery storage capacity from the minimum capacity to the maximum capacity. Figure 5.12 shows the power system operating cost was higher with more BTM battery storage and lower with more grid-scale battery storage, with a difference of approximately £100 million between Min and Max cases. Similarly, the minimum scenario, with more grid-scale battery storage, resulted in the lowest centralised wind curtailment (far left green bar), while the highest was with maximum BTM battery storage (far right green bar). The total increase in curtailed wind energy from Min scenario to Max scenario was 150 GWh.

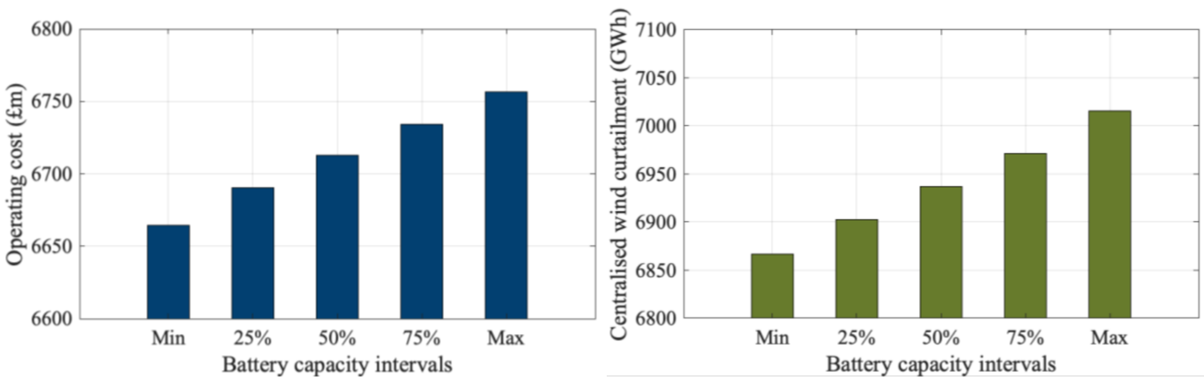

Figure 5.12 Results for Scenario A2, showing power system operation cost on the left (navy) and centralised wind curtailment on the right (green).

The results presented in Figure 5.12 show the grid-scale battery storage, controlled by the power system, resulted in the lowest power system operating cost. Similarly, where grid-scale battery storage was moved BTM, the power system suffered an increase in centralised wind curtailment. Therefore, moving battery storage capacity from in-front of the meter to BTM reduced power system efficiency and increasing power system GHG emissions. These results demonstrate the optimal scenario for the power system is to have central control over flexibility.

5.5.2 Behind-the-meter battery storage operating strategies

This section analyses the impact of various operating strategies on the value of BTM battery storage systems. The maximum case was used or for this section, with no grid-scale battery storage. The battery value is analysed in four ways: LES's operating cost, power system operating cost, wholesale electricity price and wind curtailment.

5.5.2.1 Local energy system operating cost

Figure 5.13 shows the LES's operating cost broken down into its component parts, which are the LES's operating cost from participating in the wholesale electricity market, the revenue from FFR and the revenue from DC. Negative values in Figure 5.13 indicate an overall profit for the year. Therefore, all scenarios resulted in an annual profit. The self-consumption scenario (Scenario B.1) resulted in the highest aggregated LES operating cost, of -£21 million. Performing price arbitrage in the wholesale day-ahead electricity market resulted in an operating cost of -£168 million. Stacking price arbitrage with FFR and DC further reduced the operating cost. The combination with the lowest operating cost was Scenario B.4 with price arbitrage and DC, with an operating cost of -£1,359 million.

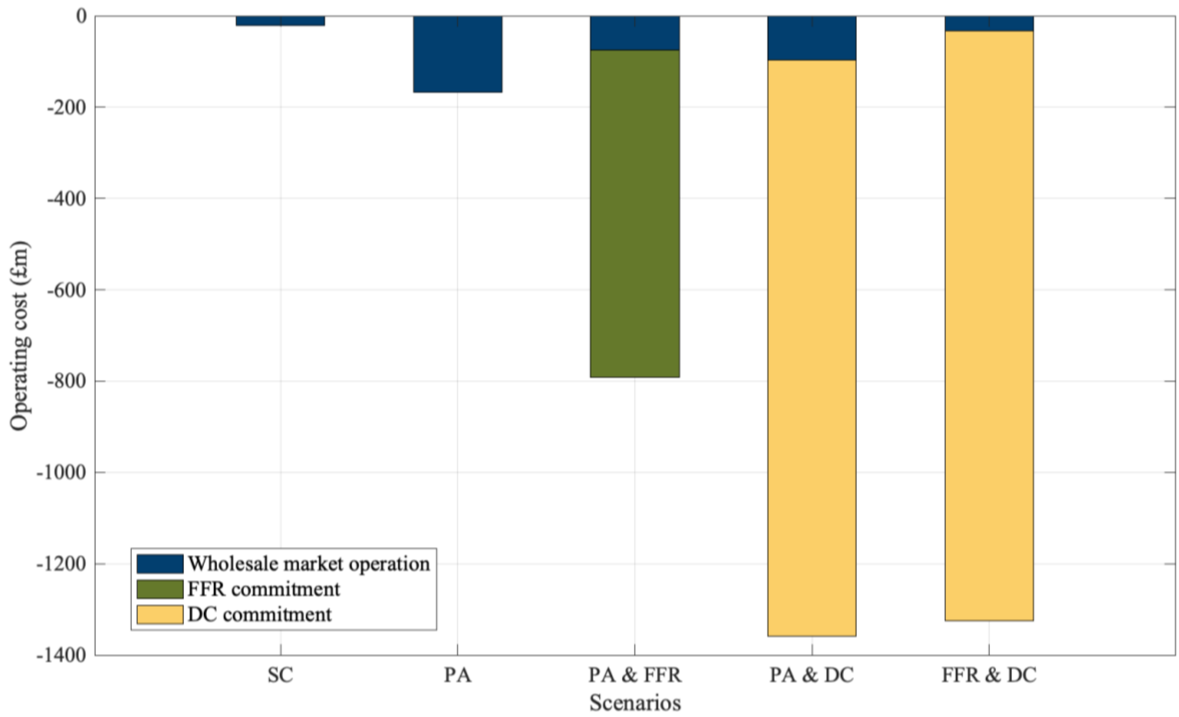

Figure 5.13 Annual local energy systems operating cost.

Figure 5.13 shows that trading BTM battery storage in more than one market provides increased value to LESs. Although self-consumption may be suitable for some applications such as off-grid energy systems, higher cost savings can be made where electrical energy and power capacity can be traded in electricity and ancillary services markets. Furthermore, stacking frequency response services with price arbitrage significantly reduces the LES's operating cost.

5.5.2.2 Power system operating cost

The power system operating cost was calculated using (5.23), as described in Section 5.5.1. The power system operating cost is the cost of meeting total power system demand. Equation (5.23) neglects LES frequency response revenue. Therefore, when LESs commit power capacity to frequency response, the power system sees a reduction in BTM battery capacity being used for price arbitrage.

The annual power system operating cost is shown in Figure 5.14, segmented into the component parts:

- Generating cost (navy)
- Cost of power exchange with the LESs (green).

In the self-consumption scenario, the LESs utilised PV generation onsite, reducing their export power. From the power system perspective, this gave the lowest cost of power exchange with LESs but the highest cost of centralised generation. Self-consumption gave the second lowest power system operating cost.

From the power system perspective, the remaining scenarios were affected by the capacity of BTM battery storage used for price arbitrage. As no frequency response services were considered in Scenario B.2, price arbitrage capacity was at maximum. The result was the lowest centralised generating cost, highest cost of power exchange with the LESs and the highest total power system operating cost. This outcome was due to LESs purchasing electricity at low prices (when wind electricity was available) and selling electricity when the price was high (when costly fossil fuel electricity was available). Therefore, replacing the cost of centralised generation with the cost of trading electricity with LESs.

The battery capacity available for price arbitrage was higher for DC than FFR, due to the difference in dispatch duration (DC = 0.25 h, FFR = 0.5 h). Therefore, Scenario B.4 (with price arbitrage and DC) had the second highest capacity available for price arbitrage and Scenario B.3 (with price arbitrage and FFR) had the second lowest capacity available for price arbitrage. In Scenario B.5 (with FFR and DC), no battery capacity was available for price arbitrage. Therefore, from the power system perspective, there were no BTM battery storage systems performing price arbitrage.

When performing price arbitrage, the LESs act to utilise low-cost centralised generation and displace expensive centralised generation. Therefore, with more capacity available for price arbitrage, the power system centralised generating cost was reduced. However, the cost was replaced by the cost of power exchange with the LESs, as the LESs export electricity to the grid at the highest price possible.

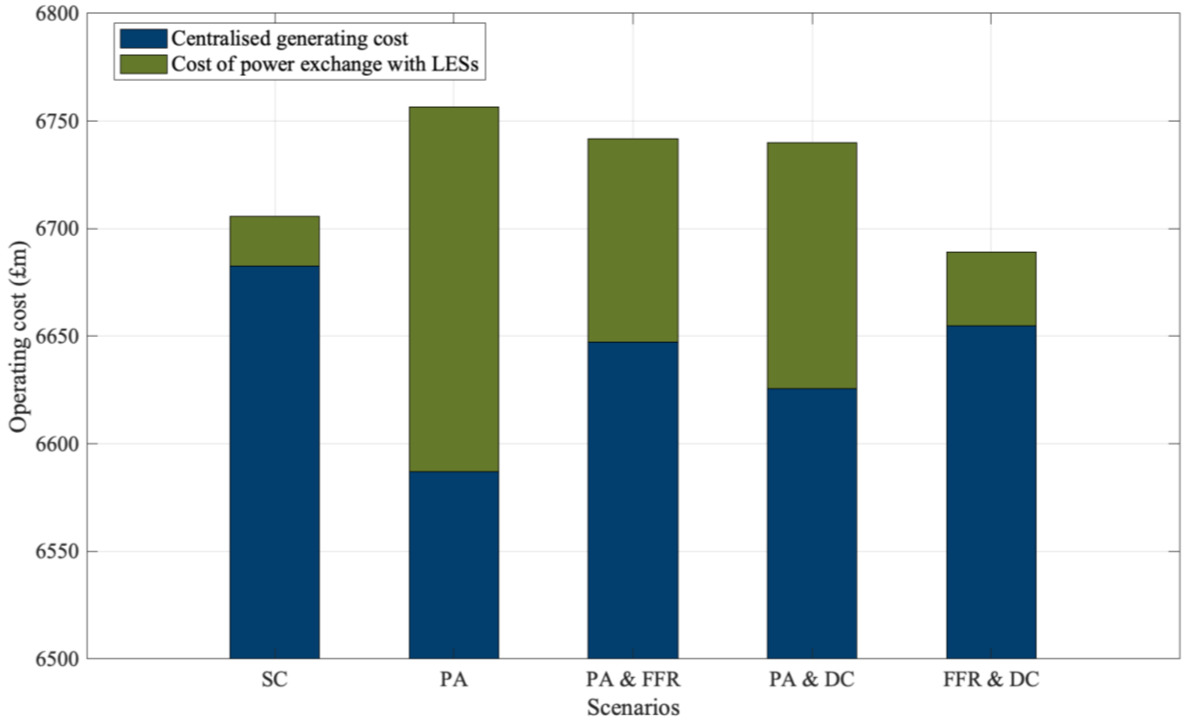

Figure 5.14 Components of power system operating cost, where cost of power exchange with the local energy systems was: $cost\ of\ power\ purchased\ from\ LESs\ -\ income\ from\ power\ sold\ to\ LESs$.

Figure 5.14 clearly demonstrates the operating strategy of LESs impacts the operating cost of the power system. Therefore, operating strategies affect the value of BTM battery storage systems to the power system. LESs that operate for price arbitrage reduce centralised generating costs and the total annual emissions of the power system. However, those centralised generating cost savings are more than replaced by the cost of power exchange with LESs. Therefore, the total power system operating cost was highest when more LESs performed price arbitrage only and lowest when no price arbitrage was performed (in FFR & DC).

5.5.2.3 Wholesale electricity price

The duration curve of the endogenous wholesale electricity price is presented in Figure 5.15, for Scenarios B.2 to B.5. These scenarios were chosen because their operating strategies affect the wholesale electricity price. A section of the duration curve is highlighted in a box to clearly show the changes in electricity price.

The differences in wholesale electricity price shown in Figure 5.15 are related to the battery capacity available for price arbitrage. This is most evident in the highlighted section, where Scenario B.5 (no battery capacity available for price arbitrage) had the highest wholesale electricity price and Scenario B.2 (maximum battery capacity available for price arbitrage) had the lowest wholesale electricity price. Therefore, at this price range, the application of price arbitrage happened to reduce wholesale electricity price. At lower prices, the LESs performed price arbitrage by charging their batteries, which tended to increase the wholesale electricity price, in the range £3/MWh to £32/MWh.

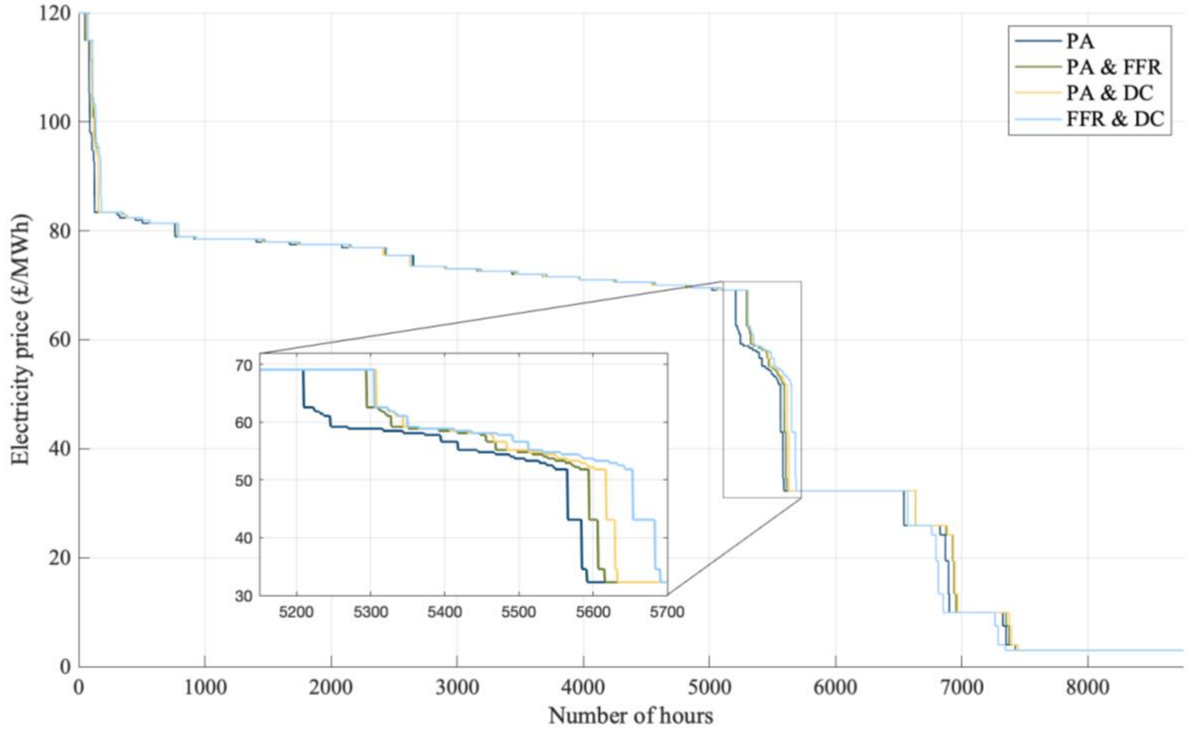

Figure 5.15 Wholesale electricity price duration curve, endogenously calculated within optimisation.

The results presented in Figure 5.15 show that price maker BTM battery storage systems tend to increase low electricity prices (by charging the batteries at low prices) and decrease high electricity prices (by discharging the batteries at high prices), when operated for price arbitrage. However, charging at low prices and discharging at high prices is relative and only affected over 24-hours due to the rolling horizon optimisation. Therefore, charging and discharging occurs at almost all prices. Notwithstanding this, price arbitrage tends to decrease the highest prices. This characteristic is evident in the results presented in Figure 5.16.

In Figure 5.16, the wholesale electricity price was averaged in each hour of the day, for every day of the year. The result is a representation of wholesale electricity price for an average 24-hours. In Figure 5.16, the scenario with the highest variation in average wholesale electricity price is FFR & DC, where no LESs operated for price arbitrage. The scenario with the lowest variation in average wholesale electricity price was price arbitrage only.

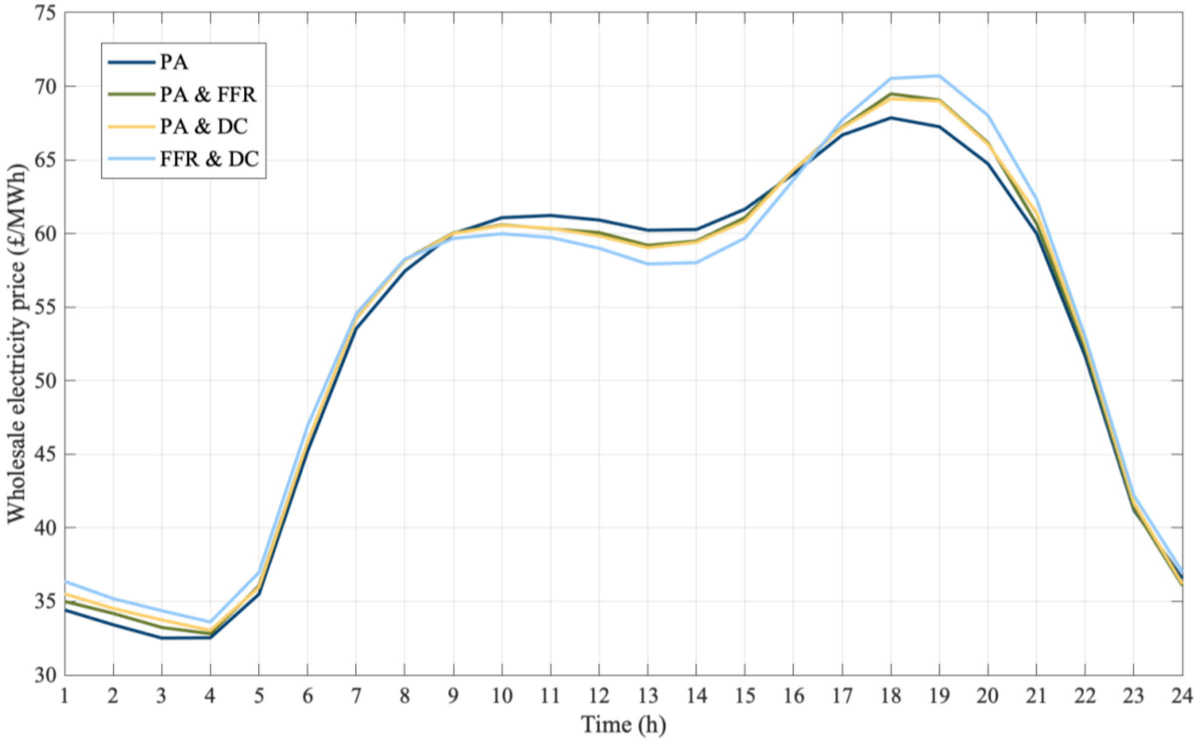

Figure 5.16 Wholesale electricity price for an average 24-hours.

The results presented in Figure 5.16 show that BTM batteries, that are operated for price arbitrage, lower the highest wholesale electricity prices. Furthermore, operating BTM batteries for price arbitrage reduces variation in wholesale electricity prices, acting to smooth out the price profile in an average 24-hours.

5.5.2.4 *Wind energy curtailment*

The wind curtailment for the five operating strategy scenarios is shown in Figure 5.17. The scenario with the highest wind curtailment was Scenario B.1 with self-consumption. This is justified because the LESs utilised their own onsite generation, which reduced the transmission level demand seen by the power system. Therefore, less centralised generation (including wind generation) was required to meet demand. This resulted in higher levels of wind curtailment in comparison to other scenarios.

Similar to previous results, the remaining scenarios depend on how much battery capacity was available for price arbitrage. Scenario B.2 (with price arbitrage only) resulted in the lowest wind curtailment. As the capacity available for price arbitrage decreased, the wind curtailment increased. Therefore, Scenario B.5 (with FFR and DC) resulted in the second highest wind curtailment.

When performing price arbitrage, the LESs utilised low-cost electricity such as wind generation and displace high-cost generation such as OCGT and CCGT. Consequently, price arbitrage reduced wind curtailment and reduced utilisation of conventional generating technologies. Furthermore, increasing the utilisation of wind generation reduced total power system GHG emissions.

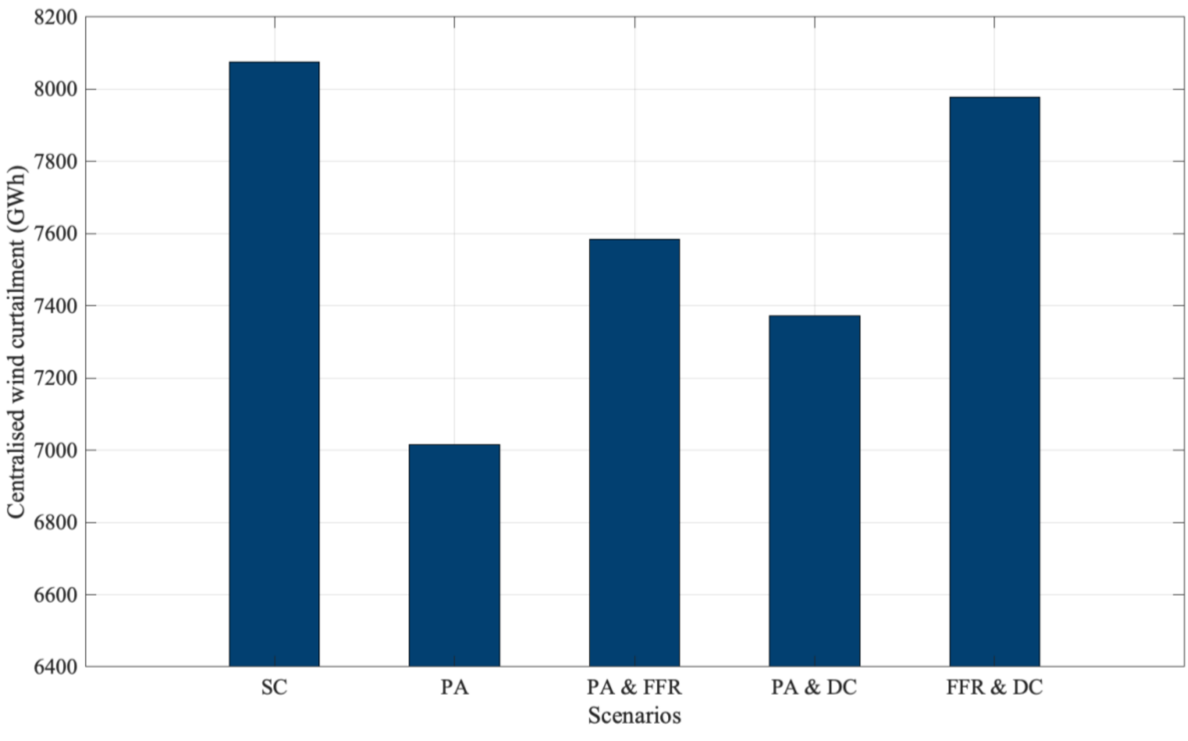

Figure 5.17 Total wind curtailment for the one year time horizon.

Availability for price arbitrage was the source of impact on wind curtailment in Scenarios B.2 – B.5. This demonstrates that price arbitrage reduces wind curtailment and power system GHG emissions. In this study, participation in frequency response services reduced the battery capacity available for price arbitrage. Consequently, there was higher wind curtailment when participating in frequency response services. Self-consumption reduced the demand seen by the power system, which reduced the utilisation of centralised generation, leading to higher wind curtailment.

5.6 Chapter summary

This chapter quantified the value of behind-the-meter battery storage to low-carbon power systems. The methodology accounts for behind-the-meter battery storage as autonomous decision makers, that affect prices in the wholesale electricity market. The power system performs an economic dispatch optimisation based on merit order of marginal electricity costs.

In the case study, local energy systems with behind-the-meter battery storage interact with the power system through power exchange and wholesale electricity price signals. The case study was used to investigate the impact of increasing penetration of behind-the-meter battery storage, in comparison to grid-scale, centrally controlled battery storage. In addition, the methodology was adjusted to analyse the impacts of local energy system operating strategy on the power system.

Increasing the penetration of behind-the-meter battery storage (effectively increasing total power system energy storage capacity) increased the total power system operating cost. Furthermore, moving grid-scale battery storage to behind-the-meter (effectively keeping total power system storage capacity constant) also increased power system operating cost. The results show that increasing behind-the-meter battery capacity to increase total power system storage capacity was not beneficial for the power system. Moreover, centrally controlled grid-scale battery storage was more beneficial than behind-the-meter battery storage, from the power system perspective.

When analysing various local energy system operating strategies, the power capacity available for price arbitrage determined their impact on the power system. When more capacity was available for price arbitrage, the power system had reduced centralised generating cost, reduced wind curtailment and lower greenhouse gas emissions. However, due to increased cost of power exchange with the local energy system, the overall power system operating cost increased when more capacity was available for price arbitrage.

This study demonstrates the value of behind-the-meter battery storage systems with respect to decreased centralised generating cost, renewable curtailment and greenhouse gas emissions. However, grid-scale centrally operated battery storage systems are more beneficial from the power system perspective. Finally, the operating strategy significantly affects the value of behind-the-meter battery storage systems from both the local and power system perspective. Therefore, incentive and market design are essential to encourage the adoption of behind-the-meter battery storage systems and ensure they provide value to the power system.

The outcomes of this study are subject to the following key limitations. Firstly, the power generation cost curve defined in this work is an estimation that was designed to represent the GB marginal supply curve in 2030. The accuracy of this cost curve impacts the results. However, the conclusions of this work come from scenario comparisons, which ensure the conclusions are unaffected by the definition of the cost curve. Secondly, the case study represented aggregated local energy systems that operated as one. This assumption neglects the decision making of individual local energy systems. Finally, the exogenous frequency response prices create a disconnect between the power system and the frequency response services. Future work could study the influence of behind-the-meter battery storage on endogenous frequency response prices.

5.6.1 Discussion of wholesale market configuration

“All models are wrong but some are useful” [162]. The aim of building a model is to recreate specific characteristics of real situations. However, any model that focuses on particular characteristics of a situation will neglect other characteristics. Nevertheless, models that accurately recreate the characteristics under investigation are useful for that purpose.

The aim of this study was to investigate the impact of autonomous BTM battery storage on the operation of the power system. The operational characteristics investigated were power system operating cost, renewable curtailment and variation in electricity price. This analysis required a market structure that incorporated variation in electricity price, relative to total power system demand and available renewable generation.

The marginal cost curve and subsequent economic dispatch of centralised generation was designed to represent the wholesale electricity market in GB. However, the GB wholesale electricity market is extremely complex, with a plethora of factors influencing the outcome. Furthermore, the purpose of this formulation was not to accurately recreate real price data but to represent an electricity price with variation. Therefore, the market representation was simplified with respect to many characteristics. Below is a non-comprehensive list of simplifications.

- All centralised generation (excluding CCGT) was aggregated by technology. This neglects the autonomy of individual power plants and their trading strategies.
- All centralised generators make offers according to marginal price alone. This neglects trading autonomy during times of scarcity or low de-rated capacity margin and the influence of generator operating limits on trading strategy.
- The power system operator had complete control over grid-scale storage, which was aggregated by technology.
- The bidding strategy of other market participants such as retailers, aggregators and large consumers was neglected.
- This formulation neglects forward and real time trading markets. Therefore, it assumes all power system demand is cleared in only this market.

These simplifications result in an output that does not represent accurate electricity price data in terms of numerical value but does create the characteristic of variation in electricity price. Therefore, the formulation was adequate for addressing the challenges identified in this study. Furthermore, a more complex representation capable of accurately replicating real electricity prices would not impact the conclusions of the study.

Chapter 6

Conclusion and future work

6.1 Summary of the research

A review of applications and benefits of behind-the-meter battery storage systems was carried out. Firstly, to identify possible revenue streams the battery operator can target to increase their revenue and secondly, to highlight the ways that behind-the-meter battery storage systems can contribute to reliable, secure and safe operation of the power system. In addition, an appraisal of existing methods for optimising distributed flexibility operation from local and power system perspectives was carried out to provide a compendium of current works and a summary of research gaps.

Having identified the applications of behind-the-meter battery storage, the most suitable applications were applied to a revenue maximisation methodology, focused on the local perspective. A simulation of battery degradation was integrated into the methodology, to account for the impact of various revenue streams on battery lifetime. A case study was defined to examine the methodology, stacking up to three revenue streams simultaneously. The investment viability of the behind-the-meter battery storage system was assessed for various combinations of revenue streams.

Another methodology was presented to account for behind-the-meter battery storage as an autonomous decision maker in the power system. The methodology considered the power flow interactions between the power system economic dispatch model and the behind-the-meter battery storage revenue maximisation. The methodology employed bilevel optimisation to account for two autonomous decision makers.

The developed methodology was compared to a conventional approach, using a case study power system and local energy system configuration. The conventional approach simplified the problem by assuming the behind-the-meter battery storage systems were centrally controlled by the power system operator. Several retail tariffs were evaluated to reveal their importance for unlocking the value of behind-the-meter battery storage to the power system.

The previous work assumed behind-the-meter battery storage systems were price takers in the wholesale electricity market. This assumption was addressed by considering an endogenous wholesale electricity price in a development of the bilevel optimisation, allowing the battery storage systems to be price makers. Furthermore, the battery storage systems were able to simultaneously participate in frequency response service markets, as price takers, to increase their revenue.

A detailed case study of the 2030 GB power system with many local energy systems was used to assess the value of behind-the-meter battery storage. The number of behind-the-meter battery storage systems and their operating strategies were used to assess their impact on the power system.

6.2 Conclusions

The technical chapter outcomes and conclusions are given in the last section of each chapter: Section 2.6, 3.6, 4.6 and 5.6. The following conclusions connect the research findings with their real world implications.

6.2.1 Investment viability

Previous studies have shown that the high capital cost of behind-the-meter battery storage systems necessitates stacking of multiple revenue streams to achieve investment viability.

This study provides a method for scheduling battery operation in electricity and frequency response markets. The results also corroborate previous studies and provide a detailed narrative of the benefits of stacking multiple revenue streams, including the impacts of different revenue streams on battery degradation.

To enable widespread adoption of behind-the-meter battery storage, they must present viable investments. If behind-the-meter batteries can offer an attractive investment, they will provide opportunities for consumers to lower their electricity bills, reduce their greenhouse gas emissions and reduce their reliance on the grid.

This research allows prospective behind-the-meter battery storage investors to understand the value of stacking revenue streams and to plan their scheduling across those revenue streams. Furthermore, research now shows that frequency response alongside price arbitrage extends the lifetime of behind-the-meter batteries.

6.2.2 Approach capability

Previous studies have demonstrated the potential of bilevel optimisation to account for distributed flexibility as autonomous decision makers in power systems. This study presents an approach for considering behind-the-meter battery storage, integrated within a local energy system configuration, as autonomous decision makers in the power system.

Considering behind-the-meter battery storage as an autonomous decision maker is key to their realistic representation within power systems. Therefore, having a suitable methodology reduces the risk of overestimating the value of behind-the-meter battery storage and facilitates useful insights for power system operators. This research clarifies the most suitable existing methodology for optimising behind-the-meter battery storage operation within power systems.

6.2.3 Value to the power system

Research has focused on a variety of distributed flexibility technologies, such as flexible demand, electric heating and thermal energy storage. The capability of these technologies to support the transition to low-carbon power systems has been studied.

This study provides detailed insights into the capability of behind-the-meter battery storage systems to provide support to low-carbon power systems. Furthermore, the results show strong links between behind-the-meter battery operating strategies and their value to the power system.

Notably, these findings show that increasing flexibility through distributed sources, such as behind-the-meter battery storage, will either contribute to more efficient low-carbon power systems, or increase costs. Furthermore, the discoveries are vital for enabling power systems to harness the potential of behind-the-meter battery storage systems.

This research identifies opportunities to unlock the most value from behind-the-meter battery storage systems. Furthermore, it provides a foundation for efficient market design that enables effective utilisation of behind-the-meter battery storage.

6.2.4 Role of market design

Previous research has indicated that retail contracts play a role in unlocking value from distributed flexibility. Insights in this study reveal the significant influence that retail contracts have on the value of behind-the-meter battery storage systems, from both the local and power system perspectives.

This information is critical to unlocking the potential of behind-the-meter battery storage, to support high penetrations of renewable generation. The evidence in this study can enable efficient design of effective retail contracts that encourage behind-the-meter battery storage to operate in line with power system objectives.

Research now gives clear signals for the design of retail contracts to unlock maximum value from behind-the-meter battery storage systems.

6.2.5 Real world implications and recommendations

To improve investment viability, behind-the-meter battery storage systems must increase their revenue through simultaneous participation in multiple markets. To make this possible, a variety of markets must be available to participate in. Therefore, market creators and operators must reduce the barriers to entry for existing markets, to allow smaller, independent operators to participate. Furthermore, new markets must be developed that target retail consumers to incentivise behind-the-meter consumers to invest in and utilise flexibility. This will provide extra revenue streams for behind-the-meter battery storage and other sources of behind-the-meter flexibility such as electric vehicles, electric heating systems and thermal energy storage systems. Consequently, effective retail market design will reduce consumer electricity bills, reduce consumer reliance on the grid and alleviate peak demands.

To ensure synergetic operation of behind-the-meter battery storage systems within the power system, the markets that are available to distributed flexibility must a line their objectives with power system objectives.

Given the unprecedentedly high electricity prices, in GB, at the time of writing, acceleration towards a net zero emission power system must be a priority to reduce reliance on expensive and insecure fossil fuel technologies, such as natural gas. Behind-the-meter battery storage systems can support this transition; however, appropriate market mechanisms must be available. A key finding is for markets to reflect the real time operation of the power system. Such operating factors could include: the marginal generating technology, the grid emission factor and congestion in the transmission and distribution network.

6.3 Future research

The research presented in this thesis made some assumptions to simplify the methodologies or case studies. The bullet points below identify the simplifications and suggests research opportunities to address them.

- All results are based on deterministic optimisations. Therefore, the results assume perfect foresight of price, renewable generation and demand. In reality, this is not the case. Future research could use stochastic optimisation to account for uncertainties in all forecasted inputs. Accounting for uncertainties would be more representative of behind-the-meter battery storage system operators that utilise forecasts to plan future operation.
- The focus of this thesis was behind-the-meter battery storage systems. However, there are many more distributed flexibility technologies (electric vehicles, electric heating, thermal energy storage, smart appliances, etc) that could provide value to behind-the-meter energy system operators. Future research could focus on distributed flexibility, incorporating more technologies would provide insights into the value of distributed flexibility more generally.
- This thesis considers the behind-the-meter battery storage system operator and the power system operator. However, there are many other decision makers in power systems that optimise their own objectives. For example, virtual power plant operators, retailers, aggregators, central generators, large industrial consumers and other flexibility operators. Future research could address this by developing the methodology into a single leader, multiple follower optimisation that accounts for the autonomy of more decision makers in the power system.
- This research focused on operational optimisation and considered multiple power system participants using bilevel optimisation. However, operational optimisation is not the only method for analysing the operation of flexibility and bilevel optimisation is not the only method for evaluating multiple participants simultaneously. Therefore, future work could widen the scope to include approaches such as agent based modelling or rule based modelling and make comparisons between the approaches.
- The conclusions of this study highlight the importance of incentive and market design for maximising the value of BTM battery storage. Although this study makes suggestions for technical characteristics, they are not comprehensive. Future research could go beyond this by

analysing market and incentive structures and the specific technical requirements that would maximise the value of BTM battery storage.

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Appendix A

Optimisation is the process of finding the optimal or best of something. Optimisations can be formulated as mathematical problems with an objective function, variables, parameters and constraints. The objective function is a mathematical equation defining the value to be optimised. Variables are the values that can vary to move the objective value closer to an optimal solution. Parameters are input values that cannot be changed. Constraints are the equations that apply limits to the variables.

Bilevel optimisation has a hierarchical structure where the objectives of more than one optimisation can be considered simultaneously. Sinha et al. [163] define a bilevel optimisation as a

"mathematical program, where an optimisation problem contains another optimisation problem as a constraint".

Bilevel optimisations are suited to many applications including toll setting, network design and supply chain management [163]. Bilevel optimisation is also accounts for the hierarchical structure of energy systems with multiple autonomous decision makers interacting but all optimising their own objectives. The remainder of this Section is dedicated to the general understanding of bilevel optimisation, including the: structure, standard form, solution methodologies and linearisation.

A.1 Structure

Typically, research has focused on linear bilevel optimisations, also known as linear Stackelberg games. The most common bilevel optimisation problem constrains an optimisation with another optimisation. The optimisations are split into two levels, the first one known as the '*leader*' (or upper level) optimisation problem and the second known as the '*follower*' (or lower level) optimisation problem. Both optimisations have their own objectives, decision variables and set of constraints. The follower optimisation is solved with respect to the follower decision variables, while the leader variables act as parameters. The follower constrains the leader optimisation, such that the optimal solution for the leader must result in an optimal solution for the follower [163]. The formulation below represents the standard form of a single leader, single follower bilevel optimisation [164]. Although this is the most common type of bilevel optimisation, multiple follower and multiple leader optimisations are possible.

For $\boldsymbol{x} \in X \subset \mathbb{R}^n$, $\boldsymbol{y} \in Y \subset \mathbb{R}^m$, $F: X \times Y \rightarrow \mathbb{R}^1$ and $f: X \times Y \rightarrow \mathbb{R}^1$, the mathematical bilevel optimisation problem can be written as:

$$\min_{x \in X} \quad F(x, y^*) \tag{A.1}$$

$$\text{subject to} \quad G_n(x, y^*) \leq 0, n = 1, \dots, N \tag{A.2}$$

$$H_m(x, y^*) = 0, m = 1, \dots, M \tag{A.3}$$

$$y^* \in \ argmin \quad \{ f(x, y) \tag{A.4}$$

$$\text{subject to} \quad g_k(x, y) \leq 0, k = 1, \dots, K \tag{A.5}$$

$$h_j(x, y) = 0, j = 1, \dots, J \, \}. \tag{A.6}$$

Where G_n and H_m are the leader's constraints and g_k and h_j are the follower's constraints. In this representation, n, m, k and j are the set of constraints, where N, M, K and J are the total number of constraints. Although the leader variable $\boldsymbol{x}$ is present in the follower optimisation, when the leader selects a value for $\boldsymbol{x}$, it becomes a parameter in the follower optimisation. Figure A.1 visualises the structure of a single leader, single follower bilevel optimisation.

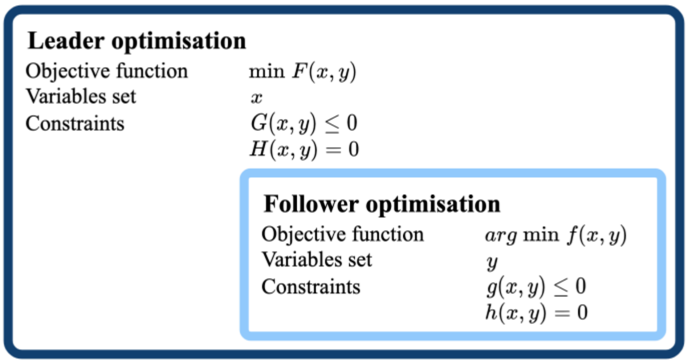

Figure A.1 Visualisation of the standard linear bilevel optimisation formulation.

In the interest of clarity, the simple mathematical example given in [165] is detailed next. Consider a bilevel optimisation with $x \in \mathbb{R}^1$, $y \in \mathbb{R}^1$, $X = \{x \geq 0\}$ and $Y = \{y \geq 0\}$.

$$\min_{x \geq 0} \quad F(x,y) = x - 4y \tag{A.7}$$

$$\text{subject to} \quad \min_{y \geq 0} \quad f(y) = y \tag{A.8}$$

$$\text{subject to} \quad -x - y \leq -3 \tag{A.9}$$

$$-2x + y \leq 0 \tag{A.10}$$

$$2x + y \leq 12 \tag{A.11}$$

$$-3x + 2y \leq -4 \tag{A.12}$$

Constraints (A.9) - (A.12) are graphically represented in Figure A.2, highlighting the '*Constraint region*' defined by the constraints. The follower objective function aims to minimise y, shown as line f. Note that x is chosen by the leader and is treated as a fixed value in the follower optimisation. Therefore, there is an optimal value of y in the follower optimisation, for each feasible value of x. This creates the '*inducible region*', representing the solutions that are feasible for the leader and optimal for the follower. The leader objective line is shown as F. The leader objective function aims for the highest value of y. However, the leader's feasible solutions are limited to the inducible region. The highest y value in the inducible region is (4,4). Therefore, this is the bilevel optimal solution, with the following outputs:

$$F(x, y) = x - 4y = -12 \tag{A.13}$$

$$f(y) = y = 4 \tag{A.14}$$

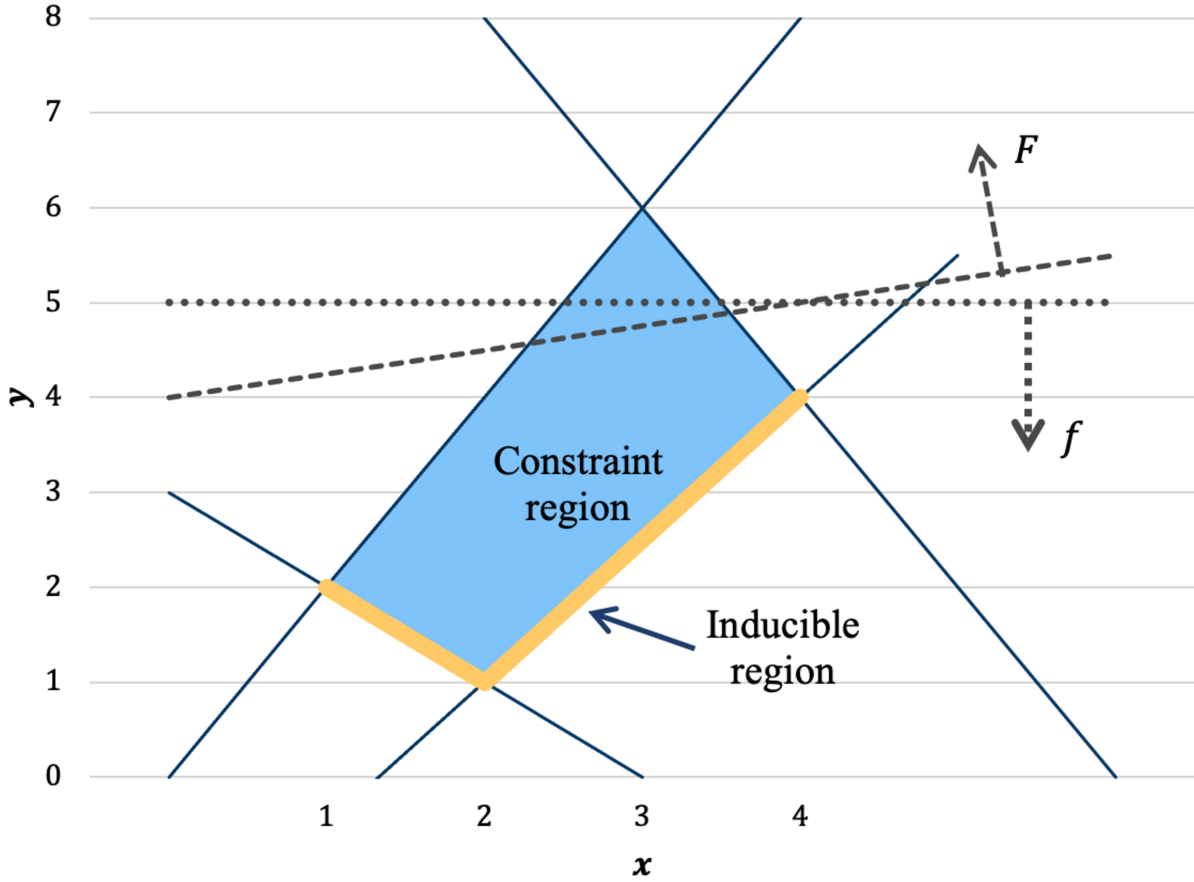

Figure A.2. Graphical representation of the simple linear bilevel optimisation example.

To better understand the difference between the separate, sequential and bilevel optimisations, their individual results are compared. Firstly, an optimal solution for the follower optimisation only is (2,1), with an optimal solution of $f = 1$. Whereas an optimal solution for the leader optimisation only is (3,6), with an optimal solution of $F = -21$. Secondly, a sequential optimisation would require an input value for x, which would lead to an optimal solution for the follower, with no freedom to optimise for the leader. This demonstrates how the bilevel optimisation gives a result that is sub-optimal for each individual optimisation, but finds the best result for the leader, given the followers requirements. For further details on this example and bilevel optimisation theoretical properties, refer to [165].

A.2 KKT conditions

Since the 1970s, several methodologies have been proposed for solving bilevel optimisations. These vary in terms of ease of implementation and efficiency. Five are suggested by Bard et al. [165] as the most successful, including Kth-Best Algorithm, Kuhn-Tucker Approach, Complementarity Approach, Variable Elimination Algorithm and Penalty Function Approach. The most direct approach to solving linear bilevel optimisations is using Kuhn-Tucker Approach, using '*Karush-Kuhn-Tucker'* or '*KKT'* conditions. This section describes KKT conditions, provides a standard formulation and a numerical example.

The KKT approach reformulates the bilevel optimisation as a single level problem [166]. For linear programming problem, any solution that satisfies the KKT conditions must be an optimal solution [118]. Therefore, the linear follower optimisation can be reformulated as a set of KKT conditions that are included as constraints in the leader optimisation problem. Specifically, (A.1) - (A.6) becomes [163], [164], [167]:

$$\min_{x,y,\lambda,\mu} \quad F(x,y) \tag{A.15}$$

subject to

$$G_n(x,y) \leq 0, n = 1, \dots, N \tag{A.16}$$

$$H_m(x,y) = 0, m = 1, \dots, M \tag{A.17}$$

$$g_k(x,y) \leq 0, k = 1, \dots, K \tag{A.18}$$

$$h_j(x,y) = 0, j = 1, \dots, J \tag{A.19}$$

$$\nabla_y L(x,y,\lambda,\mu) = 0 \tag{A.20}$$

$$\lambda_k g_k(x,y) = 0, k = 1, \dots, K \tag{A.21}$$

$$\lambda_k \geq 0, k = 1, \dots, K \tag{A.22}$$

where

$$L(x, y, \lambda, \mu) = f(x, y) + \sum_{k=1}^{K} \lambda_k g_k(x, y) + \sum_{j=1}^{J} \mu_j h_j(x, y) \tag{A.23}$$

Equations (A.18) and (A.19) are the follower constraints that have been applied to the leader optimisation. The KKT reformulation is constructed with the Lagrangian constraints (A.20) and a set of complimentary slackness conditions (A.21). The KKT reformulation introduces new variables to the optimisation, called '*dual variables*'. The first set are positive variables that are coupled with the inequality constraints in the follower optimisation, represented by λ_k. The second set are uncontrolled variables that are associated with the equality constraints, represented by μ_j.

To further clarify the KKT reformulation, a numerical example is given next. The following bilevel optimisation is defined.

$$\min_{x,y\geq 0} \quad F(x, y, z) = x + y - 2z \tag{A.24}$$

$$s.t. \qquad \min_{z} \quad f(z) = 3z \tag{A.25}$$

$$s.t. \qquad -x - y - z \geq -7, \quad \lambda_1 \tag{A.26}$$

$$x - y + z \geq 2, \qquad \lambda_2 \tag{A.27}$$

$$2x - y - 2z = 5, \quad \mu \tag{A.28}$$

$$x, y, z \geq 0 \tag{A.29}$$

In this example, x and y are variables in the leading optimisation and are treated as parameters in the follower optimisation. Whereas z is decided in the follower optimisation. There are two inequality constraints and one equality constraint in the follower optimisation. Therefore, the positive dual variables λ_1 and λ_2 and the uncontrolled dual variable μ are defined. The KKT reformulation of this bilevel optimisation is shown below.

$$\min_{x,y\geq 0} \quad F(x, y, z) = x + y - 2z \tag{A.30}$$

$$s.t. \qquad 2x - y - 2z - 5 = 0 \tag{A.31}$$

$$\nabla L(z) = 3 + \lambda_1 + \lambda_2 - 2\mu = 0 \tag{A.32}$$

$$0 \leq \lambda_1 \perp (x + y + z - 7) \geq 0 \tag{A.33}$$

$$0 \leq \lambda_2 \perp (2x - y - 2z - 5) \geq 0 \tag{A.34}$$

$$x, y, z \geq 0 \tag{A.35}$$

The follower optimisation has been replaced with its equality constraint (A.31), the Lagrangian condition (A.32) and two complimentary slackness conditions (A.33) and (A.34). Where the complementary slackness conditions are shown in the form $0 \leq a \perp b \geq 0$, which is equivalent to $0 \leq a$, $0 \leq b$ and $ab = 0$. The latter condition ($ab = 0$) introduces multiplication of variables, leading to a non-linear optimisation problem. These components of the complementary slackness conditions can be linearized using the Fortuny-Amat reformulation [147]. The following section provides a description of this process.

A.3 Fortuny-Amat

The Fortuny-Amat formulation uses binary variables corresponding to each complementary slackness condition and a large constant. Whereby, the standard form of $0 \leq a \perp b \geq 0$, can be replaced by the following set of constraints.

$$0 \leq a, b \tag{A.36}$$

$$a \leq MU \tag{A.37}$$

$$b \leq M(1 - U) \tag{A.38}$$

Where, U is a binary variable and M is a large enough constant. The non-linear constraint $ab = 0$ is replaced by two constraints (A.37) and (A.38). For optimisations with more than one complementary slackness condition, U becomes a set of binary variables.

Considering the complementary slackness conditions (A.33) and (A.34), the Fortuny-Amat reformulation is as follows.

$$0 \le \lambda_1, \lambda_2 \tag{A.39}$$

$$0 \le x + y + z - 7 \tag{A.40}$$

$$0 \le 2x - y - 2z - 5 \tag{A.41}$$

$$\lambda_1 \le MU_1 \tag{A.42}$$

$$\lambda_2 \le MU_2 \tag{A.43}$$

$$x + y + z - 7 \le M(1 - U_1) \tag{A.44}$$

$$2x - y - 2z - 5 \le M(1 - U_2) \tag{A.45}$$

Although this reformulation linearises the complementary slackness conditions, it introduces binary variables, which changes the problem into a mixed integer linear programming (MILP) problem.

Appendix B

B.1 GB flexibility market summary

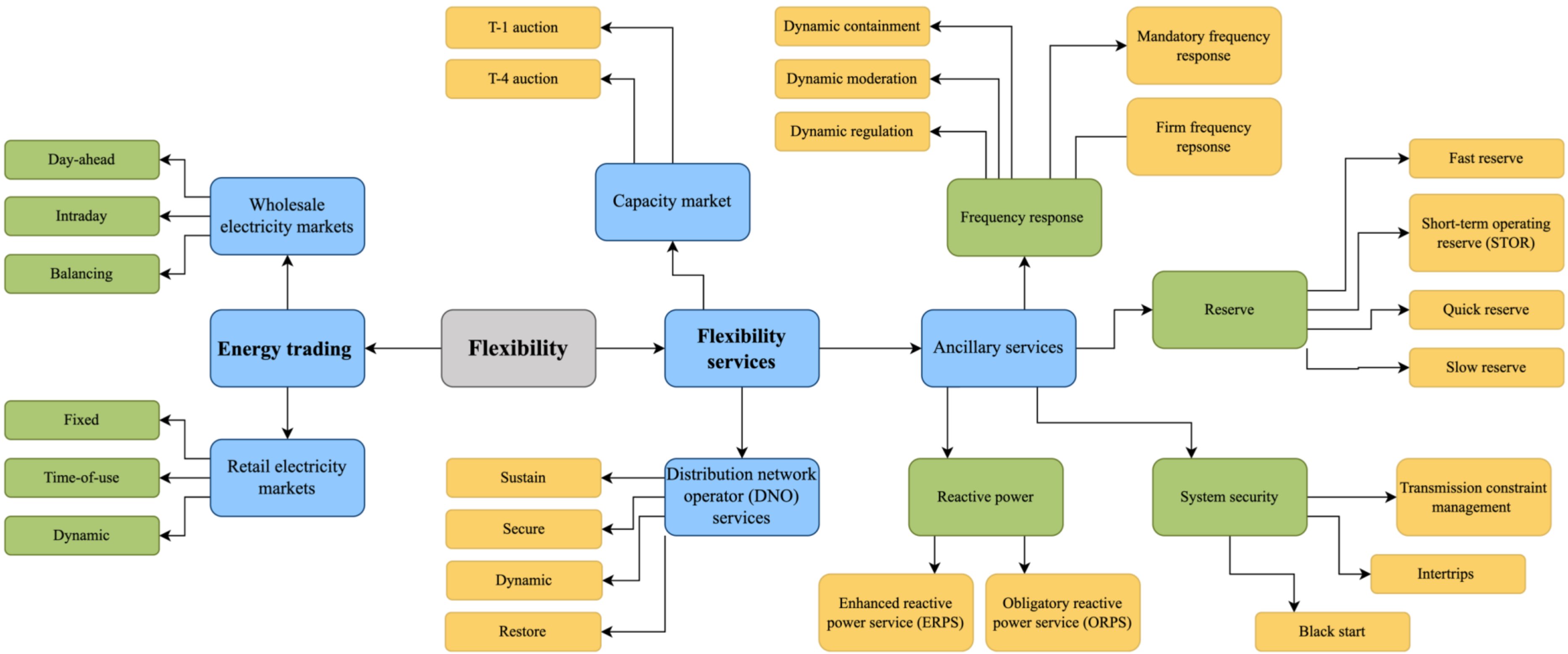

Figure B.1 Schematic of some of the revenue opportunities for flexibility in GB.

B.2 Chapter 3 nomenclature

Indices

b	Frequency response block
day	Days in the year time horizon
m	Frequency response low services
n	Frequency response high services
s	Seconds
t	Time (hourly)
y	Years

Constants

Bn	Total number of frequency response blocks
E^{ini}	Initial energy stored in battery (kWh)
$\overline{E}_y$	Battery energy storage capacity for each year (kWh)
$\overline{E}$	Battery energy storage capacity (kWh)
I	Battery storage investment cost (£)
i	Discount rate (10%)
$K_{b,m}^{FR,l}$	Availability price of frequency response low (£/kW)
$K_{b,n}^{FR,h}$	Availability price of frequency response high (£/kW)
$K_{b,t}^{bal}$	Balancing price (£/kWh)
$K_{b,t}^{E}$	Electricity market price (£/kWh)
$K_{b,t}^{REP}$	Price for service dispatch, or '*response energy payment*' (£/kWh)
$K_{b,t}^{REP,DCL}$	Response energy payment for Dynamic Containment (£/kWh)
$K_{b,t}^{REP,FFR}$	Response energy payment for Firm Frequency Response (£/kWh)
$K_{b,t}^{DUoS}$	Distribution use of system charges (£/kWh)
Mn	Total number of frequency response low services
Nn	Total number of frequency response high services
$\overline{P}^{bat}$	Battery power rating (kW)
$P_{b,t}^{D}$	Local power demand (kW)
$P_{b,t}^{Ren}$	Local renewable power generation (kW)
Sn	Total number of seconds in each time interval
$T_{m}^{FR,l}$	Duration of frequency response low service (h)
$T_{n}^{FR,h}$	Duration of frequency response high service (h)

Tn	Total number of time steps
Yn	Total number of years
η^{ch}	Battery charging efficiency (%)
η^{dis}	Battery discharging efficiency (%)
τ	Time interval (h)
$\varphi^{FFR,disp}$	Income for Firm Frequency Response dispatch (£)
$\varphi^{SFR,disp}$	Income for service dispatch (£)
Δf_s	Change in system frequency (Hz)

Variables

DOD_t	Depth of discharge (%)
$E_{b,t}$	Energy stored in battery (kWh)
$E_{b,t}^{FFR,disp}$	Total energy dispatched in each time step for Firm Frequency Response (kWh)
$E_{b,t}^{SFR,disp}$	Total energy dispatched in each time step (kWh)
NPV	Net present value (£)
N_t^{cyc}	Number of cycles to end-of-life at time t
OCS_y	Operating cost savings (£)
P_b^{SFR}	Power committed to each service (kW)
$P_{b,m}^{FR,l}$	Power committed to each frequency response low service (kW)
$P_{b,n}^{FR,h}$	Power committed to each frequency response high service (kW)
$P_{b,t}^{ch}$	Battery charging power (kW)
$P_{b,t}^{dis}$	Battery discharging power (kW)
$P_{b,t}^{ex}$	Power exported from local energy system (kW)
$P_{b,t}^{im}$	Power imported to local energy system (kW)
$P_{b,t,s}^{DCL,\%}$	Dynamic response percentage dispatch (%)
$P_{b,t,s}^{FFRH,\%}$	Firm Frequency Response high percentage dispatch (%)
$P_{b,t,s}^{FFRL,\%}$	Firm Frequency Response low percentage dispatch (%)
$P_{b,t,s}^{SFR,\%}$	Symmetrical frequency response service percentage dispatch (%)
Π	Objective value (£)
δ^{PA}	Annual battery degradation resulting from price arbitrage operation (%)
δ^{Total}	Total annual battery degradation (%)
δ_{day}^{cal}	Daily calendar degradation (%)
δ_{day}^{cyc}	Cycle aging in each day (%)
δ_{day}^{total}	Total degradation per day (%)
δ_t^{cyc}	Cycle aging in each time step (%)

Appendix C

C.1 Chapter 4 nomenclature

Indices

i	Renewable generation index
j	Conventional generation index
k	Grid-scale energy storage index
t	Time index

Constants

C^{bat}	Total battery energy storage capacity (MWh)
$\overline{E}^{bat}$	Maximum state of charge limit (%)
$\underline{E}^{bat}$	Minimum state of charge limit (%)
$\overline{E}_k^{GES}$	Grid-scale energy storage capacity (MWh)
In	Number of renewable generation types

Jn	Number of conventional generation types
K_i^R	Marginal cost of renewable generation (£/MWh)
K_j^C	Marginal cost of conventional generation (£/MWh)
K_t^{ex}	LES retail contract sell price (£/MWh)
K_t^{im}	LES retail contract purchase price (£/MWh)
Kn	Number of grid-scale energy storage types
$\overline{P}^{bat}$	Total battery power rating (MW)
$\overline{P}^{ex}$	Maximum local energy system export power (MW)
$\overline{P}^{im}$	Maximum local energy system import power (MW)
$\overline{P}_j^C$	Maximum conventional generating power (MW)
$\underline{P}_j^C$	Minimum conventional generating power (MW)
$\overline{P}_k^{GES}$	Maximum grid-scale energy storage charge/discharge power (MW)
$\overline{P}_{t,i}^R$	Maximum available renewable generation (MW)
$\underline{P}_{t,i}^R$	Minimum available renewable generation (MW)
P_t^{LD}	Total local power demand (MW)
P_t^{LR}	Total local renewable power generation (MW)
P_t^{TD}	Inflexible power demand seen by the transmission system (MW)
Tn	Number of time steps
$\eta^{bat,ch}$	Battery charging efficiency (%)
$\eta^{bat,dis}$	Battery discharging efficiency (%)
η_k^{GES}	Grid-scale energy storage round trip efficiency (%)
τ	Time interval (h)

Variables

E_t^{bat}	Total energy stored in batteries (MWh)
$E_{t,k}^{GES}$	Energy stored in grid-scale energy storage (MWh)
$P_t^{bat,ch}$	Total battery charging power (MW)
$P_t^{bat,dis}$	Total battery discharging power (MW)
P_t^{ex}	Power exported from local energy systems (MW)
P_t^{im}	Power imported to local energy systems (MW)
$P_{t,i}^R$	Renewable power injected into grid (MW)
$P_{t,j}^C$	Conventional centralised power generation (MW)
$P_{t,k}^{GES,ch}$	Grid-scale energy storage charging power (MW)
$P_{t,k}^{GES,dis}$	Grid-scale energy storage discharging power (MW)
Π^F	Follower objective value (£)
Π^L	Leader objective value (£)

C.2 Bilevel optimisation solution methodology

As described in Appendix A, the standard method for solving a bilevel optimisation is to reformulate the two level bilevel optimisation into a single level, using KKT conditions. As the bilevel optimisation approach described in Chapter 4, Section 4.2.4 is linear, it can be reformulated into a single level, non-linear optimisation. Hence, the following KKT conditions were derived from equations (4.11)-(4.17).

$$K_j^C\tau - \lambda_{t,j}^1 + \lambda_{t,j}^2 - \mu_t^1 = 0, \qquad \forall t, j \in Tn, Jn \tag{C.1}$$

$$K_i^R\tau - \lambda_{t,i}^3 + \lambda_{t,i}^4 - \mu_t^1 = 0, \quad \forall t, i \in Tn, In \tag{C.2}$$

$$-\lambda_{t,k}^5 + \lambda_{t,k}^6 + \mu_t^1 + \tau\eta_k^{GES}\mu_{t,k}^2 = 0, \quad \forall t, k \in Tn, Kn \tag{C.3}$$

$$-\lambda_{t,k}^7 + \lambda_{t,k}^8 - \mu_t^1 - \tau\mu_{t,k}^2 = 0, \quad \forall t, k \in Tn, Kn \tag{C.4}$$

$$-\lambda_{t,k}^9 + \lambda_{t,k}^{10} - \mu_{t,k}^2 + \mu_{t+1,k}^2 = 0, \quad \forall t, k \in Tn, Kn \tag{C.5}$$

$$0 \le \lambda_{t,j}^1 \perp \left(P_{t,j}^C - \underline{P}_j^C\right) \ge 0, \quad \forall t, j \in Tn, Jn \tag{C.6}$$

$$0 \le \lambda_{t,j}^2 \perp \left(\overline{P}_j^C - P_{t,j}^C\right) \ge 0, \quad \forall t, j \in Tn, Jn \tag{C.7}$$

$$0 \le \lambda_{t,i}^3 \perp \left(P_{t,i}^R - \underline{P}_{t,i}^R\right) \ge 0, \quad \forall t, i \in Tn, In \tag{C.8}$$

$$0 \le \lambda_{t,i}^4 \perp \left(\overline{P}_{t,i}^R - P_{t,i}^R\right) \ge 0, \quad \forall t, i \in Tn, In \tag{C.9}$$

$$0 \le \lambda_{t,k}^5 \perp \left(P_{t,k}^{GES,ch}\right) \ge 0, \quad \forall t, k \in Tn, Kn \tag{C.10}$$

$$0 \le \lambda_{t,k}^6 \perp \left(\overline{P}_k^{GES} - P_{t,k}^{GES,ch}\right) \ge 0, \quad \forall t, k \in Tn, Kn \tag{C.11}$$

$$0 \le \lambda_{t,k}^7 \perp \left(P_{t,k}^{GES,dis}\right) \ge 0, \quad \forall t, k \in Tn, Kn \tag{C.12}$$

$$0 \le \lambda_{t,k}^8 \perp \left(\overline{P}_k^{GES} - P_{t,k}^{GES,dis}\right) \ge 0, \quad \forall t, k \in Tn, Kn \tag{C.13}$$

$$0 \le \lambda_{t,k}^9 \perp \left(E_{t,k}^{GES}\right) \ge 0, \quad \forall t, k \in Tn, Kn \tag{C.14}$$

$$0 \leq \lambda_{t,k}^{10} \perp \left(\overline{E}_k^{GES} - E_{t,k}^{GES}\right) \geq 0, \quad \forall t, k \in Tn, Kn \tag{C.15}$$

The stationary constraints are defined in (C.1)-(C.5), corresponding to each follower variable ($P_{t,j}^{C}$, $P_{t,i}^{R}$, $P_{t,k}^{GES,ch}$, $P_{t,k}^{GES,dis}$, $E_{t,k}^{GES}$). The complementary slackness conditions are defined in (C.6)-(C.15), where $0 \leq \alpha \perp \beta \geq 0$ is equivalent to $0 \leq \alpha, \beta \geq 0$ and $\alpha\beta = 0$. The complementary slackness conditions and follower constraints were integrated into the leader optimisation to give a single level, non-linear optimisation problem. The non-linearity came from the $\alpha\beta = 0$ constraint in all complementary slackness conditions. The complementary slackness conditions were linearized using the Fortuny-Amat method [147]. The Fortuny-Amat transformation replaces the complementary slackness conditions, given by $0 \leq \alpha \perp \beta \geq 0$, with the following:

$$0 \leq \alpha, 0 \leq \beta, \alpha \leq MU, \beta \leq M(1 - U),$$

Where U is a binary variable corresponding to a complementary slackness variable and M is a constant that is sufficiently large enough not to limit α or β. The bilevel optimisation given by equations (4.1)-(4.17) has been reformulated into a single-level, linear optimisation, given by a mixed-integer linear program (MILP). The objective function is given in (4.1), subject to the constraints (4.2)-(4.10), (4.12)-(4.17), (C.1)-(C.5) and the linearised equivalents of (C.6)-(C.15).

Appendix D

D.1 Chapter 5 nomenclature

Indices

b	Frequency response block index
i	Renewable generation index
j	Conventional generation index
k	Grid-scale energy storage index
m	Frequency response low index
n	Frequency response high index
t	Time index

Constants

Bn	Number of frequency response blocks
$\overline{E}^{bat}$	Maximum state of charge limit (%)
$E^{bat,ini}$	Initial battery state of charge limit (MWh)

$E^{bat,TET}$	Battery total energy throughput before end-of-life (MWh)
$\overline{E}_k^{GES}$	Grid-scale energy storage capacity (MWh)
$E_k^{GES,ini}$	Initial grid-scale energy storage state of charge (£/MWh)
In	Number of renewable generation types
Jn	Number of conventional generation types
$K_{b,m}^{FR,l}$	Frequency response low availability price (£/MW/h)
$K_{b,n}^{FR,h}$	Frequency response high availability price (£/MW/h)
$K_{b,t}^{DUoS}$	Distribution use of system charges (£/MWh)
K_i^R	Marginal cost of renewable generation (£/MWh)
K_j^C	Marginal cost of conventional generation (£/MWh)
Kn	Number of grid-scale energy storage types
Mn	Number of frequency response low markets
Nn	Number of frequency response high markets
$\overline{P}^{bat}$	Total battery power rating (MW)
$\overline{P}^{ex}$	Maximum local energy system export power (MW)
$\overline{P}^{im}$	Maximum local energy system import power (MW)
$\overline{P}_{b,m}^{FR,l}$	Maximum frequency response low power commitment (MW)
$\overline{P}_{b,n}^{FR,h}$	Maximum frequency response high power commitment (MW)
$P_{b,t}^{LD}$	Total local power demand (MW)
$P_{b,t}^{LR}$	Total local renewable power generation (MW)
$P_{b,t}^{TD}$	Inflexible power demand seen by the transmission system (MW)
$\overline{P}_j^C$	Maximum conventional generating power (MW)
$\underline{P}_j^C$	Minimum conventional generating power (MW)
$\overline{P}_k^{GES}$	Maximum grid-scale energy storage charge/discharge power (MW)
$\overline{P}_{b,t,i}^R$	Maximum available renewable generation (MW)
$\underline{P}_{b,t,i}^R$	Minimum available renewable generation (MW)
$T_m^{FR,l}$	Duration of frequency response low service (h)
$T_n^{FR,h}$	Duration of frequency response high service (h)
Tn	Number of time steps
$\eta^{bat,ch}$	Battery charging efficiency (%)
$\eta^{bat,dis}$	Battery discharging efficiency (%)
η_k^{GES}	Grid-scale energy storage round trip efficiency (%)
τ	Time interval (h)

Variables

$E_{b,t}^{bat,a}$	Available battery energy capacity (after degradation) (MWh)
$E_{b,t}^{bat}$	Total energy stored in batteries (MWh)
$E_{b,t,k}^{GES}$	Energy stored in grid-scale energy storage (MWh)
$K_{b,t}^{bid}$	Local energy system bid price to sell electricity (£/MWh)
$K_{b,t}^{offer}$	Local energy system offer price to buy electricity (£/MWh)
$P_{b}^{DC,h}$	Power committed to each frequency response high service (kW)
$P_{b}^{DC,l}$	Power committed to each frequency response low service (kW)
$P_{b}^{FFR,h}$	Power committed to Dynamic Containment high (kW)
$P_{b}^{FFR,l}$	Power committed to Dynamic Containment low (kW)
$P_{b,m}^{FR,l}$	Power committed to Firm Frequency Response low (kW)
$P_{b,n}^{FR,h}$	Power committed to Firm Frequency Response high (kW)
$P_{b,t}^{bat,ch}$	Total battery charging power (MW)
$P_{b,t}^{bat,dis}$	Total battery discharging power (MW)
$P_{b,t}^{ex}$	Power exported from local energy systems (MW)
$P_{b,t}^{im}$	Power imported to local energy systems (MW)
$P_{b,t}^{LR,curt}$	Local renewable power curtailed (MW)
$P_{b,t,i}^{R}$	Renewable power injected into grid (MW)
$P_{b,t,j}^{C}$	Conventional centralised power generation (MW)
$P_{b,t,k}^{GES,ch}$	Grid-scale energy storage charging power (MW)
$P_{b,t,k}^{GES,dis}$	Grid-scale energy storage discharging power (MW)
$\mu_{b,t}^{1}$	Shadow price from follower optimisation (dual variable for follower power balance equation) (£/MWh)
Π^{F}	Follower objective value (£)
Π^{L}	Leader objective value (£)

D.2 Bilevel optimisation solution method

D.2.1 KKT reformulation

The bilevel optimisation defined in Chapter 5 was solved by applying the KKT solution method described in Appendix A and Appendix C. As the follower optimisation in Chapter 5 is linear, KKT conditions were formulated to ensure optimality of the follower objective function. The following KKT conditions were defined.

$$K_j^C\tau - \lambda_{b,t,j}^1 + \lambda_{b,t,j}^2 - \mu_{b,t}^1 = 0, \qquad \forall b,t,j \in Bn,Tn,Jn \tag{D.1}$$

$$K_i^R\tau - \lambda_{b,t,i}^3 + \lambda_{b,t,i}^4 - \mu_{b,t}^1 = 0, \quad \forall b,t,i \in Bn,Tn,In \tag{D.2}$$

$$-K_{b,t}^{bid}\tau - \lambda_{b,t}^5 + \lambda_{b,t}^6 + \mu_{b,t}^1 = 0, \quad \forall b,t \in Bn,Tn \tag{D.3}$$

$$K_{b,t}^{offer}\tau - \lambda_{b,t}^7 + \lambda_{b,t}^8 - \mu_{b,t}^1 = 0, \quad \forall b,t \in Bn,Tn \tag{D.4}$$

$$-\lambda_{b,t,k}^9 + \lambda_{b,t,k}^{10} + \mu_{b,t}^1 + \tau\eta_k^{GES}\mu_{b,t,k}^2 = 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.5}$$

$$-\lambda_{b,t,k}^{11} + \lambda_{b,t,k}^{12} - \mu_{b,t}^1 - \tau\mu_{b,t,k}^2 = 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.6}$$

$$\begin{aligned} &-\lambda_{b,t,k}^{13} + \lambda_{b,t,k}^{14} - \lambda_k^{15}\big|_{b=Bn,t=Tn} - \mu_{b,t,k}^2 + \mu_{b+1,t=1,k}^2\big|_{b<Bn,t=Tn} + \mu_{b,t+1,k}^2\big|_{t<Tn} \\ &= 0, \quad \forall b,t,k \in Bn,Tn,Kn \end{aligned} \tag{D.7}$$

$$0 \le \lambda_{b,t,j}^1 \perp \left(P_{b,t,j}^C - \underline{P}_j^C\right) \ge 0, \quad \forall b,t,j \in Bn,Tn,Jn \tag{D.8}$$

$$0 \le \lambda_{b,t,j}^2 \perp \left(\overline{P}_j^C - P_{b,t,j}^C\right) \ge 0, \quad \forall b,t,j \in Bn,Tn,Jn \tag{D.9}$$

$$0 \le \lambda_{b,t,i}^3 \perp \left(P_{b,t,i}^R - \underline{P}_{b,t,i}^R\right) \ge 0, \quad \forall b,t,i \in Bn,Tn,In \tag{D.10}$$

$$0 \le \lambda_{b,t,i}^4 \perp \left(\overline{P}_{b,t,i}^R - P_{b,t,i}^R\right) \ge 0, \quad \forall b,t,i \in Bn,Tn,In \tag{D.11}$$

$$0 \le \lambda_{b,t}^5 \perp \left(P_{b,t}^{im}\right) \ge 0, \quad \forall b,t \in Bn,Tn \tag{D.12}$$

$$0 \le \lambda_{b,t}^6 \perp \left(\overline{P}^{im} - P_{b,t}^{im}\right) \ge 0, \quad \forall b,t \in Bn,Tn \tag{D.13}$$

$$0 \le \lambda_{b,t}^7 \perp \left(P_{b,t}^{ex}\right) \ge 0, \quad \forall b,t \in Bn,Tn \tag{D.14}$$

$$0 \le \lambda_{b,t}^8 \perp \left(\overline{P}^{ex} - P_{b,t}^{ex}\right) \ge 0, \quad \forall b,t \in Bn,Tn \tag{D.15}$$

$$0 \le \lambda_{b,t,k}^9 \perp \left(P_{b,t,k}^{GES,ch}\right) \ge 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.16}$$

$$0 \le \lambda_{b,t,k}^{10} \perp \left(\overline{P}_k^{GES} - P_{b,t,k}^{GES,ch}\right) \ge 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.17}$$

$$0 \le \lambda_{b,t,k}^{11} \perp \left(P_{b,t,k}^{GES,dis}\right) \ge 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.18}$$

$$0 \le \lambda_{b,t,k}^{12} \perp \left(\overline{P}_k^{GES} - P_{b,t,k}^{GES,dis}\right) \ge 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.19}$$

$$0 \le \lambda_{b,t,k}^{13} \perp \left(E_{b,t,k}^{GES}\right) \ge 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.20}$$

$$0 \le \lambda_{b,t,k}^{14} \perp \left(\overline{E}_k^{GES} - E_{b,t,k}^{GES}\right) \ge 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.21}$$

$$0 \le \lambda_k^{15} \perp \left(E_{b=Bn,t=Tn,k}^{GES} - E_k^{GES,ini}\right) \ge 0, \quad \forall b,t,k \in Bn,Tn,Kn \tag{D.22}$$

Equations (D.1)-(D.7) are the stationary conditions, corresponding to the follower variables ($P_{b,t,j}^{C}$, $P_{b,t,i}^{R}$, $P_{b,t}^{im}$, $P_{b,t}^{ex}$, $P_{b,t,k}^{GES,ch}$, $P_{b,t,k}^{GES,dis}$, $E_{b,t,k}^{GES}$). Equations (D.8)-(D.22) are the complementary slackness conditions, where $0 \le \alpha \perp \beta \ge 0$ is equivalent to $0 \le \alpha,\ \beta \ge 0$ and $\alpha\beta = 0$. The complementary slackness conditions and follower constraints are integrated into the leader optimisation.

D.2.2 Linearisation

There are two sources of non-linearity in the single level reformulation. The first is related to the constraint $\alpha\beta = 0$ in all complementary slackness conditions. The second is the $\mu_{b,t}^{1}\left(P_{b,t}^{im} - P_{b,t}^{ex}\right)$ term in the leader's objective function.

The complementary slackness conditions were linearized using the Fortuny-Amat method [147]. The Fortuny-Amat transformation replaces the complementary slackness conditions, given by $0 \le \alpha \perp \beta \ge 0$, with the following:

$$0 \le \alpha,\ 0 \le \beta,\ \alpha \le MU,\ \beta \le M(1-U),$$

Where U is a binary variable corresponding to a complementary slackness variable and M is a constant that is sufficiently large enough not to limit α or β.

Duality theory was used to address the second source of non-linearity by replacing the $\mu_{b,t}^{1}\left(P_{b,t}^{im} - P_{b,t}^{ex}\right)$ term in the objective function with an equivalent set of linear terms. The steps of the duality reformulation are as follows.

Define the follower optimisation dual objective function:

$$\begin{aligned}\max \quad \Pi^{LL,dual} = \sum_{b=1}^{Bn}\Bigg(\sum_{t=1}^{Tn}\Bigg(&\sum_{j=1}^{Jn}\left(\underline{P}_j^C\lambda_{b,t,j}^1 - \overline{P}_j^C\lambda_{b,t,j}^2\right) + \sum_{i=1}^{In}\left(\underline{P}_{b,t,i}^R\lambda_{b,t,i}^3 - \overline{P}_{b,t,i}^R\lambda_{b,t,i}^4\right)\\
&-\overline{P}^{im}\lambda_{b,t}^6 - \overline{P}^{ex}\lambda_{b,t}^8\\
&-\sum_{k=1}^{Kn}\Big(\overline{P}_k^{GES}\left(\lambda_{b,t,k}^{10}+\lambda_{b,t,k}^{12}\right) - \overline{E}_k^{GES}\lambda_{b,t,k}^{14} + E_k^{GES,ini}\lambda_k^{15}|_{b=Bn,t=Tn}\\
&+\mu_{b,t,k}^2 E_k^{GES,ini}|_{b=1,t=1}\Big) + \mu_{b,t}^1 P_{b,t}^{TD}\Bigg)\Bigg)\end{aligned} \tag{D.23}$$

The optimal solution of the follower optimisation is equal to the optimal solution of the dual optimisation ($\Pi^{LL} = \Pi^{LL,dual}$). Therefore, rearranging will give:

$$\sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\tau\left(K_{b,t}^{offer}P_{b,t}^{ex} - K_{b,t}^{bid}P_{b,t}^{im}\right) = \Pi^{LL,dual} - \sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\tau\left(\sum_{j=1}^{Jn}\left(K_j^C P_{b,t,j}^C\right) + \sum_{i=1}^{In}\left(K_i^R P_{b,t,i}^R\right)\right). \tag{D.24}$$

Equations (D.3) and (D.4) are multiplied by their corresponding variables to give:

$$K_{b,t}^{bid}P_{b,t}^{im}\tau = -\lambda_{b,t}^5 P_{b,t}^{im} + \lambda_{b,t}^6 P_{b,t}^{im} + \mu_{b,t}^1 P_{b,t}^{im} \tag{D.25}$$

$$K_{b,t}^{offer}P_{b,t}^{ex}\tau = \lambda_{b,t}^7 P_{b,t}^{ex} - \lambda_{b,t}^8 P_{b,t}^{ex} + \mu_{b,t}^1 P_{b,t}^{ex}. \tag{D.26}$$

Therefore,

$$\tau\left(K_{b,t}^{offer}P_{b,t}^{ex} - K_{b,t}^{bid}P_{b,t}^{im}\right) = \lambda_{b,t}^7 P_{b,t}^{ex} - \lambda_{b,t}^8 P_{b,t}^{ex} + \mu_{b,t}^1 P_{b,t}^{ex} + \lambda_{b,t}^5 P_{b,t}^{im} - \lambda_{b,t}^6 P_{b,t}^{im} - \mu_{b,t}^1 P_{b,t}^{im}. \tag{D.27}$$

From the KKT conditions,

$$\lambda_{b,t}^5\left(P_{b,t}^{im}\right) = 0 \tag{D.28}$$

$$\lambda_{b,t}^6\left(\overline{P}^{im} - P_{b,t}^{im}\right) = 0 \equiv \lambda_{b,t}^6\overline{P}^{im} = \lambda_{b,t}^6 P_{b,t}^{im} \tag{D.29}$$

$$\lambda_{b,t}^7\left(P_{b,t}^{ex}\right) = 0 \tag{D.30}$$

$$\lambda_{b,t}^8\left(\overline{P}^{ex} - P_{b,t}^{ex}\right) = 0 \equiv \lambda_{b,t}^8\overline{P}^{ex} = \lambda_{b,t}^8 P_{b,t}^{ex}. \tag{D.31}$$

Substituting (D.28)-(D.31) into (D.27) gives:

$$\tau\left(K_{b,t}^{offer}P_{b,t}^{ex} - K_{b,t}^{bid}P_{b,t}^{im}\right) = -\lambda_{b,t}^{8}\overline{P}^{ex} - \lambda_{b,t}^{6}\overline{P}^{im} + \mu_{b,t}^{1}\left(P_{b,t}^{ex} - P_{b,t}^{im}\right). \tag{D.32}$$

Substituting (D.32) into (D.24) gives:

$$\begin{aligned}\sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\left(-\lambda_{b,t}^{8}\overline{P}^{ex} - \lambda_{b,t}^{6}\overline{P}^{im} + \mu_{b,t}^{1}\left(P_{b,t}^{ex} - P_{b,t}^{im}\right)\right)\\ = \Pi^{LL,dual} - \sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\tau\left(\sum_{j=1}^{Jn}\left(K_j^C P_{b,t,j}^C\right) + \sum_{i=1}^{In}\left(K_i^R P_{b,t,i}^R\right)\right).\end{aligned} \tag{D.33}$$

Cancel out terms, invert signs to create $P_{b,t}^{im} - P_{b,t}^{ex}$ and rearrange to give:

$$\begin{aligned}&\sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\left(\mu_{b,t}^{1}\left(P_{b,t}^{im} - P_{b,t}^{ex}\right)\right)\\
&= -\sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\left(-\sum_{j=1}^{Jn}\tau\left(K_j^C P_{b,t,j}^C\right) - \sum_{i=1}^{In}\tau\left(K_i^R P_{b,t,i}^R\right) + \sum_{j=1}^{Jn}\left(\underline{P}_j^C\lambda_{b,t,j}^1 - \overline{P}_j^C\lambda_{b,t,j}^2\right)\right.\\
&+ \sum_{i=1}^{In}\left(\underline{P}_{b,t,i}^R\lambda_{b,t,i}^3 - \overline{P}_{b,t,i}^R\lambda_{b,t,i}^4\right)\\
&- \sum_{k=1}^{Kn}\left(\overline{P}_k^{GES}\left(\lambda_{b,t,k}^{10} + \lambda_{b,t,k}^{12}\right) - \overline{E}_k^{GES}\lambda_{b,t,k}^{14} + E_k^{GES,ini}\lambda_k^{15}|_{b=Bn,t=Tn}\right.\\
&\left.\left. + \mu_{b,t,k}^{2}E_k^{GES,ini}|_{b=1,t=1}\right) + \mu_{b,t}^{1}P_{b,t}^{TD}\right).\end{aligned} \tag{D.34}$$

Finally, (D.34) is a set of linear terms that is equivalent to the non-linear terms in the leader's objective function. Therefore, the first term in (5.1) can be replaced to give the linear objective function shown in (D.35).

$$
\begin{aligned}
\text{Min} \quad \Pi^{UL} = \sum_{b=1}^{Bn}\sum_{t=1}^{Tn}\tau\Bigg(\Bigg(&\sum_{j=1}^{Jn}\tau\left(K_j^C P_{b,t,j}^C\right) + \sum_{i=1}^{In}\tau\left(K_i^R P_{b,t,i}^R\right) - \sum_{j=1}^{Jn}\left(\underline{P}_j^C \lambda_{b,t,j}^1 - \overline{P}_j^C \lambda_{b,t,j}^2\right) \\
&- \sum_{i=1}^{In}\left(\underline{P}_{b,t,i}^R \lambda_{b,t,i}^3 - \overline{P}_{b,t,i}^R \lambda_{b,t,i}^4\right) \\
&+ \sum_{k=1}^{Kn}\left(\overline{P}_k^{GES}\left(\lambda_{b,t,k}^{10} + \lambda_{b,t,k}^{12}\right) - \overline{E}_k^{GES}\lambda_{b,t,k}^{14} + E_k^{GES,ini}\lambda_k^{15}|_{b=Bn,t=Tn}\right. \\
&\left. + \mu_{b,t,k}^2 E_k^{GES,ini}|_{b=1,t=1}\right) - \mu_{b,t}^1 P_{b,t}^{TD}\Bigg) + K_{b,t}^{UoS} P_{b,t}^{im}\Bigg) \\
&- \sum_{b=1}^{Bn}\left(\sum_{n=1}^{Nn}\left(K_{b,n}^{FR,h} P_{b,n}^{FR,h}\right) + \sum_{m=1}^{Mn}\left(K_{b,m}^{FR,l} P_{b,m}^{FR,l}\right)\right)
\end{aligned} \tag{D.35}
$$

The bilevel optimisation has been reformulated and linearised into a single level mixed-integer linear programming (MILP) problem. The final problem has the objective function in (D.35), the constraints defined in (5.2)-(5.8) (leader constraints), (5.10)-(5.19) (follower constraints), (D.1)-(D.7) and the linearised versions of (D.8)-(D.22).

D.3 Case study input data

Table D.I Conventional generation power limitations and price [168].

Conventional generation technology	Max power capacity (MW)	Min power capacity (MW)	Marginal price (£/MWh)
Nuclear	5,200	2,600	10.0
BECCS	1,200	0	25.9
Biomass	4,340	0	32.3
CCGT N1	1078.4	0	69.1
CCGT N2	1078.4	0	69.6
CCGT N3	1078.4	0	70.1
CCGT N4	1078.4	0	70.6
CCGT N5	1078.4	0	71.1
CCGT N6	1078.4	0	71.6
CCGT N7	1078.4	0	72.1
CCGT N8	1078.4	0	72.5
CCGT N9	1078.4	0	73.0
CCGT N10	1078.4	0	73.5
CCGT E1	919	0	75.5
CCGT E2	1341	0	77.0
CCGT E3	2208	0	77.5
CCGT E4	1526	0	78.0
CCGT E5	3536	0	78.5
CCGT E6	907	0	79.0
CCGT E7	2624	0	81.4
CCGT E8	625	0	81.9
CCGT E9	1389	0	82.4
CCGT E10	429	0	82.9
CCGT E11	3668	0	83.4
OCGT	2,404	0	115.0
Interconnectors	18,650	0	120.0

Table D.II Penetration scenarios for behind-the-meter battery storage [126].

	Scenario 1			Scenario 2		
Totals	**BTM battery power rating (MW) / energy capacity (MWh)**	**Grid battery power rating (MW) / energy capacity (MWh)**	**Total power system battery storage power rating (MW) / energy capacity (MWh)**	**Power rating (MW) / energy capacity (MWh)**	**Grid battery power rating (MW) / energy capacity (MWh)**	**Total power system battery storage power rating (MW) / energy capacity (MWh)**
Maximum (2030)	5555 / 6754	0 / 0	5555 / 6754	5555 / 6754	0 / 0	5555 / 6754
75%	4420 / 5298	0 / 0	4420 / 5298	4420 / 5298	1135 / 1456	5555 / 6754
50%	3284 / 3842	0 / 0	3284 / 3842	3284 / 3842	2271 / 2912	5555 / 6754
25%	2149 / 2386	0 / 0	2149 / 2386	2149 / 2386	3406 / 4367	5555 / 6754
Minimum (2020)	1014 / 930	0 / 0	1014 / 930	1014 / 930	4541 / 5823	5555 / 6754