# Investigating the potential value of electricity storage through market mechanisms in Great Britain

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# Declaration

I confirm that this is my own work and the use of all material from other sources

has been properly and fully acknowledged.

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## Abstract

The energy landscape of Great Britain is undergoing substantial changes, not least with rapidly increasing renewable generation and the closure of large fossil fuel plants. Energy storage has been advocated as an essential solution for mitigating the negative impact these changes may bring. Despite the apparent benefits, the uptake of energy storage in GB has been low, partly due to the uncertainty surrounding its economic feasibility. This study investigates the value of electricity storage as traded in currently available markets; three mechanisms are examined - a wholesale market, the Balancing Mechanism and the potential to provide '*ancillary services*' to the System Operator.

Optimisation models were developed to identify the maximum potential value in each market under a perfect foresight assumption, before applying a co-optimisation approach to assess a multi-market strategy. The sensitivity to perfect foresight was evaluated by testing simple storage management strategies. An econometric approach was then applied to examine the impact of increased wind generation on the markets and to extend this to a 20GW assumed scenario.

The results showed that substantially larger revenues were generated under co-optimisation compared to single market participation; these were also shown to be more resilient to inter-annual variability and market constraints due to the flexibility of the storage system in adjusting participation accordingly. Cost data from previous studies suggests that such revenues are still insufficient to support the deployment of Lithium-Ion batteries and Vanadium-Redox flow batteries. Pumped Hydro Energy Storage was shown to be the most economically viable, followed by Compressed Air Energy Storage, Advanced Adiabatic Compressed Air Energy Storage and Iron-Chromium Flow batteries. Replacing perfect foresight with alternative strategies caught between 52%-62% of revenues, highlighting the importance of forecasting accuracy when drawing on optimisation models. A 20 GW wind penetration scenario showed a clear depressing effect on prices. However, in most cases examined, additional revenues were generated for storage due to the increased price volatility presenting greater arbitrage opportunities. These results imply that while energy storage can be viable, caution should be made in the choice of technology and operational strategy with a clear preference for the co-optimisation of revenues across the three market mechanisms considered.

## Acknowledgements

This project would not have been possible without my supervisors Phil and Jacopo; Phil whose advice and guidance enabled me to turn an MSc dissertation topic into this PhD research project. I really appreciated your insights and reminders of the many facets of energy storage research. My great debt of gratitude also goes to Jacopo for sharing his perspective through much of this work, as fellow economists (or so I like to think). I am grateful to my examiners, Dr Phil Grünewald and Dr Ben Potter, for their very useful insights and in the process making this thesis a stronger piece of work.

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## List of Acronyms and Abbreviations

| | |
|---|---|
| **AACAES:** | Advanced Adiabatic Compressed Air Energy Storage |
| **APX:** | Amsterdam Power Exchange |
| **AR**: | Autoregressive (regression model) |
| **BSC**: | Balancing and Settlement Code |
| **BETTA**: | British Electricity Trading and Transmission Arrangement |
| **Bin**: | Binomial Distribution |
| **BM:** | Balancing Mechanism |
| **CAES:** | Compressed Air Energy Storage |
| **CAISO:** | California Independent System Operator |
| **CCGT:** | Combined Cycle Gas Turbine |
| **$CH_4$:** | Methane (Energy Storage) |
| **CSPA:** | Cross System Price Arbitrage |
| **D-CAES:** | Diabatic Compressed Air Energy Storage |
| **DECC:** | Department of Energy and Climate Change |
| **DUoS**: | Distribution Use of System |
| **ECVN:** | Energy Contract Volume Notification |
| **EFR:** | Enhanced Frequency Response |
| **EPRI:** | Electric Power Research Institute |
| **EU-ETS:** | European Union Emission Trading Scheme |
| **FCDM:** | Frequency Control by Demand Management |
| **Fe-Cr:** | Iron-Chromium (flow battery) |
| **FFR:** | Firm Frequency Response |
| **FGLS:** | Feasible Generalised Least Squares |
| **FPN:** | Final Physical Notification |
| **GBP:** | Great British Pound |
| **HH:** | Half-hourly |
| **$H_2$:** | Hydrogen (Energy Storage) |
| **Li-ion:** | Lithium-Ion (batteries) |
| **LP:** | Linear Programming |
| **MCP:** | Market Clearing Price |
| **MFR:** | Mandatory Frequency Response |
| **MILP:** | Mixed Integer Linear Programming |

**MINLP:** Mixed Integer Non-Linear Programming

**MISO:** Midcontinent Independent System Operator

**NaS:** Sodium Sulphur (Batteries)

**NETA:** New Electricity Trading Arrangements

**NIV:** Net Imbalance Volume

**NPSHYD:** Non-Pumped Storage Hydro

**NPV:** Net Present Value

**NYISO:** New York Independent System Operator

**OCGT:** Open Cycle Gas Turbine

**OLS:** Ordinary Least Squares

**PAR:** Price Average Reference

**PHES:** Pumped Hydro Energy Storage

**PJM:** Pennsylvania, New Jersey and Maryland (interconnection)

**RE:** Renewable Energy

**ROC:** Renewable Obligation Certificate

**RTE:** Round-Trip Efficiency

**SBP:** System Buy Price

**SMP:** System Marginal Price

**SO:** System Operator

**SOC:** State of Charge

**SSP:** System Sell Price

**ST:** Static (regression model)

**STOR:** Short Term Operating Reserve

**T & D:** Transmission and Distribution

**TRIAD:** Three half-hour settlement periods with highest electricity demand on the transmission system

**UC:** Unit Commitment

**Unif:** Uniform Distribution

**UPHES:** Underground Pumped Hydro Energy Storage

**VoLL:** Value of Lost Load

**VRB:** Vanadium Redox Battery

## List and description of variables

a: Parameter of the discrete uniform distribution representing the minimum range (1 MWh)

*APXPLAG:* APX price lags. Lags by 1 and 2 periods are shown as APXPLAG1 and APXPLAG2 respectively.

*APXV*: Traded volume in the APX market in MWh

*Arb:* Arbitrage Revenues

$AV_{FFR}$: Availability payment in £/MW/h. Initially this is set at £5/MW/h.

$Averageavcap$: The average STOR capacity which is actually available as opposed to declared capacity

b: Parameter of the discrete uniform distribution representing the maximum range (25 MWh)

britnedimport: England-Netherlands interconnector power flows. Takes a -ve value for export from GB and a +ve value for imports into GB.

$C$: Charge Volume in MWh

CCGT: Transmission level generation from Combined Cycle Gas Turbine power plants in MW

$D$: Discharge Volume in MWh

eastwestimport: Wales-Ireland interconnector power flows. Takes a -ve value for export from GB and a +ve value for imports into GB.

$effd$: Discharge Efficiency

$effc$: Charge Efficiency

frenchimport: French-England interconnector power flows. Takes a -ve value for export from GB and a +ve value for imports into GB.

imbapricelag: Imbalance price lag.

$k$: Number of parameters estimated in the restricted model of an F-test.

$m$: Number of parameters estimated in the unrestricted model of an F-test.

monthintdummy: Dummy variables for each month from February to December

moyleimport: Scotland-Northern Ireland interconnector power flows. Takes a -ve value for export from GB and a +ve value for imports into GB

$n$: Total number of time periods, equivalent to 17520 half-hourly periods in 2013.

*NIV*: Net Imbalance volume in the BM in MWh. NIV is -ve during system surplus and +ve during system shortage

*NPSHYD:* Transmission level generation from conventional hydroelectric power plants in MW

*NUCLEAR:* Transmission level generation from Nuclear power plants in MW

*OCGT:* Transmission level generation from Open Cycle Gas Turbine power plants in MW

*OIL*: Transmission level generation from oil/diesel power plants in MW

$P_{APX}$: Half-hourly APX spot market price in £/MWh

| | |
|---|---|
| pumping: | Transmission level demand from PHES facilities in pumping mode in MW |
| q: | Binomial distribution parameter representing the probability of success (20%) |
| quarterlypricefuelCOAL: | Quarterly fuel price of COAL in £/MWh |
| quarterlypricefuelGAS: | Quarterly fuel price of COAL in £/MWh |
| quarterlypricefuel OIL: | Quarterly fuel price of COAL in £/MWh |
| $RSS$: | Residual Sum of Squares |
| *RTE:* | Round-trip efficiency |
| $SBP$: | System Buy Price in £/MWh |
| $Seasonhrs$: | The total number of hours STOR was contracted for each season |
| $selfdis$: | Self-charge factor equivalent to 0.001 per half-hour |
| $SF$: | Low frequency scaling factor, for utilisation payments. equivalent to 1.25 |
| SPintdummy: | Dummy variable for each settlement period (from 2-48_ |
| $SSP$: | System Sell Price in £/MWh |
| $ST$: | Storage Volume (Level) in MWh |
| $ST_{MAX}$: | Maximum Storage Volume (Level) in MWh initially set at 600 MWh |
| $STORUVOL$: | The total volume of STOR serviced utilised in MWh |
| $UT$: | Utilisation Volume for the provision of FFR service in MWh |
| V: | Constant set a 25 |
| W: | Constant set at -25 |
| weekeffdummy: | Dummy variable representing weekdays, used to investigate weekday-weekend effect. |
| WIND: | Transmission level generation from wind farms in MW |
| $\pi_{CO-OP}$: | Co-optimised revenues in £ |
| $\pi_{APX}$: | APX arbitrage revenues in £ |
| $\pi_{BM}$: | BM arbitrage revenues in £ |
| $\pi_{FFR}$: | Revenues from the provision of FFR in £ |
| $\alpha$: | Binary variable in the APX market. Takes a value of 1 when discharging, zero otherwise. |
| β: | Binary variable in the BM market. Takes a value of 1 when discharging, zero otherwise. |
| $\lambda$: | Binary variable used for modelling charging and discharging bounds. |
| $\gamma$: | Binary variable taking a value of 1 when an FFR window is active, zero otherwise. |
| $\sigma$: | Binary variable taking a value of 1 when the FFR service is utilised, zero otherwise. |

# Chapter 1. Introduction

## 1.1. The need and role for electricity storage in GB

The energy landscape of Great Britain is set to witness substantial changes over the near future; there is a growing need for low carbon energy sources as the awareness of climate change and its impact increases. Furthermore, government policy has emphasised the need for greater energy security as well as affordability with the recent Energy Market Reforms being a testament to this need.

As a result of these drivers, the level of renewable energy penetration has steadily increased to 24.7% of total electricity generation in 2015 (DECC 2015). The growth in renewables has been largely driven by wind generation, until in recent years where solar PV generation has seen a remarkable growth. A high level of renewable energy penetration does not necessarily increase variability, especially when a mix of sources is considered (Coker 2011). However, this could increase renewable energy curtailment, a problem energy storage could alleviate by storing excess electricity.

The large combustion plant directive, a European directive which seeks to limit emissions, led to the shutdown of 7.7 GW of Coal power plants and 3.7 GW of Oil power plants as of 2016 (DECC 2016). The fall in capacity has reduced the system margin to low levels and highlighted the need for the Capacity Mechanism. Energy storage is expected to play a greater role in securing capacity during system stresses in the future.

From a demand side perspective, several major changes could potentially occur; over the next decades the total and peak demand for electricity could increase substantially depending on the extent of electrification of both heat and transport. The likelihood of such scenarios happening is unclear. National Grid has used future energy scenarios to model the variations in energy pathways[1]. Besides the impact of heat and transport on demand, solar PV embedded at distribution level effectively reduces demand, especially seen at the transmission level. National Grid (2015) estimates that demand could drop as low as 16.7 GW in 2020 and 5 GW by 2030 under the 'Consumer Power' scenario. Yet again, storage is one of the solutions to these problems, effectively able to shift demand from undesired peak periods to off-peak periods. Under a merit order of generation, electricity is likely to be cheaper during off-peak times compared to peak times and hence energy storage could also provide electricity cost savings to end-users. Furthermore, a fall in peak demand postpones the need for network reinforcements potentially at both transmission and distribution level.

[1] National Grid used four future energy scenarios; Consumer Power, Gone Green, No Progression and Slow Progression. More details of the scenarios can be found at National Grid (2015).

Finally, from a system balancing perspective, the need for very fast response ancillary services such as frequency response is expected to increase with the increase in renewable energy; as conventional generation is displaced from the grid, less synchronised rotating mass is present at any one time. This mass, in turn, determines the system inertia or rate of change of frequency when a fault is present. Therefore, with higher renewable energy levels, system inertia is lower and fast response services are required in even shorter timescales (National Grid 2015g).

Not all types of storage technologies can respond to rapid changes in frequency, batteries, however, are exceptionally fast with response times in milliseconds range. A large 6MW/10MWh lithium-ion battery installation at Leighton Buzzard provides frequency response to National Grid (Cooper et al. 2015). Storage is expected to play a bigger role in balancing demand and supply in the near future.

With extensive deployment of energy storage, synergies could occur such as the overall system efficiency gains from generation plants operating at their optimal levels (Strbac et al. 2012). Thus far, there is a clear need and role for storage within Great Britain’s energy future.

## 1.2. Barriers to the extensive deployment of energy storage

Although there is growing recognition of the benefits energy storage at an institutional level (such as DECC and National Grid) and even consumer level, there is a relatively low level of deployment. Besides the traditional pumped hydro energy storage facilities which still comprise the vast majority of energy storage capacity, less geographically constrained technologies have had a slow adoption. The two largest non-pumped hydro storage facilities in the UK are the 10 MW (100 MW planned) facility in Carrickfergus, Ireland and 6 MW facility in Leighton Buzzard, England(Renewable Energy Association 2015).

The small scale of these installations relative to power flows on the energy networks, despite significant benefits, indicates the presence of fundamental barriers. Through a wide array of studies, explored in Chapter 2, the uncertainty facing the economic feasibility of energy storage was highlighted. Römer et al., (2012) conducted interviews with german energy industry experts who stated that the business case for storage is not present and battery technologies are too expensive. Grunewald et al., (2012) show that industry opinion in GB is divided on whether storage is currently economically viable.

Storage systems are capital intensive and without guaranteed revenues, investment is risky. Under deregulated markets, the emphasis on competitivity means long-term ancillary services contract are deemed uncompetitive and thus not awarded to technologies which could benefit from the long-term financial security these contracts offer, as highlighted by Anuta et al., (2014).

Regulatory barriers extend further; energy storage does not as of yet have a clear classification in the networks and can be seen as both generation and/or demand depending on location and activity. Typically transmission and distribution network users pay either a generation or consumption (demand) tariff. Storage in this respect faces the double tariff problem potentially liable for a consumption and generation tariff.

Furthermore, legislation prevents network owners from owning large generation assets[2] and thus prevents an alignment of benefits. As a result, Grunewald et al., (2012) show that a choice of energy storage ownership on a commercial basis is not clear. They further stress that the fragmentation of benefits is a major challenge to the deployment of storage; for example, regulation currently prevents energy large-scale storage from being owned by a network owner and generating market revenue through arbitrage and "ancillary" services.

Recent studies (Moreno et al. 2015; Locatelli et al. 2015) investigate storage value by considering both wholesale market and ancillary service markets but do not evaluate the Balancing Mechanism (BM) as a source of revenues for storage. Yet the BM is a crucial component of energy balancing and quite often sees prices fluctuate in greater magnitude to those on the wholesale market.

In short, a clear knowledge of pure market-based storage value in Great Britain is still unknown. Yet there are clear opportunities for storage as new market mechanisms are created such as the Capacity Mechanism and the Enhanced Frequency Response 'ancillary' service by National Grid.

### 1.3. Aims & objectives

***The aim of this thesis is to investigate the maximum potential value of electricity storage within Great Britain under three different market mechanisms; a wholesale market, balancing mechanism and an ancillary service.***

This study will specifically investigate the following research questions:

- What type of market revenues storage can access in GB and how do they contribute to storage value?
- How do storage operations and value differ when a single market revenue stream is accessed compared to multiple revenue streams accessed simultaneously?
- How does storage value change in the presence of imperfect foresight or under a high wind penetration scenario?

[2] See (Anuta et al. 2014) for a more in depth discussion.

## 1.4. Scope and significance

The geographical focus of this research is on the GB system and half-hourly resolution data was gathered for all analyses. The study also approaches storage value from a market revenue perspective, without assuming a specific owner of the storage system. Rather, storage is owned and operated independently with the purpose of maximising economic returns. While the model used is technology neutral i.e. the complex physical modelling of each storage technology is not considered, basic parameters which distinguish these technologies from each other are included, such as Round-Trip Efficiencies (RTE), capital and O&M costs as well as other fundamental parameters.

The investigation of wind power impact under a high penetration scenario takes a simple approach, especially around wind power extrapolation, as an extensive wind power output forecasting model is not an objective of this study. Similarly, the econometric approach to investigate the impact of wind power on prices, applies the fundamental econometric theory in the design and evaluation of the regression models. Advanced forecasting techniques, drawing from the fields of econometrics, statistics and machine learning are beyond the scope of this research.

Nevertheless, the ability to answer the research questions lies within the scope of this study which investigates the potential value of storage from different market mechanisms which in turn determine the feasibility of storage investment. This aspect is critical for the successful deployment of storage and the lack of clarity on this issue is a concern for potential energy storage investors, as put forward by several studies (Grunewald et al. 2012; Römer et al. 2012; Anuta et al. 2014).

Initially, the maximum potential of storage value is determined, using a '*best case*' scenario (such as perfect foresight). These values do not represent a real-world operation but are rather indicative of the potential value. This distinction is further discussed in the limitations section of this thesis. Since energy storage projects are long-term investments with lifetimes spanning decades, some long-term consideration was made in terms of economic feasibility. Investigating the impact of wind power on storage value would raise the level of readiness of storage owners with respect to the changing aspects of the energy future landscape. Thus, the findings of this study are of particular significance to both, the academic community as well as the energy industry.

## 1.5. Structure overview

This thesis is structured as follows; Chapter 2 places this thesis in the context of other studies relating to the broader context of storage value. The thesis also describes the approaches taken by other authors in investigating similar problems, synthesizes their findings and critically evaluates their strengths and relevance with respect to the thesis.

Chapter 3 explains the background characteristics of the revenue mechanisms and how they indicate a potential avenue for storage revenues. A brief overview of the different types of market revenue mechanisms in GB is given as well as their role in generating storage revenues.

With the potential for revenue determined, the next step involves looking at how to capture this value. Thus, in Chapter 4, the methods used to investigate storage value is described, examined and evaluated. The chapter also explains the derivation of the models developed as well as the fundamental assumptions underlying the research approach.

Partial results from these models are shown in Chapter 5 which confines its findings to those of storage operation determined by a single revenue stream. As storage provides a single service at one time, effects such as seasonal and annual impacts are explored. The impact of optimisation horizons and other parameters on revenues is derived.

When other revenues are combined, differences in storage operation and value arise; these are explored in Chapter 6. Specific effects which drive those differences are isolated and analysed. A sensitivity analysis is carried out to gauge the impact of parameters, such as efficiency and energy capacity, on storage operation and value. The lifetime economic feasibility of six storage technologies is evaluated based on those revenues, identifying the most suitable type of energy storage.

Chapter 7 relaxes the perfect foresight assumption to investigate how simple strategies fare in capturing storage value. Wind power is expected to play a greater role in the UK's energy future; however, its impact on the value of storage is not clear and this is explored in this chapter. The findings of Chapters 5,6 and 7 are discussed in Chapter 8. The impact, implications and limitations of the research are argued. Finally, Chapter 9, summarises the key findings, their significance and conclusions that arise from this whole thesis.

# Chapter 2. A survey of studies on storage value

## 2.1. Introduction

There are numerous studies exploring storage value; they differ in scope, geographical focus and general approach. As a result, wide variations in values have been reported, hence limiting their usefulness, especially within the context of GB. This Chapter analyses the major studies which have sought to address storage value, highlighting their contribution to how our understanding of storage value has improved, as well as pointing out the areas which remain unknown and merits further investigation.

Quantifying storage value is challenging; on one hand, there is no clear absolute measure of value and on the other hand, the benefits themselves can be difficult to quantify. Markets provide a means to estimate the willingness to pay for storage services; however not all storage benefits are traded in a market. System benefits of energy storage such as Transmission and Distribution (T&D) investment deferral are usually measured as the opportunity cost of providing these benefits; in other words, the savings storage can achieve by foregoing the next best alternative, usually traditional reinforcement. These measures are inconsistent since the willingness to pay for the reliable provision of electricity can its cost of production, often by a substantial amount; the industry uses the Value of Lost Load (VoLL) to measure the cost of not providing electricity. In a study by London Economics (2013), it was shown that the VoLL ranges between £7,000/MWh and £40,000/MWh. By comparison, the APX (short-term) market price for electricity ranged from £0/MWh-362/MWh in 2014.

Some storage benefits are rewarded with a clear revenue stream from market mechanisms; for example, the provision of power to stabilise system frequency response is compensated by payments by the System Operator (SO) – National Grid. Other benefits are not currently valued explicitly by the markets such as the deferral of investment into generation assets, which is a clear added benefit of storage. The benefits of storage are listed in figure 2.1, showing that there are at least 4 types of benefits for the whole system which are not currently compensated in the markets.

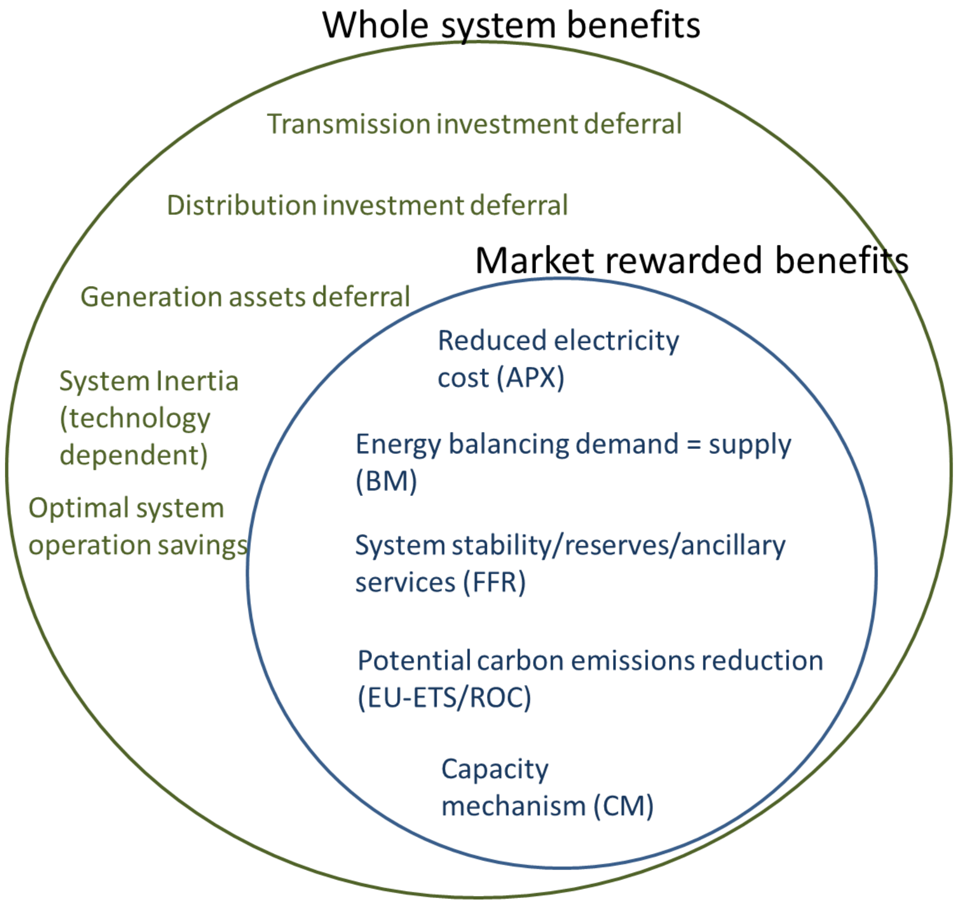


***Figure 2.1:*** *Representation of the disparity between whole system benefits of storage and the market rewarded benefits, with an example of the market mechanism given in brackets.*

The distinction in storage valuation is important as market mechanisms directly support storage investment which is critical to its successful deployment. This approach is directly relevant to stakeholders expecting a positive return on investment. A whole system benefits approach is more relevant to policy makers, giving a comprehensive overview of all potential benefits storage may bring and therefore adjust policy accordingly. Strbac et al., (2012) have used precisely a whole system modelling approach to evaluate the benefits of storage under energy future scenarios of varying levels of RE penetration and Electric Vehicles uptake.

In the introduction, one of the main barriers to the deployment of energy storage was the lack of clear profitability, as stakeholders have previously expressed (Grunewald et al. 2012). Therefore, in order to determine the potential revenues to a private investor, a market-oriented approach is necessary and assumed throughout this thesis.

## 2.2. Revenues under a pure revenue maximising objective

In the presence of two different prices, a 100% efficient storage system will generate a profit by charging at the low prices and discharging at any higher price. This process is commonly referred to as arbitrage. Arbitrage revenue is the most accessible form of revenues for storage and also, as a result has been the focus of the vast majority of studies. This section describes previous studies on arbitrage revenues storage operation generates, showing the wide range of values found. A direct comparison of arbitrage revenues across the studies is difficult due to parameter differences such as Round-Trip Efficiency (RTE), market characteristics and modelling approaches. However, there is sufficient evidence to support the claim that arbitrage revenues are market specific and hence cannot be generalised. A storage system seeking to maximise arbitrage revenues can be dedicated solely to market operation. Under this configuration, Walawalkar et al., (2007) investigated arbitrage revenues in the New York power market – they specifically focused their study on Sodium Sulphur (NaS) batteries and flywheels. Through an NPV analysis, they showed that arbitrage revenues alone are not sufficient to support these storage technologies, in all regions of New York, except New York City. Arbitrage revenues ranged from \$25/kW-yr to \$240/kW-yr across three regions. Using market data from four regional US markets, Drury et al., (2011) show that arbitrage revenues are strongly influenced by annual and locational variations in prices, by a factor of up to 3 times whereas reserves revenues are not significantly affected by such variations. Similarly, Bradbury et al., (2014) focused their investigation on market revenue variability on a wider selection, 7 US markets. Using the same parameters across all markets, they were able to show that arbitrage revenues varied between \$145/kW-yr and \$255/kW-yr based solely on the market prices. These studies, however, all focused on US markets.

At an international level, arbitrage revenues vary considerably; Connolly et al., (2011) showed that under the low-cost conditions of €470/kW at 3% discount rate, economic feasibility is achieved for three of the 6 markets, shown in figure 2.2. At a high cost of €2170/kW and a 6% discount rate none of the six markets show consistent profits. Their study is of particular importance in highlighting storage revenue variation across several countries; since they use the same storage model for all countries, a direct comparison and interpretation are possible. Inevitably, such comparative work is influenced by fluctuations in exchange rates, fuel costs and other economic conditions. Nevertheless, specific market differences are reflected in the arbitrage values; while Connolly et al., (2011) found high arbitrage values in the Alberta market in Canada, Safaei & Keith (2014) who studied the same market explain that the Alberta market experiences conditions which favour high peak prices such as the low capacity factor of peak plants, prices being determined in real time and lack of capacity market.

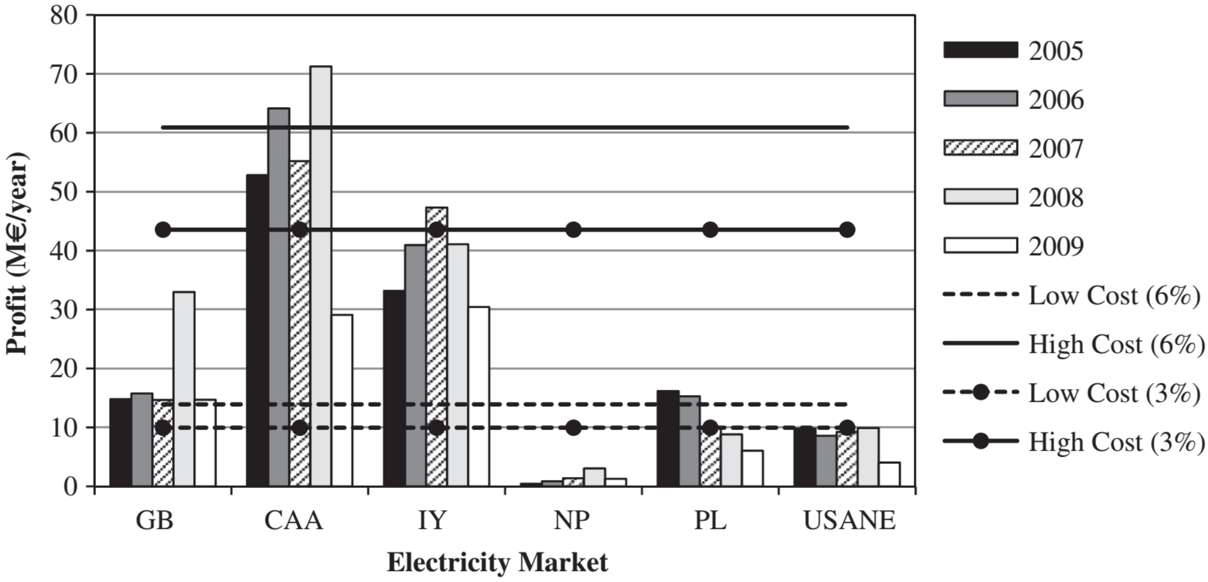


***Figure 2.2:*** *Variation in arbitrage revenues across six markets Great Britain(GB), Alberta in Canada (CAA), Italy (IY), Nordpool (NP), Portugal (PL) and New England (USANE) from 2005-2009. Source: Connolly et al. (2011)*

The highest revenues in figure 2.2 were over 20 times higher than the lowest revenues. Large variations in arbitrage revenues across regions imply that generalisation of storage value is not possible and instead should be evaluated within the context of the specific market. Consequently, several studies have focused entirely on arbitrage revenues from specific market locations; Sioshansi et al., (2009) use a technology-neutral model, to calculate the maximum revenues storage can achieve in the Pennsylvania, New Jersey and Maryland (PJM) market. Over a 6-year period, they found arbitrage revenues vary between \$60/kW-yr to \$115/kW-yr. The study also addressed the practical issues concerning optimised storage operation such as energy capacity sizing for arbitrage revenues, the absence of perfect foresight and the reduction of arbitrage revenues from a storage system's own operations. Yucekaya (2013) calculated the value of a CAES system deriving pure arbitrage revenues over 30 years in the Turkish power market. More recently, McConnell et al., (2015) modelled storage operation in Australian markets and showed revenues ranging from \$50-350/kW-yr (Australian dollars). These studies show that arbitrage value not only varies substantially across markets but also from one year to the next and therefore caution should be exercised for any value stemming from a single year.

### 2.2.1. Reserve and other revenues

Apart from arbitrage revenues, storage systems can offer services to a system operator, usually in the form of reserves. These offer fixed payments in return, usually independent of arbitrage revenues. Storage can offer reserve services as a completely dedicated unit or allocate part of its capacity to those services and, at the same time, derive revenue from other sources like arbitrage. Walawalkar et al., (2007) also considered the provision of frequency response in their study; shown in figure 2.3, they found that flywheels dedicated to the provision of frequency response are more profitable than a

Sodium-Sulphur (NaS) battery deriving arbitrage revenues. Hence, they put forward the possibility of a niche market for NaS batteries.

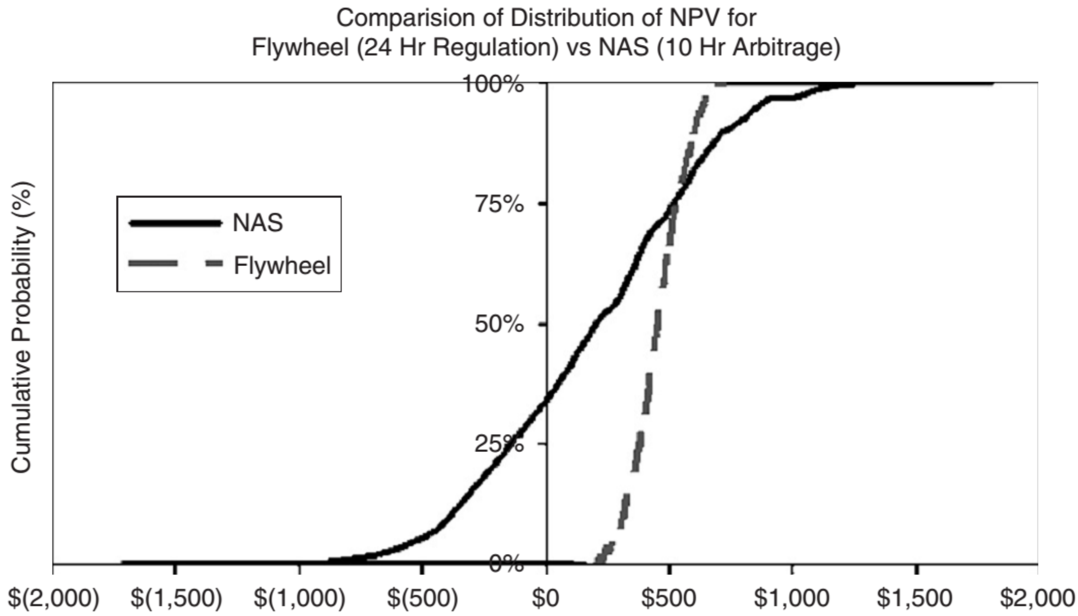


***Figure 2.3:*** *Probability distribution of revenues from arbitrage for a NaS storage system compared to revenues frequency regulation provision by Flywheels storage in New York. Source: Walawalkar et al., (2007)*

In Denmark Ekman & Jensen (2010) considered a number of alternative revenue sources besides spot market arbitrage; the storage system provided regulating power, balancing demand and supply, primary reserves, secondary reserve and black start services. They showed that while arbitrage revenues were not adequate to cover the costs of storage, there are viable niche opportunities for the provision of reserves, shown in figure 2.4.

In Texas, Fares et al., (2014) have looked at how VRB can provide frequency response. They use an optimisation model with storage providing both upregulating and downregulating service to the SO. The preference for reserves revenues has also been shown by Das et al., (2015); under higher levels of wind penetration the authors show that CAES favour ancillary services revenues at the expense of arbitrage revenues, at times even incurring a loss from arbitrage revenues at 60% wind penetration in order to derive additional ancillary services revenues.

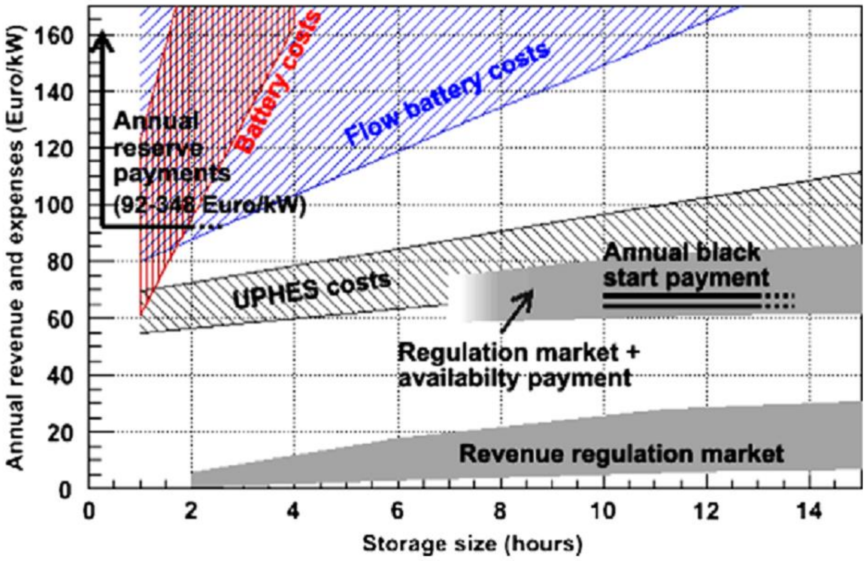


***Figure 2.4:*** *Relative revenues from batteries and Underground Pumped Hydro Energy Storage (UPHES) in Denmark. Source: Ekman & Jensen (2010)*

Safaei & Keith (2014) investigated the difference between a traditional CAES system and one whereby the compressor is sited close to a heat load such that the waste heat from compression can be used for district heating, referred to as D-CAES. The authors optimise storage operation for arbitrage revenues; however, with D-CAES additional payments from heat generation are also factored in the total revenues. D-CAES was shown to be more profitable than CAES when the separation distance between the storage caverns and the compressor is below 75 km.

These studies thus show that additional payments can support additional capital costs and change the economics of a project. In fact, reserve payments have often been shown to surpass arbitrage revenues favouring the provision of reserves rather than wholesale market operation under such circumstances.

## 2.3. Storage revenues as a secondary objective

Another approach to investigating storage value is pre-defining a function of storage and subsequently evaluating its benefits. In those cases, arbitrage revenues are used as a measure of storage profitability; however, profit maximisation is not its primary function. A common example of this is storage paired with wind generation. A large number of studies have looked at arbitrage value storage can achieve when paired with wind generation.

Within a whole system's model (EnergyPLAN as the modelling tool), Lund & Salgi (2009) investigate the value of CAES under high wind penetration in Denmark. Primarily, the objective is not to maximise arbitrage revenues but rather to minimise wind curtailment and fossil fuel consumption. Additionally, the CAES system seeks to achieve load levelling and help integrate wind energy under one of the approaches undertaken. The arbitrage revenues derived fell far below the cost of the CAES system; however, when operated as a revenue maximising function and with the addition of reserve revenues, the storage system was found to be profitable. These findings are particularly important to the approach taken in this thesis; pre-defining an application of storage is actually sub-optimal for revenue maximisation and therefore in order to fully investigate the economic feasibility of storage, revenue maximisation has to be the primary objective of the system.

Nyamdash et al., (2010) investigate the use of storage with wind power in the Irish system; storage charges from wind power and discharges into the Single Electricity Market. Three scenarios of low, medium and high wind penetration are explored, however, none of the technologies explored were feasible based on the arbitrage revenues derived. Also using Ireland as a case study, Foley & Díaz Lobera (2013) showed a potentially negative impact of storage; in principle under a gross pool market, storage systems can charge on cheap electricity and discharge at peak time, hence reducing the high Market Clearing Prices (MCP), on average. However, they found that CAES actually increases the average MCP; this occurs due to efficiency losses of the storage system. As a result, revenues for most generators and including CAES were shown to increase.

Using a similar approach, Grünewald et al., (2011) looked at arbitrage revenues storage can generate in GB, under a high penetration scenario using merit order of generation dispatch to calculate prices. The role of storage was to reduce wind curtailment by balancing the energy system. Arbitrage benefits were also evaluated to show that at levels of renewable energy penetration greater than 30 GW, storage technologies become economically viable. On a smaller scale, wind sited storage is explored by Hessami & Bowly (2011) who couple storage and wind farms in Portland, Australia. Arbitrage revenues can be generated from wind power and the authors show that annually, 8%-15% of return on capital investment can be expected from such a configuration.

Denholm & Sioshansi (2009) compare the case where CAES operates as a load sited system to the case where the system is sited with a wind farm, and hence save on transmission investment and reduce wind curtailment. To the wind farm owner, the benefits of choosing storage over transmission capacity upgrade become more apparent as transmission costs increase. Taking into account the intermittent nature of wind power, the authors argue, there is a danger of oversizing and thus underutilized transmission capacity. The study looks at wind and storage in two configurations: firstly, wind and storage being decoupled and operated independently as 2 separate entities and secondly, wind and storage being co-sited but operated in such a way as to maximise benefits. Under the latter configuration, transmission investment is reduced, however at the expense of storage operation flexibility. In other words, greater arbitrage opportunities are available to CAES operating as a load sited system with no restriction rather than wind sited operation constrained by transmission capacity and wind farm output. The fact that coupling storage with wind farms reduces value was also shown by Lund & Salgi (2009); They evaluated the benefits of CAES under very high wind penetration (59% and more); these benefits consist of the variable and fuel cost savings with CAES over excess electricity and higher operational costs without CAES. The results show, despite different fuel costs assumptions, that the values are far below the annual investment cost. Even in the most optimistic case, the value is less than a third of investment costs. However, when they use CAES as a business oriented case, co-optimising revenues from spot market arbitrage and reserves, they show that the system is profitable.

Fertig & Apt (2011) use a similar approach to investigate CAES co-located with wind farms. Four configurations are explored: In the first configuration, the system operates on hourly energy prices and determines when the wind farm is injecting power into the grid, to the CAES system or spilling energy, based on price thresholds. The second configuration looks at a capped maximum price with a capacity payment. The third configuration the Wind-CAES system operates at a fixed contract price equivalent to the annual average price to simulate a baseload generator operating at 80% capacity factor. Finally, the Wind-CAES system's operation in the regulation market is investigated separately. These configurations respectively generated $900 million, £300 million, £110 million and £100 million. Comparatively, the standalone wind farm generated $245 million profit.

Besides arbitrage in the wholesale market and the provision of reserves, storage value can be calculated in terms of penalty avoidance for not meeting scheduled power for a wind farm. Turker et al., (2013) consider the direct balancing cost of forecast errors from wind power and the extent to which storage can mitigate these costs. They cite the model of the Spanish market whereby penalties are imposed at 10% of the current market price. The chosen storage technology is VRB which the authors find to be economically unfeasible; however, if the penalty multiplier was increased by 1.5 times the market price, the storage system would have a payback of 10 years, beyond which the investment would have recovered its total costs and generated profits.

A more comprehensive study on the potential of storage value, under different future energy pathways, was undertaken by Strbac et al., (2012). Using a whole system approach in GB, whereby the objective function is to minimise costs of generating electricity, the authors calculate the transmission and distribution investment deferral, generation investment foregone and operational savings arising from generators operating within their optimal range. This system approach is particularly useful to investigate the potential value of storage which is not realisable under current market conditions, as shown earlier in figure 2.1. The study, by choosing optimal capacities for storage, interconnector capacity and demand side response shows that there is a distinct need for energy storage within the future GB energy requirements, even in the presence of alternatives.

In order to understand the market value of storage under a high wind penetration scenario in GB, an understanding of the impact of wind generation on the GB markets is required. Green & Vasilakos, (2010) explored the impact of a high wind penetration scenario on the wholesale market in Great Britain. Using weather data, a 30 GW wind penetration scenario is simulated using the supply cost function for each type of generation to effectively create a merit order curve. The authors show that under a high wind penetration scenario, the price volatility increases. They also investigate the competitive behaviour of generators under such a scenario; initially they used 6 symmetric firms to represent the supply function and later this is reduced to 2 symmetric firms. Under the latter, prices were higher and therefore, while the cost of wind generation is generally lower than mid-merit and peaking plants, prices may rise as competition falls. More recently, Cleary et al., (2016) have used *PLEXOS* modelling software to simulate high wind penetration scenarios for the UK. Contrasting a 14 GW and 25 GW wind penetration levels, the authors show that the System Marginal Price is lower as wind increases. This is further shown as wind energy imports from Ireland is allowed, depressing prices even more.

As shown from these previous studies, there is an overwhelming focus on energy storage value when confined to the support of wind generation. They differ from those mentioned in the previous sections as they have a primary function different from revenue generation and subsequently, their profitability is evaluated with respect to this function. Such a situation was shown to be sub-optimal for revenue maximisation, however, there is a clear application for storage. In other words, the approach to storage operation can be viewed as either one that is completely defined by market revenues or one that is defined by a specific application.

## 2.4. Modelling approaches towards storage value

Studies investigating storage value have used models with distinct attributes; some characteristics are featured in some and absent in others, such as self-discharge and start-up costs. However, the general common feature of all these models is a core net revenue function - the difference between revenues and costs. These revenue functions can be optimisation models or simply based on fixed dispatch strategies. Special consideration should be paid to some modelling parameters; for example, in the case of an optimisation model, an optimisation horizon has to be chosen. While such considerations are model specific, there are broader considerations faced by storage revenue models such as the treatment for the foresight of prices and other market conditions. This section investigates the treatment of foresight by previous studies as well as alternatives in its absence.

### 2.4.1. Energy storage technologies and value

The concept of energy storage is defined by a set of parameters, which stem from a specific energy storage technology; for example, the round-trip efficiency parameter of an energy storage system, in practice, is dependent on the type of energy storage technology and processes involved during its operation. In the short run, these parameters affect revenues. In the long run, the capital costs of these technologies affect the economic feasibility of the project.

Few studies have explored the revenues generated by storage systems, without a specific choice of technology; Sioshansi et al., (2009) have used a generic energy storage system to look at arbitrage revenues in the Pennsylvania, New Jersey and Maryland (PJM) electricity market. Bradbury et al., (2014), similarly, explored arbitrage revenues across several US markets. McConnell et al., (2015) used a generic storage system to calculate arbitrage and other revenues in the Australian markets.

On the other hand, CAES and PHES, as relatively mature large scale energy storage technologies, have been the focus of several studies on storage value (Lund et al. 2009; Deane et al. 2010; Sioshansi et al. 2011; Drury et al. 2011; Loisel 2012; Yucekaya 2013; Foley & Díaz Lobera 2013; Pérez-Díaz et al. 2015; Chazarra et al. 2016). Nevertheless, other relatively less mature technologies have been investigated for their potential for specific applications such as Vanadium Redox Batteries (VRB) for the provision of frequency response in Texas by Fares et al., (2014) and Advanced Adiabatic Compressed Air Energy Storage (AACAES) for the provision of reserves and generate arbitrage revenues (Drury et al. 2011). These applications have also been the focus of Underground Pumped Hydro Energy Storage (UPHES) by Ekman & Jensen, (2010). A general review of the energy storage technologies including their applications, advantages and parameters is given by Chen et al., (2009)

In this thesis, the approach to calculating storage revenues initially assumes a generic energy storage system, with focus on the market revenues. Subsequently, a number of parameters relating to six technologies, namely PHES, CAES, AACAES, VRB, Lithium-Ion (Li-ion) and Iron-Chromium flow batteries (Fe-Cr), are featured in the model for a lifetime assessment of their economic viability. These models and parameters are described in Chapter 4.

### 2.4.2. Optimisation models, horizons and algorithms

A storage revenue optimisation model in its simplest form can be modelled a Linear Programming (LP) problem; Denholm & Sioshansi (2009) used LP to evaluate arbitrage revenues in the PJM market. (Bradbury et al. 2014) similarly used linear optimisation to investigate arbitrage values across several storage technologies. In Austrian power markets, Kloess & Zach (2014) used an LP model to operate on arbitrage values taking into account variable costs. More recently McConnell et al., (2015) also used an LP model to determine arbitrage values in the Australian markets.

More complex models have been evaluated using Mixed Integer Linear Programming (MILP); storage optimisation problems often have binary variables at their core and hence the use of MILP. Drury et al., (2011) have used MILP to compare the performance of CAES vs AACAES under co-optimisation of revenues. He et al., (2011) used MILP to determine a business strategy for storage while Yucekaya (2013) used MILP, to evaluate a CAES revenue model with several binary variables. More recently Moreno et al., (2015) use MILP to evaluate co-optimised storage operation embedded in distribution networks whereas Chazarra et al., (2016) use an MILP model to schedule PHES output.

Storage has also been modelled through the unit commitment and economic dispatch problem; Foley & Díaz Lobera (2013) have used PLEXOS (Energy Exemplar n.d.) to model CAES participation in Ireland.

The objective function is the minimisation of the whole system electricity cost for each period, consisting of generation costs and uplift costs for each generator[3]. Similarly, Das et al., (2015) investigate the co-optimised value of storage in the US under different wind penetration scenarios. The model first solves the Unit Commitment problem of conventional generation based on wind and load forecasts. The next phase looks at determining the most economic dispatch solutions taking into account locational marginal prices and Market Clearing Prices (MCP) for wholesale and ancillary services respectively. The authors use an MILP technique to minimise within the transmission system, the cost of wholesale energy, spinning reserve, non-spinning reserve, upregulating reserve and downregulating reserve as well as penalty payments for not serving the load.

While these studies have clearly presented an optimisation model; other studies refer to the use of optimisation without the explicit description of an optimisation algorithm or mathematical notation. Rather the term 'optimisation' is used to refer to a profit generating regime rather than profit maximising one. For example, Ekman & Jensen (2010) refer to their arbitrage strategy as one that maximises revenues; the authors argue that by imposing the efficiency adjusted selling price to be greater than the buying price, maximum revenues are derived, shown in equation 2.1. Variables n and p represent the energy volume and prices respectively. $P_{buy}$ and $P_{sell}$ are price thresholds for buying and selling, shown in figure 2.5. The use of price thresholds is sub-optimal as a true optimisation algorithm cannot use fixed price thresholds as a criterion in the presence of price variations.

Similarly Locatelli et al., (2015) refer to their approach as an optimisation method, however, it is not clear whether the model actually performs an optimisation. They propose that storage operates similar to a generator, discharging when efficiency adjusted prices are greater than the marginal cost, in their model this being the variable operating cost. This is also one of the conditions Ekman & Jensen (2010) used. While this is a necessary condition for maximum profitability it is not a sufficient one. As opposed to an optimisation algorithm, the use of price thresholds to determine charging and discharging results in missed opportunities for arbitrage trade. Under this approach, when the net selling price is greater than the threshold (any price above marginal costs), discharging will take place immediately irrespective if there is a better trade later. By contrast an optimisation models will pick the best trades over the optimisation horizon even if this means foregoing present discharge for a more lucrative discharge later.

For example, a storage system which has a choice between discharging 1 MWh of energy at a £25 profit now or a £75 profit in the next period will choose the former approach (that marginal revenues

[3] Uplift costs are defined as additional costs to marginal costs such as start-up costs and other variable and fixed costs.

is greater than marginal cost or an equivalent price threshold). However, an optimisation algorithm would defer discharge for the next period to maximise profits.

A further limitation of Locatelli et al., (2015) is the treatment of Round Trip Efficiency (RTE); it is not explicitly included in the model. Instead, efficiency is included as a fixed cost, calculated by the efficiency loss on the average price of electricity at £34/MWh. As an example, the authors show that an 85% RTE PHES would lose £5.1 per MWh (charged and discharged). This static treatment of efficiency, through the utilisation of a fixed cost, is likely to result in sub-optimal dispatch and hence sub-optimal profits.

$$income = \int_{P_{sell}}^{\infty} n \cdot p \cdot dp - \int_{0}^{P_{buy}} n \cdot p \cdot dp$$

(2.1); (Ekman & Jensen 2010, p.1146)

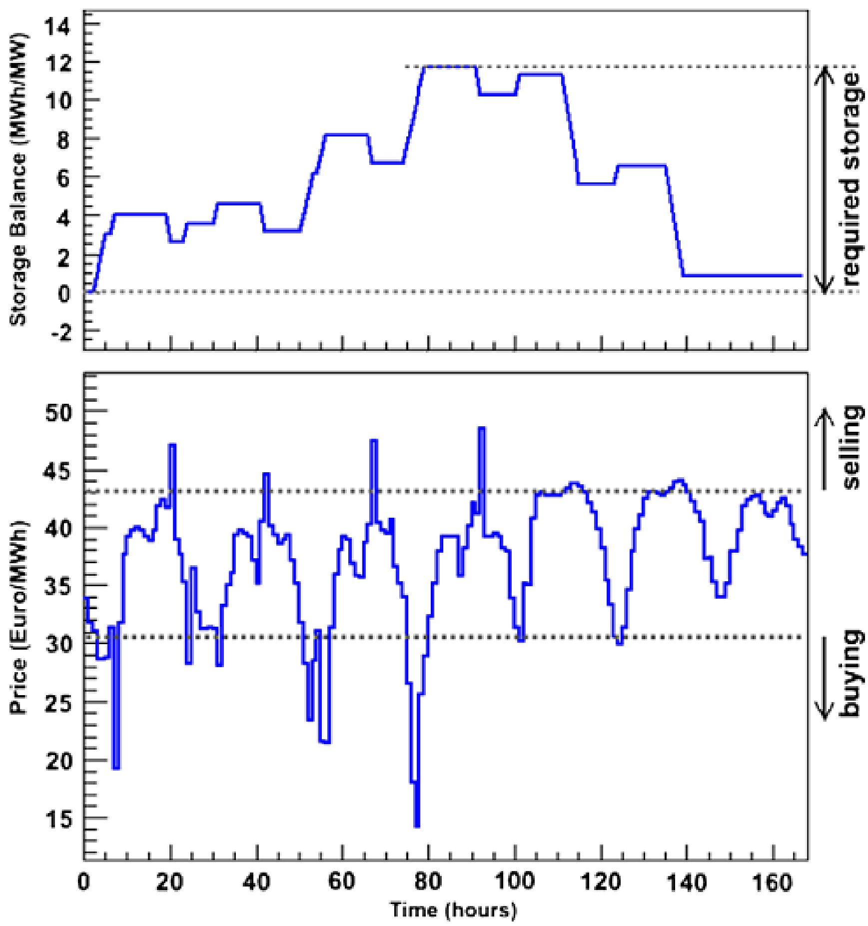


***Figure 2.5:*** *Example of a storage energy capacity scheduling (top) and trading strategy (bottom)*
*Source: Ekman & Jensen (2010)*

Generally, an optimisation model returns the value of an objective function and the decision variables associated with this value. For a storage problem, the decision variables are usually charging and discharging volumes for discrete time periods. Hence the number of decision variables evaluated determines the time period considered for the optimisation problem; for example, evaluating storage operations for two half-hourly periods implies the model is evaluated over a one-hour optimisation horizon.

In previous studies the length of the optimisation horizon has been chosen, without explicit justification; Chazarra et al. ,(2016) and Sioshansi et al., (2011) use a 1-week horizon. Sioshansi et al., (2009) and Drury et al., (2011) used a 2-week optimisation horizon in their model to allow for inter and intra-day trades. Kloess & Zach (2014) and Yucekaya (2013) used a 1-year optimisation horizon. Therefore, there is particular merit in exploring the impact of optimisation horizons on storage value and whether clear preferences exist.

### 2.4.3. Foresight and bidding strategies

An optimisation model will maximise revenues from any price differentials, large or small. Therefore, accurate price forecasts are essential, especially in the presence of small price differentials otherwise, the arbitrage trade may result in a loss. Many studies have used perfect foresight assumptions initially to evaluate their model (Ekman & Jensen 2010; Kanakasabapathy & Shanti Swarup 2010; Drury et al. 2011; Locatelli et al. 2015). While this approach is justified when exploring revenue potential, other studies have taken a more realistic approach by including operational strategies to capture storage value. This section looks at the different storage operating and bidding strategies previous studies have proposed.

Sioshansi et al., (2009) used the past 2 weeks' prices to derive the storage operation schedule but calculate the value from actual prices, a technique they refer to as backcasting. In their study, the two-week backcasting method yields between 85-90% of maximum possible revenues. This is possible due to price patterns occurring cyclically. At two weeks, weekday-weekend effects are captured and the horizon is sufficiently small to capture seasonal effects but not long enough to capture short term effects such as disturbances which persist on a daily-weekly scale. In a later study, Sioshansi et al., (2011) have used a 1-week backcasting lag; there are no clear criteria for the choice of a backcasting lag. There is uncertainty surrounding the optimal backcasting lag and by shedding light on this problem, more information would be gained on how persistence at different timescales affect storage revenues.

Other more advanced strategies have been proposed to capture value; He et al., (2011) argued against co-optimisation and propose storage power and energy capacities are allocated in sequential auctions based on the timescales to actual power delivery. To illustrate this point, they choose a week ahead auction representing a generation company which may not wish to use its peaking plants and hence enters a contract with the storage owner to provide power. This auction is followed by a day ahead auction which represented a trader looking for price arbitrage. Finally, an hour ahead auction is carried out, with a System Operator (SO) who wishes to utilise the remaining capacities for frequency response. This strategy does not require co-optimisation across markets but manages to allocate storage capacities to the three stakeholders.

This strategy is particularly interesting as the sequential allocation of capacity by delivery timescales is feasible. The authors note that this strategy benefits from neutralising actions whereby commitments from a week ahead auction and those from the day-ahead auction cancel each other. For example, if the week ahead auction requires the storage system to discharge 10 MW at a specific time t while the day ahead auction requires that the storage charges by 10 MW for the same period, these actions cancel each other out and there is an efficiency gain since no charging or discharging occurred as a result.

There is an important aspect which the authors do not address and this remains unclear; based on the sequence of auctions, the bulk of the allocations should take place on the week ahead auction. Implicitly less capacity is available to the day ahead auction and consequently even less so to the hour ahead auction. As the short-term markets generally tend to be more volatile than longer-term ones, there is a possibility that this strategy performs the worst. In the example presented the authors chose a generation company that underutilizes storage capacity at the week ahead auction, shown in figure 2.6.

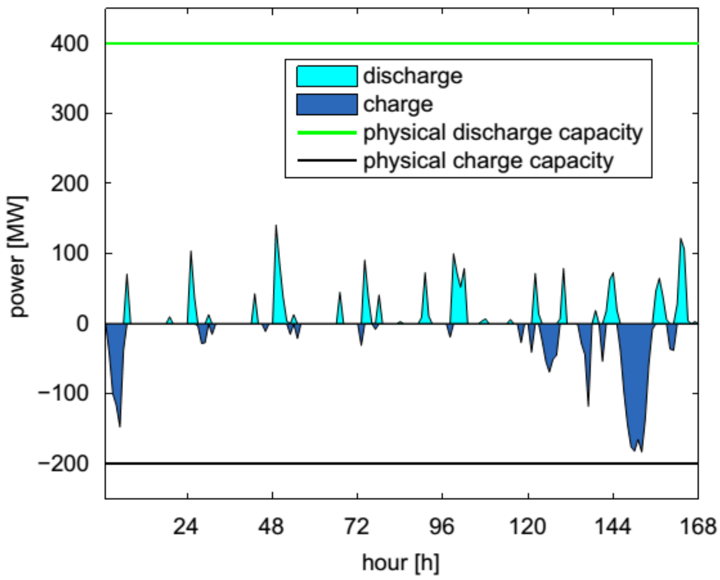


***Figure 2.6**: Storage capacity allocation to a generation company at the week ahead auction. Source He et al., (2011)*

With a larger number of generation companies participating at the week ahead auction, less capacity will be available for the later auctions. This raises the question of how to optimally allocate/reserve capacity between the three revenue mechanisms. In the absence of perfect foresight, this is difficult to achieve. In fact, the authors recognise this and state:

"*However, the exact amount of storage's value in each auction depends essentially on the specific case setup and the input data. The numerical results should therefore be interpreted with caution*." He et al., (2011, p.1584) .

Nevertheless, the operating strategy has further potential; if the contracts were non-binding (or have low penalties), the storage owner could utilise each auction mechanism to select the highest revenue service and even reverse previous commitments. Such a strategy could potentially be close to the co-optimised values but in reality, such low penalty conditions and non-binding contracts are not common and hence not explored further in this thesis.

Alternative ways to deal with imperfect foresight have been used; in order to assess the business case for CAES under a profit maximising objective in 2030, Lund & Salgi (2009) are required to forecast the future prices, at an hourly resolution. They use an average expected price of 54 Euro per MWh for 2030, a figure which Danish authorities expect (cited by the Lund & Salgi 2009). The authors then scale this average price to mirror the price variations in 2005, deemed as a typical year. In essence, the hourly 2030 price is an extrapolation of 2005 data.

This approach however fundamentally assumes that the price distribution of 2005 will be similar to 2030 at an hourly resolution. However, with renewable energy generation, demand side response and other changes in demand such as electrification of heat or electric vehicles, this technique cannot be applied within the GB context. Furthermore, inference from average prices are not very useful for storage value; mathematically an average price of 54 Euro/MWh price could simply be a constant price for the whole period or an infinite number of variations of peaks and troughs such that their averages are 54 Euro/MWh. It is specifically the magnitude and frequency of these peaks and troughs that are of relevance to storage arbitrage.

Long term price forecasting has also been used by Yucekaya (2013). The author conducts 100 simulations of hourly prices 30 years into the future using Monte Carlo simulations. The author utilises two random variables, one for the electricity price and the other for the price of natural gas. These are fed into the costs (and revenues) of the model since discharging and charging variable costs depend on the price of gas and electricity respectively. This technique is an alternative to the provision of a short-term operating strategy; its disadvantage, however, is that over such long timescales simulated prices can be substantially different. This challenge is endemic to forecasting methods in general and hence why specific scenarios are used to predict the impact of the changes. National Grid (2015c) for example have modelled energy futures using scenarios of high renewables penetration, electric vehicles…etc.

If a future generation mix (and demand level) is known, it is possible to use the merit order of generation dispatch to simulate market clearing price. Foley & Díaz Lobera (2013) used this technique to simulate the future prices in 2020, scaling wind penetration. This technique is particularly effective and relevant to markets where prices are determined through a gross pool, such as the Irish market Foley & Díaz Lobera (2013) investigated. To evaluate future prices and storage value, Grünewald et al., (2011) also make use of the merit order of generation dispatch. Storage operation depends on whether the system is long, in which case the energy storage system absorbs excess (thus acting as demand) or short, whereby power is discharged instead meet the deficit and reduce generation from peaking plants. There are clear advantages of using the merit order of generation dispatch to calculate prices – they are potentially more resilient to future changes as they are based on sound principles. By comparison, price forecasting techniques which rely solely on historical data are less likely to fare well under changing market conditions.

Other studies (Walawalkar et al. 2007; Nyamdash et al. 2010) used fixed dispatch strategies for storage operation; the charging and discharging times are chosen so as to match the periods of lowest and highest prices respectively. Fixed dispatch techniques are particularly simple to use and represent a basic strategy for capturing arbitrage revenues.

This section showed that the majority of storage revenue problems have been formulated as LP or MILP problems. In the absence of perfect foresight, however, several approaches were undertaken to estimate prices. These techniques broadly included price forecasting, backcasting, merit order dispatch and fixed dispatch strategies.

### 2.4.4. Co-optimisation

Lund & Salgi (2009) present a business-oriented approach whereby the CAES system operates in both the Spot market and the regulating power market. Under a single market participation, the system is unable to recover its cost. A strategy to co-optimise revenue is proposed whereby the compressor charges from electricity purchased from the spot market while the turbine provides regulating power for which a payment is made, on a fixed monthly availability basis.

Drury et al., (2011) used a co-optimisation approach to explore the value of CAES and AACAES in 4 wholesale markets; California Independent System Operator (CAISO), Midcontinent Independent System Operator (MISO), New York Independent System Operator (NYISO) and PJM. They look at the day ahead hourly market for arbitrage revenues whilst also deriving revenues from spinning and non-spinning reserves. In all markets and value locations explored, they show that a co-optimised dispatch yields 13-22% more revenues compared to arbitrage only dispatch. In addition, on average a co-optimised dispatch yields an extra $15 per kW of capacity irrespective of revenues in arbitrage only dispatch.

He et al., (2011) have argued against the current approach to co-optimisation; for example, they refer to studies undertaken on storage value in the US such as Sioshansi et al., (2009) to make the point that market structures differ and therefore many models in the existing literature cannot be applied to other countries. They emphasize the fact that several storage functions can be more easily bundled and offered as a service in other countries whereas in Europe, the deregulation of electricity markets pose a challenge. Although the authors do not use co-optimisation, their business model aggregates value and shows that revenues under aggregation is much higher than those derived from single revenue mechanisms.

Nevertheless, co-optimisation is gaining in popularity and growing evidence supports aggregation of revenues; Moreno et al., (2015) used co-optimisation to investigate storage revenues when embedded within a distribution network in GB. The system generates arbitrage revenues as well as reserve revenues while operating within the low voltage restrictions. More recently, Chazarra et al., (2016) investigate a PHES specific optimisation in both energy and reserve markets. Their modelling includes more elaborate engineering aspects of PHES operation namely water levels, local topography, water-flow restrictions due to irrigation or navigation, and so on. They found that when the system participates in both energy and reserve markets over 130 euros per MWh is generated compared to approximately 90 euros per MWh for energy market participation only.

## 2.5.Impact of storage parameters on storage value: Efficiency

Round-Trip Efficiency (RTE) is one of the most important storage parameters; it defines the very concept of storage by dictating how much energy the system can retain. Losses occur on charging, as power flows increase the State of Charge (SOC) of the system and also on discharging where the opposite occurs. The RTE is the total energy lost, arising from a charge-discharge cycle and therefore systems with low RTE incur substantial energy losses which negatively affect total revenues.

In a study by Kloess & Zach (2014) the authors used historic data to show that arbitrage revenues fell by over 60% for PHES from 2007-2011 and by over 80% for a methane storage system. The reason for the disparity in impact between the two technologies was attributed to their respective RTE; technologies with lower cycle efficiencies suffer the most due to their inability to make a profit from small price differentials. This finding is consistent with that of Sioshansi et al., (2011) who also highlight the importance of capturing small price differentials .

In a recent study, McConnell et al., (2015) argue that RTE of the storage system does not significantly change the revenues. This finding is in stark contrast to other studies; Sioshansi et al., (2009) showed that a round trip efficiency increase from 50% to 90% increases storage value from $20/kW-yr to $90kW-yr, clearly more than proportionate impacts. In principle, efficiency changes, under perfect foresight assumptions, should have a dramatic effect on revenues in a volatile market as small price differentials, previously infeasible due to efficiency losses now become a viable arbitrage trade.

McConnell et al., (2015) support their argument through the following example: a 2 MWh system charged with 50% RTE and costing $50/MWh to be sold at $13,100/MWh is similar to a 1 MWh system charged with 100% RTE and sold at the same price (McConnell et al. 2015, p.427). The increase in revenues from the increase in efficiency, they calculate, is only 0.4%. However, a comparison between a 2MWh system and a 1 MWh system is ambiguous. According to the very same example but with equal capacities, a 2MWh 100% RTE system would earn a net revenue of $26,100 whereas a 2 MWh 50% RTE would earn $13,000. Therefore, doubling RTE from 50% to 100% would increase net revenues by 101%. The authors ignored the effect of discharge efficiency and appear to apply RTE to charging costs only. In fact, discharge efficiency dictates how much electricity is actually delivered, based on which the payment is made and, at such high prices, should make a larger difference. This effect is specifically highlighted by Grünewald et al., (2011) who contrast the difference in impact of a 5% change in charge and discharge efficiency; discharge efficiency is substantially more important.

Unlike other studies, Hittinger et al., (2012) focus purely on the impact of efficiency, power capacity, capital and fixed operating costs on storage value. In the study, storage has specific application and is not operated under a profit maximising regime. More specifically, the four chosen technologies, namely NaS, Li-ion, Flywheels and Supercapacitors perform 4 functions; peak shaving, the provision of baseload power and load following to support wind generation, and finally frequency regulation. The authors evaluate storage value in terms of the cost of providing these functions. The impact of storage properties is therefore measured by the extent to which this cost of service is reduced following changes in the property, such as efficiency. The authors find that the impact of storage properties on its value is determined not only by the technology but also by the function of storage. For example, the impact of RTE for the provision of frequency regulation varies; in Li-ion batteries a 1% increase in RTE brings about a 0.6% decrease in the cost of service whereas with flywheels the same 1% increase in RTE decreases the cost of service by 0.1%. The findings of Hittinger et al., (2012) while not directly relevant due to their non-profit maximising objective, nevertheless makes an important point, that the impact of storage properties cannot be generalised and is dependent on both the technology and application. In light of the findings of Hittinger et al., (2012), one cannot generalise the impact of a particular storage parameter and therefore the impact of energy storage parameters on revenues in Great Britain merits further investigation.

### 2.6. Power and energy capacity impacts

The power capacity of a storage system defines its output potential; a high power capacity enables high power flows in and out of the system. However, the extent to which these power flows can be sustained depends on the energy capacity of the system. Energy capacity determines the volume of energy that can be stored. Power and Energy capacities can be sized independently; storage sizing is critical to maximise revenues; under-sizing leads to a loss of potential revenues whereas oversizing results in excessive capital costs. For arbitrage revenues, Sioshansi et al., (2009) found that the majority of storage value lies in the intraday period with 8 hours' storage energy capacity capturing 85% of total revenues and at 20 hours, this figure rises to 95%. The authors show that this trend remains unchanged in the presence of annual fluctuations in prices from 2002-2007.

Subsequent studies have also demonstrated a clear preference for relatively short energy capacities (with power capacity fixed); in the Turkish power market, Yucekaya (2013) showed that the optimal energy capacity for a CAES system was 10 hours for a generation capacity of 360 MW with 40 MW of compressor capacity. Kloess & Zach (2014) found that an energy capacity of 7-8 hours yields the greatest arbitrage value for PHES and therefore argue that the technology is suitable for day-ahead storage. Bradbury et al., (2014) found that the energy capacities greater than 10 hours yield diminishing marginal returns and almost maximised at 15 hours. McConnell et al., (2015) show that 90% of storage value lies an energy capacity equivalent to 4 hours.

When storage is dedicated to the sole provision of frequency response, Fares et al., (2014) have shown that larger energy capacities tend to negatively affect the NPV due to additional capital costs. Diminishing returns also occurs with increasing power capacity; Das et al., (2015) show that a 50 MW CAES system under a 22% wind penetration level pays for itself in 15 years. Scaling the system to a 100 MW device, however, reduces profitability and the project does not pay for itself at 22% wind penetration level and requires almost 20 years to pay off at the 40% wind penetration level.

While these studies clearly show a preference for storage energy capacities between 4-10 hours, it should be stressed that these were in cases where revenue maximisation was the primary objective. In the case where storage and wind generation are coupled, longer energy capacities are preferable; Grünewald et al., (2011) demonstrated that a 1.5 GW/21 GWh flow battery is optimal whereas for CAES a 3.9GW/314 GWh system yields the highest NPV. Hessami & Bowly, (2011) showed that the optimal energy capacities for storage coupled with wind farms are 10 hours for pumped seawater storage hydro, 17 hours for CAES and 23 hours for thermal energy storage.

An important implication from a study by Sioshansi et al., (2011) is that the energy capacity of a storage system, ideally, should take into account foresight accuracy. The authors show that a higher energy capacity of 20 hours fares worse than an 8-hour energy capacity in capturing arbitrage value under imperfect foresight. Conversely, McConnell et al., (2015) used the day ahead price forecast to show that the opposite is true; 70% of perfect foresight revenues was captured with a 3-hour energy capacity system and at 8 hours, this rises to 90%. The authors explain this as possibly due to an increased inflexibility of storage stating that the ability to change dispatch schedules may be constrained for smaller devices. For comparison, the revenues under imperfect foresight are shown for Sioshansi et al., (2011) in figure 2.7 and for McConnell et al., (2015) in figure 2.8.

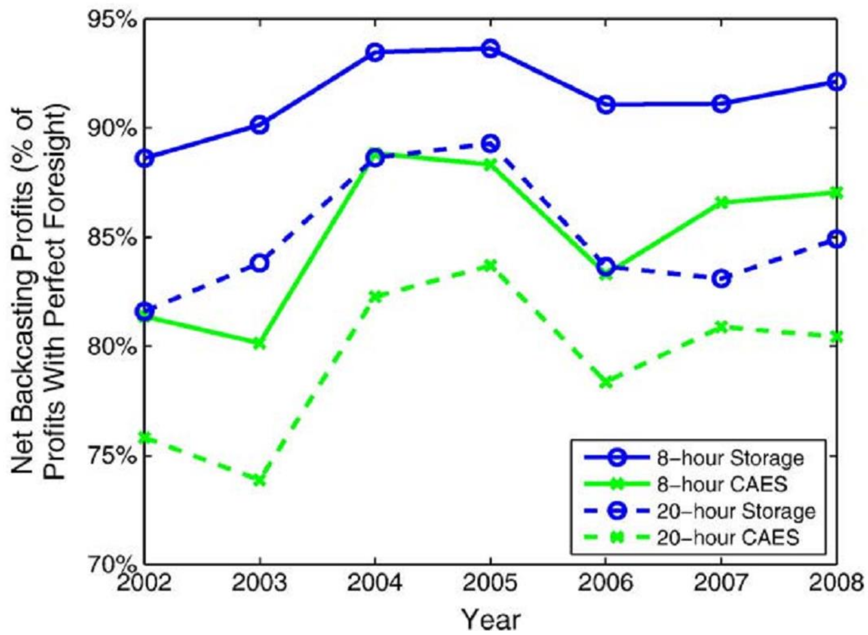


***Figure 2.7:*** *Relative arbitrage revenues of an 8-hour energy storage compared to a 20-hour capacity, derived under imperfect foresight. Source: Sioshansi et al., (2011)*

Sioshansi et al., (2011) explain the inverse relationship, between storage energy capacity and arbitrage values under imperfect foresight, by pointing out that larger storage systems need to utilise a significantly greater number of small price differentials to maximise profit potential whereas a smaller system for example, derives most of its profits from the large price differentials between peak and off-peak. In the case of the latter, small price differentials would have negligible effects on total profits and more importantly, those large price differentials are more likely to be predictable due to the time of use nature of electricity prices. The impact of energy capacity on the ability to capture arbitrage revenues is investigated later in Chapter 7.

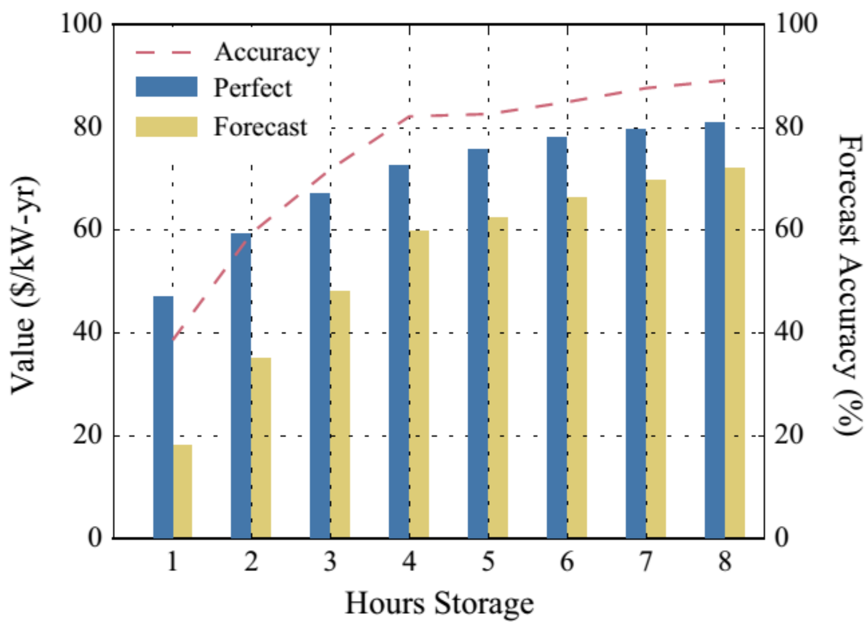


***Figure 2.8:*** *Impact of various energy capacities on storage revenues under imperfect foresight. Source: McConnell et al., (2015)*

## 2.7. Storage technology and Impacts on economic feasibility

CAES remains one of the most studied storage technologies for economic feasibility; with the ability to couple and decouple compression and expansion, the CAES system can operate as both gas peaking plant and a CAES system. The expander is usually sized at a greater capacity than compression, a configuration beneficial for revenue mechanisms. Additionally, the relatively low capital costs and long lifespan play in favour of the project economics.

Safaei & Keith (2014) investigate the value of CAES in Alberta, Canada using a distributed configuration (D-CAES); while conventionally, the compressor and generator are sited in proximity to the storage caverns they propose splitting the compressor next to a heat load which could use the otherwise wasted heat, such as a district heating system for a municipal heat load. The compressed air is sent through a pipeline, set initially at 50 km, to the storage site where the expander is also located. While D-CAES show better profitability they show that pipeline lengths longer than 75 km from the heat load to the storage site are not economically viable under the market conditions. Yucekaya (2013), using the Turkish power market as a case study found CAES to be profitable under simulated prices. CAES has been shown to outperform ACAES in locations where peak prices are very high (Drury et al. 2011), such that the marginal costs of natural gas utilised during discharge is cost effective. This is similar to a gas peaking plant which generates high profits due to very high peak prices using relatively cheaper gas.

A number of studies have compared the relative performance of storage technologies; Kloess & Zach (2014) investigated the value of AACAES, PHES, Hydrogen ($H_2$) and Methane ($CH_4$) storage in the Austrian power market. None of the technologies investigated are feasible based solely on arbitrage revenues, with PHES performing the best followed by AACAES, $H_2$ and $CH_4$.The authors also explore seasonal storage for H2 and CH4 as niche applications by allowing an unlimited energy capacity whilst power capacity is held at 300 MW. In GB, Locatelli et al., (2015) show that the revenues are insufficient to support PHES, CAES and AACAES based on revenues from wholesale market arbitrage and short-term operating reserves. Bradbury et al., (2014) found the most profitable storage technologies for arbitrage were PHES, CAES, Supercapacitors and Sodium Nickel Chloride batteries. On the other hand, lithium-ion batteries and VRB were amongst the worst performers, yielding negative NPV. These comparative studies highlight the greater profitability of the conventional bulk storage technologies PHES and CAES against battery technologies.

The feasibility of specific storage technologies has also been evaluated where the primary objective was not a profit maximisation one; Lund et al., (2009) showed the integration of CAES within a system with high wind penetration does not generate sufficient arbitrage revenues to recover its cost.

However, with the co-optimisation of reserves revenues, the storage system becomes feasible. In another study, Grünewald et al., (2011) show that at wind penetration levels above 40 GW, all storage technologies demonstrate positive NPVs and reach a maximum between 60-80 GW range. In that range, they found that CAES was the most profitable, followed by Hydrogen and Flow batteries. Hessami & Bowly, (2011) evaluate arbitrage from CAES, pumped seawater hydro storage and thermal energy storage operating with a wind farm in Portland, Australia. All technologies were shown to be well above the threshold of economic feasibility, CAES was shown to be the most profitable, followed by pumped seawater hydro and thermal energy storage.

## 2.8. Conclusion

In this chapter, it was shown that there is a disparity between whole system benefits and market rewarded benefits. The former approach is particularly relevant to a policy maker whereas the latter is of interest to a private investor seeking a positive return. Previous studies investigating storage value can be broadly categorized as those in which storage has a profit maximising function and those whereby profit maximisation is a secondary objective. From previous studies investigating storage value, even lesser emphasis was placed on storage operations; rather the focus has been on the revenues storage generated. The optimal charging and discharging patterns required to maximise revenues in GB markets is still unknown and investigated in Chapters 5 and 6.

In the profit maximising category, the findings support the conclusion that profitability is very specific to a market as a wide variability of revenues was shown to exist. In GB, the value of pure arbitrage revenues is not known and hence merits further investigation. A number of studies have also pointed towards reserve service providing substantial revenues and in some cases even exceeding arbitrage revenues. The type of reserve varied across studies, and similar to the case for arbitrage, these results cannot be generalised, hence requiring an evaluation within the GB market context.

In studies where storage profitability is a secondary function, overwhelmingly, the primary objective related to some form of wind generation support. This would include wind output smoothing, conversion of wind to baseload power, wind output curtailment reduction and deferring transmission investment.

A review of the modelling approaches for storage value studies was also undertaken; the majority of models were optimisation models with a larger number of MILP models compared to LP models. While each optimisation model had subtle variations relating to the additional of a cost feature such as start-up costs or self-discharge, essentially the models were very similar. In two cases, the models did not optimize revenues despite described as optimisation models, highlighting the need for the distinction between a profit generating regime and a profit maximising one.

In section 2.4.2, the choice of an optimisation horizon remains unclear as choices made in the existing literature appear arbitrary. Since these horizons have a direct impact on revenue potential, there is value in investigating the most beneficial optimisation horizons taking into account computational efficiency as well, explained further in Chapter 4.

Inherently, by building a model, assumptions about foresight and bidding strategies have to be made; In the literature, foresight has been dealt with in a number of ways. Techniques applied included backcasting, forecasting, merit order cost functions and fixed dispatch. There is an emerging pattern from these studies, whereby merit order cost functions are preferred in relatively more distant future scenarios whereas backcasting and forecasting approaches are predominantly applied in near future scenarios.

A growing number of studies are also adopting a co-optimisation approach whereby revenues are optimally aggregated. This aggregation generates higher revenues compared to the case where storage participates in a single market. Co-optimisation models have been chosen due to their ability to aggregate revenues; however, additional benefits or drawbacks of co-optimisation model have not been explored further and hence are investigated in this thesis.

Revenues, in general, were seen to be sensitive to storage parameters such as efficiency, power and energy capacity. However, conflicting studies were also found, especially in relation to the impact of efficiency on revenues and the impact of energy capacity under imperfect foresight. More specifically, while efficiency was generally found to be a strong driver for revenues, this is not always true as section 2.5 showed. Similarly, there is a conflicting evidence surrounding the impact of imperfect foresight on revenues with varying energy capacities, explained earlier in section 2.6. The impact of storage parameters on revenues are explicitly investigated in Chapter 5 and 6. Additionally these conflicting results from previous studies are explicitly addressed in these chapters.

From the studies explored, there were no clear preference for the optimisation horizons chosen. Since these determine the arbitrage trading opportunities available, several optimisations are investigated in this thesis, to assess their impact on revenues.

There is some merit in investigating storage value with a technology neutral approach as the focus can be shifted onto the market revenues. Ultimately, however, these revenues support specific projects and hence several studies have also compared the economic performance of storage technologies. Conventional storage technologies such as PHES and CAES were largely superior to the relatively less mature ones such as VRB. In order to place these revenues into perspective, some technology specific capital and operational cost parameters are taken into consideration to determine the NPV of these technologies. Furthermore, the power to energy ratio factor is adjusted to investigate the potential profitability of these technologies with different power to energy configurations.

The value of energy storage under high wind penetration scenario has been extensively explored in the previous studies. However, these studies investigated cases where storage is coupled with wind for avoid curtailment, output smoothing rather than investigate how increased wind generation may affect the markets and hence affect the potential revenues for storage. This approach is important especially for cases where storage is owned and operated independently, drawing revenues from market mechanisms. Therefore, the potential impacts of wind on the market revenues for energy storage is investigated in Chapter 7.

The value of the optimally combined revenue streams has been investigated previously in other markets such as the US and in Denmark, however remains relatively unexplored in GB markets. Furthermore, there has been little focus on the storage operations required to achieve such optimal revenues and whether there are other benefits to a co-optimisation approach. The next chapter describes these market mechanisms available to a storage owner and how they contribute to storage revenues.

# Chapter 3. The opportunity for storage in the GB system; markets and implications

## 3.1. Introduction

Chapter 2 showed that storage value in GB markets is relatively unknown and these values vary widely across geographical regions. This Chapter explores the characteristics of revenue mechanisms and how they generate value for energy storage. Broad categories of revenue mechanisms were explored and three were subsequently chosen. The first mechanism is representative of the short-term wholesale power market, the half-hourly spot market on the APX power exchange. The second category is the Balancing Mechanism (BM) whose structure is, to the author's knowledge unique to GB. The third mechanism is Firm Frequency Response (FFR), as a type of ancillary service. STOR is another commonly used ancillary services and is investigated to a limited extent in Chapter 5. The choice of these three types of mechanisms is broadly representative of what types of revenues a storage owner could derive by offering its services. The prospects of energy storage operating within these mechanisms are investigated as a preliminary analysis, in order to determine whether these avenues are worth pursuing further.

Since the structure and characteristics of these mechanisms are fundamental in understanding how they could contribute to storage value, this section briefly describes them. At the end of this Chapter, a better understanding of the chosen mechanisms, changes in price patterns and their potential for storage value is achieved. The outcome of this section provides a basis for pursuing a more formal approach in Chapter 4.

## 3.2. Electricity demand

One of the basic principles of a market, from economic theory, is the interaction between demand and supply. Demand is driven by the needs/wants for the commodity or service whereas supply is driven by the pursuit of profits. In the electricity market, the same principles apply, with demand traditionally assumed to be inelastic and supply as being flexible. Thus, to a large extent, the market price of electricity is driven by demand.

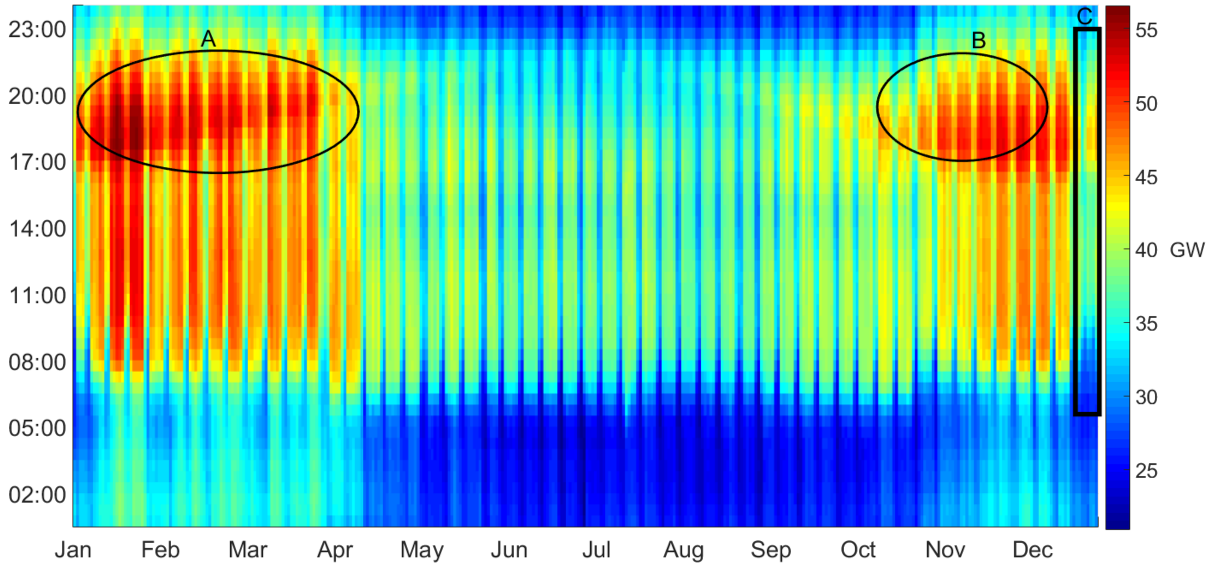


***Figure 3.1:*** *The daily and seasonal variability of electricity demand in 2013*

Figure 3.1 shows the electricity demand in GB across 2013. The electricity demand shown here represents the total demand on the transmission system including station load, PHES in pumping mode and interconnector exports (National Grid 2015b). Intraday variations in demand level are clearly visible being with demand substantially higher between 8am-11pm. Seasonal effects on demand are also prominent with peak demand occurring in mid-January between 5pm-8pm. From mid-April to mid-September, demand is at its lowest both during the corresponding peak hours as well as the off-peak ones. An interesting trend is also visible from the figure; winter peak demand tends to occur later as summer approaches shown as circle A. The transition from summer to winter shows the opposite effect, that is, peak demand occurring earlier shown as circle B. The evening peak demand fades in magnitude during the summer. Since it is generally assumed that electricity demand drives prices, it is worth investigating whether these transitionary effects in demand from season to season, are reflected in the short-term wholesale prices.

Over a longer period, from 2009-2015 the summary statistics for demand were calculated and shown in figure 3.2. During the six-year period, demand averaged 36 GW and ranged from 19 GW to 60 GW; the maximum demand was over three times the minimum demand. The histogram of demand during that period highlights the difference in spread between high demand and low demand; electricity demand levels above the median at 36 GW is spread over a much wider range as opposed to levels below the median. This suggests an asymmetry in variability, with more variability present at high demand levels.

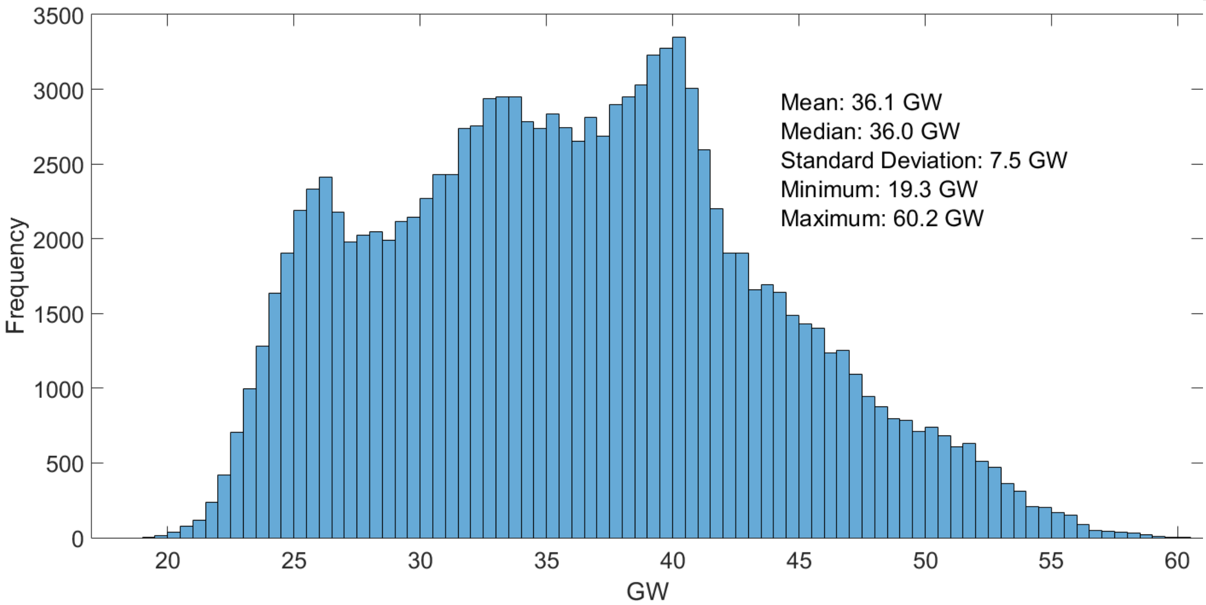


***Figure 3.2:*** *The distribution of electricity demand at transmission level from 2009-2015 in GB.*

Electricity demand variability has several implications for energy storage; from a system perspective, Transmission and Distribution (T&D) infrastructure should be sufficiently large to accommodate maximal power flows. The lack of adequate network capacity would result in curtailment of generation and/or forced demand reduction. Energy storage could alleviate this issue and result in network reinforcement investment deferral. These savings have been explored in future scenarios by Strbac et al., (2012) showing that storage value is expected to rise.

The basis of economic dispatch is the short run marginal costs of generation. This stems from economic theory of revenue maximisation being conditional to marginal revenues exceeding marginal costs. The latter effectively becomes the supply curve of the power plant. Renewable energy such as wind tend to have relatively low marginal costs and combined with the fact that output cannot be conventionally scheduled means that this energy is dispatched first. This holds true for a supplier with a large portfolio of various generation types, which compared to wind power can be more easily adjusted. For these reasons, wind power is often at the bottom of the merit order curve and therefore peak shaving or load shifting could yield benefits in the form of lower costs and potentially lower emissions. However, the latter is not clear as studies have found different results (Das et al. 2015; Foley & Díaz Lobera 2013). This approach is known as the merit order of generation.

The use of energy storage systems to store off-peak energy and discharge during peak time would shift the production costs associated with expensive peak power generation, usually oil or gas power plants, to baseload power such as nuclear and coal or even renewable energy. In doing so the storage system generates arbitrage revenues, from the markets. It is interesting to note that a storage system which seeks to derive arbitrage revenues is likely to defer investment into T&D networks, as peak demand is reduced.

Due to the correlation between wholesale prices and electricity demand, storage systems undertaking arbitrage trades are likely to reduce peak demand. The revenues reflect the difference in electricity prices during peak and off peak periods. However, these actions would also reduce the need for network investments but these benefits are poorly reflected in the arbitrage revenues. While there are some incentives to reduce peak electricity demand such as the TRIAD charges avoidance at transmission level and time-banded network (DUoS) charges at distribution level, these would unlikely be reflected in the wholesale prices.

## 3.3. Wholesale power market

Under the New Electricity Trading Arrangements (NETA) in 2001 and its successor, the British Electricity Trading and Transmission Arrangement (BETTA) in 2005, electricity suppliers can enter into bilateral agreements to trade directly with each other as well as trade through a wholesale market (UK Parliament 2011). From 1990 to 2001, electricity was traded through a gross pool, known as the Electricity Pool of England and Wales (Murray 2009; RWE n.d.). Despite the abolition of the gross pool under NETA, the principle of economic dispatch implies that a merit order of generation is still maintained by generation.

Under the deregulated GB electricity markets, suppliers and generators trade in bulk electricity through bilateral forward contracts up to a year or more ahead. Closer to actual delivery, between a month ahead to an hour ahead, electricity can be traded in the power exchange (APX 2015; APX n.d.). APX power UK was established in 2000 and enables anonymous trading continuously (24/7) for Spot, Auction and Prompt power contracts (APX 2016a). The spot market is used for very short term trading, opening 24.5 hours ahead of actual delivery. The spot market allows the trading of electricity in 4-hour, 2-hour, 1-hour and half-hourly blocks as shown in table 3.1:

| Contract | Period Covered | Hrs | Opens for Trading |
|---|---|---|---|
| 4 Hrs block | 6 blocks/day, block 1 begins 23:00; block 6 ends 23:00 | 4 | Rolling 7 days |
| 2 Hrs block | 12 blocks/day, block 1A begins 23:00; block 6B ends 23:00 | 2 | 49 1/2 Hrs prior to start of delivery |
| 1 Hr block | 24 blocks/day, block 23 begins at 23:00; block 22 ends 23:00 | 1 | 48 Hrs prior to start of delivery |
| Half hour block | 48 periods/day, 1/2 Hr 1 begins 00:00; 1/2 Hr 48 to end 00:00 | 0.5 | 49 1/2 Hrs prior to start of delivery |

*Table 3.1: The four products available on the spot market in 2013 and their opening times for trading Adapted from* APX (2013).

The Auction facilitates trade on a day-ahead basis between anonymous parties. Unlike the spot market there are no predetermined blocks of electricity in the auction market and therefore the spot market offers greater flexibility in this respect. The prompt market covers longer products such as off-peak or peak contracts as shown in table 3.2.

| Contract | Period Covered | Hrs | Opens for Trading |
|---|---|---|---|
| Weekend base | 23:00 Fri – 23:00 Sun | 48 | Rolling 2 weekends, open at any time |
| Base | 23:00 – 23:00 | 24 | Rolling 7 days |
| Peak | 07:00 – 19:00 | 12 | Rolling 7 days |
| Extended peak | 07:00 – 23:00 | 16 | Rolling 7 days |
| Off peak | 23:00 – 7:00 + 19:00 – 23:00 | 12 | Rolling 7 days |
| Blocks 3 + 4 | 07:00 – 15:00 | 8 | Rolling 7 days |
| Overnight | 23:00 – 07:00 | 8 | Rolling 7 days |

*Table 3.2: The prompt market products. Adapted from* APX (2013).

Given the opportunities for trading in the Spot, Auction or Prompt market, the choice of market and product for storage participation is guided by the arbitrage opportunities; trading at a finer resolution such as half-hourly enables a greater number of arbitrage trades. Since the spot market is also used for adjustment purposes with parties adjusting their final positions before gate closure, this market is also more likely to be exposed to very short-term market shocks.

Market shocks could arise from forecast errors by trading parties, their inability to clear the imbalance position in other markets such as the auction market or any other unexpected events. These shocks drive greater price fluctuations as shown in table 3.3 which compares summary statistics between the auction and spot markets as an example. While the average price of electricity is not significantly different, the standard deviation, as well as minimum and maximum values show that the half hourly spot market price has a greater volatility. Since arbitrage takes advantage of price differentials, from a revenue maximising perspective storage participation in the spot market is preferred to the auction market. The prompt market is excluded since the longer products further limit the number of arbitrage trades possible within a fixed period.

| | Auction | Spot - HH |
|---|---|---|
| **Total volume traded - MWh** | 11,152,591 | 10,684,226 |
| **Average price - £/MWh** | 42.02 | 42.04 |
| **Standard Deviation** | 11.73 | 13.78 |
| **Minimum Price - £/MWh** | 9.98 | 0 |
| **Maximum Price - £/MWh** | 195.73 | 362.15 |

*Table 3.3: The summary statistics between the Auction and Spot market from APX power UK in 2014.*

Similar to figure 3.1, the half hourly APX spot market price across 2013 is shown in figure 3.3. Prices shown in the figure is capped at £100/MWh in order to highlight the more subtle price differences. The transitionary effect of peak demand from winter to summer in the demand figure 3.1, is even more prominent in figure 3.3. The magnitude of the price changes, however, is substantially greater than that of demand changes. In contrast with demand, prices appear to rise during the late morning and drop midday before the evening peak. This is true even in summer, although similar to the peak demand, follows the transitionary trend and peaks earlier between 5pm-6pm. In short, the highest prices occurred during the morning peak period and at evening peak while the lowest prices occurred consistently between 3am-6am.

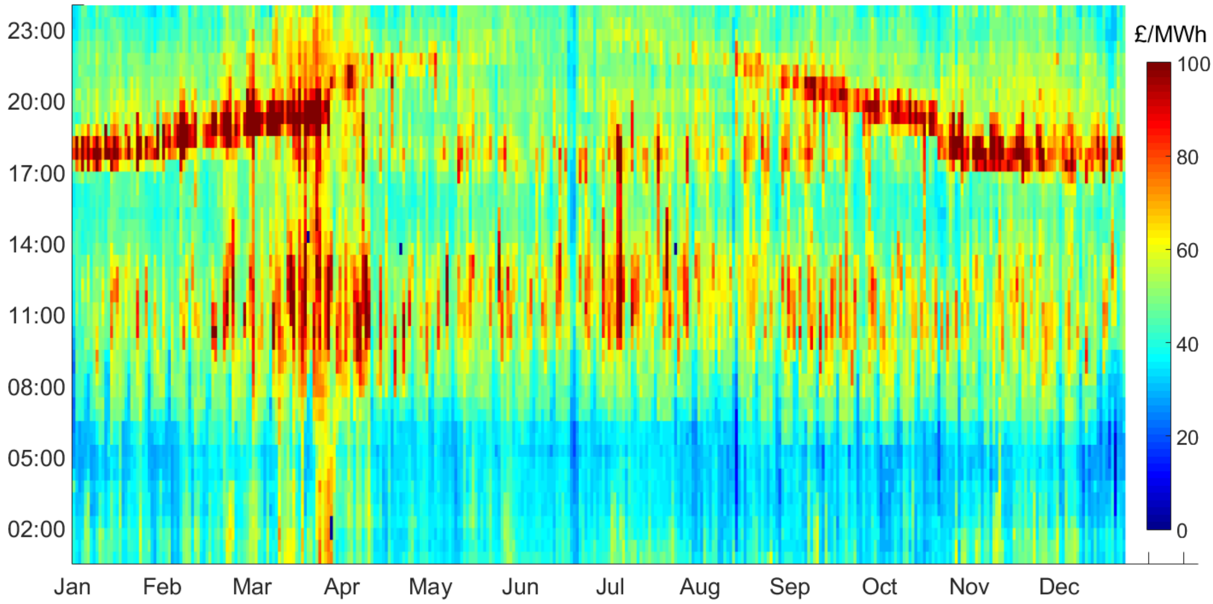


***Figure 3.3:*** *The daily and seasonal variability of the half hourly spot market price in 2013.*

The very short term nature of the spot market explains the price volatility. Figure 3.4 shows the distribution and summary statistics for the half hourly (HH) APX price from 2009-2015 – extreme values are not displayed in the figure but shown in the summary statistics instead. Compared to the statistics for demand, there is a greater symmetry in APX prices. The extreme prices, however, are far larger than the differences in demand.

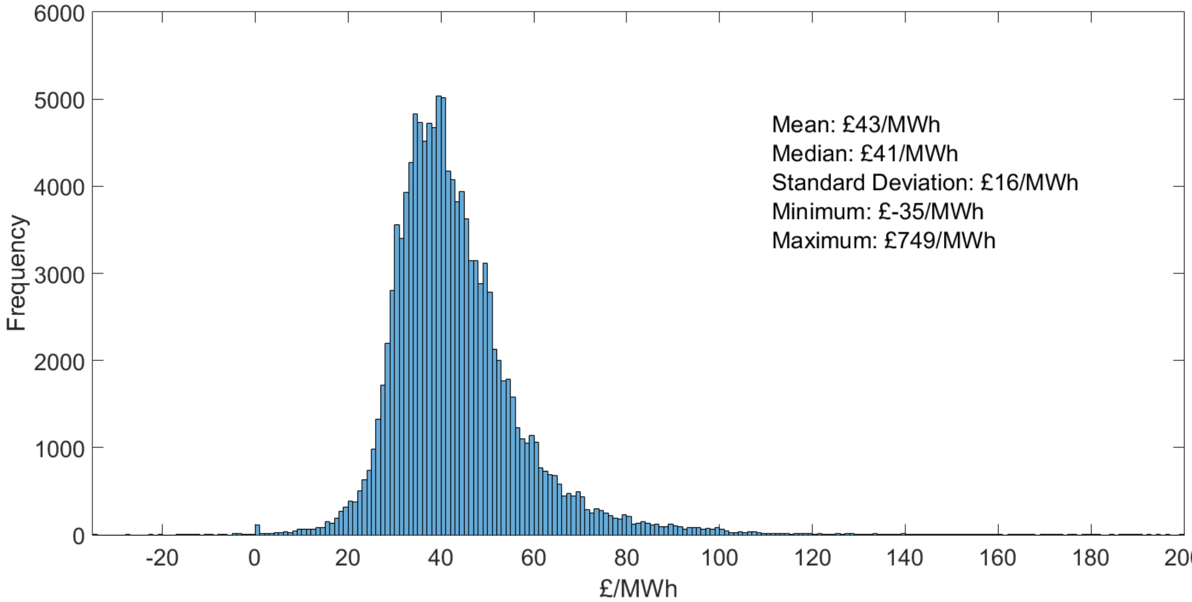


***Figure 3.4:*** *The APX price distribution from 2009-2015.*

While the power exchange provides an opportunity for parties to adjust their position in terms of how much demand or generation was contracted, imbalances may arise or still persist. One of the responsibilities of National Grid, as the system operator is to balance demand and supply and this is undertaken through the balancing mechanism.

## 3.4. Annual variability in wholesale prices and demand

Analysing and comparing revenues a storage system could generate requires the choice of a base year. However, the results could be influenced by a particular year being a non-typical year and therefore a comparison with other years should be undertaken to evaluate the extent of such bias.

Figure 3.5 shows the transmission level electricity demand from 2011-2014. While the general seasonal patterns are similar across the four years, there appears to be a slight but noticeable fall in demand in 2013 and 2014 compared to the previous two years. This fall is more pronounced during daylight hours all throughout the winter and summer leading to the hypothesis that this is likely to be Solar PV embedded generation reducing net demand.

The half-hourly APX spot market price is shown for each of the years from 2011 to 2014 in figure 3.6. For a better visual representation, in this figure, the colourbar only displays values in the range £20/MWh to £100/MWh. Prices which are outside these limits are shown as either ends of the spectrum.

Some of the variations can be seen from both figures; in February 2011 the spot market prices are unusually high and can be seen to coincide with a high demand level for the same period. Similarly in 2013, periods of high demand are reflected in the prices, particularly from January to April. For the latter, demand was unusually high compared to the other years, due to a cold spring. According to a report by E.ON (2013), gas reserves reached critically low levels with a degree of fullness of 9%. This also coincided with a weakening of the British Pound Sterling which pushed demand for UK gas higher.

The annual variability in arbitrage and co-optimised are explicitly investigated in this thesis. In Chapter 5 annual variations in 2005-2015 are shown (later in figure 5.4) whereas the annual and seasonal variations in co-optimisation revenues are shown from 2011-2014 in Chapter 6 (in table 6.1, figure 6.8). Longer timespans than these were not possible due to data unavailability. Besides revenues, the impact of annual variability on market participation was investigated; the extent to which a storage system would charge or discharge in a particular market under co-optimisation was shown to vary from year to year. Furthermore, in evaluating the NPV of specific technologies, an average of revenues between 2011-2014 was used rather than those relating to any specific year, to reduce bias.

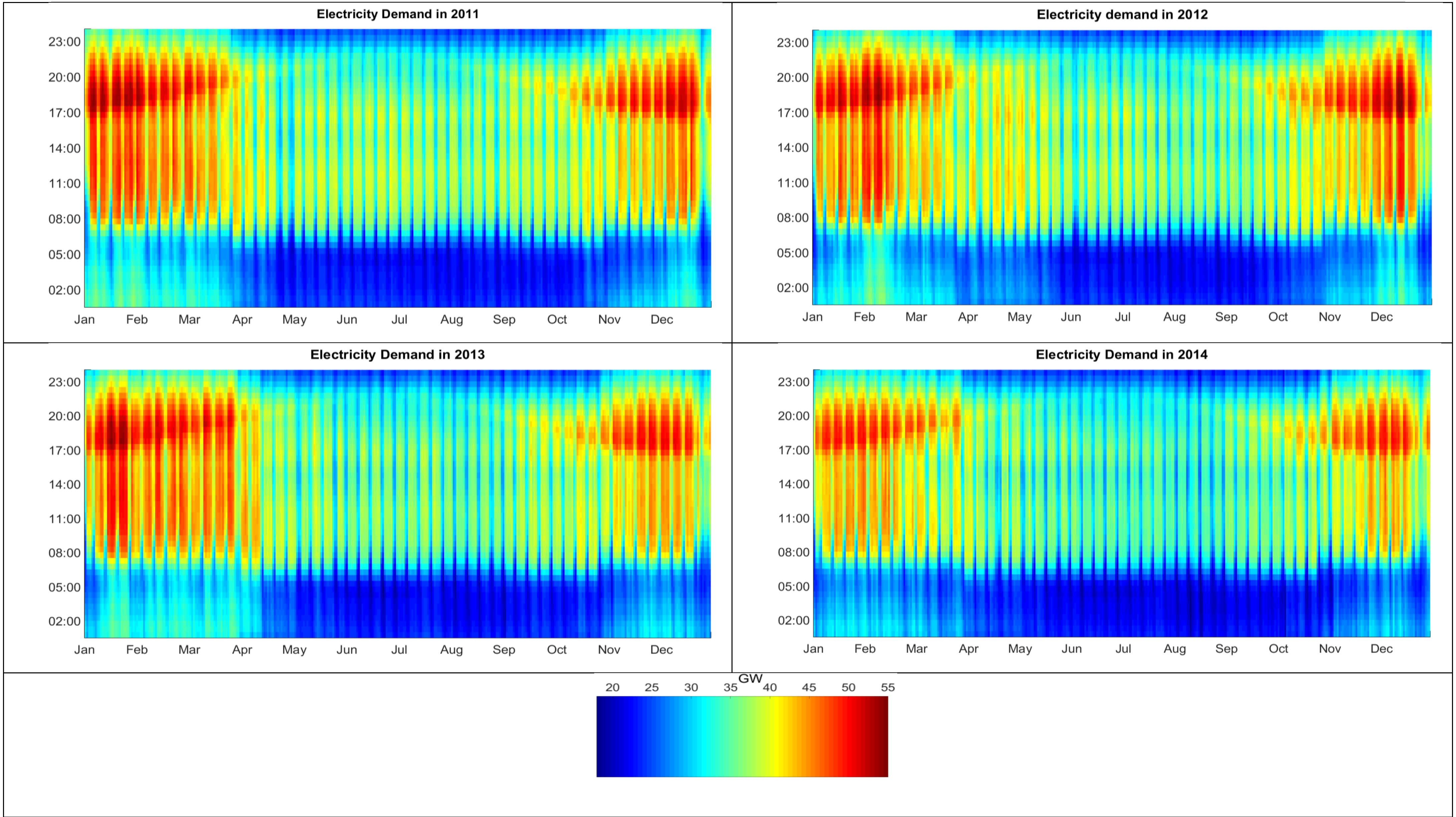


***Figure 3.5:*** *Transmission level demand from 2011-2014*

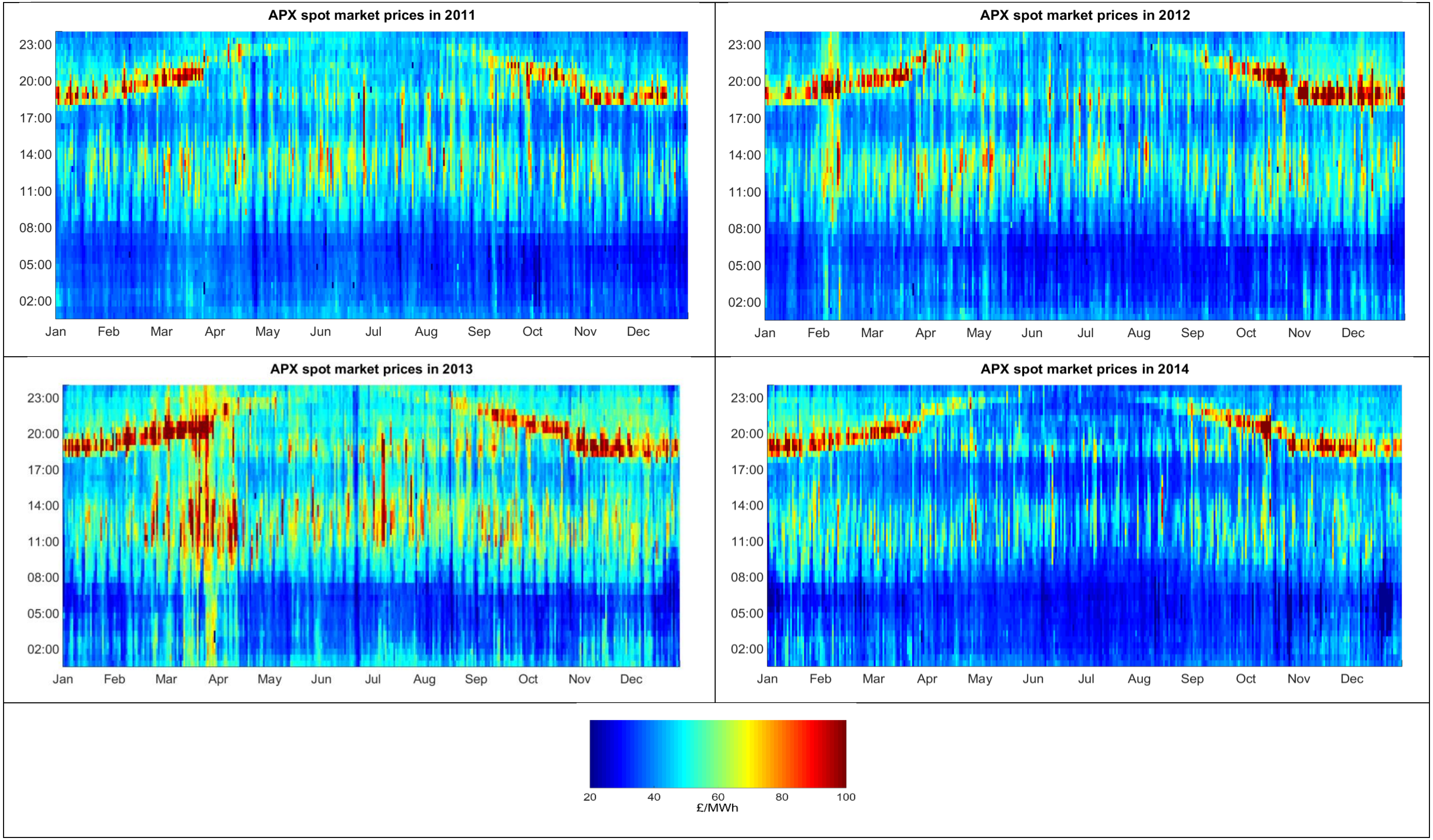


***Figure 3.6:*** *APX spot market prices from 2011-2014*

## 3.5. The Balancing Mechanism

The purpose of the Balancing Mechanism (BM) is to rectify energy imbalances which arise across the GB energy system. This is achieved through the acceptance of bids or offers by the system operator. Within the BM, a bid is defined as a proposal to increase demand or reduce generation while an offer refers to a proposal to decrease demand or increase generation (Elexon 2013b). While the BM is essential to the security of the physical network, specific reference to this mechanism is rare in the current body of literature relating to UK power markets. Therefore, this section summarises the fundamental principles of the BM, with comparisons to the spot market as well as discussing the potential for energy storage. More information on the operation of the balancing mechanism can be found from Elexon (2013b).

### 3.5.1. Imbalances in demand and supply

Parties are required to notify the SO of their positions through physical notifications. One hour before delivery, known as gate closure, all parties must submit their intended generation or demand, known as Final Physical Notification (FPN). This represents the level of generation or demand the party must maintain 1 hour ahead. In parallel, parties must also provide their contractual requirements as to how much electricity they are entitled to produce or consume. This requirement is known as Energy Contract Volume Notification (ECVN) and differences between the metered volume and ECVN will get charged at imbalance prices which reflect the cost of balancing actions taken by the system operator to rectify them.

### 3.5.2. Imbalance price calculation

At any time, there are two prevailing prices in the BM; a System Buy Price (SBP) and a System Sell Price (SSP) representing the price at which parties will get charged for under-generating/over-consuming and over-generating/under-consuming respectively.

The calculation of SBP and SSP depends on whether the system is long or short. When the system is short, with demand being relatively greater than generation, SBP becomes the main imbalance price as the SO seeks to accept offers. At the same time, SSP is calculated as a weighted average of short-term wholesale prices (essentially a mix of products from the APX power exchange), a process known as reverse pricing.

When the system is long, SSP is the main imbalance price and calculated as an average of accepted bids while SBP becomes the reverse price. The main imbalance pricing method penalises parties as SBP is likely to be higher than the market price and SSP lower. The reverse pricing method, on the other hand, compensates parties that are in fact helping the system as parties will be charged/paid at the short-term wholesale market rate. The relationship between the choice of pricing method and system status is shown in figure 3.7.

| | | System | |
|---|---|---|---|
| | | Long | Short |
| Party Imbalance | Long | Paid SSP (Main Price) | Paid SSP (Reverse Price) |
| | Short | Pay SBP (Reverse Price) | Pay SBP (Main Price) |

***Figure 3.7:*** *Choice of Calculation method of the SBP and SSP under system shortage or excesses. Source: Elexon (2013b)*

The purpose of the two calculation methods is to discourage parties from deviating from their contracted volumes since SBP is likely to be substantially higher than market prices while SSP tends to be lower. According to this calculation method, SBP cannot be lower than SSP and will at most be equivalent.

The Net Imbalance Volume (NIV) consists of the difference between the volume of accepted bids and offers. The imbalance prices use an average of up to 500 MWh of NIV, a process known as Price Average Reference (PAR) tagging. An example of a bid/offer acceptance together with the NIV calculation is given in Appendix A.

The Balancing and Settlement Code (BSC) code amendment of November 2015 abolished the dual prices removing the reverse pricing method. Under the new regulations both, parties that are contributing to a system deficit/excess will get charged/paid at a new single price, calculated as before using the main imbalance method (Ofgem 2015). Furthermore, a PAR volume of 50 MWh will be used instead of 500 MWh and a further reduction of PAR volume to 1 MWh is planned to take place from November 1, 2018 (Ofgem 2015).

Since this study uses historic data before November 2015, most of the analysis has been undertaken under the previous arrangements. In Chapter 7 a brief comment is provided on the implications of the new amendments for future storage value.

### 3.6. Relationship between the APX market, the BM and demand.

The markets explored in this thesis only represent a small proportion of total electricity supply as the most of the electricity in GB is traded well in advance through forward contracts. Figure 3.8 shows the relative scale of energy volumes; total annual net imbalance volume in the BM as well as the total trading volumes in the APX spot market is compared to the total electricity supply from 2011 to 2014.

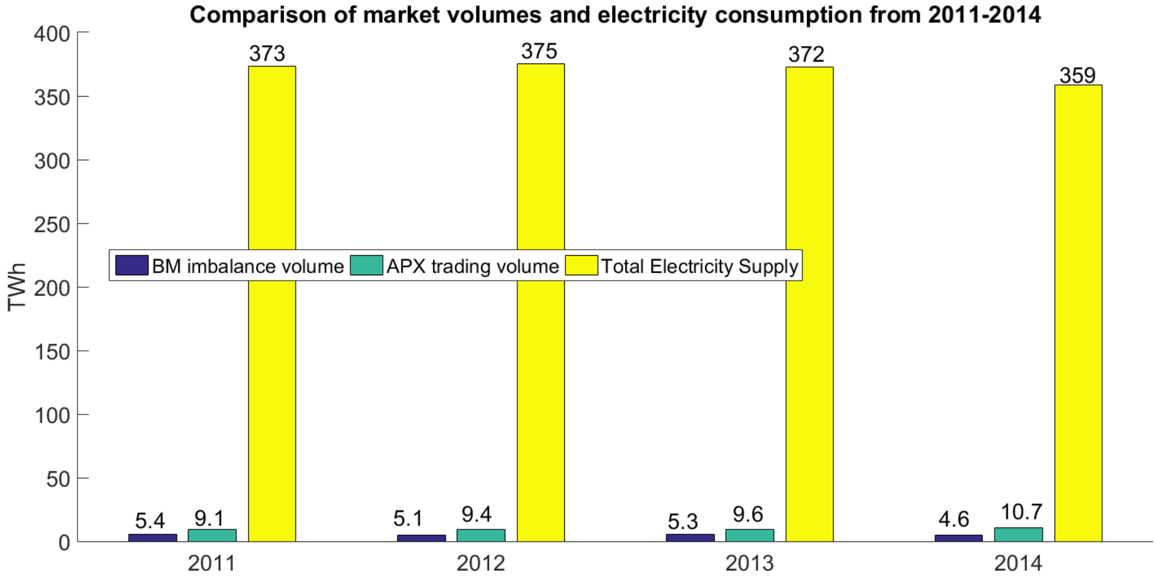


***Figure 3:*** *Relative scale of energy volume in the APX and BM compared to total electricity supply from 2011-2014. The APX trading volume refers to those in the half-hourly spot market.*

While energy volumes determine the liquidity of the market mechanisms, the relative magnitude of prices present in these mechanisms determine relative profitability. Large price variations are particularly attractive to storage systems as they increases revenue.

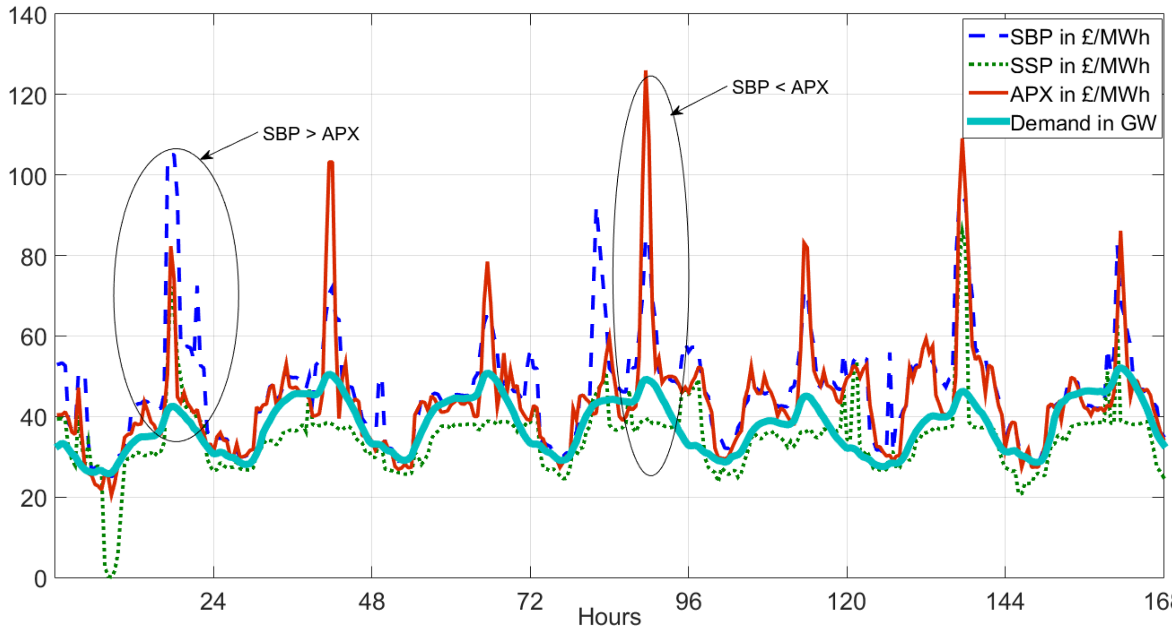


***Figure 3.9:*** *The APX and BM prices, as well as demand during the first week of January 2013.*

Figure 3.9 shows price fluctuations in the APX spot market and balancing mechanism relative to demand during the first week of 2013. Demand follows a daily cycle with peak demand occurring around 17:30-19:30 whereas its lowest levels tend to occur between 04:00-06:00. The spot market price shown as APX, generally follows the same pattern as demand with the highest prices occurring during peak demand period and the lowest prices occurring during the lowest demand period. However, the magnitude of the changes in the spot market price is not always proportional to demand changes; during the morning period between 08:00-12:00 prices rise sharply before falling during the early afternoon hours. During peak demand, the spot market prices rise disproportionately, reflecting the scarcity of electricity supply over demand in addition to further shocks such as constraints.

Furthermore, the half-hourly APX spot market is particularly prone to price volatility as trading occurs up to almost one hour ahead of delivery i.e. at gate closure (APX 2015). Since parties are required to meet their contractual positions at gate closure, the half hourly spot market represents the last opportunity to adjust their positions before the balancing mechanism operates, where they are likely to be penalised for their imbalances.

Figure 3.9 also shows the system prices in the balancing mechanism. There appears to be a certain degree of correlation between the system prices and the spot market price. Both the BM prices and the APX price can be expected to stem from a cost function somewhat analogous to a merit order. This follows from the fact that electricity produced for every period usually reflects the generation online at that time. Wholesale electricity prices do not necessarily follow marginal costs and this is especially true during peak time and short term power markets where other factors such as competitive behaviour, scarcity, forecasting errors and other disturbances weigh in. This is discussed further in Chapter 4.

## 3.7.Price volatility in the APX and BM: opportunities for storage

The volatility in prices, due to its potential for arbitrage profits merits further investigation. In the top part of figure 3.10, the spot market price is shown from 2011-2014. In the BM, imbalance prices are shown instead of SBP and SSP; the imbalance price is the price of interest as the reverse price is a reflection of the APX market, which is already shown. As a reminder, SBP is the imbalance price during a shortage and conversely SSP during an excess. The imbalance price for the same period is shown in the bottom part of figure 3.10. Since there is a greater volatility in the imbalance price, there is potential for greater arbitrage revenues.

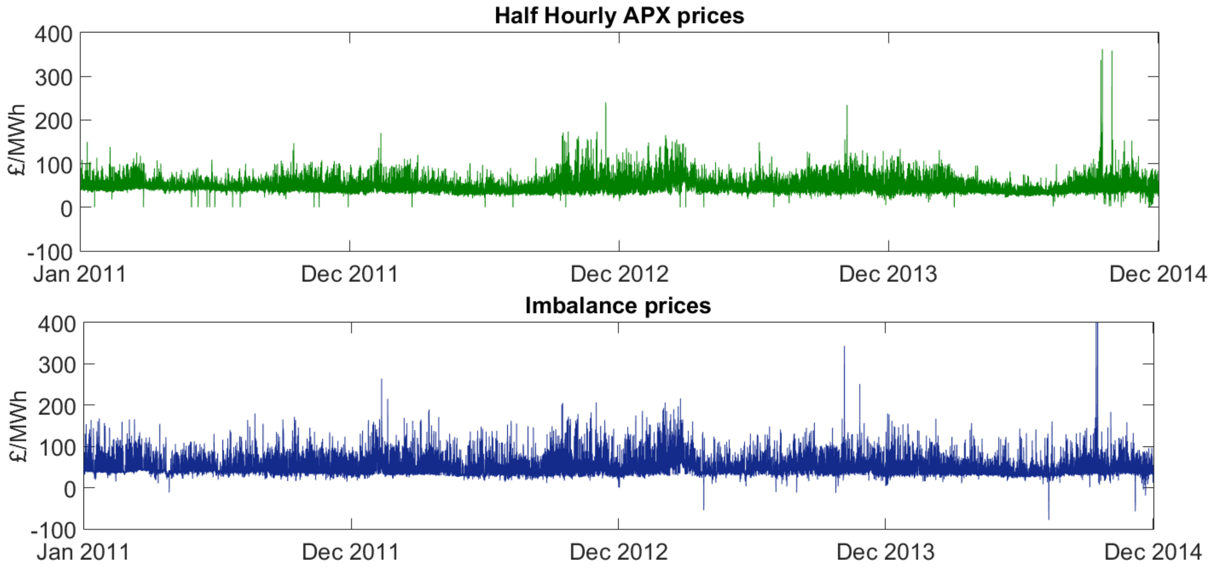


***Figure 3.10:*** *Comparative price volatility in the APX and BM from 2011-2014.*

The spot market price can exceptionally be negative unlike in the BM whereby prices have been negative on several occasions between 2011 and 2014. Generally, in a wholesale market, negative prices could arise from conventional generators who are willing to pay to stay in operation because an immediate shutdown and start up for a later scheduled generation would simply cost more. Additionally, renewable generation such as wind farms have an incentive to produce power even at a price of zero due to mechanisms such as the Renewable Obligation Certificate (ROC) or EU Emission Trading Scheme (EU-ETS). Therefore, they are likely to accept a negative price as long as the revenues outweigh the (marginal) cost.

Alternatively, the volatility can be shown in aggregate through a price distribution in figure 3.11; the APX spot market price distribution is positively skewed whereas the imbalance price distribution shows a difference between low and high prices, shown here as the price gap. An analysis of NIV is undertaken in Appendix A.2, showing that the system tends to be long more often than short which causes imbalance prices to be below the APX market price (on average) more often as shown in figure 3.11. On the other hand, occasions where the system is short are relatively fewer but result in a clear price gap. The presence of a price gap is expected since imbalance prices are either more expensive than the market price or cheaper than the market price (depending on the state of imbalance). Thus a split is likely to occur around the average APX market price, which is corroborated by the lower part of figure 3.11.

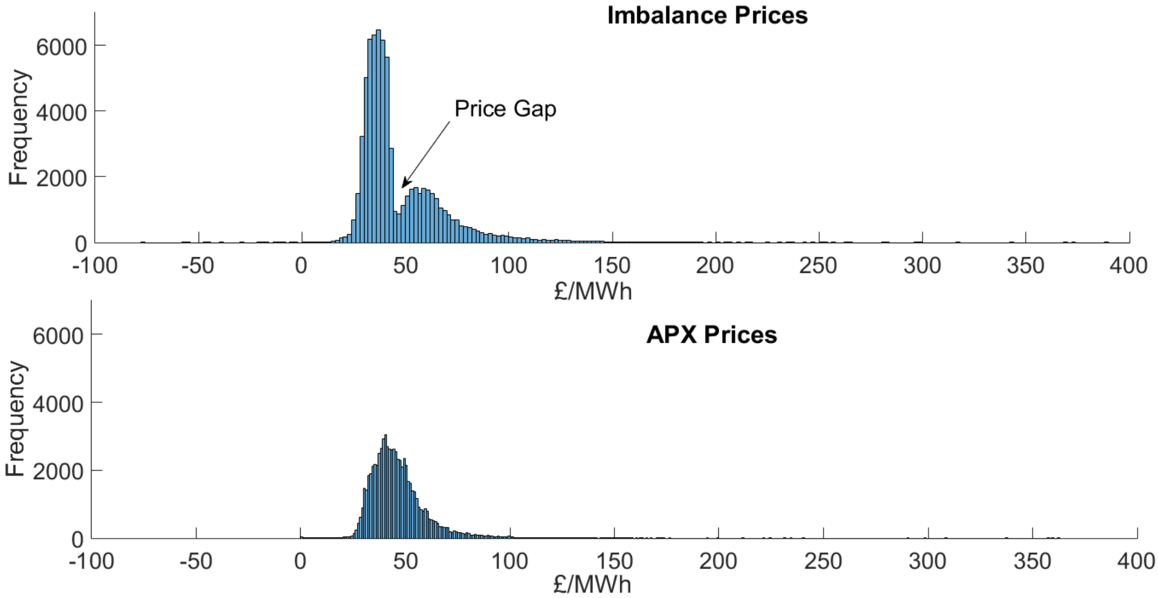


***Figure 3.11:*** *Comparative price distribution in the APX market and BM showing a price gap in the latter.*

The existence of this price gap has further implications for storage, clearly showing greater potential for arbitrage in the balancing mechanism; the greater the price gap, the greater the potential for arbitrage profits (within the BM). Examining both distributions, both have similar ranges; the imbalance price has more occurrences of low prices, allowing for the possibility of buying electricity in the BM and later selling in the APX market, possible in a model which combines both revenue streams.

## 3.8. Ancillary and other services

Energy storage systems similar to conventional generation are able to participate in other revenue mechanisms besides the wholesale and balancing mechanism. One of those additional revenue sources is payments arising from the provision of ancillary services to National Grid. In GB, National Grid acts as both the SO and the transmission network owner. There is a large number of services that National Grid currently procures to maintain system security. Appendix B.1 shows a summary of those services, their requirements along with their costs. Here, two of the most frequently used services are chosen, STOR and FFR, and their characteristics are analysed further.

### 3.8.1. Prospects for the provision of STOR by energy storage

According to National Grid, (2015b), STOR provides additional generation or demand reduction in order to cope with forecasting errors and/or unforeseen generation unavailability. Furthermore, to enable participation in this service requires a minimum capacity of 3 MW and a maximum lead time of 240 minutes after instruction whereas output should be sustained for at least 2 hours.

Payment for STOR consists of an availability payment in £/MW/h basis and a utilisation payment on a £/MWh basis. Availability and Utilisation payments for 2013 are shown in figure 3.12, exhibiting clear seasonal influence, especially utilisation payments. These variations are in line with those observed in the APX markets with substantially higher values in winter than in the summer months.

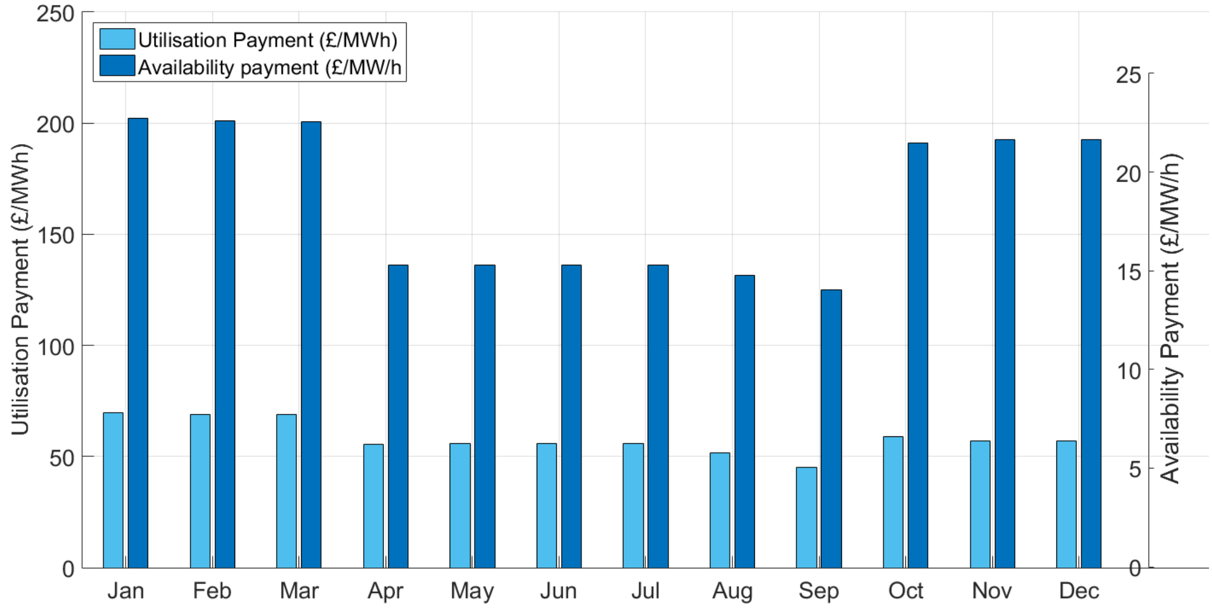


***Figure 3.12:*** *The average monthly availability and utilisation payments for STOR in 2013. Compiled using data from: National Grid (2014b).*

STOR can be a viable option for specific energy storage technologies due to its relatively longer lead/response times from instruction, compared to frequency response; CAES, for example, require start up times of 10 minutes onwards and would not be able to provide FFR (from a cold start) under its current requirements but would meet those for STOR. STOR has a minimum size entry requirement of 3 MW and a response time of up to 240 minutes; however, accepted tenders highlight the fact that the likelihood of being offered a contract with response times over 20 minutes is very small, shown in figure 3.13. In addition to the response times, figure 3.13 also shows the size ranges of STOR.

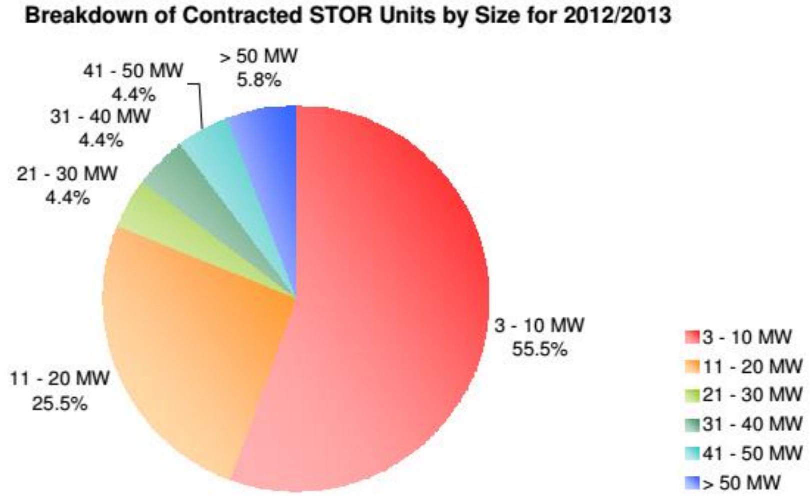



***Figure 3.13:*** *The size and response time characteristics of accepted STOR contracts for the year 2012/2013.Source: National Grid (2014b)*

Due to the nature of ancillary services in general, whereby utilisation payments are made only when the service is called out, there is a level of uncertainty associated with the revenue streams. National Grid procures STOR for specific windows depending on the season but typically from 07:30 to 13:30 and from 17:00 to 21:00 (National Grid 2013b). Actual utilisation levels for specific STOR units was unavailable and henceforth a utilisation rate could not be established. Locatelli et al., (2015) included STOR in their two revenue stream model, with an assumed utilisation rate of 50-80 hours annually. Using aggregate published values, an approximated utilisation rate was calculated in Chapter 4.

### 3.8.2. Frequency response service: types and requirements

National Grid procures frequency response through 4 distinct services; Mandatory Frequency Response (MFR), Firm Frequency Response (FFR), Frequency Control by Demand Management (FCDM) and Enhanced Frequency Response (EFR).

Mandatory Frequency Response (MFR) provision is required by all large generators (greater than 100 MW), in compliance with the grid code. Under MFR, frequency regulation is achieved through synchronised governors with a major compulsory requirement being a 3-5% *governor droop characteristic* defined as the ratio of the change of rotational speed to the change in power. FCDM is targeted to demand side response providers. The Enhanced Frequency Response (EFR) service was recently created with response time less than 1 second to fulfil the need for a faster-acting frequency response. The EFR service is expected to come into effect at latest by the 1st of March 2018 (National Grid 2016e)

While mandatory frequency response is required by all large generators, firm frequency response service can be provided optionally by units outside of the balancing mechanism. Firm frequency response is procured well ahead of delivery period and BM timescales. The minimum size requirement for FFR is 10 MW.

### 3.8.3. Timescales for frequency response

Dynamic Frequency Response is the automatic adjustment of frequency within the 0.4%, 49.8-50.2 Hz frequency range, also known as the normal operating range. Automation usually takes place through governor action. Dynamic frequency response consists of three subtypes:

1. *Primary Response* whereby automatic power increase occurs within 10 seconds following a fault and is sustained for at least 20 seconds in duration. During a power loss, this can be viewed as a “frequency containment” to reduce the loss. Primary Response requirement is determined by the national grid and is currently set at 1000 MW loss to 0.5 Hz (National Grid. 2011).

2. *Secondary Response* whereby automatic power increase occurs within 30 seconds timeframe for at least 30 minutes. Under power loss, following primary response, this can be seen as “frequency restoration” whereby frequency is brought to operational limits. Secondary response requirement is set at 1320 MW loss to 0.5 Hz (National Grid. 2011).

3. *High Frequency Response* whereby excess power is reduced within 10 seconds timeframe. High response requirement is currently set at 840 MW demand loss (National Grid. 2011).

### 3.7.4. FFR payment

There are 4 types of payment for FFR as shown in figure 3.14:

1. **Availability payment:** For the tendered frame, an availability payment is made in £/hr, representing the reward for the service provider to make itself available, irrespective of whether actual utilisation of the service has occurred. Availability payment can be seen as a holding payment for being in a state of readiness.

2. **Window Initiation Fee:** Within each tendered time frame, National Grid may (automatically) instruct the service provider to deliver energy. For initiating a window for delivery, the service provider is paid a Window Initiation Fee in £/window. Window Initiation Fee forms part of a utilisation payment.
3. **Nomination Fee**: For each utilisation period, a nomination fee is paid in £/hr. In cases where windows are revised by the national grid and accepted by the FFR provider a revised nomination fee in £/hr is paid out as a compensation.
4. **Response Energy Fee**: Upon actual energy utilisation a fee is paid per unit of energy delivered in £/MWh. Response Energy is equivalent to the market price scaled by a factor. This factor is 1.25 when system frequency is below normal and 0.75 when frequency is above, as per section 4.1.3.9 of the Connection and Use of System Charges (National Grid 2015a).

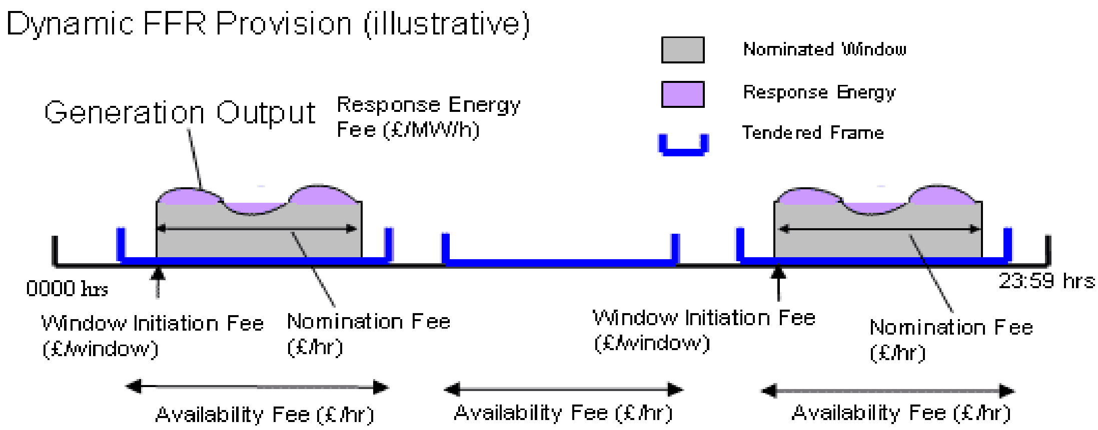


***Figure 3.14**: An overview of the payment types during the provision of FFR (National Grid. n.d.)*

In practice, however, based on FFR tender reports, window initiation fees are rarely included in the tenders and most tenders specify revenues based on availability payment (National Grid 2013a). An example of an FFR tender is given in Appendix B.2.

## 3.9. Concluding remarks

The aim of this chapter was to provide an overview of the revenue mechanisms of relevance to a storage system. Among the different products in the APX power exchange, the half hourly spot market product showed more arbitrage potential and hence was chosen to represent the short-term wholesale market. The Balancing Mechanism was described, with specific emphasis on how the imbalance prices are calculated. These imbalance prices showed high potential for storage value, evidenced by the calculation method and also noticeable from the data gathered. Volatility in both the APX market and the BM demonstrated potential value for arbitrage revenues, with more potential in the latter.

Two ancillary services were described, STOR and FFR; storage revenues from the provision of these services is different from arbitrage. These provision of these services is rewarded by an availability payment for being on stand-by and a utilisation payment when the service is actually called for. With the potential for storage value, demonstrated in those mechanisms, the next Chapter takes a more formal approach to investigating the value of storage.

# Chapter 4. Approaches to deriving storage value

## 4.1. Introduction

The presence of volatility in the APX market and BM, and the provision of ancillary services are opportunities for storage to generate revenues. However, this requires precise operation of the storage system in accordance with the prices and/or choosing the best windows to offer the ancillary service. This section, therefore, focuses on the model development to maximise revenues, showing the full potential of these mechanisms.

A formal mathematical description of the models, fully dedicated to operating in either the APX market, the BM or providing FFR, is given. This is referred to as a single market operation. Conversely, a model combining the revenues is also derived; under such a model the storage participates optimally in each revenue mechanism simultaneously. This model is referred to as the co-optimised model.

Since Mixed Integer Linear Programming (MILP) is used to evaluate the models, a brief description of this technique is given as well as its advantages and disadvantages for solving this specific problem. Specially formulated constraints under MILP are thus presented.

An NPV analysis, undertaken to show the financial feasibility of selected storage technologies, is explained, along with cost and other parameter assumptions. An econometric approach is also undertaken to isolate the wind impact on the revenue mechanisms and these models are later used to simulate prices under a 20 GW wind penetration scenario. This econometric approach is discussed, especially in the presence of known biases. Similarly, the assumptions behind the high wind penetration scenario are described and briefly discussed.

## 4.2. APX and BM model derivation

In order to investigate the value of storage in the short-term wholesale market, an optimisation model was developed. A fundamental assumption of the model, which determines the operation of the energy storage in the revenue mechanisms, is that the storage system is a generic one i.e. a technology neutral approach is adopted throughout most of this thesis, except in Chapter 6 whereby lifetime economic feasibility is assessed through Net Present Value (NPV) analysis.

Nevertheless, some initial parameters broadly reflective of a technology are required for the model. Since the most extensively deployed form of electricity storage is PHES (Deane et al. 2010), the efficiency parameter is broadly chosen to be reflective of a modern PHES system. The Round Trip Efficiency(RTE) of PHES systems in previous studies vary; Sioshansi et al., (2009) assume an 80% RTE, citing the 80.3% efficiency of Bath County PHES in the PJM region. Connolly et al., (2011) have used a symmetric charging and discharging efficiency of 0.92 for a RTE of 0.85, citing the American Society of

Civil Engineers. Hessami & Bowly (2011) used an efficiency of 84.3% RTE for a PHES using seawater, obtained from confidential industry quotations. In this thesis, the initial parameters are chosen as follows; charging and discharging efficiencies are symmetric at 90%, representative of a pumped hydro storage system with round-trip efficiency of 81% for example. Storage power capacity is initially set at 50 MW, therefore setting half-hourly maximum energy charge and discharge at 25 MWh per half-hourly period.

The choice of a 50 MW power capacity is guided by general considerations that large storage systems influence the markets to such an extent that the price taker assumption becomes increasingly unrealistic. Furthermore, in the Balancing Mechanism, parties with generation or demand exceeding 50 MW need to provide physical notifications (Elexon 2013a) and consequently get penalised for not meeting them. On the other hand, storage systems need to be sufficiently large to trade profitably on the power exchanges, irrespective of trading volume; for example, a full trading membership of the APX power exchange costs approximately £58,260 annually as fixed fees (APX 2016b).

The energy capacity is chosen at 12 hours' equivalent or 600 MWh, to investigate daily revenues energy storage could provide without being restricted. On a 24-hour optimisation horizon, the maximum energy capacity a storage would require would be 12 hours (of consecutive charging, followed by 12 hours of consecutive discharging). In reality, however, this is likely to be oversized and the relationship between energy capacity (with power capacity fixed) and revenues is investigated in Chapter 6. The choice of this energy capacity was also guided by previous studies earlier in Chapter 2; these studies showed that a small energy capacity in the range of 10 hours or less was preferred for revenue maximisation purposes. A 12-hour energy capacity is thus sufficiently large to avoid restricting storage operations.

$$\pi_{APX} = \sum_{t=1}^{n} \alpha_t * -D_{APX,t} * effd * P_{APX} - (1-\alpha_t) * C_{APX,t} * P_{APX} \tag{4.1}$$

$$\pi_{BM} = \sum_{t=1}^{n} \beta_t * -D_{BM,t} * effd * SBP_t - (1-\beta_t) * C_{BMt} * SSP_t \tag{4.2}$$

$$ST_{APX,t} = ST_{APX,t-1} + (1-\alpha_t) * effc * C_{APX,t} + \alpha_t * D_{APX,t} \tag{4.3}$$

$$ST_{BM,t} = ST_{BM,t-1} + (1-\beta_t) * effc * C_{BM,t} + \beta_t * D_{BM,t} \tag{4.4}$$

$$0 \le C_t \le 25 \;\forall\, t \tag{4.5}$$

$$-25 \le D_t \le 0 \;\forall\, t \tag{4.6}$$

$$0 \le ST_t \le 600 \;\forall\, t \tag{4.7}$$

$$\left|C_{APX,t}\right|,\left|D_{APX,t}\right| \leq APXV_t \;\forall\, t \tag{4.8}$$

$$max(C_{BM,t}) = \begin{cases} C_{BM,t} & if \quad C_{BM,t} < -NIV_t \\ -NIV_t & if \quad 0 < -NIV_t < C_{BM,t} \\ 0 & if \quad NIV_t \geq 0 \end{cases} \tag{4.9}$$

$$min(D_{BM,t}) = \begin{cases} D_{BM,t} & if \quad -D_{BM,t} \leq NIV_t \\ -NIV_t & if \quad 0 < NIV_t < -D_{BM,t} \\ 0 & if \quad NIV_t \leq 0 \end{cases} \tag{4.10}$$

Whereby

$\pi_{APX}$: APX arbitrage revenues in £

$\pi_{BM}$: BM arbitrage revenues in £

*APXV*: Traded volume in the APX market in MWh

$C$: Charge Volume in MWh

$D$: Discharge Volume in MWh

$effd$: Discharge Efficiency

$effc$: Charge Efficiency

$n$: Total number of time periods, equivalent to 17520 half-hourly periods in 2013.

*NIV*: Imbalance volume in the BM in MWh. IMBV is -ve during system surplus and +ve during system shortage

$P_{APX}$: Half-hourly APX spot market price

$SBP$: System Buy Price in £/MWh

$SSP$: System Sell Price in £/MWh

$ST$: Storage Volume (Level) in MWh

$\alpha$: Binary variable in the APX market. Takes a value of 1 when discharging, zero otherwise.

β: Binary variable in the BM market. Takes a value of 1 when discharging, zero otherwise.

The generic storage system charges on low prices and discharges at higher prices thereby generating arbitrage profits. The decision variables, in this case, are charge and discharge volumes at each time period. The model is an optimisation problem and the objective function for the APX model is given by equation (4.1), where $\pi_{APX}$: represents the total arbitrage revenues in the APX market. *C* and *D* are the storage system's energy charges and discharges respectively in MWh. Throughout the models in this thesis, charging is shown as a positive value and discharging is negative, chosen as such to simplify the energy balance equation in (4.5). *APXP* is the APX market price in £/MWh, *effd* is the discharge efficiency, expressed as a fraction and $\alpha$ is a binary variable which prevents simultaneous charging and discharging. The subscript *t* refers to each half-hourly period over which the model is evaluated.

Similarly, in the BM the arbitrage revenues are generated when the system charges at System Sell Price (SSP), analogous to National Grid accepting bids to reduce generation or increase demand (usually during excess power) and discharges at System Buy Price (SBP) representing a state where National Grid seeks additional power during shortages. The BM model is given by equation (4.2) whereby β represents a binary variable to prevent charging and discharging, similar to $\alpha$ in equation (4.1).

Both models include binary variables α and β to prevent charging and discharging simultaneously. It should be noted that the discharging efficiency affects the revenues but charging efficiency affects the state of charge of the system which is determined by the energy balance equation in (4.3) and (4.4) whereby $ST$ is the state of charge in MWh and *effc* is the charging efficiency.

Charging, which is shown as a positive value is bounded by the inequality in (4.5) and similarly, Discharging which is negative, is bounded by the inequality in (4.6).

The maximum storage energy capacity is 12 hours' output at 600 MWh as explained at the beginning of this chapter. Thus the energy capacity of the storage system is bounded by (4.7). This limit is relaxed later during sensitivity analysis. The choice of the energy capacity of the storage system was guided by previous studies, stated earlier in Chapter 2; these studies showed that a small energy capacity in the range of 10 hours or less was preferred for revenue maximisation purposes. A 12-hour energy capacity is thus sufficiently large to avoid restricting storage operations, and this confirmed in Chapter 5.

The model is initially evaluated without market constraints in Chapter 5. In this case, it is assumed that the markets have sufficient liquidity to absorb the storage system's operations. In the APX market, this would imply that the trading volumes are sufficiently large that storage operation can be absorbed. This assumption is relaxed later in Chapter 6 to investigate the impact of market constraints on APX revenues. In order to do so, the constraint (4.8) is applied to the APX optimisation model. $APXV$ represents the market traded volume on the half-hourly spot market price, in MWh and the inequality (4.7) limits the charging and discharging of the storage system to that possible under historic market conditions.

Similarly, for the BM, further constraints are imposed later in Chapter 6; this stems from the unlikelihood of bids/offers being accepted when they aggravate the system imbalance. Thus the constraints reflect the fact that the storage system can only charge during a system energy excess and up to the magnitude of the excess. Conversely, the storage system can only discharge during a (BM) system shortage, up to the magnitude of the energy shortage. These are implemented using constraints (4.9) and (4.10). $NIV$ represents the imbalance volume in MWh; by convention excess power on the Balancing Mechanism is shown as a negative number whereas shortage of power is shown is a positive number. Equation (4.9) dictates that the storage system can charges to its maximum as long as the excess imbalance volume is sufficiently large. In case the imbalance excess is too small to allow for a full capacity charge, the imbalance volume is the maximum energy the storage system is allowed to charge. When the imbalance volume arises as a shortage of power in the balancing mechanism, charging is set to zero and aligns with the interest of the System Operator.

## 4.3. The FFR model

In general, for the provision of frequency response, a storage system can inject energy into the network during low frequency events or reduce output/absorb energy from the network in case of high frequency events. The nature of the service provision that is to provide low or high frequency response is determined bilaterally between National Grid and participants, through a process of tender rounds. These participants can thus offer low frequency response, high frequency response or both. Similarly, availability payments are agreed bilaterally. Using data from the tender rounds in 2013, published by National Grid (2013), a total of 5488MW of contracts were awarded for the year for the provision of low frequency response. In the case of high frequency response, this figure was 1913MW, showing a bias in favour of the procurement of low frequency response. Furthermore, additional difficulties arise in considering the provision of high frequency response; from the tender round data, participants providing both high and low frequency response are paid a total fee as availability payment. It is therefore difficult to distinguish between the proportion that is paid solely for the provision of high or low frequency response as each tender is bilaterally agreed and varies. Hence, for simplicity, the storage system is assumed to provide low frequency response throughout this thesis. Using data for the two generators at Dinorwig PHES (DINO-1 and DINO-5), adjusted for power capacity and the number of hours the PHES system is available, an availability payment was calculated. This was approximately £5/MW/h of power capacity. This value is similar to those relating to the provision of Mandatory Frequency Response (MFR) whereby most availability payments were in the range of £2.5/MW/h to £7/MW/h. It should be stressed that both generators at Dinorwig power station offered only low frequency response.

The FFR model is based on the assumption of a fully dedicated unit which only provides frequency response under the Firm Frequency Response service, which National Grid currently procures (National Grid. n.d.). In the previous section, the APX and BM models derived revenues through arbitrage which was determined by optimisation. In this case, the FFR model derives revenues from ancillary services payment and derived through simulation. While there are additional forms of payment made to the FFR provider, the model only takes into account an availability payment and a utilisation payment which corresponds to the term '*response energy payment*'; these are scaled by a factor of 1.25 times wholesale prices during low frequency and 0.75 times that of wholesale prices during high-frequency events as per section 4.1.3.9 of the Connection and Use of System Charges (National Grid 2015a). This low-frequency scaling factor is included in the model but not the high-frequency scaling factor, as the

FFR model is only assumed to provide power during low-frequency events. Other payment types have been omitted given that these are rarely specified, based on the post-tender reports gathered.

As an FFR dedicated system, the model includes a self-discharge factor to account for long periods of idle time. During non-idle times, charging and discharging losses are assumed to include the self-discharge losses. Other than the self-discharge parameter, the other storage system parameters for the FFR model are identical to the APX and BM models.

Due to the lack of data on actual frequency response utilisation for a similar sized generator (to the storage system), a probability function is derived similar to the approach undertaken by Loisel et al. (2011). The authors studied wind-storage configuration providing reserves in France; they cite primary reserves as power required within 30 seconds whereas secondary reserves require immediate activation following a disturbance and reaches full capacity within 5 minutes. Tertiary reserves are required to reach their full capacity within 15 minutes. Due to their choice of technology, CAES, only secondary and tertiary reserve are considered for the provision of reserves; the authors use a 15% probability of being used for secondary reserves and 2% for tertiary reserve. In this thesis, a probability of being utilised for the provision of FFR of 20% is chosen. This is slightly higher than Loisel et al. (2011)'s values to include the primary reserve service probability since the FFR timescales encompasses those of primary, secondary and tertiary reserve. Furthermore, in an EPRI report (Rastler 2011), an 18-20% capacity factor was assumed when storage system's function was to provide T & D support. Since, in Chapter 5, it is shown that major source of revenue is availability rather than utilisation payments, revenues are unlikely to be strongly sensitive to changes in this probability factor.

An artificial utilisation profile is generated using a random binomial distribution to determine when frequency response is required and a random discrete uniform distribution to determine the volume of frequency response required when called for. These signals are assumed to occur 20% of the time and require capacity between 1 and 50 MW.

Equations (4.11) and (4.12) show the FFR revenue and SOC of the system shown as '$\pi_{FFR}$' and '$ST_t$' respectively.

$$\pi_{FFR} = \sum_{t=1}^{n} \gamma_t * effd * AV_{FFR} + \gamma_t * \sigma_t * \mathrm{SF} * effd * D_{FFR,t} * P_{APX,t} - (1 - \gamma_t) * C_{FFR,t} * P_{APX,t} \tag{4.11}$$

$$ST_t = ST_{t-1} - ST_{t-1} * selfdis + effc * C_{FFR,t} + \alpha * D_{FFR,t} \tag{4.12}$$

$$C_{FFR,t}:\begin{cases} C_{FFR,t} = 25 & if\ \ ST_{MAX} - ST_{t-1} \geq 25\ and\ \gamma_t = 0 \\ C_{FFR,t} = ST_{MAX} - ST_{t-1} & if\ \ 0 < ST_{MAX} - ST_{t-1} < 25\ and\ \gamma_t = 0 \\ 0 \leq C_{FFR,t} \leq (1 - \gamma_t * \sigma_t) * 25 & \forall\, t \\ C_{FFR,t} = 0 & \text{Otherwise} \end{cases}$$

(4.13)

$$UT = f(Bin(n, q), Unif\{a, b\}) \tag{4.14}$$

$$D_{FFR,t}:\begin{cases} -25 \leq D_{FFR,t} \leq 0\ \forall\, t \\ D_{FFR,t} = \text{UT} & if\ \ \gamma_t = 1,\ \sigma_t = 1 \\ D_{FFR,t} = 0 & Otherwise \end{cases} \tag{4.15}$$

Whereby

| | |
|---|---|
| $\pi_{FFR}$: | Revenues from the provision of FFR in £ |
| a: | Parameter of the discrete uniform distribution representing the minimum range (1 MWh) |
| $AV_{FFR}$: | Availability payment in £/MW/h. Initially this is set at £5/MW/h. |
| b: | Parameter of the discrete uniform distribution representing the maximum range (25 MWh) |
| $C$: | Charge Volume in MWh |
| $D$: | Discharge Volume in MWh |
| $effd$: | Discharge Efficiency |
| $effc$: | Charge Efficiency |
| $P_{APX}$: | Half-hourly APX spot market price in £/MWh |
| q: | Binomial distribution parameter representing the probability of success (20%) |
| $selfdis$: | Self-charge factor equivalent to 0.001 per half-hour |
| $ST$: | Storage Volume (Level) in MWh |
| $ST_{MAX}$: | Maximum Storage Volume (Level) in MWh initially set at 600 MWh |
| $SF$: | Low frequency scaling factor, for utilisation payments. equivalent to 1.25 |
| $UT$: | Utilisation Volume for the provision of FFR service in MWh |
| $\gamma$: | Binary variable taking a value of 1 when an FFR window is active, zero otherwise. |
| $\sigma$: | Binary variable taking a value of 1 when the FFR service is utilised, zero otherwise. |
| $n$: | Total number of time periods, equivalent to 17520 half-hourly periods in 2013. |

In equation (4.11), $\gamma$ is a binary variable, taking a value of 1 during a FFR window and zero otherwise. Another binary variable $\sigma$ determines the actual utilisation of the service, that is when storage is discharging. '*selfdis'* refers to the self-discharge rate of 0.1% per half-hour. This value is broadly representative of a lithium battery which loses about 5% of its energy in the first 24 hours (Technical University of Munich 2016).

From equation 4.12, charging occurs as soon as the 12-hour FFR window terminates. This could imply charging at unnecessarily high prices, hence by varying period covered by the 12 hour window FFR revenues can increased (This is shown later in figure 5.9). In other words, even though the FFR model is not an optimisation model, by varying the starting time, it is possible to determine which 12-hour window generates the most revenues. With a half-hourly resolution, there are 48 possible start times for the 12-hour windows and since the system is designed to charge by purchasing power from the APX market, the storage system is able to reduce its costs depending on charging times.

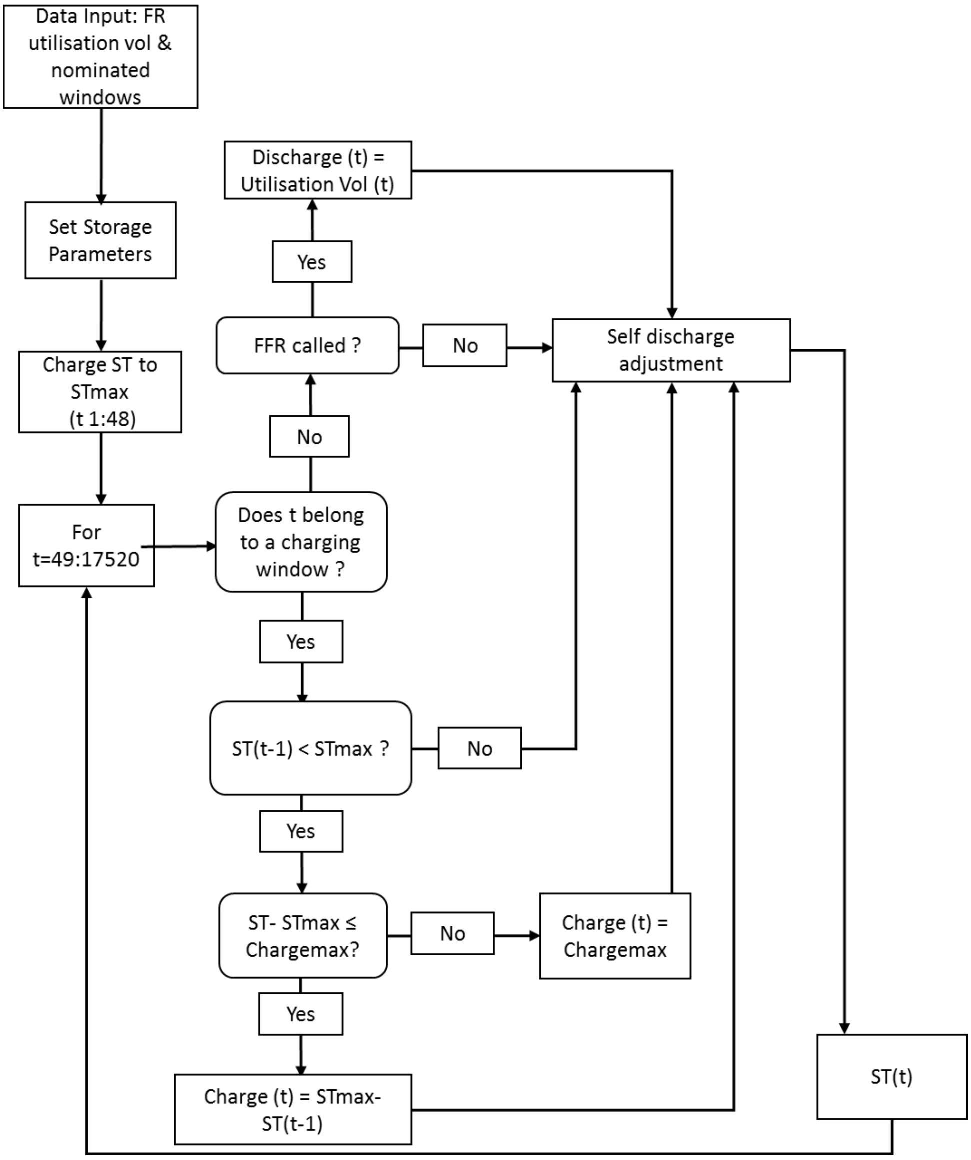


***Figure 4.1:*** *Schematic representation of the FFR simulation model.*

Figure 4.1 shows the simulation of revenues from the FFR model. Frequency response windows are set in advance for a duration of 12 hours starting initially for the period from midnight to noon. This represents the windows whereby the SO could require the power from the storage system, referred to as FFR window. During the first day of operation, the storage system needs to be fully charged, to its maximum energy capacity shown as '*STmax*'. For each half-hourly period, there is a self-discharge factor and if this period falls outside of its FFR window and the state of charge is below its maximum energy capacity, charging occurs. Otherwise, the storage system remains on standby until either its service provision is required or the self-discharge reduces the state of charge.

## 4.4. The STOR model

The STOR model is very similar to the FFR model; both ancillary services require an allocated window during which there is a possibility of utilisation. The primary difference is the utilisation price; while availability payments are similar for frequency response and STOR, both at approximately £5/MW/h, utilisation payments are higher ranging from £125/MWh-£202/MWh (National Grid 2015e). Using an average, the utilisation payment in the model was calculated at £168/MWh.

For the STOR model, a utilisation rate was determined based using equation (4.16).

$$Utilisation\ Rate_{STOR} = \frac{\sum_{i=1}^{6} STORUVOL_i}{\sum_{i=1}^{6} Seasonhrs_i \times AverageavCap} \tag{4.16}$$

Whereby

| | |
|---|---|
| $STORUVOL$: | The total volume of STOR serviced utilised in MWh |
| $Seasonhrs$: | The total number of hours STOR was contracted for each season |
| $Averageavcap$: | The average capacity actually available as opposed to declared capacity |

STOR is contracted for 6 seasons spanning a year between 2012/2013. (National Grid 2014b) have published aggregate STOR utilisation volumes (MWh) and the number of hours of holding capacity for each season. The capacity of STOR contracted on a daily basis during 2012-2013 was on average 3178 MW. However, the average availability capacity was equivalent to 2374 MW.

Equation (4.16) derives a utilisation rate based on absolute energy requirements (MWh). Alternatively, National Grid (2014) have also published data on the total number of hours the service was called in 2012/2013 and together with the total availability hours contracted, a time based utilisation rate could have been derived instead but this method suffers from over/underestimation as an hour's utilisation between a small and large generator differs substantially. Using equation (4.16), a utilisation rate of 1.81% was calculated. Tender reports show a large number of units offering their services for STOR with a much smaller proportion being accepted.

With the models described, figure 4.2 shows how each model contributes to the determination of storage value in GB. While each avenue of value is estimated individually they are combined towards the end, using co-optimisation to evaluate the total revenues generated from the markets.

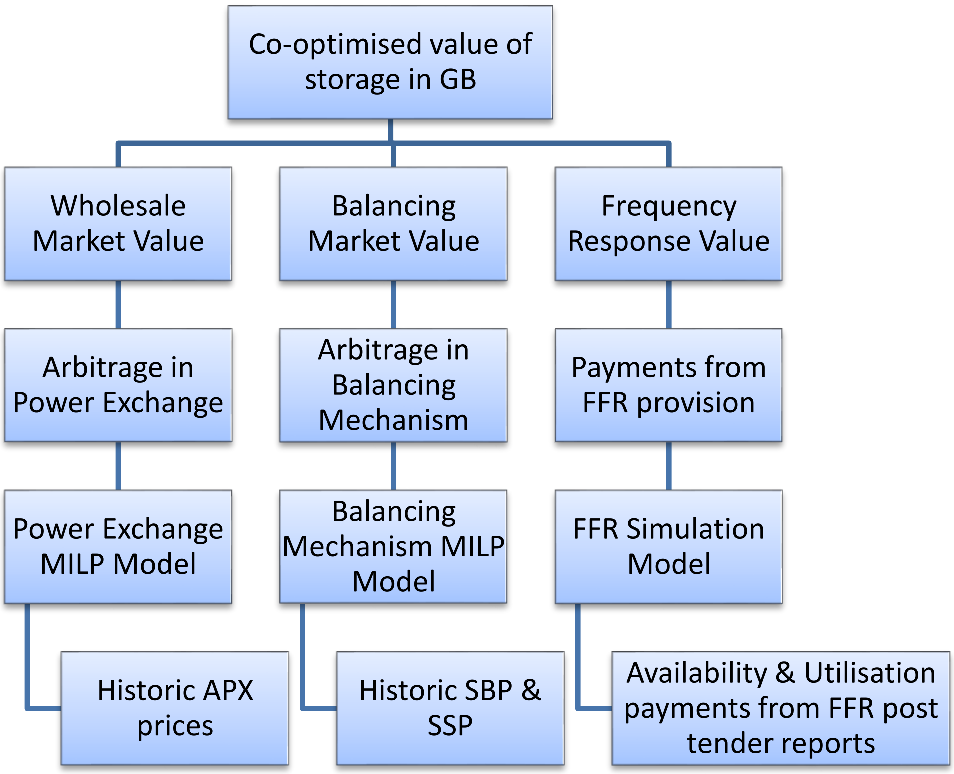


***Figure 4.2:*** *An overview of the inputs and processes required to calculate the potential value of energy storage.*

## 4.5. Linear, Mixed Integer Linear Programming and model complexity

In section 2.3 it was shown that the main approach used in previous studies to derive storage value was optimisation. While Linear Optimisation models are still used, there was a shift to more advanced techniques such as Mixed Integer Linear Programming. The APX and BM models were initially evaluated using linear optimisation, also known as Linear Programming (LP). These problems consist of a linear objective function usually bounded by linear equality and inequality constraints, defining the feasible region. The corner-points, defined as the intersection of two or more constraints, are of interest since they represent a point where the constraints are still active. In linear programs, the optimum solution, if it exists, is always a corner-point of the feasible region. The Simplex algorithm works by evaluating these corner-points, which are finite as opposed to an infinite number of points in the feasible region. The stopping criteria occur when all the adjacent corner-points are less or equal to the current corner-point solution, for a maximisation problem (see Chinneck, 2012). There are several algorithms for solving linear programming problems, however, the Simplex algorithm and the Interior Point Method are the most commonly used.

Several studies have used LP models to evaluate storage value; Safaei & Keith (2014) have used linear programming while investigating the revenues from CAES and D-CAES systems in Canada. McConnell et al., (2015) have also used linear programming to evaluate their arbitrage revenue model in

Australian markets. Similarly Kloess & Zach (2014) used LP to model arbitrage and revenues in the Austrian and German markets.

A Mixed Integer Linear Programming (MILP) solution first involves a first stage known as '*relaxation*' whereby the problem is solved without applying the integer constraints. This phase is usually implemented by a standard linear programming algorithm which returns a solution. The prevailing assumptions are first that any feasible solutions to the MILP problem are also a feasible solution to the LP problem but not vice versa. Secondly, the optimal solution for the MILP problem is always less than or equal to that of the LP problem (in the case of a maximisation problem). In other words, the MILP solutions are a subset of the LP solutions set. MILP problems use a branch and bound algorithm to split the LP feasible regions and explore them for optimal solutions. Several authors have used MILP models to evaluate storage revenues (He et al. 2011; Drury et al. 2011; Moreno et al. 2015; Foley & Díaz Lobera 2013).

Chazarra et al., (2016) highlight the computational intensity of MILP and caution against an excessive number of decision and binary variables. For non-linear problems, MILP is not appropriate and Mixed Integer Non-Linear Programming (MINLP) is required. However, as is the case generally with non-linear optimisation techniques, MINLP cannot guarantee global optimality. In their study, (Chazarra et al. 2016) dismiss MINLP based on computational complexity, in terms of runtimes and algorithm complexity.

The concern about the efficiency of algorithms for storage optimisation problems has also been expressed by Pimm et al., (2015) who present an alternative algorithm. The algorithm referred to as optimal operation algorithm is an extension of Lund et al. (2009) and Connolly et al., (2011)'s algorithm which captures arbitrage value; the Pimm et al., (2015) add additional steps which account for the interaction between the two energy stores. The authors demonstrate its computational efficiency against the more commonly used interior point method algorithm. Their model is implemented in MATLAB and the algorithms compared in runtimes; the optimal operation algorithm is significantly faster than the interior point algorithm which MATLAB uses as default in the '*fmincon*' function, shown in figure 4.3.

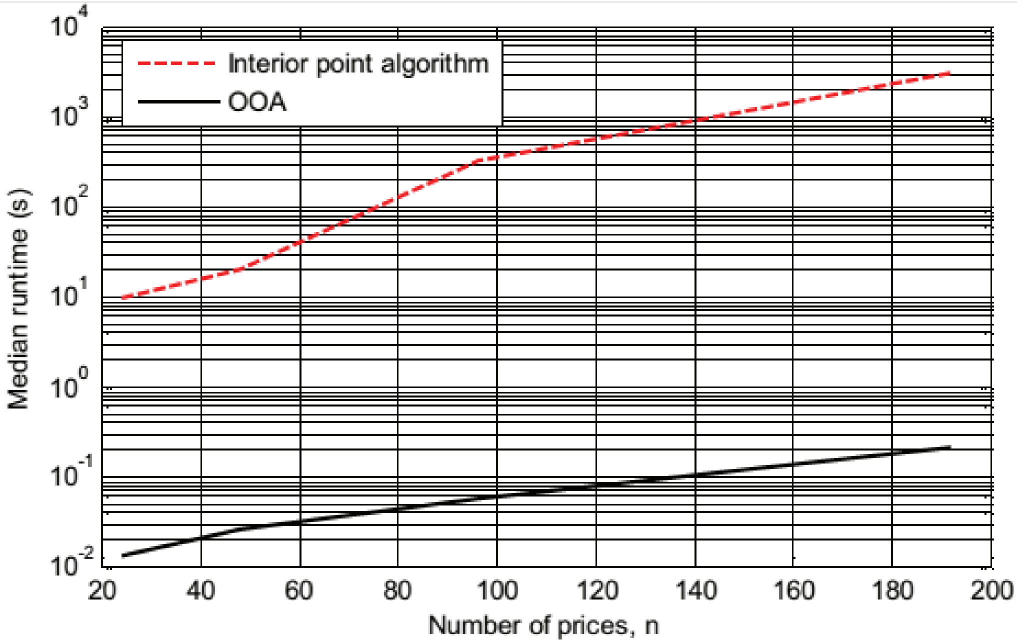


***Figure 4.3**: Pimm et al., (2015), show the efficiency of their Optimal Operation Algorithm (OOA) compared to the more commonly used interior point algorithm.*

The non-linear optimisation algorithm presented by Pimm et al., (2015) is not directly applicable to the co-optimisation problem presented in this thesis; however, the algorithm can potentially be adapted and shows merit for future consideration due to computational efficiency gains. Nevertheless, Pérez-Díaz et al., (2015), in reviewing studies on PHES storage operation, have shown that Mixed integer programming remains the most commonly used method for the unit commitment and economic dispatch problems. In this thesis, the optimisation models are solved using MILP; the first stage LP problem is solved using the Simplex algorithm and subsequently the branch and bound algorithm are applied for integer solutions. These algorithms are present in MATLAB (v. 2013-2015a), in which all models are coded.

## 4.6. Co-optimisation model features

The co-optimisation model utilises the same storage parameters as those in the other models; RTE was 81% whereas power and energy capacities were 50 MW and 600 MWh respectively. Under this model however, energy storage participates in all markets and services simultaneously. Similar to the APX and BM optimisation models, the Co-optimisation model prevents the storage system from charging and discharging at the same time in all three markets. In other words, while simultaneous participation is allowed conflicting modes are avoided; for example, the system is not allowed to charge and discharge at the same time. This prevents incoherent behaviour that might result from optimisation otherwise.

The co-optimisation model includes one ancillary service to represent a different type of revenue mechanism. In reality, a storage system could offer many ancillary services, as long as their requirements and contractual obligations are met. However, this thesis explores the nature of different types of revenues; for a revenue stream which reflects short-term wholesale prices, the half-hourly APX spot market was chosen. For a revenue stream which reflects energy balancing costs, the BM was chosen and for a revenue stream which reflects the ancillary service, FFR was chosen over STOR. This is guided by the findings from trials at the UK Leighton Buzzard storage facility which provided both STOR and FFR, citing that FFR represents viable economic opportunities unlike STOR (Papadopoulos 2016b; Papadopoulos 2016a)

For the provision of FFR, if a window is allocated to this service, participation in the APX market and BM are excluded; In other words, the system is fully dedicated to providing FFR during that window and will only discharge to provide frequency response. The SOC of the storage system has a further requirement under FFR; enough energy must be stored to provide ancillary services for the windows they are on standby for. In choosing the FFR window, the co-optimisation model is not restricted to choose the same window for each optimisation horizon. This assumption allows the investigation of the full potential of co-optimising storage across the three revenues mechanisms, however in practice contracts are awarded on a fixed window basis. Some dispatch strategies can take this restriction into account such as the fixed dispatch schedule described later in section 4.8.

The co-optimisation model formulated has 6 types of decision variables for any given time period. Since the system operates in the APX and BM markets, there is a charge and discharge decision variable for each of them. In addition, there are two binary variables, one deciding when FFR is being allocated to the window and the other to implement MILP constraints, described further in the next section. The approach of using two distinct types of decision variables for charging and discharging as opposed to a single variable, has also been used by Fares et al., (2014) who explore the value of frequency response provision by VRB systems in Texas.

While having charging and discharging as separate decision variables simplify the objective function, this comes at a cost of computational efficiency. MILP problems become increasingly more difficult to solve the larger the number of variables. As a consequence, while exploring the effect of horizon length on the value of storage in single markets the computational requirements prohibited lengths greater than three months. However, this was not of significant concern in this case since the trend showed a clear convergence at much shorter horizons, shown in Chapter 5.

## 4.7. The Co-optimisation model derivation

The revenue streams from each type of revenue mechanism can be combined into one model; under this co-optimisation model, both the allocation of capacity and derivation of revenues are calculated simultaneously using optimisation and perfect foresight. The perfect foresight assumption is later relaxed in Chapter 7. The objective function is given in equation (4.17) which combines revenue functions for the APX, BM and FFR models previously described.

$$\pi_{CO-OP} = \pi_{APX} + \pi_{BM} + \pi_{FFR} \tag{4.17}$$

### 4.7.1. Mixed Integer Linear Programming constraints

In optimisation problems it is not possible to directly program if-then execution statements; however, these can be implemented as constraints by using binary variables. The following constraints were implemented to restrict the model behaviour to one that is consistent with storage operation as described in the previous section:

$$0 \leq C_{APX,t}, C_{BM,t,} C_{FFR,t} \leq 25 \tag{4.18}$$

$$-25 \leq D_{APX,t}\,, D_{BM,t}\,, D_{BM,t} \leq 0 \tag{4.19}$$

$$\lambda_t * W \leq C_{APX,t} + C_{BM,t} \leq (1-\lambda_t) * V \tag{4.20}$$

$$\lambda_t * W \leq D_{APX,t} + D_{BM,t} \leq (1-\lambda_t) * V \tag{4.21}$$

$$C_{APX,t} + C_{BM,t} \leq (1-\gamma_t) * V \tag{4.22}$$

$$D_{APX,t} + D_{BM,t} \geq (1-\gamma_t) * W \tag{4.23}$$

$$0 \leq C_{APX,t+1} + C_{BM,t+1} + D_{APX,t+1} + D_{BM,t+1} + ST_t \leq 600 \tag{4.24}$$

$$\gamma_t * V \leq ST_{t-1} \tag{4.25}$$

$$ST_t = effc * (C_{APX,t} + C_{BM,t}) + D_{APX,t} + D_{BM,t} + ST_{t-1}\ \forall\, t \tag{4.26}$$

Whereby

| | |
|---|---|
| $C$: | Charge Volume in MWh |
| $D$: | Discharge Volume in MWh |
| $effc$: | Charge Efficiency |
| $ST$: | Storage Volume (Level) in MWh |
| V: | Constant set a 25 |
| W: | Constant set at -25 |
| $\lambda$: | Binary variable used for modelling charging and discharging bounds. |
| $\gamma$: | Binary variable taking a value of 1 when an FFR window is active, zero otherwise. |

Constraints (4.18) - (4.21) prevent storage from charging and discharging at the same time; when $\lambda$ is equal to 1, charging in both markets is bounded between 0 and -25 MWh. However, since they are also bounded between 0 and 25 MWh from (4.18), it follows that the only solution which satisfies both constraint is when they take on zero values, implying that charging is not allowed. At the same time, from equation (4.21) discharge is bounded between -25 and 0 MWh, which is identical to constraint (4.19). Thus discharging is permitted. The opposite is true when $\lambda$ is equal to zero. The constraints also restrict the combined charge or discharge volume to 25 MWh irrespective of whether the charging or discharging is occurring in a single market or both markets. The constraint in (4.24) defines SOC as a function of charge and discharge as well as setting the upper and lower limits.

Constraints (4.22) and (4.23) dictate that when an FFR window is active, with the value of $\gamma$ equal to 1, charging and discharging are both zero. A value of 1 for $\gamma$ forces charging in (4.22) to be less than or equal to zero, but since (4.18) showed that charging cannot take negative values, the solution is charging equal to zero. At the same time, the discharge constraint (4.23) is forced to be greater than or equal to zero. From (4.19), the only solution that satisfies all the constraints when a FFR window is active is a value of zero for both charging and discharging. Therefore, the system is fully dedicated to FFR during the active window and will neither charge or discharge in other mechanisms during that time. Finally, constraint (4.25) ensures that there is enough energy stored ahead of the active FFR window, to provide the service effectively.

### 4.7.2. Optimisation horizon

The period of time over which charging and discharging are optimised is known as the optimisation horizon, representing the scheduled dispatch based on available information at the time. In order to investigate the potential value of storage in the markets, initially, a perfect foresight horizon is assumed. In practice, the knowledge of future prices and volumes is limited (to forecasting accuracy). Ideally, a longer optimisation horizon is preferred as it permits better planning and the ability to perform better trades by looking for greater price differentials between buying and selling prices. However, the computational complexity increases (exponentially in MILP problems) with each horizon period and therefore becomes a limiting factor in exploring the effect of perfect foresight on storage value. Additionally, an infinite perfect foresight horizon is of limited relevance since foresight accuracy is assumed to be generally better in the short run. A finite and practical horizon is thus of significant relevance as it represents a more feasible scenario.

Four foresight horizons are chosen for optimisation; One-day, two-day, one-week and one-month horizon. At the end of the horizon periods all parameters are reset to their original values – in particular, SOC is back to zero before moving to the next horizon until there are no more horizons to explore.

### 4.7.3. Optimality of revenues and validating approaches undertaken

In order to improve processing speed, parameters of the MILP algorithm parameters have been adjusted as follows; The relative tolerance gap between the upper and lower bound has been increased from the default 0.0001 to 0.001. The absolute tolerance gap (between the same bounds) has been increased from 0 to 1. These tolerances ensure that the value of objective function lies within 0.1% of the optimal solution or within +/-1 absolute value range. These parameters form part of the stopping criteria, that is, when solutions that match these parameters are found, the algorithm stops.

The impact of this parameter change means that some optimality is sacrificed; for example, the optimal solution for the co-optimisation problem run on the 1st of January 2011 (24 hour period) is shown in figure 4.4. Note that the value is negative since the optimisation problem is formulated as a minimization one (equivalent to a revenue maximisation one).

In this example the solution is revenue of £16,573 and the stopping criteria that the solution lies within 0.1% was applied. This means that there could be potentially better solutions that lie between £16,573 and £16,590 but have not been explored to improve on time efficiency. Hence the optimal revenues found in this thesis are not necessarily the absolute maximum but close to 0.1% or nearest £1.

```
MATLAB Command Window                                                  Page 1

LP:                Optimal objective value is -16860.478491.

Cut Generation:    Applied 14 Gomory cuts, and 1 mir cut.
                   Lower bound is -16675.333280.

Heuristics:        Found 1 solution using rounding.
                   Upper bound is -16517.910573.
                   Relative gap is 0.95%.

Cut Generation:    Applied 10 Gomory cuts.
                   Lower bound is -16666.018996.
                   Relative gap is 0.89%.

Branch and Bound:

   nodes     total   num int        integer       relative
explored  time (s)  solution           fval        gap (%)
     184      0.31         2  -1.657331e+04   3.545869e-02
     204      0.32         2  -1.657331e+04   1.010240e-03

Optimal solution found.

Intlinprog stopped because the objective value is within a gap tolerance
of the optimal value, options.TolGapRel = 0.001 (the selected value). The
intcon variables are integer within tolerance, options.TolInteger = 1e-05
(the default value).
```

***Figure 4.4:*** *MATLAB output of a two-period co-optimisation model with focus on the stopping criteria for the MILP algorithm.*

In order to validate the optimisation models, a simulation model was developed. In the simulation model, the charging and discharging profiles were imported from the optimisation model and revenue functions built based on the operation of storage. For example, if the storage system was set (by the optimisation model) to charge by buying power from the APX market for a particular period, the separate simulation model would calculate the cost of charging. Similarly, the simulation model calculates the revenues generated when the system discharged.

The optimisation model determines the maximum revenues and the optimal storage operations required to generate these revenues. The simulation model uses this storage operational profile to calculate revenues independently. The total revenues from the simulation model and the optimisation model should be identical. However, this simulation model does not determine whether these solutions are optimal but rather seeks identify errors in coding or modelling.

The GB-based study by Moreno et al. (2015) can be used to give a sense of magnitude to this results; In this thesis, the co-optimised revenues generated by the storage system in 2011 was £3,708,403 for a 50MW/600MWh storage system (shown in table 6.1), whereas Moreno et al. (2015) showed that a 6MW/10MWh storage system providing frequency response (both up and down), energy arbitrage, a reserve (not specified) and DNO services (active and reactive power) generated £311,353 for the same year. Scaling their result to match capacity rating of 50 MW and ignoring the power ratio issue, this represents £2,594,608. It is essential to point out that although the market location (GB) and year (2011) are both the same, a direct comparison of these results is not appropriate due to the power-energy ratios and the different types of services offered by the storage system.

In another study in the GB context, Locatelli et al. (2015) have shown that a PHES system with a 7-hour energy capacity generated approximately £20,000/MW/yr equivalent to a £1 million for a 50 MW system. These revenues, consisting partly of arbitrage and STOR revenues are much lower due to the non-optimal dispatch strategy and the chosen services as explained in section 2.4.2.

Earlier, Connolly et al. (2011) modelled arbitrage revenues across several markets worldwide, including GB. Using an optimisation model for a 300 MW/2000MWh PHES system with a round trip efficiency of 0.85, their model is similar to the APX model used in Chapter 5. Connolly et al. (2011) found that from 2005-2009, arbitrage revenues were approximately 15 million Euros, except for 2008 where exceptionally high prices resulted in approximately 33 million Euros (numbers inferred from figure 2.2). There are many similarities in their model to the APX model in terms of round trip efficiency (85% vs 81% in this thesis), years explored[4] and data[5]. Despite the difference in the energy capacities are different namely 6.7 hours in their study compared to 12 hours in the early parts of this thesis, later in Chapter 5, it is shown that almost all of the maximum revenues are captured with an energy capacity of 6 hour and hence any additional energy capacities generate very little revenues. For these reasons, a comparison is possible and the total revenues should be similar between their study and this thesis.

Using an exchange rate, in November 2009, of £1 = €1.1 (exchangerates.org, 2009) and scaling for a 50MW system, total revenues from Connolly et al. (2011)'s study amount to approximately £5 million

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[4] The 2005-2009 range of arbitrage values is shown in figure 5.4

[5] Connolly et al. (2011) used a weighted index of APX spot products known as Market Index Data (MID) while this thesis uses APX half-hourly spot market data.

compared to £5.1 million in this thesis in 2008. For the years 2005, 2006, 2007 and 2009 their values would be approximately equal to £2.3 million compared to £2.2-2.5 million from this thesis.

### 4.7.4. The impact of energy storage operations on the market

The price taker assumption is more reasonable given a small storage system operating in a large market. In this model, the storage system can influence the market through 25 MWh of energy charge or discharge at any half-hourly period. The volume constraints allow storage charging and discharging not to exceed trading volume in the APX market and the Net Imbalance Volume in the BM; in the latter, storage can only charge or discharge to reduce the net imbalance volume. While this constraint prevents the storage system from operating outside of historic market volumes, it does not address the possibility that the storage system could absorb all trading or imbalance volumes when they fall below 25 MWh and in those cases, have a likely distortionary impact on prices.

Using the trading volume data from the APX half-hourly spot market, a histogram and Cumulative Distribution Function (CDF) was produced to represent the scale of the storage operations compared to the market volumes, shown in figure 4.5. Between 2011-2014, the trading volume fell less than 25 MWh for approximately 1% of the time.

In the BM, occasions where the imbalance volume were between 25 MWh and -25 MWh represented approximately 6% of the time, shown in figure 4.6. Thus, the volume charged from and discharge into the markets are relatively small.

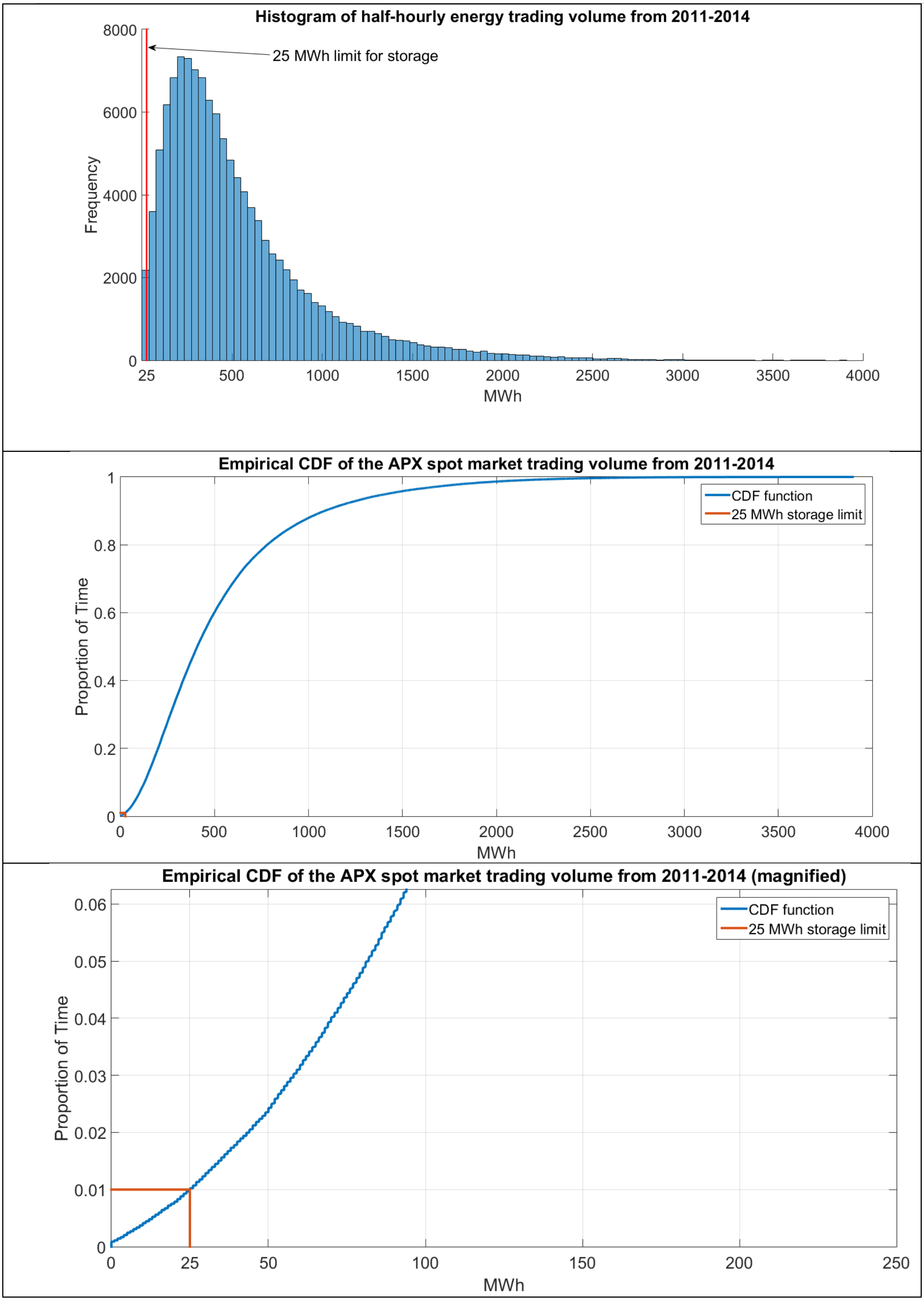


***Figure 4.5:*** *The scale of storage operations compared to the trading volumes on the APX half-hourly spot market from 2011-2014.*

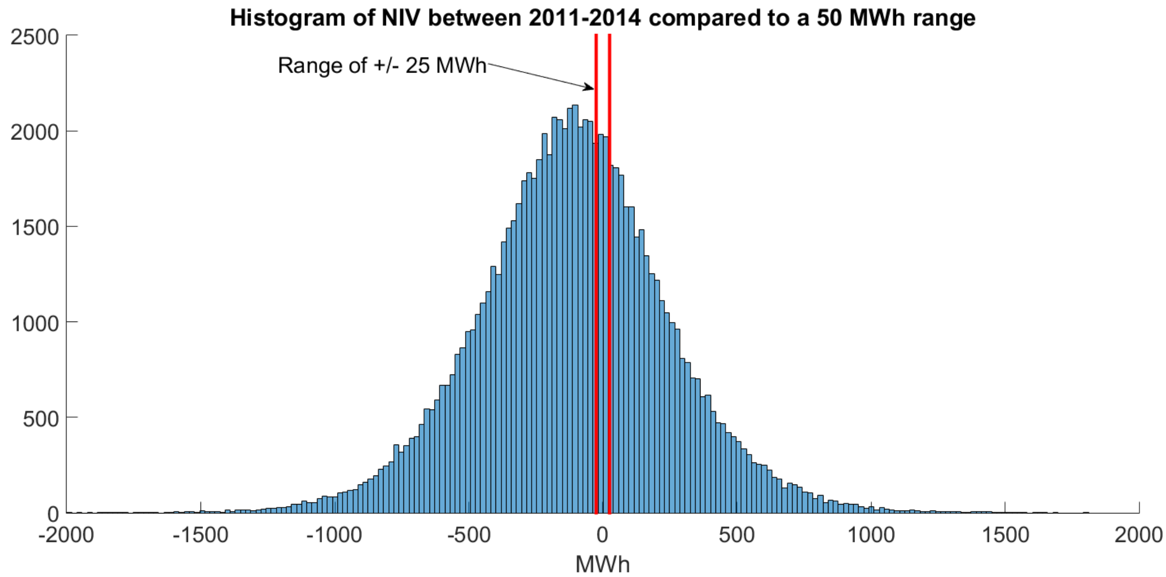


***Figure 4.6:*** *The scale of storage operations compared to the Net Imbalance Volumes on the Balancing Mechanism from 2011-2014.*

There would be merit however in exploring this impact further as the power and energy capacity of the storage system grows, to avoid overestimating revenues. Sioshansi et al., (2009) and Fertig & Apt (2011) have approached this problem using econometric techniques to isolate the impact of demand on prices and assume that energy storage is participation is fully reflected through demand. Hence when the energy storage charges net demand would be shown as an equivalent increase and the opposite would happen when the storage system discharges.

However, extending this approach to the GB context would not fare well since a simple regression between demand and prices shows are relatively poor fit; While Sioshansi et al. (2009)'s regression model was shown to fit the data well as represented in figure 4.7 a similar regression in GB had $R^2$ between 0.20 and 0.45 showing a rather poor fit.

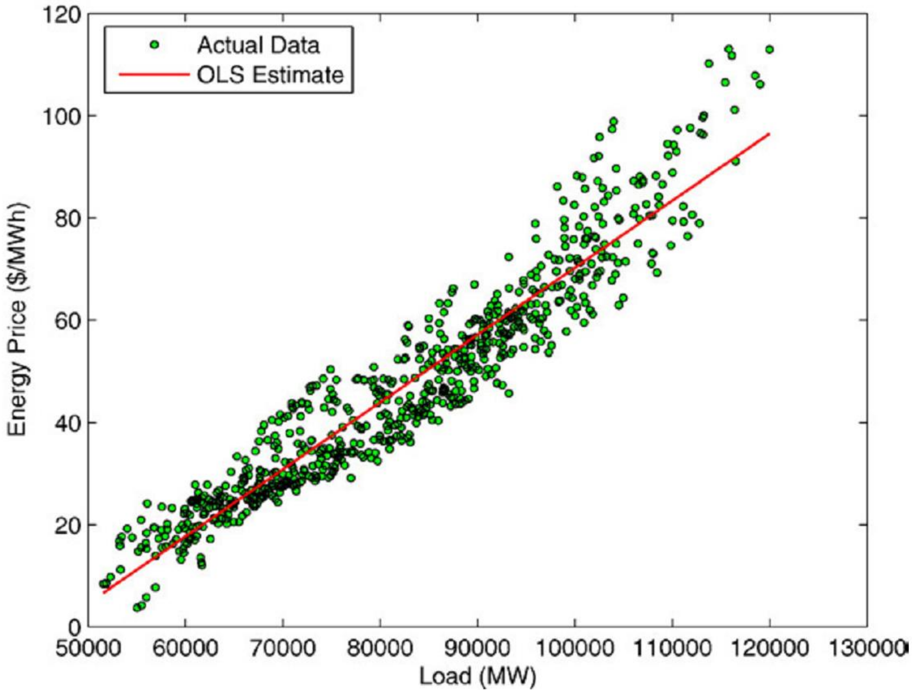


***Figure 4.7:*** *The relationship between wholesale electricity price and demand for June 2006 in the PJM market. Source: Sioshansi et al. (2009)*

Their unit commitment model however partially contradicted their econometric results; while the UC results showed that energy storage displaced peaking and mid-merit generation such that overall cost of production was reduced, the SMP was not always lower. In fact, SMP, on average was higher as storage operation caused the mid-merit plants to be the marginal price setting generation more frequently during off-peak periods. This also arose due to the inflexibility nature of some of the cheaper mid-merit plants. Foley & Díaz Lobera (2013) also showed that the average SMP price rose with the addition of CAES (under a 2020 wind penetration scenario).

Due to the different structure of power markets in GB, the UC model used by Nyamdash & Denny (2013) cannot be directly extended. The authors modelled the whole energy system whereas in this thesis, the half-hourly spot market price is used representing a short-term market. Hence, it is important to point out that most of the energy is purchased months to years ahead of delivery whereas the spot market clears very close to delivery, up to the hour preceding delivery. Consequently, besides the marginal costs, there may be additional factors which are strongly influential in determining prices such as forecast errors and bidding behaviour which takes advantage of very short term energy scarcity. Furthermore, there is fundamental difference between a pay as clear mechanism operating in a gross pool such as the SEM compared to a pay as bid mechanism operating in GB markets (as this extends to bilateral contracts).

In other words, there is conflicting evidence on the impact of a storage system on the market prices and may vary depending on the market structure including the generation portfolio participating in each market. In GB, the direct impact of storage operations on price and indirect impacts as other parties adjust their bidding behaviour accordingly is a complex problem. Modelling these impacts would require an understanding of competitive behaviour of bidding parties in the APX spot market as well as the likelihood of National Grid accepting bids and offers in the Balancing Mechanism. Given the complexity of this problem and the different modelling approach required, this thesis does not investigate this issue. Nevertheless, the storage system power capacity was purposely chosen to be as small as possible to make the price taker assumption as realistic as possible. In most studies investigating storage value in the markets using historical data, the price taker assumption has been used (Lund & Salgi 2009; Lund et al. 2009; Connolly et al. 2011; Drury et al. 2011; Safaei & Keith 2014; Locatelli et al. 2015; Moreno et al. 2015). However, this is still a limitation of this thesis and represents an area for further work.

### 4.7.5. Special precautions for energy storage optimisation models

There are special circumstances whereby market fluctuations combined with the model specification distort the results; Fertig & Apt (2011) show that a model which optimises capacity based on price signals runs the dangers of oversizing the storage system, under the price taker assumption. They found the optimal CAES size to be 24 GW. This arises mathematically as the optimisation models take prices as given and assumes that irrespective of the CAES size, the price will remain unchanged. The greater the fluctuation in prices the more exaggerated this effect and unrealistic the results will be. In fact, looking at their results in figure 4.8, it can be seen that the system discharges a large volume of energy at the very high prices in excess of $500/MWh. Naturally, a model would favour power capacity increase to take advantage of such short-lived but phenomenal price spikes.

There are different ways of mitigating this problem; one solution is to relax the price-taker assumption (which the authors do later) by including a price as a function of total energy, ideally empirically derived. Sioshansi et al., (2009) for example, used linear regression to estimate the impact of storage operation on prices and hence increases in energy storage capacity generate a feedback loop whereby peak prices fall as a result. Caution however should be exercised in the presence of extreme prices as non-linearity effects are most likely present and linear regression may not properly address this issue.

A simpler, yet more effective, solution would be to include the market volume as constraints, as this thesis does. If the extreme prices are driven by a small energy volume, then by constraining storage operation to market volumes, oversizing is avoided. It is useful to point out that these methods would be more realistic the smaller the system is relative to the market size.

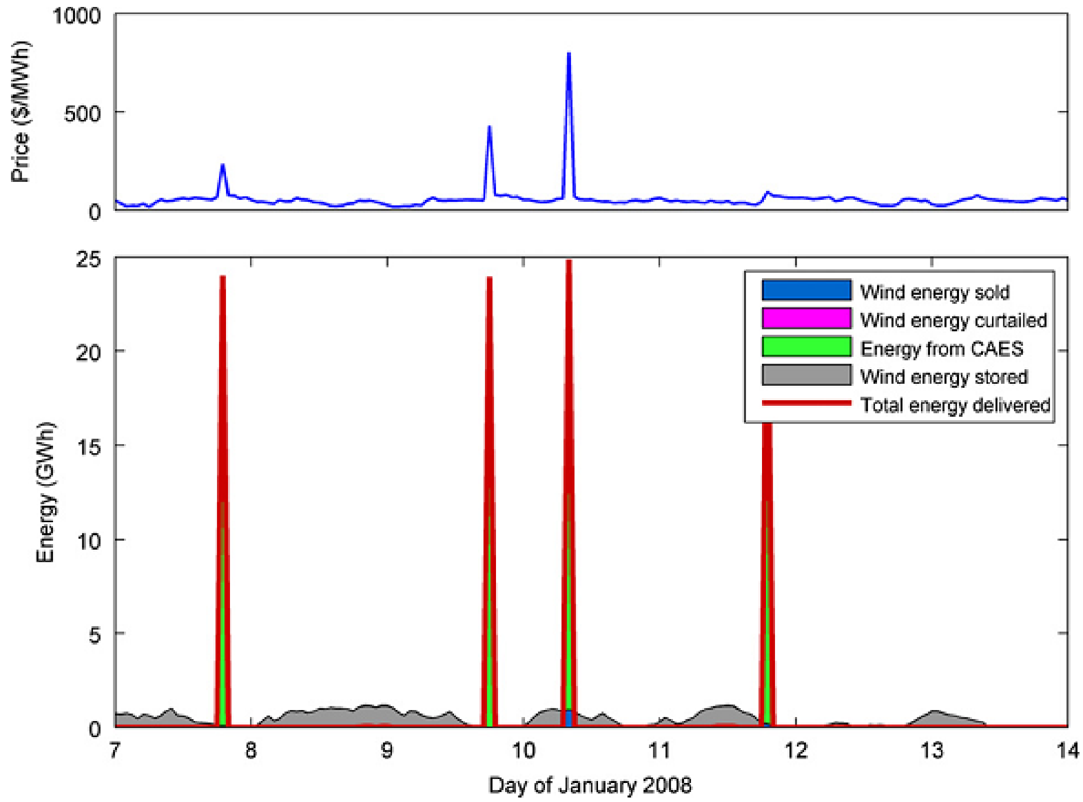


***Figure 4.8***: *Extreme price distortions having an impact on storage power capacity sizing. Source: Fertig & Apt (2011)*

## 4.8. Strategies to capture storage value: Fixed 12 on 12 off schedule

To test the implication of perfect foresight, storage revenues are evaluated using a number of simple strategies. These would represent the minimum realisable revenues. The simplest operation strategy is to schedule storage dispatch based on a fixed 12 hours on and 12 hours off schedule. This approach has been taken by Nyamdash et al., (2010) who explored the storage operation to balance wind power and generate arbitrage profit as well. This approach is investigated as a practical strategy to capture storage value in the markets.

### 4.8.1. Average co-optimised fixed dispatch

For each half-hourly period, the optimisation model generated a charging or discharging volume. The average of these charges and discharges were calculated for each period. This is effectively a dispatch strategy which is derived from the optimisation results and captures the time-of-day effects on revenues. However, this strategy does not capture variations over longer periods, such as seasonal impacts. The advantage of this strategy lies, as in the case of the Fixed 12 on 12 off approach, in its simplicity and ease of implementation.

### 4.8.2. Backcasting technique

Sioshansi et al., (2011) have shown that 85% of the maximum arbitrage value of storage value can be captured in the PJM market using a two-week backcasting method whereby the optimised dispatch is performed on prices two weeks prior. This follows a repetitive pattern of prices in the short term and merits investigation whether such trends exist in the GB markets and to what extent revenues can be captured.

## 4.9. Economic feasibility of energy storage technologies

The co-optimised revenues were generated under the assumption of technology neutrality in order to investigate the market potential for storage. In order to evaluate the feasibility of storage, characteristics dependent on storage technology also need to be considered. These characteristics are Capital Costs, Operation and Maintenance costs, and the lifespan of the selected technologies. An annual average of revenues from 2011 to 2014 is calculated and represents the assumed annual revenue of the storage system over its lifetime.

The chosen technologies and their parameters are given in table 4.1. Input costs vary widely in studies due to the unique nature of specific projects or commercial development. Deane et al., (2010) have shown that PHES costs exhibit large variations even though this form of energy storage is the most mature of all storage technologies. Project specific parameters have a strong impact on the economics of the system; however, those cannot be fully anticipated and hence lie beyond the scope of this study.

CAES was included for NPV analysis despite the fact that uncertainty about future gas prices adds further complexity to the analysis. Yucekaya (2013) has used Discrete Time Markov chain Monte Carlo simulations in an attempt to forecast future electricity prices as well as gas prices. The co-optimisation model uses quarterly gas prices as inputs from 2011-2014 to determine revenues.

CAES technical characteristics are drawn from literature; Lund et al., (2009) have used an expander to compressor ratio of 1.7:1 and the same ratio is adopted in the model. A fuel ratio representing gas fuel over electricity output of 1.202 is chosen as well as a turbine efficiency of 2.441 (Salgi & Lund 2008; Lund & Salgi 2009). Quarterly wholesale gas prices from 2011-2014 are used as input costs.

The lifespan of Lithium-ion batteries is expressed in the total number of cycles at a full depth of discharge, rather than in the standard number of years. Using the result from the co-optimisation, the lifespan of the lithium ion battery is estimated by calculating the average number of full charge and discharge cycles from 2011-2014. More precisely, the total charging volume is divided by the storage energy capacity as an approximation of the number of full cycles. This approach is similar to that undertaken by Pimm et al., (2015) which they refer to as equivalent number of cycles.

While it is accepted that full DOD cycles reduce the lifespan of the battery, this study looks at the revenue maximisation from market signals as the main objective rather than battery management. Lithium ion battery operation could potentially be optimised based on its technical characteristics such that its lifespan is extended without a dramatic fall in annual revenues generating higher NPV values.

However, to determine the optimal operation of battery operation would require a full electro-chemical study into power and energy capacity degradation over its lifespan due to its cycling depth.

| Storage System | Efficiency (%) | Lifespan | Power Cost | Energy Capacity Cost | O&M | Source: |
|---|---|---|---|---|---|---|
| Pumped Hydro | 81 (70-85) | 60 years (50-100) | £1000/kW (423-2113) | £7/kWh (0-13) | £5.5/kW/yr | a,b |
| Vanadium Redox Battery | 70 | 20 years | £298/kWh | | £11/kW/yr (3-27) | a,c,d |
| Iron-Chromium Redox Battery | 68 | 20 years | £129/kWh | | £7.3/kW/yr | |
| Lithium Ion battery | 94 | 6000 Full cycles | £613/kWh | | £6.1/kW/yr (6-25) | a,e,f |
| AACAES | 72 | 30 years | £563/kW (281-563) | £50/kWh (4-70) | £9.5/kW/yr | a,g,h |
| CAES | 56 | 30 years | £476/kW (305-1000) | £5.3/kWh (0.9-5.3) | £5.8/kW/yr | g,i,j,k |

a: Huff et al., (2013)
b: Deane et al., (2010)
c: Zeng et al., (2015)
d: Viswanathan et al., (2014)
e: Mayer et al., (2012)
f: Ferreira et al., (2013)
g: Drury et al., (2011)
h: Kloess & Zach (2014)
i:Pimm et al., (2015)
j:Lund & Salgi (2009)
k:Salgi & Lund (2008)

***Table 4.1:*** *The input parameters for the NPV calculation of selected storage technologies. The range of parameters is given in brackets.*

The choice of discount rate is chosen at 5%, similar to the rate Locatelli et al., (2015) have used; generally, the discount rate represents a return rate expected by investors and is dependent on the financing of the project. As such, the discount rate usually lies between a risk-free rate of return such as government bonds and a market return on equity capital based on a capital asset pricing model for example. A sensitivity analysis is carried out to assess the impact of efficiency, power and energy capacity as well as O&M cost. These are evaluated in both Chapter 5 and 6.

One of the findings, later from figure 5.12 in Chapter 5, is that energy storage capacities beyond 6 hours' equivalent do not generate any additional revenues on a 1-day optimisation horizon, in both the APX and BM, that is, almost all market revenues have been captured. Hence, in evaluating the NPV of different energy storage technologies, an energy capacity of 6 hours' equivalent was assumed. Other parameters such as RTE was allowed to vary, as shown in Table 4.1. Hence the NPV values are reflective of the capital costs, O&M costs, lifespans and RTE.

## 4.10. An econometric approach to isolate wind impact on prices

Econometrics applies statistical and mathematical techniques to data in order to determine the relationship between variables. An econometric model is developed to isolate the impact of wind generation on prices, using regression techniques. In this section, the classical linear regression model is initially chosen and subsequent adjustments are undertaken to improve the model. As a result, two models are presented with distinct differences and each with their own merit, the Autoregressive (AR) model and the Static (ST) model. As the two models isolate varying impacts of wind power on the prices, two sets of simulated prices are calculated, under a 20 GW wind penetration scenario. These results are used in the optimisation models (including the co-optimisation model), to calculate storage value under the new prices. Figure 4.9 gives an overview of this process.

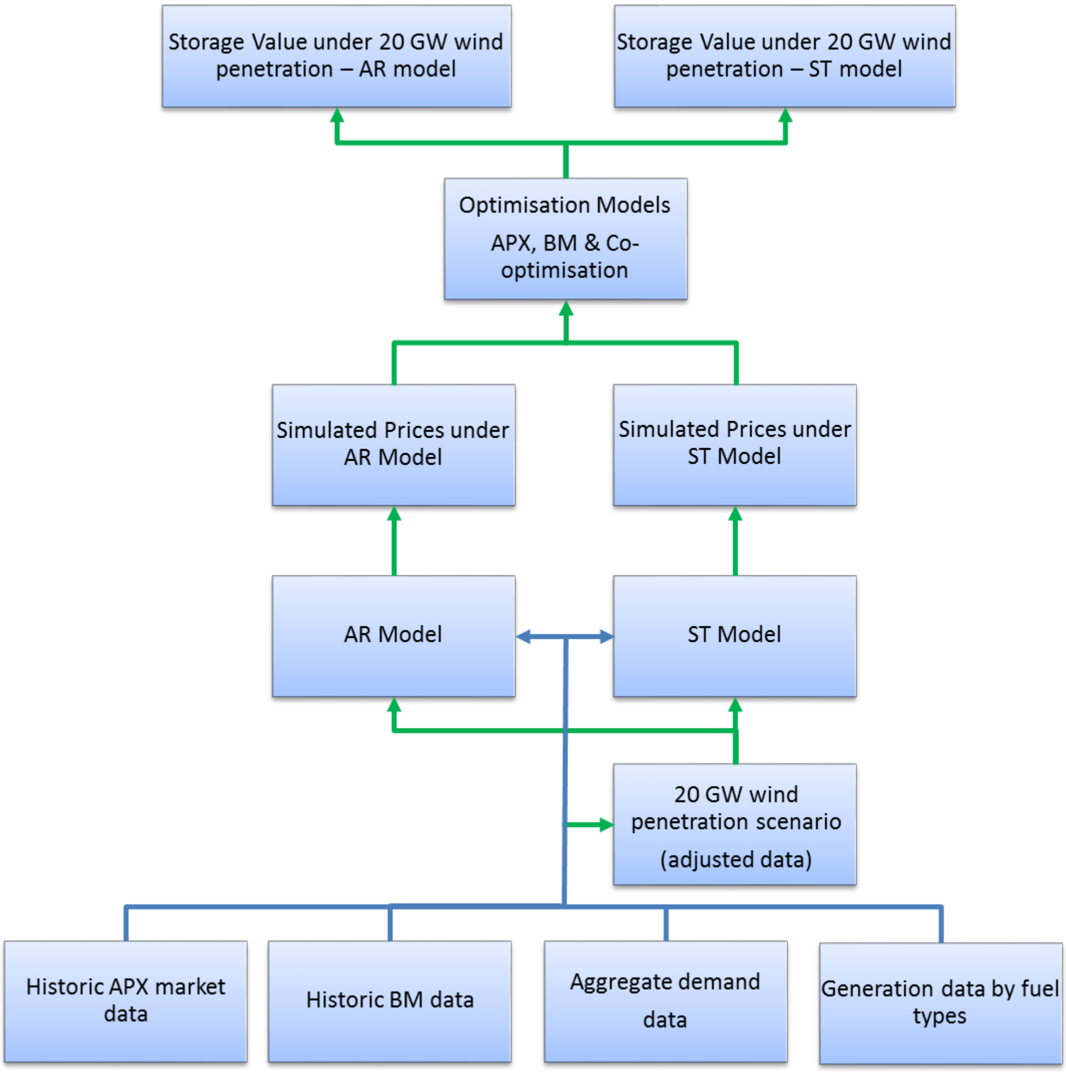


***Figure 4.9**: A representation of the inputs and processes required to calculate the value of storage under a high wind penetration scenario.*

## 4.11. The linear regression model

An econometric model using the absolute values of each variable is developed. Alternative specifications such as a logarithmic model or a mean deviation model were also evaluated but did not demonstrate any substantial improvement. Using variables in their absolute values follows from the underlying hypothesis that changes at any levels directly and equally impact the independent variable, that is half-hourly APX price in this case. In the case of wind power as an independent variable for example, the unit change is 1 MW or effectively 0.5 MWh when considering the half-hour time resolution.

A simple regression between prices and wind generation is too simplistic; in order to investigate the impact of wind generation on the market prices, the impact of other variables should also be considered otherwise resulting in omitted variable bias (Dougherty, 2011). The independent variables chosen are power generation from open cycle gas turbines (OCGT), power from combined-cycle gas turbine (CCGT), generation from oil power plants (OIL), Nuclear power (NUCLEAR), Non-pumped storage hydro-power generation (NPSHYD), coal power generation (COAL), aggregate electricity demand, net imbalance volume, system buy price (SBP), system sell price (SSP), interconnector power flows (Moyle, East-West, France), coal prices, gas price and oil prices (quarterly).

### 4.11.1. Dummy and multiplicative variables

Generally, in regression analysis, the impact of seasonal effects can be investigated using dummy variables. These can be additive or multiplicative and both may be added to avoid any implied restrictions; for example, the inclusion of only additive seasonal dummy variables would imply that the coefficients of all other independent variables are the same throughout all seasons. This may not be true in the case (for example if) APX prices are more responsive with respect to changes in other independent variables, such as OCGT in the winter period. This could be due to increasing marginal costs in winter which cause bidding prices to be higher and therefore affect APX prices more.

Thus the econometric model includes dummy variables to capture seasonal effects, weekday compared to weekend effects and time of the day effects – especially peak time. However, the addition of both the additive and multiplicative dummy variables unreasonably complicates the model; the number of variables jumps to 767. Similarly, the addition of all quadratic variables raises this number to 1400. By most standards, this specification of the model is too complex and is not justified as the increase in the number of variables does not substantially improve the model fit; for example, adjusted $R^2$ increases from 0.842 to 0.879 in the APX AR model. An F-test given by equation 4.24 (Dougherty 2011) show that the small improvement in fit is not justified.

$$F_{(m-k,n-m)} = \left(\frac{(RSS_k - RSS_m)/(\mathrm{m}-k)}{(RSS_m)/(n-\mathrm{m})}\right) \tag{4.24}$$

Whereby

$m$: Number of parameters estimated in the unrestricted model.

$k$: Number of parameters estimated in the restricted model

$n$: Number of observations

$RSS$: Residual Sum of Squares

*Where RSS is the residual sum of squared errors, k and m are number of parameters estimated in the restricted and unrestricted models respectively. n is number of observations.*

More advanced criteria such as Akaike Information Criterion or Bayesian Information Criterion are not formally tested but are unlikely to justify the added complexity. Therefore, a simpler model specification is preferred.

### 4.11.2. APX and BM econometric model

The APX model includes seven generation variables distinguished by their fuel types/technology. Four interconnectors power flows are also included and refer to those between GB-Netherlands (britnedimport), Wales-Ireland (eastwestimport), GB-France (frenchimport) and Scotland-Ireland (moyleimport). Representing the time of day effect on prices, there are forty-seven half-hour dummy variables (SPintdummy2-48) with the reference period being the half-hour between 00:00-00:30. Similarly, monthly dummy variables are added to investigate seasonality effects, the reference period is January. Finally, a weekday-weekend effect is also accounted for by using an additional dummy variable, with the weekday being the reference period. Coal prices, gas price and oil prices are also included, using quarterly data. The APX market price, as lagged dependent variables (APXPHHLAG1, APXPHHLAG2) and the traded market volume (APXVHH) were added as they are thought to have a direct influence on prices. The regression equation for the APX model is given in (4.25).

$$\begin{aligned}
&\mathrm{APX}_t = \beta_0 + \beta_1\mathrm{OIL}_t + \beta_2\mathrm{OCGT}_t + \beta_3\mathrm{CCGT}_t + \beta_4\mathrm{COAL}_t + \beta_5\mathrm{NUCLEAR}_t + \beta_6\mathrm{NPSHYD}_t + \\
&\beta_7\mathrm{WIND}_t + \beta_8\mathrm{NIV}_t + \beta_9\mathrm{pumping}_t + \beta_{10}\mathrm{britnedimport}_t + \beta_{11}\mathrm{eastwestimport}_t + \\
&\beta_{12}\mathrm{frenchimport}_t + \beta_{13}\mathrm{moyleimport}_t + \beta_{14}\mathrm{APXV}_t + \beta_{15}\mathrm{APXPLAG1}_t + \beta_{16}\mathrm{APXPLAG2}_t + \\
&\beta_{17}\mathrm{imbapricelag2}_t + \beta_{18}\mathrm{quarterlyfuelpriceCOAL}_t + \beta_{19}\mathrm{quarterlyfuelpriceGAS}_t + \\
&\beta_{20}\mathrm{quarterlyfuelpriceOIL}_t + \beta_{21}\mathrm{SPintdummy2}_t + \cdots + \beta_{67}\mathrm{SPintdummy48}_t + \\
&\beta_{68}\mathrm{monthintdummyfeb}_t + \cdots + \beta_{78}\mathrm{monthintdummydec}_t + \beta_{79}\mathrm{weekeffdummyweekday}_t + \varepsilon_i
\end{aligned} \tag{4.25}$$

Using a similar specification to the APX econometric model, a BM regression model was evaluated, showing that dummy variables are not significant. This occurs due to the fact that the imbalance price is purely imbalance driven and any seasonality or time of day effects are reflected by the APX price as the independent variable (APXPHH). For this reason, the BM econometric model specification does not include dummy variables.

In the BM, although there are two prices (SBP & SSP), at any one time, the price of interest is the imbalance price since the other price is approximately equal to the APX market price. For example, if at one point, there is a shortage of energy in the BM, causing the SBP (using the imbalance pricing method) to rise to £100/MWh, the SSP (calculated using the reverse pricing method) is essentially an average of APX prices (of different products). In this case, the imbalance price is SBP whereas SSP which is roughly equivalent to the APX price is represented by the APX model above. The purpose of the BM econometric model is to determine the relationship between the imbalance price and the independent variables.

The BM model chosen was:

$$\mathrm{Imbaprice}_t = \beta_0 + \beta_1\mathrm{OIL}_t + \beta_2\mathrm{OCGT}_t + \beta_3\mathrm{CCGT}_t + \beta_4\mathrm{COAL}_t + \beta_5\mathrm{NUCLEAR}_t + \beta_6\mathrm{NPSHYD}_t + \beta_7\mathrm{WIND}_t + \beta_8\mathrm{NIV}_t + \beta_9\mathrm{pumping}_t + \beta_{10}\mathrm{britnedimport}_t + \beta_{11}\mathrm{eastwestimport}_t + \beta_{12}\mathrm{frenchimport}_t + \beta_{13}\mathrm{moyleimport}_t + \beta_{14}\mathrm{APXP}_t + \beta_{15}\mathrm{APXV}_t + \beta_{16}\mathrm{APXPLAG1}_t + \beta_{17}\mathrm{APXPLAG2}_t + \beta_{18}\mathrm{imbapricelag1}_t + \beta_{19}\mathrm{imbapricelag2}_t + \beta_{20}\mathrm{quarterlyfuelpriceCOAL}_t + \beta_{21}\mathrm{quarterlyfuelpriceGAS}_t + \varepsilon_i \tag{4.26}$$

### 4.11.3. Autoregressive vs Static models

The APX and BM econometric models in (4.25) and (4.26) have lagged dependent variables and represent an Autoregressive – AR (2) model. Since the data uses half hourly resolution, it is very likely that markets show strong effects of autocorrelation. In other words, the current disturbance term is correlated with that of the previous period. Autocorrelation can be problematic under the Ordinary Least Squares (OLS) method used to evaluate the econometric models; while the coefficients themselves are not biased, asymptotically converging towards the true value, the standard errors of the coefficients are biased (Dougherty 2011, chap.12). In order to generate unbiased standard errors, the regression model can be estimated using Feasible Generalised Least Squares (FGLS) method. In FGLS, the OLS regression is run first. The error term is then regressed on its lag to estimate the magnitude of autocorrelation. It is this relationship that is used to eliminate autocorrelation from the original equation. Dougherty (2011, pp.441–445) gives a good description of the procedure using the Cochrane-Orcutt iterative method. FGLS also reduces bias from heteroscedasticity. In time series analysis the addition of lagged dependent variables can often eliminate autocorrelation.

The addition of lagged dependent variables substantially improves the model fit; the APX model without lagged dependent variables is referred to as the Static (ST) model and has an $R^2$ value of 0.54 which rises to 0.84 under the AR model specification. However, the AR model also dramatically reduces the explanatory power of the other variables. Achen (2000) investigated this problem to show that in the presence of autocorrelation and trended independent variables, the inclusion of lagged dependent variables provides a false sense of superior fit. In fact, he shows that even when the lagged dependent variables do not belong to the model at all, the autocorrelation and trending in independent variables cause the regression results to show a strong and significant relationship.

Nevertheless, when the ST model is evaluated using FGLS it suffers from a lower $R^2$ value suggesting that a substantial variation in prices is not explained. Omitted variable bias, where the independent variables attempt to compensate for missing variables, is also of concern. Therefore, the bias likely overestimates the impact of wind under the ST model and underestimates its impact under the AR model. The results of the two types of regressions are discussed further in Chapter 7, with reference to these biases. However, with the knowledge of the extent of the bias, the true impact of wind power on prices should lie in between the two models and hence meaningful information can still de derived.

Further diagnostic tests have been used to refine the model; the Breusch-Pagan test was used to detect heteroscedasticity and the Breusch-Godfrey test for serial correlation. In order to detect possible misspecification, the Ramsey test was performed. Using the Augmented Dickey-Fuller test, the data was found to be stationary. Residual error plots are shown Appendix C. The models are evaluated using 2011-2014 data and validated using an out-of-sample testing is carried out on data in 2015.

## 4.12. A 20 GW wind penetration scenario

Wind power generation over the past nine years from 2006 to 2014 has grown significantly, in particular, offshore wind generation. More recently solar PV power generation has grown at an even faster rate. Table 4.2 displays the trend in wind power penetration from 2006-2014; wind energy grew by an average of 24% annually while wind capacity increased by an average of 27%. Solar power has also shown strong growth from 2012-2014. While the level of renewable energy penetration in the future remains uncertain, it is likely to increase, as projected by several scenarios from National Grid (2015c).

Looking towards the future, a scenario of high wind penetration was investigated; a 20 GW of wind capacity penetration was assumed, broadly representing the expected level of installed wind capacity in 2020 (National Grid 2015d). In the scenario, it was assumed that the same conditions prevailed as those during 2011-2014, this would allow for the wind generation impacts to be isolated and further investigated.

**Wind and Solar Power in the UK from 2006-2014**

| **Installed Capacity (MW)** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** |
|---|---|---|---|---|---|---|---|---|---|
| Onshore Wind | 1,651 | 2,083 | 2,850 | 3,468 | 4,060 | 4,629 | 5,904 | 7,519 | 8,486 |
| Offshore Wind | 304 | 394 | 596 | 951 | 1,341 | 1,838 | 2,995 | 3,696 | 4,501 |
| Total Wind | 1,955 | 2,477 | 3,447 | 4,420 | 5,401 | 6,468 | 8,899 | 11,215 | 12,987 |
| Solar Photovoltaics | 14 | 18 | 23 | 27 | 96 | 995 | 1756 | 2851 | 5377 |
| **Generation (GWh)** | | | | | | | | | |
| Onshore Wind | 3,574 | 4,491 | 5,788 | 7,529 | 7,182 | 10,503 | 12,232 | 16,950 | 18,611 |
| Offshore Wind | 651 | 783 | 1,335 | 1,754 | 3,073 | 5,149 | 7,603 | 11,472 | 13,404 |
| Total Wind | 4,225 | 5,274 | 7,123 | 9,283 | 10,254 | 15,652 | 19,835 | 28,421 | 32,016 |
| Solar Photovoltaics | 11 | 14 | 17 | 20 | 41 | 244 | 1352 | 1989 | 4050 |

***Table 4.2:*** *Wind and solar power growth in both power and energy, in the UK from 2006-2014. Adapted from: DECC (2015b)*

In order to produce a 20 GW wind generation profile, the existing wind generation is extrapolated and adjusted by installed capacity at that time. This inherently assumes that additional wind capacity was proportionately added to existing wind farms and with the assumption of same weather patterns occurring as those from 2011-2014, a scaling of wind generation is undertaken. These assumptions inevitably limit the implications of the results and these limitations are discussed in section 8.12. As data for installed wind capacity is on an annual basis, a linear interpolation is performed to provide a smooth function for scaling purposes; in reality, wind capacity increases are incremental and would be visible from the data, in terms of discrete blocks. This wind capacity adjustment factor from 2011 to 2014 was derived from equation (4.27) which, in turn, was estimated using linear regression. The equation is also shown graphically in figure 4.10. It should be noted that to simulated wind generation at a 20 GW scale, wake effects in wind farms and further impacts from transmission constraints are not accounted for.

$$WIND_t = 4424 + 0.1247 * t \qquad \text{for t=1:70128} \tag{4.27}$$

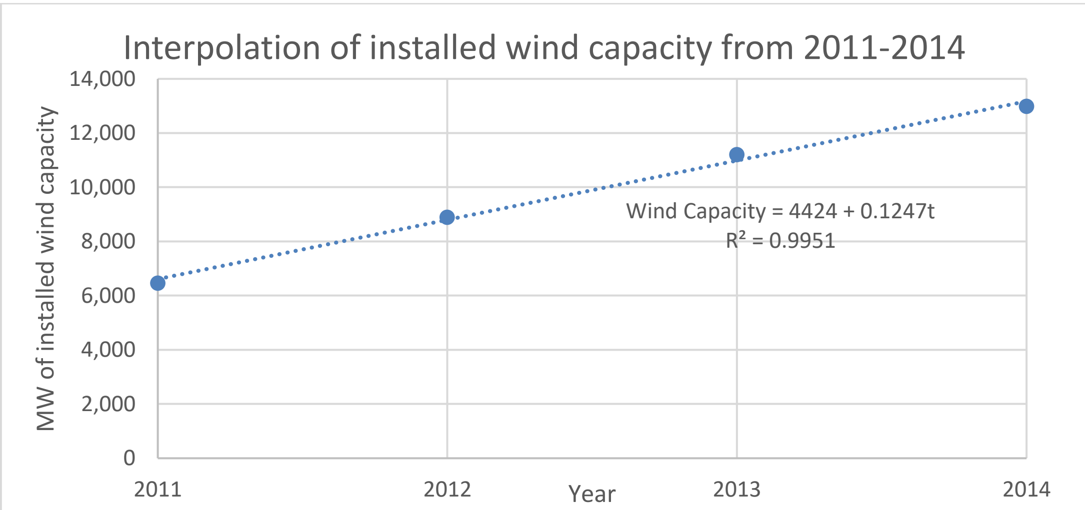


***Figure 4.10**: Wind capacity interpolation from 2011-2014*

The investigation of APX and BM prices under higher wind penetration requires further assumptions:

I. The increase in wind power output displaces generation in the following order; Oil power generation, Open Cycle Gas Turbine (OCGT) generation, Combined Cycle Gas Turbine (CCGT) Generation and Coal power generation.

*II.* If the combined Oil and OCGT generation reductions are not sufficient to account for the increase in wind power, the remaining reduction is equally split between CCGT and Coal power generation. Baseload Nuclear power remains unaffected. This method takes into account both the merit order of generation based on fuel costs and also operational reasons which prevent from adjusting the deficit solely against CCGT or Coal power. In other words, it is assumed that under a high wind output, peak generation will be eliminated completely, however, output from both types of mid-merit generation, COAL and CCGT, will be partially reduced, in this case equally, for simplicity. This assumption is not unrealistic; figure 4.11 shows the half hourly generation fuels on the system on an ordinary day, 23rd March 2015.

III. Added system complexities such as resulting APX and BM market shocks are ignored.

IV. Under increasing wind penetration, increased frequency response and other fast response reserves will be required as system inertia falls (National Grid 2015g). In 2020, projections by National Grid show an increase in primary frequency response requirement by 40% (National Grid 2015g). To reflect the increased demand for frequency response, the availability payment was scaled from £5/MW/h to £7/MW/h. The need for additional frequency response was recently highlighted with the first rounds of EFR which had an availability payment ranging from £7/MW/h to £12/MW/h (National Grid 2016e). The increase in the availability payment from £5/MW/h to £7/MW/h, in the co-optimisation model would result in less than proportionate revenues due to the fact that, on an annual basis, only a smaller proportion of its capacity is allocated to the provision of FFR compared to a fully dedicated unit. As capital costs are expected to fall further and with relatively low utilisation rates for the provision of FFR, a storage system fully dedicated to the provision of FFR would benefit substantially more from an increase in an availability payment than a co-optimisation revenue model. This is especially true for those technologies with lifespans dependent on the depth and frequency of discharge, such as Li-ion batteries.

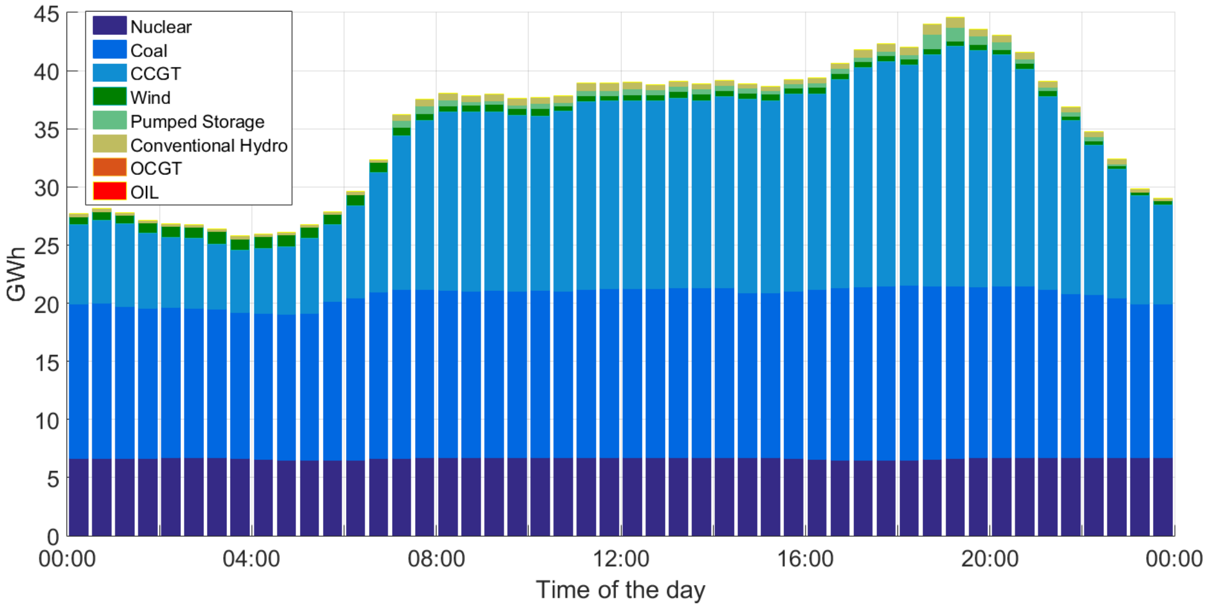


***Figure 4.11:*** *Different types of generation throughout the day on Monday, 23rd of March 2015.*

The imbalance price simulation is more complex as there are additional factors that should be considered, compared to the APX market price; the imbalance volume cannot be assumed to be the same during this scenario since it is a fundamental determinant of price influencing both choice of pricing method and as well as having a scaling effect the prices. (This is later also confirmed by regression analysis).

With wind scaled, a forecasting error distribution is used to randomly simulate forecasting errors. It is assumed that forecasting errors will directly impact the imbalance volume. Hodge et al., (2012) have modelled wind forecasting error distributions internationally. The authors show that Spain and Germany, which have installed wind capacity in the scale considered here (20 GW and 25 GW respectively), the wind forecast error distribution tends to have a higher degree of kurtosis than a normal distribution. Figure 4.12 shows the wind forecast error distribution in Germany, at an hour ahead of actual generation. However, as an approximation, a normal distribution with parameters derived from the average of both countries, is used. At an hour ahead, the wind forecast error is assumed to follow roughly a normal distribution with an average of -0.0007 and a standard deviation of 0.124.

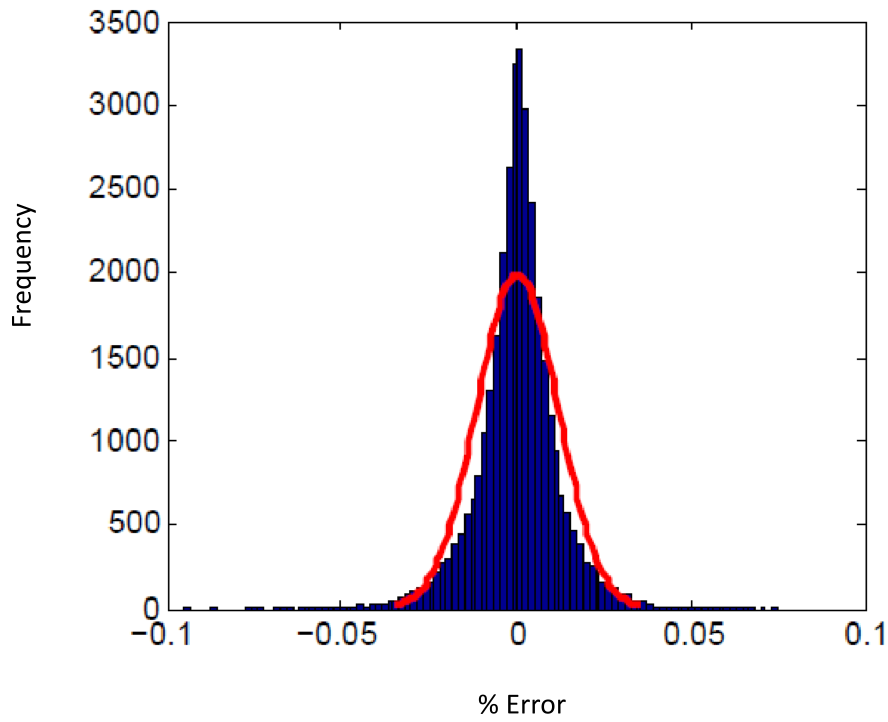


***Figure 4.12:*** *Wind forecast error distribution in Germany in 2010, an hour ahead of real time. Errors are shown as a proportion of real wind generation. Source: Hodge et al., (2012).*

Under the 20 GW simulated scenario, the APX market and BM prices can be simulated using the regression model previously developed in section 4.11.2. Together with an adjusted availability payment for FFR, the co-optimisation model can be run based on the simulated data. The revenues generated under this scenario offers a basis of comparison and hence the impact of wind on storage value can be investigated.

## 4.13. Secondary impacts of increased wind generation on prices.

There are further aspects to the high wind penetration scenario which are not considered. Earlier in section 4.7.4, it was argued that storage operations could have a direct impact on the market prices as well as an indirect impact whereby other participants react accordingly. Similarly, the displacement effect of wind generation on other forms of power generations, particularly peak time power generation could cause a reactionary behaviour as their assets are now utilized less frequently.

In other words, generators especially peaking plant generation would likely be running less often under an increased wind penetration scenario and since they seek to recover their costs over the plant's limited lifetime, their bids are likely to be higher to compensate for the loss of revenues. This would be more evident at times when wind power output is low and demand is high, requiring the use of peaking plants.

Given that electricity demand is inelastic in the short run[6] Mahoney and Denny., (2013) this could lead to high price spikes, especially as Green & Vasilakos (2010)have shown that electricity supply is not always based on marginal costs and tend to be higher especially at peak time, shown in Figure 4.13. The authors modelled a 30 GW wind generation as net of electricity demand. The study which takes into account the marginal cost of generation as well as competitive behaviour between firms (seeking to maximise their profit function) shows that high levels of wind penetration increase the volatility in wholesale prices.

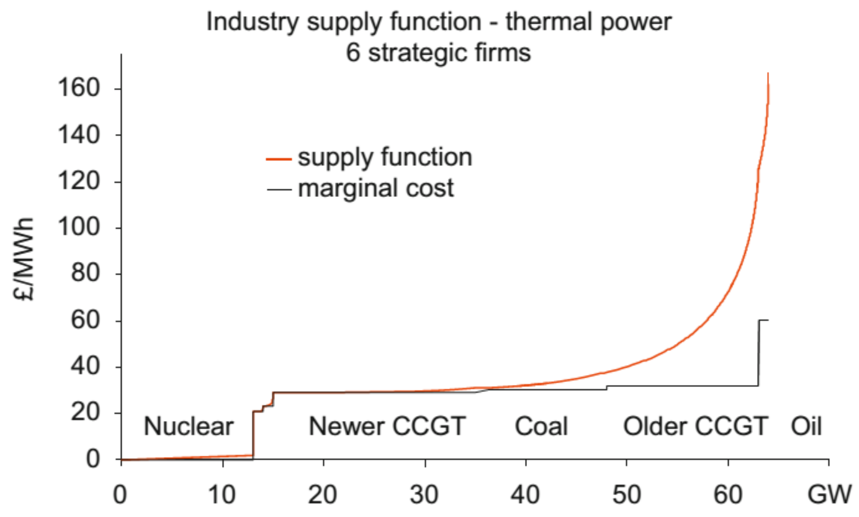


***Figure 4.13:*** *The supply function for wholesale electricity as being partly marginal cost based. Source: Green & Vasilakos (2010)*

[6] Generally assumed to be inelastic in the short run, electricity demand is however becoming more flexible with demand side response. Here, the concept of short run demand inelasticity is reinforced by the short-term nature of the spot market.

Green & Vasilakos (2010) although do not directly evaluate how peaking plant generators may change their behaviour following an increased wind penetration level, they show that following a fall in competition, prices rise sharply. By simulating prices in a market with 6 symmetric firms compared to 2 symmetric firms, they estimate the average wholesale electricity price to increase from £35/MWh to £78/MWh (still under a 30 GW wind penetration scenario). Hence this is a further aspect to peak generation displacement that merits consideration, as a reduction in competition could lead to even higher prices. In other words, the displacement effect may lead to higher prices as peaking plant generator bids not only to compensate for a loss of revenues but also take advantage of less competition and demand inelasticity.

Extending the approach by Green & Vasilakos (2010) to the APX spot market would, however, present some difficulties; this thesis uses very short term half-hourly spot market prices, whereas the model developed by Green & Vasilakos (2010) calculate wholesale prices based on total electricity demand. It is likely that the spot market prices are more volatile than the bulk of energy purchased through forward contracts. As mentioned in section 4.7.4 there are potentially other factors affecting the short term spot market such as forecast error and short-term disturbances.

Given the focus of the thesis is on evaluating the storage revenues rather than building a more advanced electricity pricing model, the indirect impacts of wind penetration on spot market prices is not explored. There are however mitigating factors to these impacts – in a high level of both wind and storage penetration scenario, either wind or storage could displace peak generation. In a scenario of low wind and high peak demand for example, energy storage could potentially provide additional energy (however, not in the scale explored in this thesis) and in doing so, reduce the need for peaking plant generation.

## 4.14. Data sources and processing

Electricity spot market data was obtained from Amsterdam Power Exchange (APX) which established UK operations since 2000(APX 2015). Half-hourly prices and trading volume were gathered from 2000-2015. In this thesis, data from 2005-2015 representing, 192,816 observations, was used when investigating the annual variation in arbitrage revenues. Raw data from the APX website is shown in Table C.1 in Appendix C. This data is imported in Matlab2013 and a script subsequently written to sort the observations; for every non-leap year, the 17,520 half-hourly resolution raw price and volume data are obtained from APX in a 365-row by 48-column matrix. The script converts this matrix into a 17,520-row by 1-column matrix with chronology respected. The purpose of this conversion is not only to facilitate the modelling implementation (coding) process but also merge this into a ‘Master dataset’, containing other types of data.

The APX spot market also allows the trading of power products of longer duration such as the one hour blocks, two hour blocks and four hour blocks as explained previously in Chapter 3. Data was gathered in the same way for these products as for the half-hour product and included in the Master dataset. However, data for these other products have not been used in this thesis, which focuses solely on the half-hourly spot market due to its potential for greatest volatility and arbitrage revenues as described in Chapter 3.

Data for the Balancing Mechanism was obtained from Elexon (2015) and consisted of the System Buy Price, System Sell Price and Net Imbalance Volumes for each half-hourly period from 2011-2014. At the time of this research work began, BM data prior to April 2010 was not available and therefore a full set of data parameters was only available from 2011 onwards.

Raw electricity demand data was obtained from National Grid for the years 2005-2015 and consisted of different types of demand such as the initial national demand outturn, demand from England and Wales as well as estimates of embedded wind and solar power. A full list of these variables, an extract of the raw data table and an accompanying description are shown in Table C.6 of Appendix C. No substantial transformations were required on this raw dataset as the format was similar to that of the Master dataset.

Generation data was obtained from Elexon and consisted of transmission level generation in MW for the years 2008-2015. These contained data for the following types of fuel/energy sources: gas power from Combined Cycle Gas Turbine (CCGT), Oil/Diesel (OIL), Coal Power (COAL), Nuclear power (NUCLEAR), Wind power (WIND), Pumped Hydro Energy Storage (PS), Non Pumped Hydro power (NPSHYD), gas power from Open Cycle Gas Turbine (OCGT) and other forms of power (OTHER). Additionally interconnector power flows were also available: interconnectors between England and France (INTFR), Norther Ireland and the republic of Ireland (INTIRL), England and the Netherlands (INTNED) and Wales and the Republic of Ireland (INTEW). Raw data for these are shown in Table C.4 of Appendix C.

FFR data was gathered from tender reports published by National Grid (2013). An example of a tender report is shown separately in Appendix B.1. Availability payments and tendered capacity for frequency response was gathered for the year 2013-2015. STOR monthly data was obtained from National Grid (National Grid 2013b) and consisted of availability volume, utilisation volume, contracted capacity in 2013. Total installed generation capacity and energy production statistics for Wind and Solar PV, as well as total electricity consumption were obtained from DECC (2015). Quarterly fuel prices, used in the econometric analysis was obtained from the UKERC for the years 1990-2014, an extract which is shown in Table C.5 of Appendix C.

## 4.15. Concluding remarks

This chapter described the models and the techniques used to evaluate them; optimisation models were described for both, operation in single markets as well as multiple markets. MILP was shown to be an appropriate method for evaluating the model and has previously been used in several studies. For the NPV analysis, using values from previous studies, input parameters for PHES, CAES, AACAES, VRB, Fe-Cr flow battery and Lithium-ion batteries were stated as well underlying assumptions.

An overview of the steps required to meet each objective was shown. While investigating the impact of wind on revenues, two econometric models namely the Autoregressive and Static models were presented each with clear advantages over each other. In the Static model, Feasible Generalised Least Squares was used to evaluate the econometric model rather than OLS due to biases arising from autocorrelation and heteroscedasticity.

A 20 GW wind penetration scenario was simulated by scaling the wind load factor for every half hour and using linear interpolation to render discrete values into a smooth continuous function. The scenario also considers indirect impacts of wind power on conventional generation and net imbalance volume. With the models described, the next step requires their evaluation using the above techniques. The results of these models are presented in Chapters 5, 6 and 7.

# Chapter 5. Storage value in single markets

## 5.1. Introduction

So far, chapter 2 has shown that while market revenues from storage operation has been addressed in several studies internationally, relatively little is known about the value of storage in GB markets. Chapter 3 demonstrated the potential for value based on preliminary analysis of prices, trends and requirements in the market mechanisms. The next step was the development of models to represent storage operation, which aim at to capturing value, these were derived in Chapter 4.

This chapter looks at the single market revenues when storage is operated as a fully dedicated unit to the revenue mechanisms. This chapter evaluates the maximum potential revenues energy storage could generate from distinct types of revenue mechanisms. It places emphasis on specific effects which create value in each mechanism. In this Chapter, the following revenue mechanisms are investigated; the APX, BM, FFR and STOR. The differences in storage operation are analysed on a short term and long term basis to highlight seasonal influences, with clear identification of the specific influences on storage value.

Further to this, sensitivity analyses are performed to investigate the impact of efficiency and energy capacity on storage operation and revenues. The impact of increasing optimisation horizons on revenues is also calculated to determine how value changes under longer horizons.

## 5.2. Wholesale market operation

A 50 MW, 600 MWh storage system was chosen to operate in the APX market, with its charging and discharging schedules determined by the optimisation model. The operational profile of the storage system for the first week of Jan 2013 is shown in figure 5.1. The system charging is shown in blue bars while discharging is shown in green bars, shown in MWh. The SOC of the system is shown in the red line as '*Storage Level'*, in MWh. In order to understand the system operation relative to the wholesale market, the half hourly spot market price is shown in a blue line in £/MWh.

The maximum energy capacity of the system is set at 12 hours' storage equivalent to 600 MWh, yet the state of charge of the system does not exceed 300 MWh or 50% of total energy capacity. The optimisation horizon is in this case 24 hours, representative of a day ahead perfect foresight horizon. Under these parameters, it would appear that the energy capacity of the system is oversized. Given that this thesis investigates the maximum potential for market revenues, the storage system was initially chosen to be sufficiently large as to not limit the arbitrage opportunities. For example, a storage system with a 1-hour energy capacity would only be able to discharge energy for one hour during peak prices and if the peak price window lasts for a few hours, then there will be missed opportunities arising from a lack of stored energy.

As seen from figure 5.1, a greater energy capacity is not required during the 1 week shown. A greater power capacity however would increase the utilisation of this fixed energy capacity, effectively changing the power to energy ratio. Revenues would scale linearly with power capacity changes (with power to energy ratio fixed) under the price taker assumption, up to the market volume (or imbalance volume) limit, as figure 5.12 later shows. In this thesis, the Impacts of the power to energy ratio changes on storage operations, total discharge volume and revenues are shown in figures 5.12, 5.13 and 6.10.

Alternatively, the optimisation model could be evaluated without a constraint for energy storage capacity; in this case, the optimisation problem is still a bounded (hence feasible) one since charging occurs at the expense of discharging and over a finite optimisation horizon, mathematically this remains a bounded problem. Figure 5.1 shows that charging clearly takes place during low price periods, occurring on a regular basis during the early hours of the morning as shown in Chapter 3. Occasionally, a mid-day charging occurs when prices drop after the morning peak period, shown here at the 87-89$^{th}$ hours, but just before a high evening peak. Discharging on the other hand is confined mostly to 2 periods; the morning peak and the evening peak.

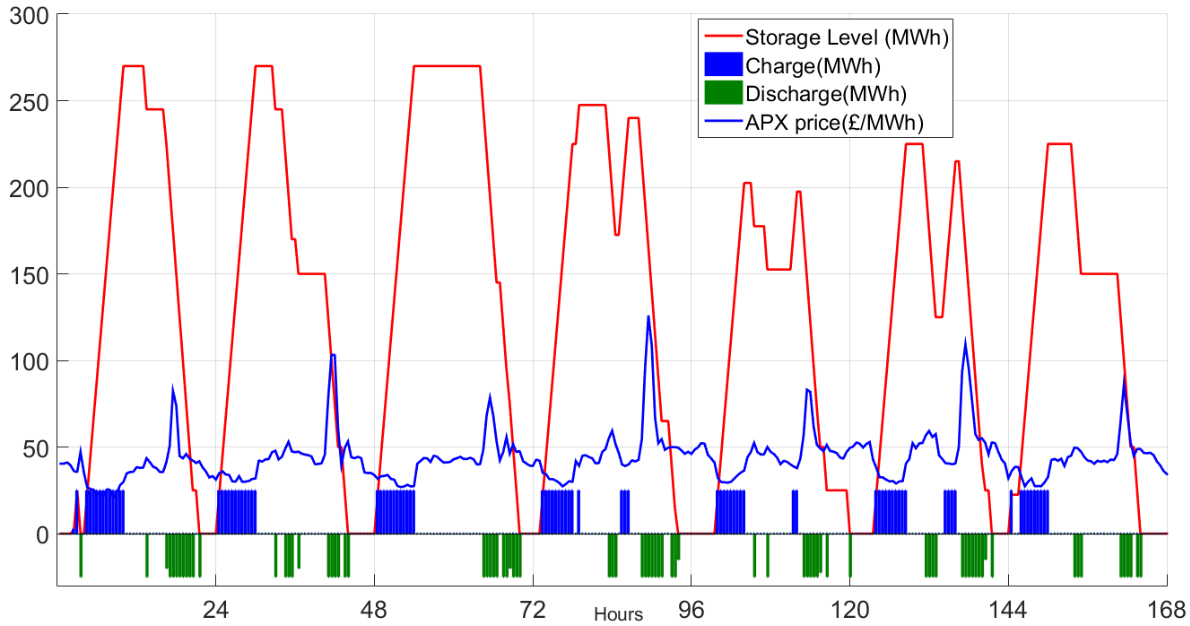


***Figure 5.1:*** *The optimal operating profile of storage in the APX market based on the half-hourly spot market price in 2013.*

In essence, the operational profile of storage is a reflection of the wholesale market price; the fairly repetitive pattern of charge-discharge occurs due to the relative price differentials which are consistent on a daily basis, a product of the merit order of generation and electricity demand. The small changes in the magnitude of price peaks and troughs do not influence the charging-discharging profile but rather the total revenues.

The implication of this low sensitivity to small price changes at those times is that, while conventionally market prices are generally hard to forecast with a high degree of precision, such precision may not be of strong relevance for the operation strategy of a storage system. This in turn opens avenues whereby storage could be operated on historic prices such as those Sioshansi et al., (2009) have explored using a two week backcasting method. Other strategies such as a dispatch based on an average of annually optimised charge-discharge could potentially capture a significant proportion of the market value. The effectiveness of such strategies, in the presence of such cyclical tendencies, is evaluated in Chapter 7.

On a longer timescale figure 5.2 displays the complete charging and discharging cycles of the system during 2013. The storage system spends a significant proportion of time being idle, shown as green in the figure. Two clear discharging phases are visible with varying times. The season-transitionary effect of peak prices seen in Chapter 3 clearly mirrors the discharge pattern. A third late night discharge phase, arguably, exists in the summer, occurring very late at night, however, these are not persistent. The spread of peak discharging is also narrowly spread in winter with consecutive periods of discharging compared to summer whereby discharges are more dispersed and possibly be interpreted as a split into two discharge phases; the summer peak and late-night discharge. On the other hand, inversely, during winter, morning peak discharges are more dispersed during winter than summer.

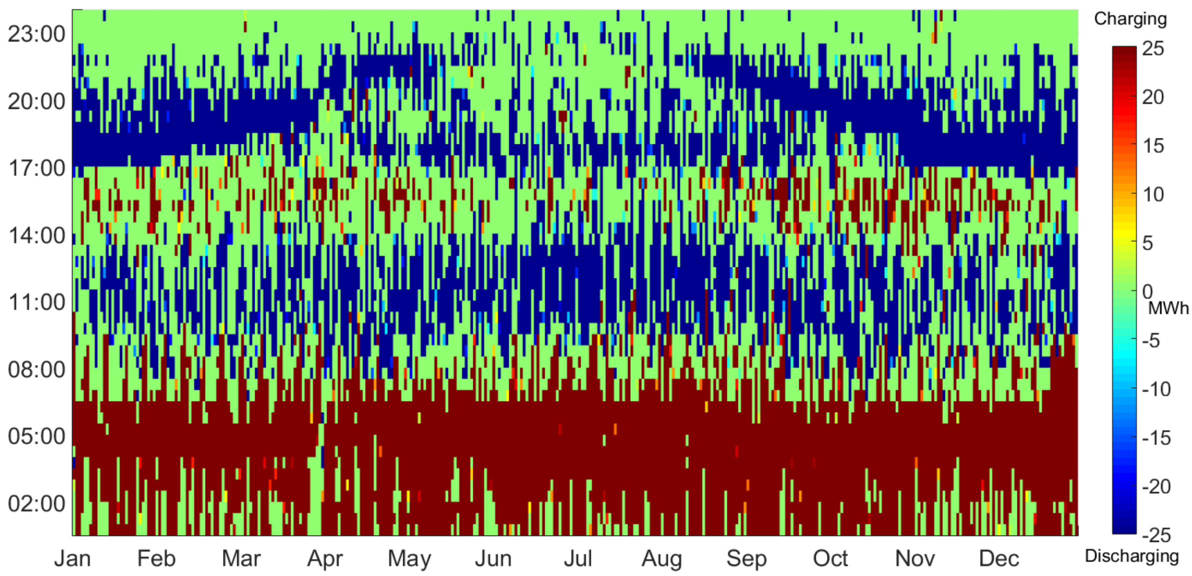


***Figure 5.2:*** *The charging and discharging patterns of the storage system in the APX market over 2013.*

Figure 5.2 also points towards a greater density in discharging during mid-day during the warmer months. This discharge pattern is driven by relative price differences between the morning peak and evening peak; in winter the evening peak price is substantially higher than the morning peak and in summer the morning peak price is often stronger than the evening peak price. This is shown graphically in figure 5.3.

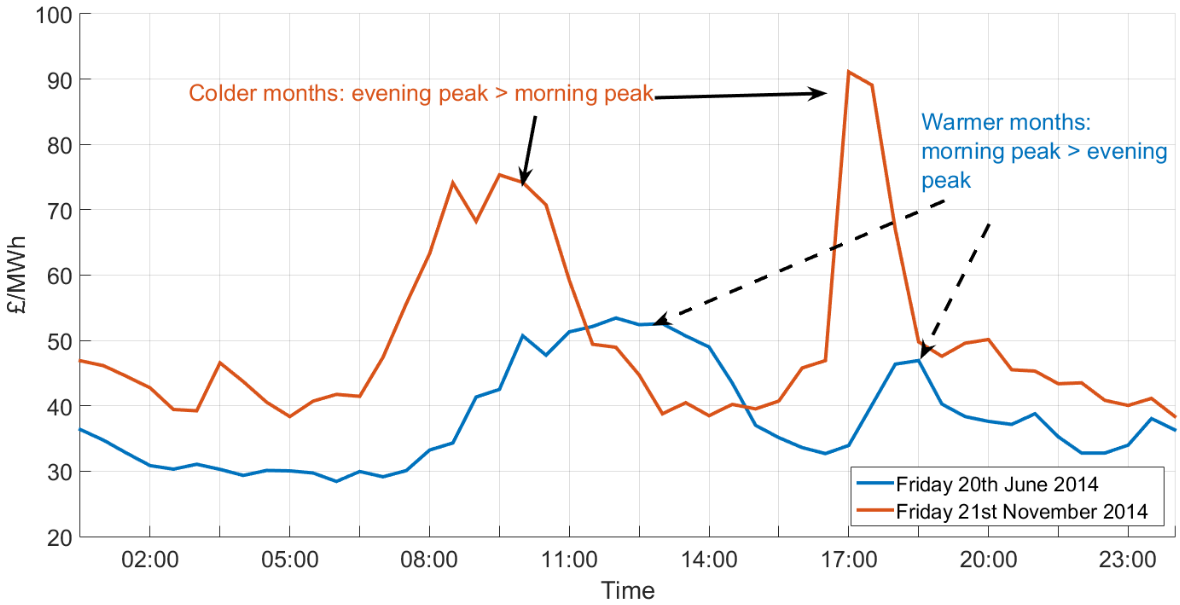


***Figure 5.3:** Morning and evening peak prices during a warm and cold day of 2013.*

Idling times, similar to charging and discharging, differ seasonally; on a 1-day optimisation horizon, the last few hours before the end of the day are opportunities for storage to empty its residual energy such that revenues are fully maximised. The time at which this residual discharge takes place is dependent, on the market price such that during winter periods they occur earlier than during summer periods. As a result, a dense or sparse discharge pattern occurs dependent on the seasons.

In contrast to discharging, charging shows little variation across the seasons with the bulk of the charging taking place in the early hours of the morning. There is also a mild presence of mid-afternoon charging, again reflective of the price drops after the morning peak observed earlier.

Besides the general trends, there are also rarer effects highlighting the state of the market; for example, at the start of the day, there are several occasions whereby the system remains idles for 3 hours or more. On such occasions, the early morning prices were sufficiently high to delay the charging.

Additionally, thus far, it has been assumed that energy storage is technology neutral and therefore assumes instantaneous power input/output. It should be noted that some technologies such as CAES require cold start procedures, taking between 10-15 minutes and output is subject to ramping rates whereas Li-Ion batteries have no such restrictions. The assumption of instantaneous power explains why charging and discharging are overwhelmingly 25 MWh and -25 MWh respectively. There are a few occasions where this is not the case; in those situations, the system charge or discharge is limited by the energy capacity of the system.

## 5.3. Arbitrage revenues from 2005-2015

In addition to the seasonal effects, the inter-annual variability of single market revenues was also explored. Weather patterns and economic conditions can have a substantial impact on revenues. For example, in 2008, pre-recession, electricity prices were very high, leading to the highest revenues within the decade.

This analysis spans a timeline sufficiently long such that inflationary effects cannot be ignored; figure 5.4 shows the potential arbitrage revenues in the APX market from 2005-2015. These revenues are Consumer Price Index (Office of National Statistics 2016) adjusted with 2015 being the base year.

Arbitrage revenues were highest in 2008 and lowest during 2011. Also, the impact of the global 2009 recession can be seen in the revenues. The annual fluctuation in arbitrage revenues shows that revenues in 2013 were not exceptional but closer to the pre-recession average. In the last few years, substantial changes influencing the market price have occurred such as the increase in the wind penetration level. Its impact is investigated more closely in Chapter 7.

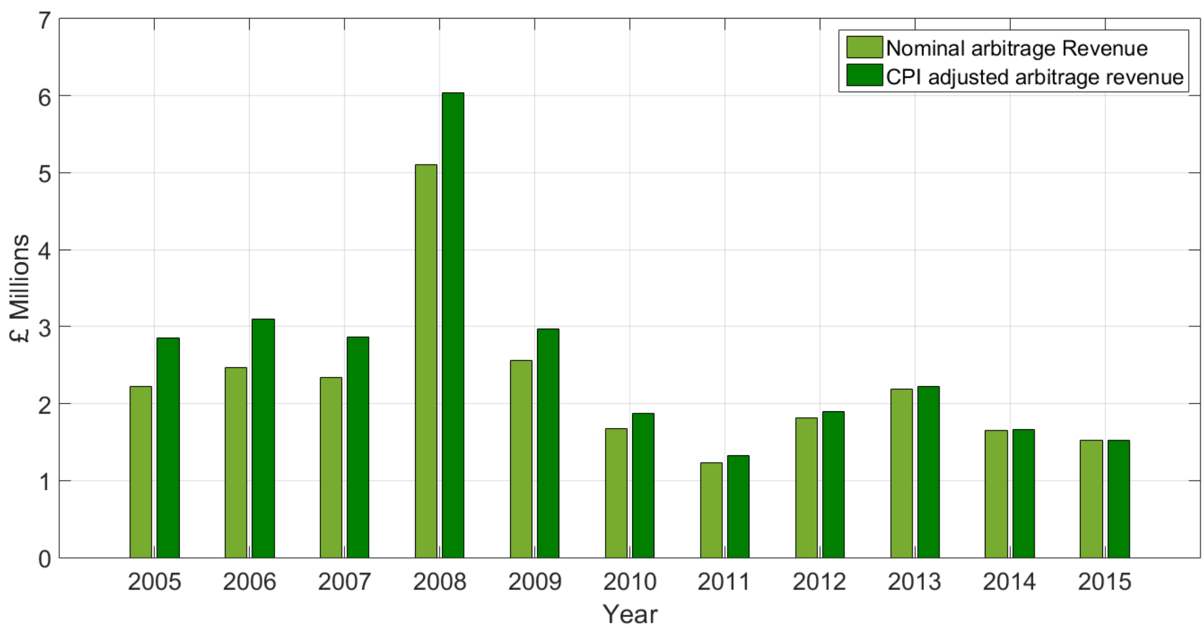


***Figure 5.4:*** *The annual variability of APX market arbitrage revenues from 2005-2015*

## 5.4. Distinct avenues of storage value in the Balancing Mechanism

The same storage system is optimised to operate within the Balance Mechanism in 2013 and the charging and discharging magnitude and frequencies are shown in figure 5.5. Compared to the operation in the APX market, charging and discharging cycles occur far more frequently in the BM. The consecutive occurrences of these cycles mean that storage energy capacity is utilised to a greater extent. In other words, consistently, the daily state of charge level is higher when participating in the BM than in the APX wholesale market. This is shown from figure 5.5, at mid-day during the 2$^{nd}$ day of the week, the SOC reaches over 475 MWh. Nevertheless, a similar trend to the wholesale market operation is observed with off-peak charging and peak discharging.

While the arbitrage strategy typically depends on the time of the day, which in turn reflects the types of generation on the system, the BM offers a different type of arbitrage – arbitrage between the system prices, which will henceforth be referred to as Cross System Price Arbitrage (CSPA). In Chapter 3, it was explained that the calculation method of the imbalance price means that the difference between the system prices is driven by bids/offers which in turn depends on the magnitude of the imbalance and its trend (excess or shortage).

In effect, the greater the difference between the prices the greater the opportunity for this type of arbitrage. The model sells at the SBP and buys at the SSP, although not simultaneously; it is assumed that there is at least one settlement period (30 mins) in between charging and discharging. Therefore, instead of the conventional peak and off-peak driven arbitrage, storage in the BM can play arbitrage on the system prices irrespective of the time of day trends.

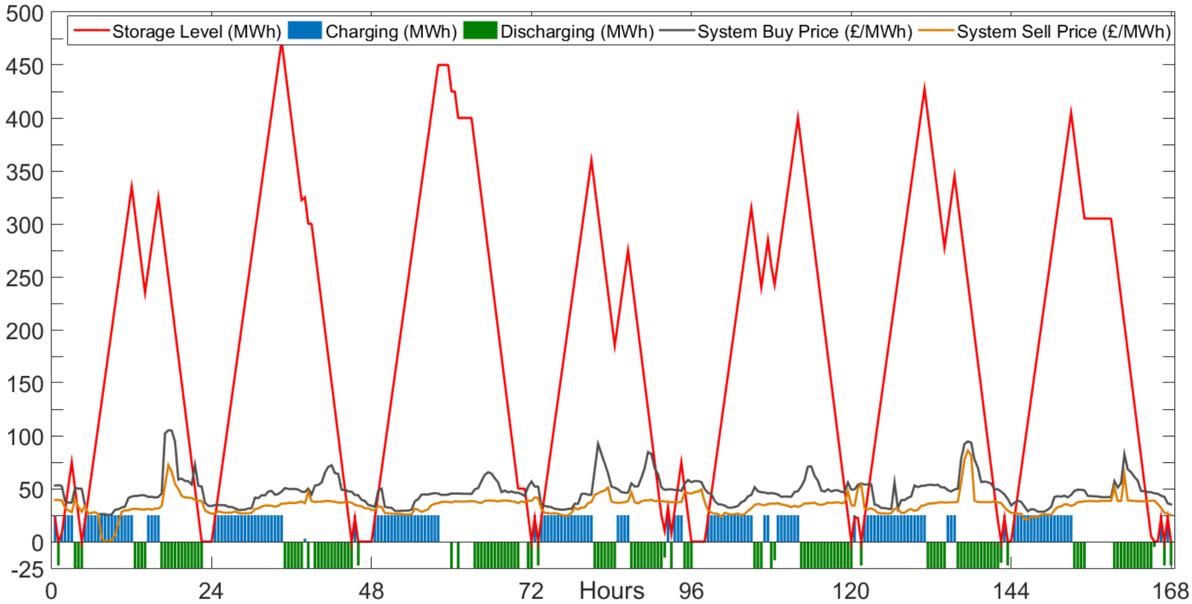


***Figure 5.5:*** *The operation of the storage system driven by the Balancing Mechanism prices during the first week of 2013*

An example of this is highlighted in figure 5.6; an arbitrage trade whereby buying (charging) and selling (discharging) takes place consecutively during the first hour past midnight, is shown as ellipse A. Had there only been a single price, the earliest discharging which generates a profit would, instead, have taken place during 03:30-04:30, encircled as B. Circle C also shows another occasion where arbitrage from a single price should not take place, since the price line is almost flat with a slight increasing trend. Hence, the difference in system prices drives the further possibility of arbitrage, CSPA.

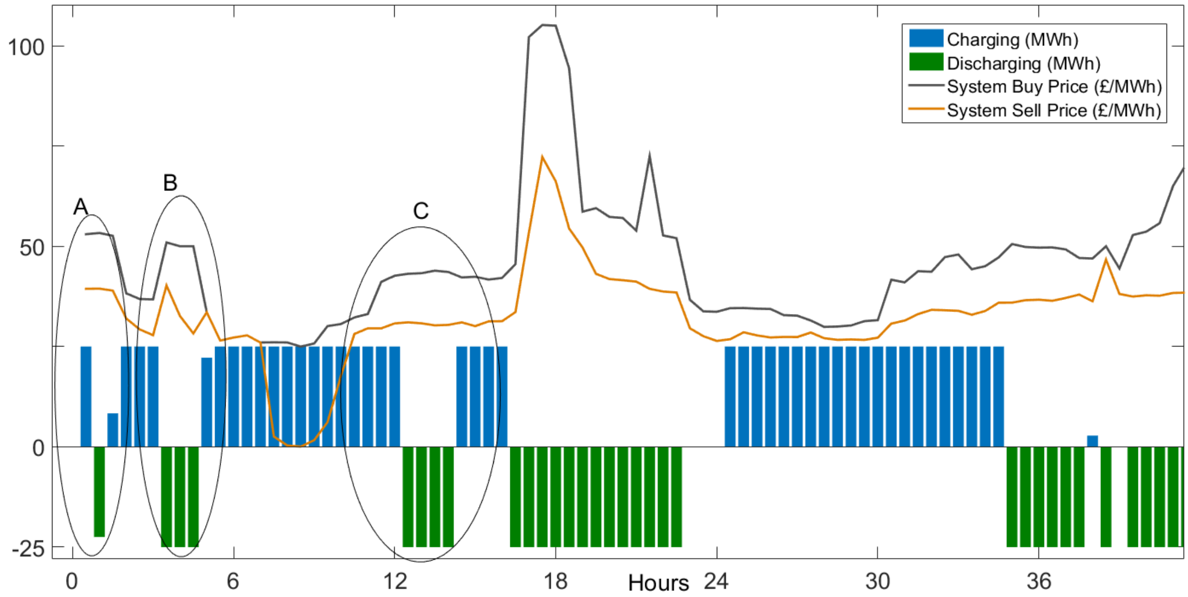


***Figure 5.6:*** *Occasions (encircled) where arbitrage is driven by the difference in system prices rather than the peak to off-peak prices.*

It is important to stress that the BM model so far assumes high liquidity and that the system operator accepts bids and offers irrespective of the system status. This assumption is relaxed, in Chapter 6 whereby storage operation is constrained by actual imbalance volume while charging and discharging can only occur in states that alleviate system imbalances. These, in turn, reflect more realistic situations for arbitrage in the BM. The likelihood of a bid/offer being accepted by the SO in the BM is dependent on the state of the system and the price of the bid/offer. In the unconstrained version, there is no restriction when the system can charge or discharge whereas in the constrained version the SO only accepts bid/offers which are helping the system; for example, SO would not accept a bid during a system shortage since ideally offers which help reduce the imbalance would be preferred.

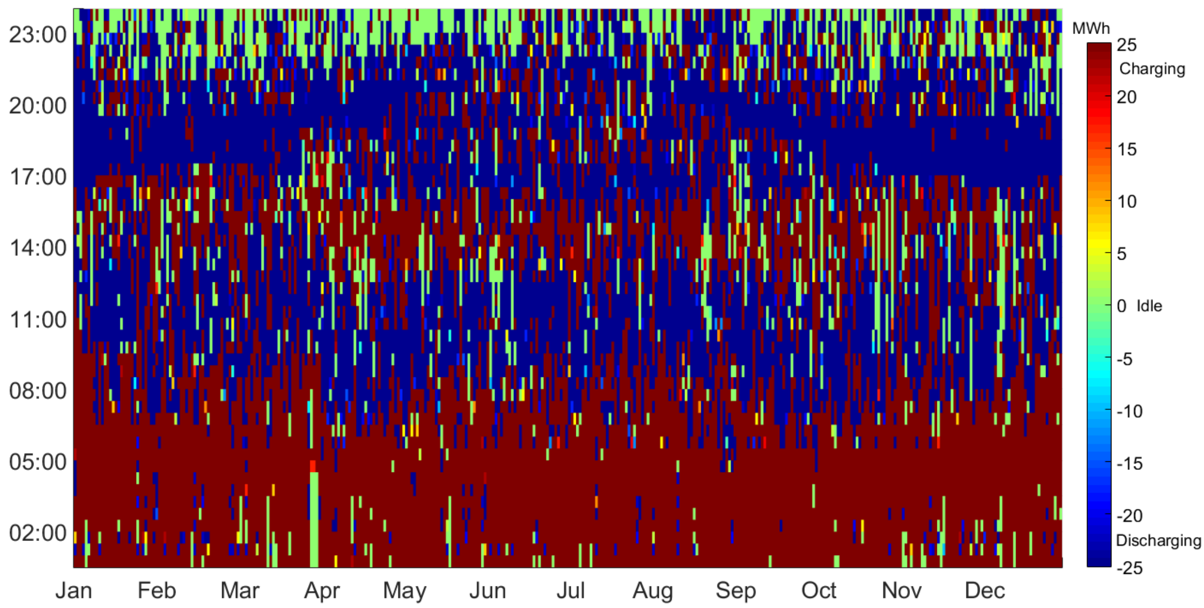


***Figure 5.7:*** *The operation of storage in the BM across 2013.*

In the balancing mechanism, the storage system is in operation a greater proportion of the time, reflected by the relatively lesser number of occasions the system is idle, shown in light green in figure 5.7. This implies a greater utilisation of asset capacity.

The increase in the number of charge-discharge cycles is driven by the smaller gap between the buying and selling prices. System price volatility accounts for this observation: since the system charges (hence buys) at SSP which less than or equal to the market price and discharges at SBP which is greater than or equal to the market price, at any time, there is an additional premium or penalty on the market price. Consequently, this results in the system being able to exercise a greater number of arbitrage trades which, in turn, leaves the system idle for a smaller proportion of time.

Besides non-profitable trades, similar to the wholesale market case, the system remains idle when its energy capacity limits are reached which in this case occurs more frequently due to a greater number of consecutive charges and discharges.

Compared to the wholesale market, the morning peak operation of storage shows slight differences; charging lasts longer well into the morning peak period which instead in the wholesale market would see the system discharging instead. Discharge in the BM takes place slightly later, followed with mid-day charging and finally the evening peak discharge.

Interestingly, while the imbalance volumes can be thought to be unpredictable/random as Chapter 3 showed, the pattern of charge-discharge shows a striking similarity with that of the wholesale market. In particular, the fact that evening discharges coincide with peak demand and peak APX prices even the system is long (excess power) and SSP is the main imbalance price for that period. A likely explanation for this pattern is the correlation between SSP, SBP and APX prices due to bidding behaviour in the BM.

Therefore, due to the correlated prices in the APX market and the BM, the charging and discharging profiles of the storage system have a great deal of similarity across both revenue mechanisms. As a result, this similarity reduces the emphasis on the imbalance volume prediction to determine storage operation.

## 5.5. Ancillary service revenue – Firm Frequency Response

Unlike the previous APX and BM revenue models which optimised storage operation to maximise revenues, the FFR model uses simulation to evaluate typical revenues the same storage system might generate for the provision of the frequency response ancillary service. The random frequency response profile which mimics the calling of the storage's services by the SO, was generated with a probability of 20% and a randomly distributed volume between 1-25 MWh. In other words, 20% of the time during the FFR window, the storage system's services would be called on with varying amounts ranging from

1-25MWh. Relative to the system's actual capacity, this represent a very low utilisation of its potential; should its services be required more frequently, not only would this result in a better asset utilisation but also increase the gap between the high-value windows and low-value windows. In short, the importance of the choice of windows increases as utilisation frequency rises.

The FFR model also models self-discharge, a parameter previously ignored in the APX and BM models, primarily because the system remains idle for long periods of time. Although self-discharge rates are technology dependent and in fact State of Charge (SOC) dependent, the self-discharge feature is assumed to be constant at 0.1% per half-hourly period. This very broadly reflects a rate consistent with a Nickel-Metal Hydride (NiMH) battery whereby approximately 5% of the stored energy is lost within the first 24 hours (Zhu et al. 2014).

The result of the FFR model simulation is shown in figure 5.8; the system provides frequency response for the 12-hour window from 12pm-12am, whereby occasionally the service is called upon and utilised, shown in blue. The pattern displays the random nature of these utilisation instructions and assumes a compliance rate of 100%, that is, the storage system never fails to deliver whenever it is called upon.

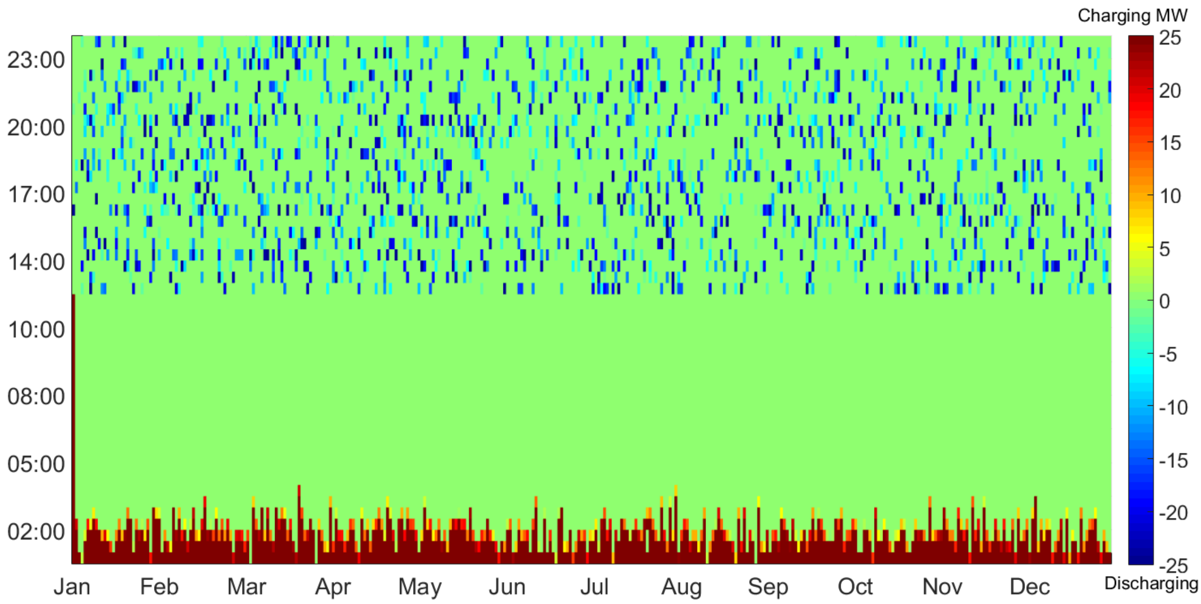


***Figure 5.8:*** *The simulated operation of an FFR-dedicated storage system offering 12 hours of frequency response capacity.*

Charging, on the other hand, is set to occur during the early hours of the morning, as specified in the FFR model, in order to maintain the state of charge at full capacity. Thus, the system will charge as soon as its FFR window ends. It should be stressed that this may not be the optimal cost reducing strategy as wholesale prices may be lower at other times rather than the first few hours of the same 12-hour charging window. This arbitrage strategy within the FFR model was excluded since its purpose was to investigate revenues relating to the provision of the ancillary service rather than perform arbitrage.

However, by varying the starting times of the 12-hour charging and discharging windows for which the system provides FFR, it is possible to gauge the effect of arbitrage on FFR, investigated here for the sake of completeness. By varying the starting times, the FFR model generated revenues from £0.61 million to £ 1.52 million.

Figure 5.9 shows the revenues with different 12-hour window starting times. The 12-hour window from 3am-3pm offered the highest revenues whereas the window associated with the worst performance was from 9:30am-9:30pm. 12-hour windows with starting times between 21:00 to 04:00 generated the highest revenues whereas the lowest revenues periods coincided with starting times between 08:00-12:00.

This pattern arises since the model relies on the APX spot market for buying electricity when charging whereas the utilisation payment consists of the market price multiplied by a premium factor (of 1.25). Therefore, FFR (discharging) windows that coincide with peak prices benefit from higher utilisation payments. On the other hand, the 12-hour charging period preceding the FFR windows benefit from off-peak prices resulting in lower charging costs.

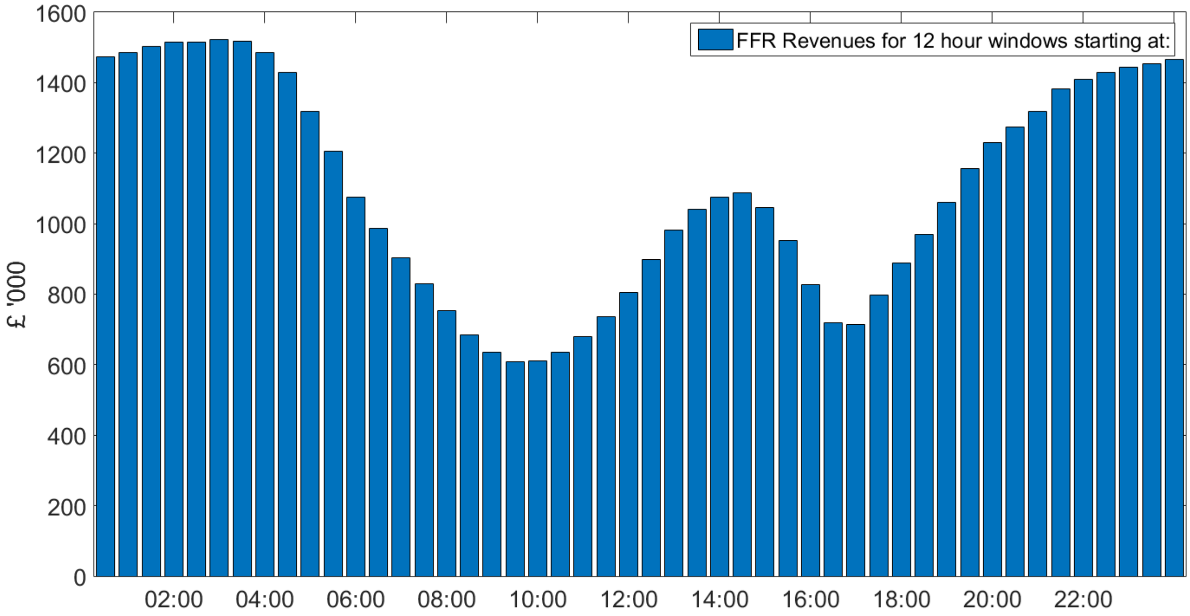


***Figure 5.9:*** *Charging windows for FFR with different values depending on their starting times.*

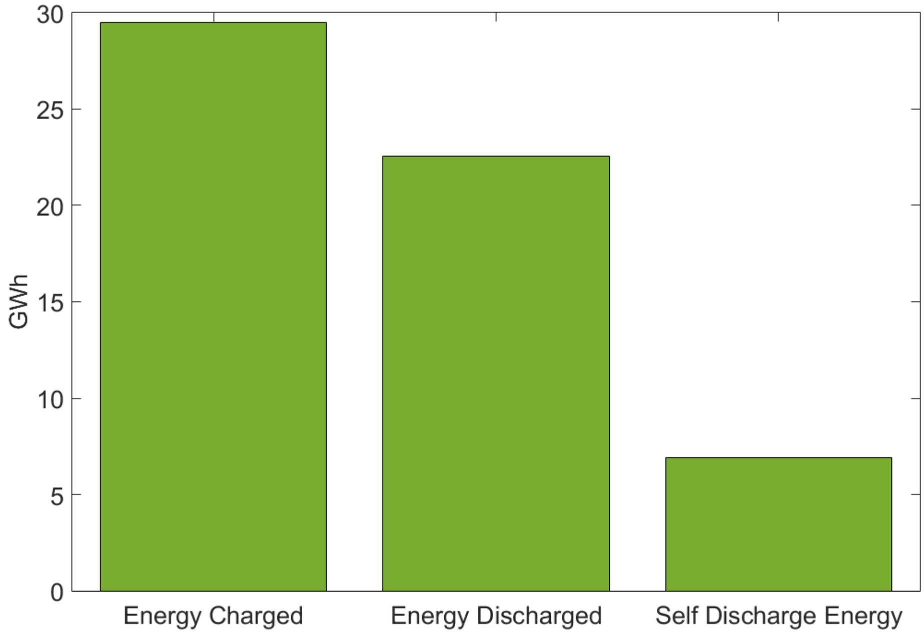


***Figure 5.10:*** *Total energy lost through charge-discharge cycles as well as self-discharge.*

Figure 5.10 shows that 20% of the energy charged is lost through self-discharge alone; in fact, energy lost through self-discharge is greater than the RTE losses. While, the model assumes a RTE of 81%, for technologies with higher efficiencies such as lithium-ion batteries at about 94%, the self-discharge rate overwhelms efficiency losses and needs to be considered.

## 5.6. Short Term Operating Reserves as an alternative ancillary service

Similar to the FFR model a STOR model was developed to investigate the revenues from the provision of another ancillary service. As opposed to FFR whereby utilisation rates were unavailable and derived on a simulated basis, STOR data published by National Grid allowed the derivation of a utilisation profile, as shown in Chapter 4. In Figure 5.11, National Grid procures STOR primarily for 2 windows relating to the peak period ranging from 07:30-13:30 and evening peak period between 17:00-21:00. The blue rectangles, representing when National Grid calls for STOR, occur during these periods only with 1.8% of the time, hence its sparse distribution. While discharging is confined to these hours, charging is split between the remaining two periods namely the overnight period from 21:00-07:30 and the mid-day period from 13:30-17:00. As seen from figure 5.11, the system charges in the earlier part of these periods for the same reasons mentioned in the FFR model.

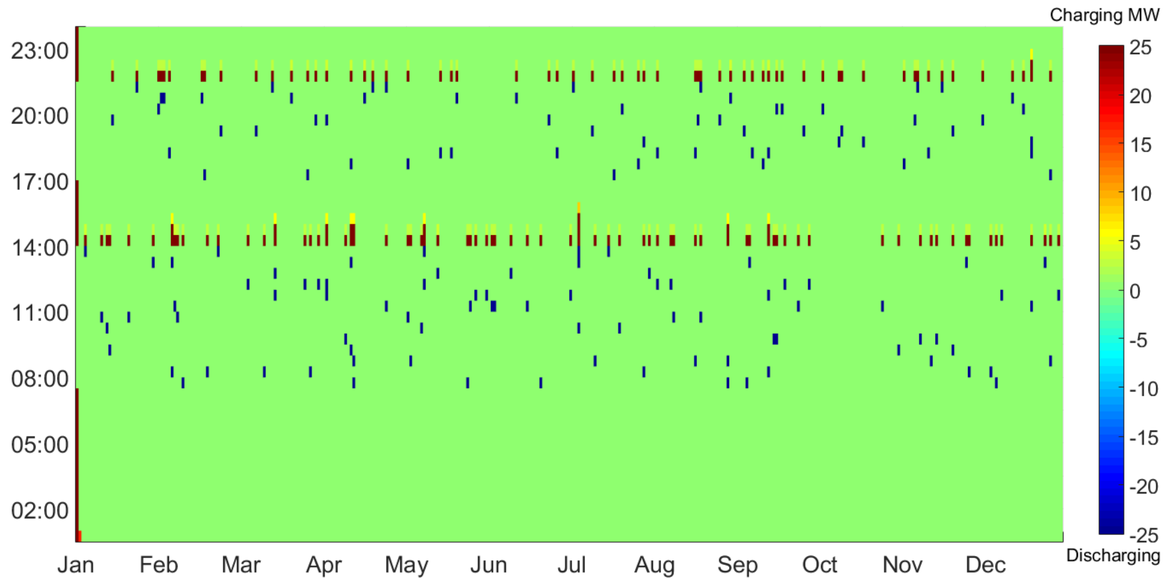


***Figure 5.11:** Charging and discharging when the system is dedicated to the provision of STOR in 2013.*

The STOR model, like the FFR model, assumes a self-discharge rate of 0.1% per half hour. A special implication applies to STOR model and to a lesser extent the FFR model; services which rely heavily on availability payments and less on utilisation payments may prove to be a niche of interest to technologies with limited cycle life – in effect, a low cycling rate improves the lifespan of the technology whilst delivering availability payments.

Batteries are good candidates for these services since both the frequency and depth of discharge affect the lifespan of the system. On the other hand, they are able to deliver high power quality, fulfilling the minimum requirements for FFR and STOR. As a result, storage systems are not only used to defer T&D network reinforcements but also contracted to provide these ancillary services. An example of this is the 6MW/10 MWh lithium-ion battery storage in Leighton Buzzard by UK Power Networks able to deliver both FFR and STOR as well as save on network upgrade costs (Cooper et al. 2015).

With a far lower utilisation rate, the system does not require long periods of charging to top up the storage energy level. In spite of this, STOR managed to generate £1,330,816 representing 9.9% less than FFR revenues. Significantly higher utilisation payments for STOR relative to FFR almost fully compensate for the lower utilisation rates modelled. The Leighton Buzzard facility offered both STOR and FFR services and found FFR revenues greater than the cost of providing the service. In the case of STOR however, costs exceeded revenues (Papadopoulos 2016b).

## 5.7. Impact of energy capacity on revenues and storage discharge

One of the key parameters of a storage system is its power to energy ratio, equivalent to the number of hours of output the system can deliver. Storage systems are usually sized specifically by function; for example, a system that provides frequency response will have a high power to energy ratio based on the fact that frequency response as a service is required for a relatively short duration until other reserves take over to bring back within operating standards. Based on the technical requirements for the provision of ancillary services, as shown in Appendix B.1, the minimum energy capacity for a system providing FFR would be 0.5 hours' storage whereas if the system were to provide a black start service, an energy capacity equivalent to several days' equivalent would be required.

While storage systems sized for ancillary services are guided by service requirements and contractual obligations, there is no clear indication of the appropriate size of storage for arbitrage. The common approach to this problem is to perform a sensitivity analysis and evaluate at what size most of the revenues have been captured. Numerous studies have utilised such approach (Sioshansi et al. 2009; McConnell et al. 2015; Kloess & Zach 2014; Safaei & Keith 2014; Bradbury et al. 2014; Locatelli et al. 2015) and while their specific findings in terms of size relate to their respective markets and therefore subject to small variations, most of them were in the 4 to 10 hours' range.

It is important to point out that none of these studies make reference to a specific optimal size but rather state the number of hours of storage energy capacity at which most of the value has been captured; for example McConnell et al., (2015, p.5) state: *"…almost 90% of the total potential value is recovered with only four hours of storage. Beyond six hours of storage, there is limited marginal value in extending the amount of storage with the additional storage providing only limited incremental arbitrage opportunities."*. This apparent lack of optimal storage size in those studies highlight the challenges in determining the ideal storage size for economic profitability using conventional optimisation models; the lifetime assessment of revenues relative to storage size would require an optimisation horizon equivalent to the storage system's lifespan, a requirement which is prohibitively difficult from a computational aspect.

A sensitivity analysis of total revenues with respect to energy capacity is shown in the top left part figure 5.12; In the APX market, with an energy capacity of one hour, 40% of the maximum revenues is captured rising to 89% at 4 hours. At 6 hours 99% of the potential value was captured. The BM revenues show a similar sensitivity to energy capacity; at 4 hours' capacity 91% of the maximum revenues was captured and at 6 hours this figure rose to 98%. Before concluding from the evidence presented, that storage energy capacity beyond 6 hours is not justified, it is important to bear in mind that the optimisation horizon is 24 hours and longer horizon, such as a week horizon, which enables inter-day arbitrage could justify greater energy capacities. This possibility is investigated in the next section.

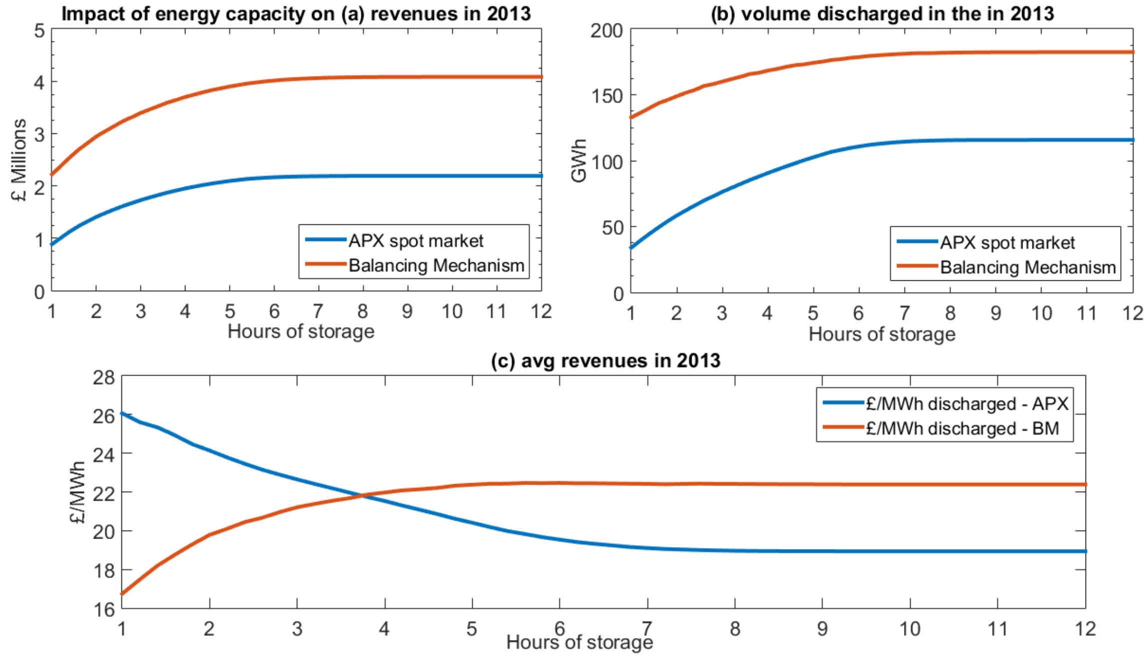


***Figure 5.12:*** *The impact of energy capacity on revenues in the APX or BM in 2013.*

The discharge volumes with respect to energy capacity in the APX power exchange and BM is shown in the top right of figure 5.12 and portray a similar trend to revenues. A notable difference is the increased sensitivity of discharge volume to energy capacity in the APX power exchange compared to the BM; at one hour the volume discharged is 34 GWh in the APX and rises to 91 GWh at 4 hours compared to the BM whereby 133 GWh and 168 GWh was discharged at the one and four hour levels respectively.

### 5.7.1. Different behaviours in average revenue in the APX and BM

The bottom part of figure 5.12 shows revenues per MWh discharged, referred to as average revenue. A stark difference in trend occurs between the spot market and BM revenues; in the spot market, average revenue, decreases at a decreasing rate, thus flattens past the 6-hour mark. On the other hand, in the BM average revenue increases until the 5-hour mark where the curve flattens as well.

The average revenue behaviour in the APX power exchange is well understood; larger energy capacities allow for a greater number of arbitrage trades which would otherwise have been constrained due to capacity limitations. Also, in line with optimisation, more profitable arbitrage trades are chosen first followed by the next less profitable. Therefore, increasing the energy capacity allows the system to capture the less profitable trades. A modest increase in revenues (since these trades are not highly profitable) divided by a large increase in discharge volume causes the average revenue in the spot market to fall.

The average revenue behaviour in the BM is driven by a different mechanism; since average revenue is simply revenues per MWh discharged, an increasing average revenue curve implies that total revenues are increasing faster than discharge volume, as energy capacity increases.

In this case, a comparison between a 1-hour and a 12-hour energy capacity storage system was carried out, to show how storage operation is constrained with high power to energy ratios. High power to energy ratios could be potentially beneficial for the provision of an ancillary service such as FFR as the storage system is able to meet its minimum requirements with a power to energy ratio of 2 (an energy capacity equivalent to half an hour). However, in the context of the APX and BM, high power to energy ratios limit the ability of the system to fully realise the arbitrage trade potential. In figure 5.12, a power to energy ratio equal to 1 captures less than 50% of the potential revenues in both the APX and BM due to the lack of stored energy. While high power to energy ratios can be detrimental to capturing market revenues this could potentially be offset by possibly lower capital costs which such configurations may bring such that the system is overall more profitable.

Figure 5.13 compares a 1-hour energy capacity operation versus a 12-hour capacity and reveals:

I. Under a 1-hour energy capacity, charging and discharging take place on an alternating basis, in order to maximise revenues; holding stored energy for very long periods comes at the cost of lost arbitrage opportunities during the waiting period. Unless there are very high price differentials, it is not economically viable to hold stored energy for very long periods, especially under small energy capacities. Instead, Cross System Price Arbitrage becomes the dominant form of arbitrage.

II. Under the 12-hour energy capacity, however, charging cycles occur consecutively as do discharging cycles. This operation strategy takes a greater advantage of peak and off-peak price differences as it enables continuous charging during low prices and continuous discharging at peak prices. In this case off-peak to peak arbitrage, becomes the dominant form of arbitrage.

Off-peak to peak arbitrage yields higher revenues than CSPA without requiring a substantially higher discharge volume, and this is the fundamental principle behind the different trends in average revenues.

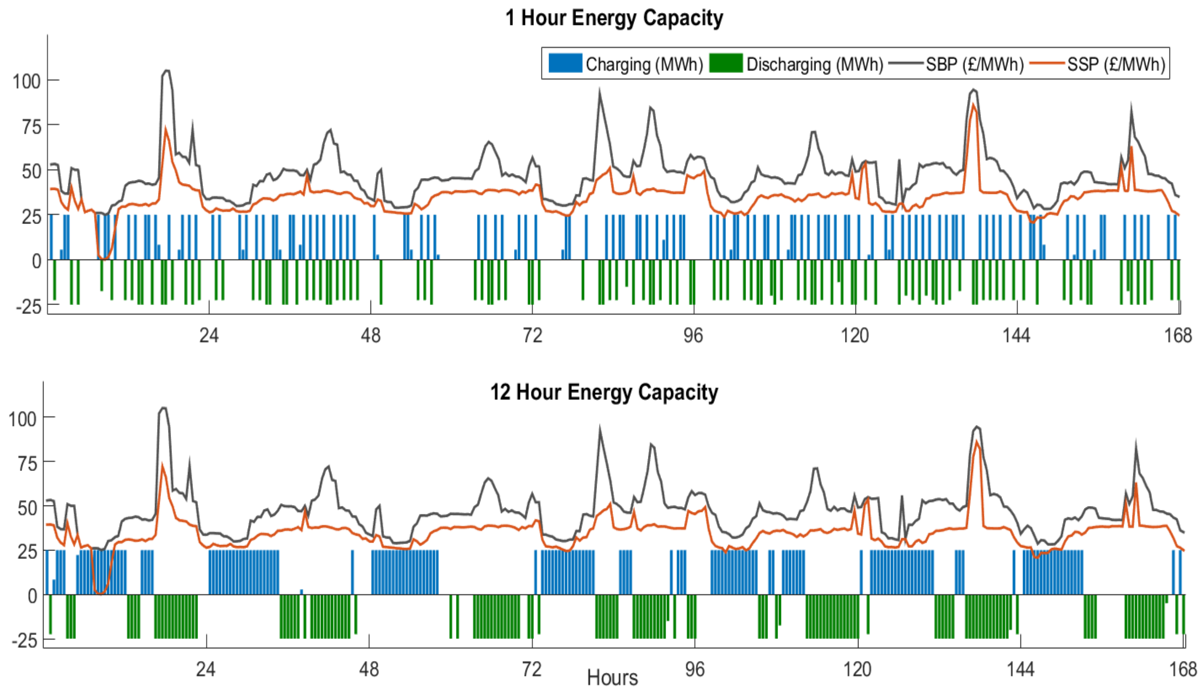


***Figure 5.13:*** *The difference between a 50MW/50MWh vs a 50MW/600MWh storage system operating under revenue maximisation objective.*

### 5.7.2. Sensitivity to efficiency

The round-trip efficiency of energy storage systems is one of the most important parameters; from an engineering perspective, this measure expresses the ability of the system to capture energy for future release. From an economic angle, with specific reference to arbitrage, RTE expresses the ability for the system to retain the price differentials instead;

The concept of price elasticity of demand, which is well known in economics, can be applied to arbitrage revenues with respect to efficiency.

The efficiency elasticity of arbitrage equation can be expressed as follows:

$$E_{rte} = \frac{(\Delta\, Arb/Arb)}{(\Delta RTE\ /RTE)} \tag{5.1}$$

*Whereby:*

*Arb:* *Arbitrage Revenues*

*RTE:* *round-trip efficiency*

In this respect, the elasticity of arbitrage revenues is greater than 1 for efficiencies above 45% as shown in the top left corner of figure 5.14; by definition, an efficiency elasticity of arbitrage revenues greater than 1 implies a more than proportionate increase in revenues following a proportionate increase in efficiency. At an RTE of less than 45%, total revenues are very low and profits arise from large price differentials which are sufficient to compensate for the large efficiency loss. As efficiency rises, revenues increase more than proportionately when two separate effects combine:

I. An efficiency gain on all existing arbitrage trades means that more revenues arise from the same trades. Revenues increase but gross discharge volume from this effect remains the same.
II. A feasibility gain whereby trades which were previously infeasible due to efficiency losses, now become feasible and contribute to the increase in revenues. In this case discharge, volume and total revenues increase as new trades become possible.

In the top right corner of figure 5.14, the discharge volume with respect to RTE is shown; the spot market discharge volume shows an efficiency elasticity greater than 1 throughout the 35%-95% range, implying that these volumes are over-proportionately responsive to small changes in efficiency. On the other hand, in the BM, revenues show a similar trend for efficiency ranges between 25%-65%, at which the curve shows an inflexion. From an efficiency level of 65% onwards, discharge volumes show a reduced rate of increase, markedly so in the 85%-95% range. Since BM revenues within the same range do not show diminishing returns, the most obvious explanation is that the rise in efficiency within that range does not bring about significant new arbitrage trade (and hence the diminishing returns trend in discharge volume) but leads to substantial increases revenues due to reduced efficiency losses.

The bottom part of figure 5.14 shows the impact of efficiency on average revenues; in both mechanisms, average revenues tend to fall in the 5%-30% range and rise again thereafter. In the APX spot market, however, there are fluctuations in the trend, i.e. average revenue falls and rises within the 5%-35% range. This is the result of the two effects mentioned earlier, the efficiency gains and the feasibility gains; when feasibility gains dominate efficiency gains such that discharge volume increase faster than total revenues, average revenues fall. Conversely, when efficiency gains dominate feasibility gains and cause revenues to rise faster than discharge volumes, average revenues rise.

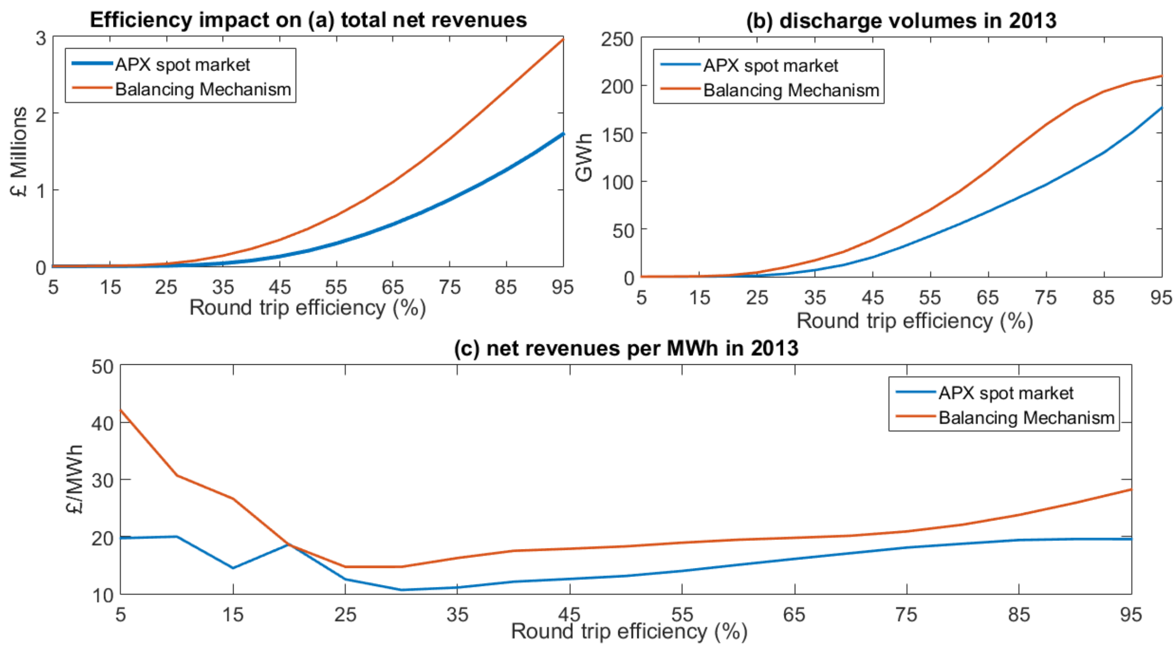


***Figure 5.14:*** *The impact of efficiency on the APX and BM revenues in 2013.*

The behaviour of efficiency gains and feasibility gains is very much market dependent; more precisely the magnitude of the price differentials and how often they occur, determine how strong the effect will be. Figure 5.15 shows the strength of these effects under different circumstances:

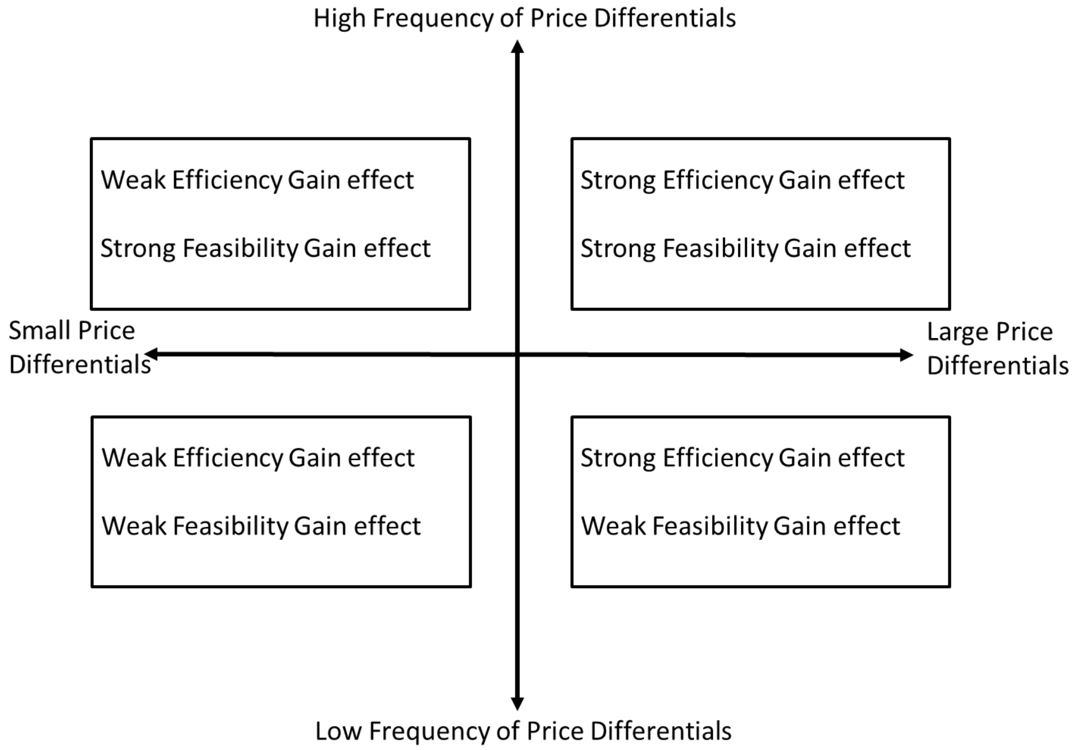


***Figure 5.15:*** *The interaction between the magnitude and frequency of price differentials which determine the overall impact of an increase in round-trip efficiency.*

## 5.8. Comparative revenues in single markets

Thus far, the emphasis was laid on the operation of storage within the market mechanisms with little reference to the absolute revenues and their implication; figure 5.16 shows the revenues which each mechanism, namely APX, BM, FFR and STOR, generated in 2013. These figures show a volume-unconstrained operation within the markets, under the assumption that sufficient liquidity exists and/or that the revenue mechanisms are so large that storage participation does not have a significant overall impact; these assumptions are relaxed in Chapter 6.

In 2013, the storage system generated over £2.7 million in the APX market and taking into account the size of the storage system, this is equivalent to £54.99/kW-yr. For every MWh discharged, a net arbitrage revenue of £13.37 was generated. Comparatively, the BM showed profitability yielding 48% more revenues than in the spot market and for each MWh discharged, the BM model earned 67% more revenues, highlighting the presence of higher price differentials.

In the FFR revenue stream, both availability payments and utilisation payments are accounted for and amounted to £1,092,000 and £1,552,603 respectively. As electricity is purchased from the spot market, for a total of £1,178,544, the net revenues totalled £1,475,745 for the year, equivalent to £65.37/MWh discharged. Comparatively, this represents 54% of spot market revenues and 36% of BM revenues. However, average returns are 3-5 times higher than in the other two mechanisms due to the fact that the system discharges less frequently and is paid even if the storage system is idle during the FFR windows (providing capacity).

The final revenue mechanism explored is STOR which similar to FFR, has an availability and a utilisation payment component. While the availability payments for both mechanisms are the same at £5/MW/h, utilisation payments differ greatly with STOR having an average utilisation payment of £168/MWh compared to £63.25/MWh for FFR. STOR was modelled, based on statistical evidence, with a lower utilisation frequency than FFR which led to a lower total revenue but a much higher average revenue at £370/MWh.

The performance of the storage system has special implications for the type of technology used; a system with a high self-discharge rate is not appropriate for a standalone ancillary service provision due to the inherent long idles times. Furthermore, systems with limited cycle life are specifically suited to these types of applications, yielding high revenues per MWh discharge, specially STOR. Batteries fall into this category, being able to provide both FFR and STOR and at the same time benefit from lower cycling rates than an arbitrage-based strategy in the APX market and BM. Conversely, conventional bulk storage technologies such as PHES and CAES are suited for arbitrage due to their long lifespan and by design being able to store large amounts of energy.

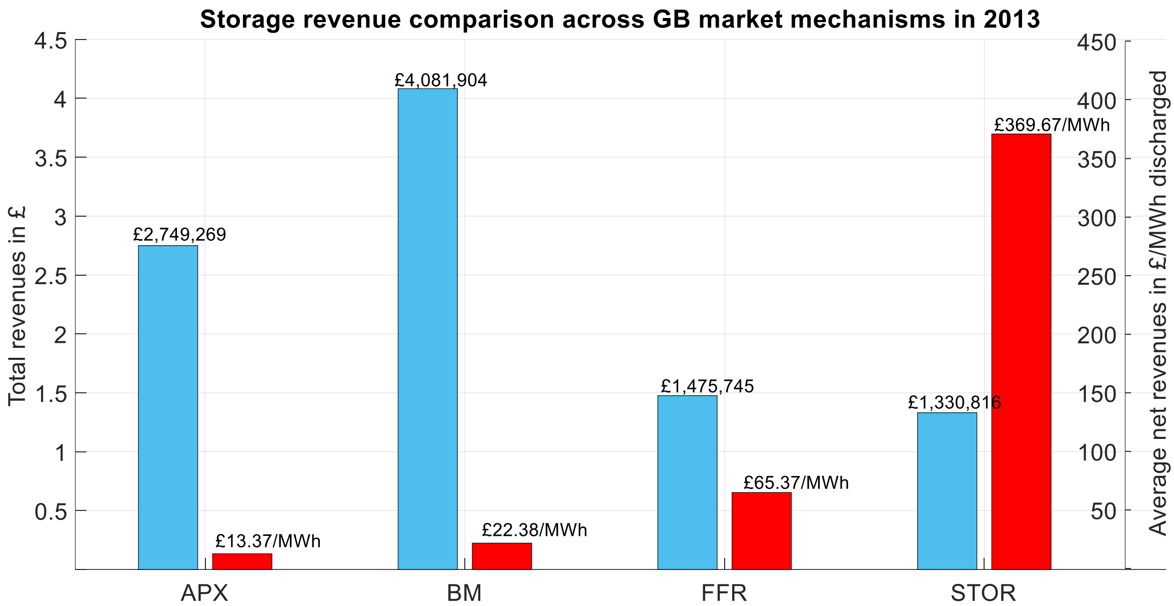


***Figure 5.16:*** *A comparison of maximum potential revenues from four revenue mechanisms in 2013.*

## 5.9. Choice and impact of optimisation horizons

An optimisation horizon is effectively the number of decision variables the model optimises, and in this case, because each decision variable is tied to a half-hourly period, the optimisation horizon can be expressed more meaningfully in terms of time. A 1-day optimisation horizon in the APX MILP model consists of 24 charging variables, 24 discharging variables and 24 binary variables. Similarly, a 1-week optimisation horizon consists of 336 charging, 336 discharging variables and 336 binary variables.

Different optimisation horizons have different solutions; this is analogous to finding better solutions with more information/inputs. For example, a weekly optimisation horizon has a full week's input simultaneously and solutions are optimal over the whole 1-week period. On the other hand, a 1-day optimisation horizon run consecutively for a week, only has 1-day's input which in turn can only produce daily optimal solutions.

Ideally, it would be preferable to have an optimisation horizon covering the whole problem set, that is, all the decision variables are optimised simultaneously. However, this may be computationally prohibitive in large problems and a trade-off has to be determined between theoretical and practical solutions. Identifying a trend with optimisation horizons is helpful in justifying the choice its length.

In the case of the storage models, varying horizon length provides an insight into a converging limit. Figure 5.17 shows the APX and BM models evaluated under 4 horizons; 1-day, 2-days, 1-week and 1-month. The models were run over a 1-year period using the different horizons, based on 2013 data.

As expected, longer horizons are able to provide better solutions, seen by an increase in total revenues; however, these increases are small and show diminishing returns. In the APX market, longer horizons generated very small increases in total revenues; a 1-day, 2-day, 1-week and 1-month generated 2.75, 2.85, 2.93 and 2.96 million GBP respectively. Similarly, average returns were 13.37, 13.49, 13.67 and 13.75 GBP per MWh respectively. In the BM, total revenues fare slightly better; 1-day, 2-day, 1-week and 1-month horizons yielded 4.08, 4.29, 4.46 and 4.53 million GBP respectively. Average returns for the BM were 22.39, 22.75, 23.04 and 23.92 GBP per MWh discharged respectively. The increase in average returns points to the underlying mechanism behind the increase in total revenues with increasing optimisation horizons; since arbitrage trades occur within the horizon, a longer horizon offers potentially better arbitrage trades. For example, a weekly horizon can take advantage of both inter-day and intra-day arbitrage trade but a daily horizon only has access to intra-day arbitrage trades.

The diminishing return trend occurs due to the opportunity cost of such trades; under longer horizons, whenever a more profitable trade is found, it involves holding stored energy for a specific discharge period at a higher price at a later time, both of which would not be accessible under shorter horizons – for simplicity this shall be referred to as long period arbitrage. However, long term arbitrage comes at the cost of missed arbitrage opportunities in the meantime, effectively short term arbitrage. The longer the horizon the more profitable the long term arbitrage trade has to be to compensate for the missed short term arbitrage trades. This gives rise to a diminishing return effect. For example, inter-day arbitrage trades need to be sufficiently high to justify foregoing intra-day ones.

Figure 5.17 also highlights the fact that the vast majority of revenue potential falls within the 1-day horizon and this has further implications for forecasting; a day ahead forecasting is of greater relevance to storage than a week ahead for example. In addition, given that shorter optimisation horizons are computationally less intensive, there is a strong case for focusing effort on improving short-term price forecasting accuracy and conversely a weaker case for long-term price forecasting with respect to arbitrage revenues.

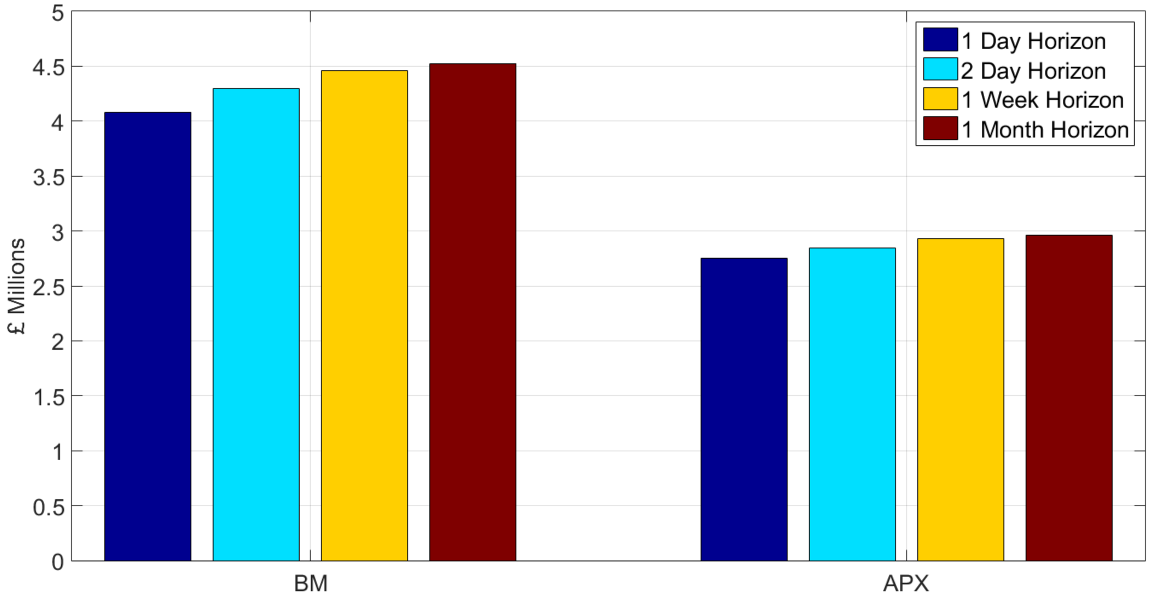


***Figure 5.17:*** *Revenue differences between a 1-day, 2-day, 1-week and 1-month optimisation horizon in 2013.*

The incidence of revenues in the 1-day horizon also points towards the strong effect of the daily peak and off-peak prices, albeit less so in the balancing mechanism which benefits slightly more from longer horizons. From a practical perspective, forecasting with volatility ahead of real time is a challenge and therefore a more predictable trend such as in the APX spot market may be preferred instead. The ability to realise potential revenue from both mechanisms is explored in chapter 7.

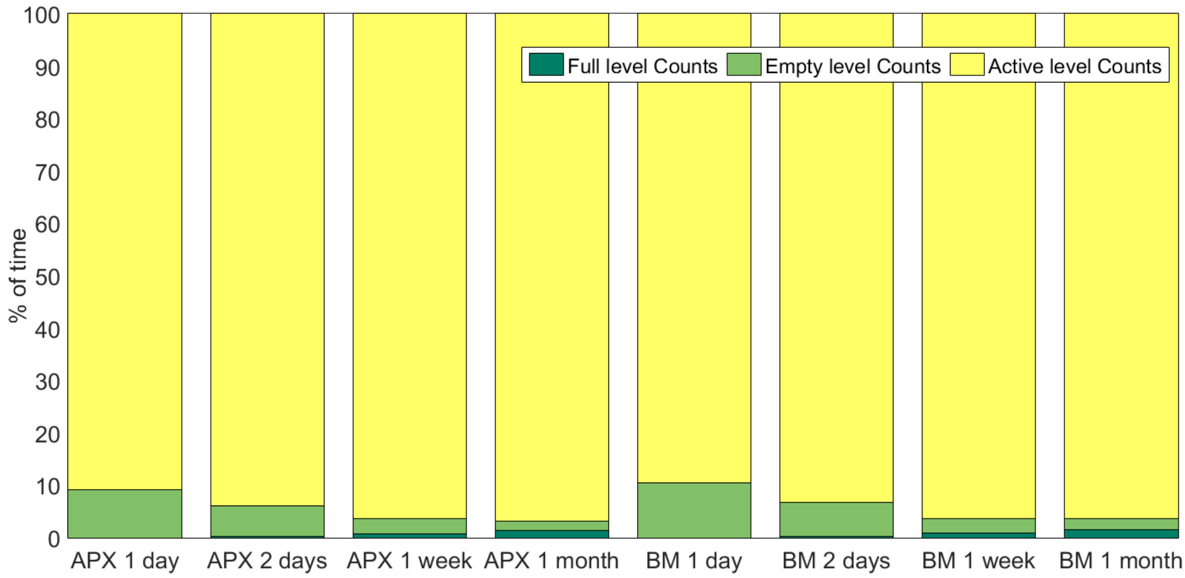


***Figure 5.18:*** *The utilisation of storage capacity under 4 optimisation horizons.*

Optimisation horizons do not only increase revenues but also impact on the frequency and cycling depth of a storage system. Figure 5.18 shows the proportion of time the storage system reaches full capacity, is empty or is actively utilised but with spare capacity available. These can be interpreted as an indicator energy capacity utilisation rate; a system which reaches full capacity more frequently clearly indicates a better utilisation of its potential.

In the APX market, an increase in the optimisation horizon increases the proportion of time the SOC is full and decreases the number of times this value remains at zero. The energy capacity assumed in figure 5.18 is the default 12 hours' full output; although this is oversized as seen previously, in this case, storage's energy capacity is irrelevant with respect to the impact of optimisation horizons. In other words, irrespective of the system's energy capacity, longer horizons increase full capacity utilisation.

This effect highlights another facet of storage sizing; careful consideration should be made not only based on the relationship between market revenues and energy capacity but also the optimisation horizon the system is expected to operate. Special precautions should be taken against oversizing, even in the presence of long optimisation horizons due to diminishing returns.

## 5.10. Conclusion

This Chapter set out to investigate the operational differences of storage as a dedicated unit and the effects which generate revenue. It was shown that the BM yielded the highest potential for revenues due to the larger magnitude of price differentials. Furthermore, a clear and separate effect has been identified, which generates additional value compared to traditional arbitrage, namely a cross-system price arbitrage.

Storage operation in the APX market generated the second highest revenues relying on conventional arbitrage revenues. These are higher than the FFR and STOR ancillary services revenues. The ancillary services' inferior revenues are due to the low utilisation rates, which in turn mean a relatively low revenue stream. Patterns of charging and discharging are similar on a daily basis and also across both the APX and BM, occurring due to the cyclical trend in prices, a correlation driven by demand.

Seasonal influences on APX and BM prices, in turn, have impacts on arbitrage revenues. As a result, storage operations are different in summer compared to winter months; discharging patterns are more compact around winter peak time and more spread during winter morning periods, indicating a clear preference for evening peak prices than the morning peak prices. In summer the opposite was discovered, that storage discharge is concentrated around the morning period due to the morning peak prices but dispersed around the summer evening peak, sometimes even splitting into one further late night discharge phase.

Storage operation in the ancillary services market is markedly different; long idle times result in a large amount of energy lost due to the self-discharge feature. FFR revenues are strongly dependent on the choice of 12-hour windows; a 9pm-4am charging window offers the highest value.

In all four mechanisms explored 12 hours' storage was oversized as full capacity was rarely reached, even though this was more common in the BM than the other revenue mechanisms. A sensitivity analysis confirms this; the majority of revenues are captured within the four hours of energy capacity and at 6 hours 98-99% of maximum possible revenues was captured in the APX and BM.

A change in round-trip efficiency was shown to result in a more than proportionate change in revenues due to two different effects; an efficiency gain effect whereby all existing trades generate more income and a feasibility gain whereby new trades become feasible under higher efficiency and this leads to additional revenues.

Finally, the impact of optimisation horizons on storage operation was investigated; longer horizons generate more revenue, however with diminishing returns. The vast majority of maximum revenues - 93%, is captured within the 1-day horizon. On the other hand, longer horizons do increase utilisation of power capacity.

# Chapter 6. Storage value under multiple revenue mechanisms

## 6.1. Introduction

Chapter 5 explored the potential value of storage under single revenue mechanisms. With the understanding of storage operation and revenues in single market mechanisms achieved, the next step is to investigate how they differ under combined operation. Storage systems are versatile in their abilities to participate in several market mechanisms and/or deliver additional benefits. In fact, a growing number of studies are investigating storage providing multiple services simultaneously (Drury et al. 2011; Das et al. 2015; Moreno et al. 2015). Accessing multiple revenue streams simultaneously requires the appropriate allocation of capacity and energy to each service to derive optimal value.

Therefore, this Chapter investigates how storage operation under multiple revenues differ compared to participation in single mechanisms only. Specific patterns in charge and discharge are identified. Unlike in Chapter 5, storage operation is constrained by market trading and imbalance volumes. In the Balancing Mechanism, only storage operation that alleviates imbalances is allowed, reflecting a greater degree of realism.

Similar to the single revenue mechanism case, seasonal and annual variability in revenues are also investigated under co-optimised revenues. Furthermore, a comparison of revenues between the single and multiple revenue streams is drawn, isolating the effects causing the differences to arise. Besides a sensitivity analysis, the Net Present Values of selected storage technologies are calculated to determine whether revenues under co-optimisation are sufficient to support their economic feasibility. In other words, this Chapter shows how co-optimised revenues differ from single market revenues and explores their implications for specific storage technologies.

One of the major assumptions thus far relate to perfect foresight; this assumption in itself is not unjustified when the purpose of the research is to investigate the potential value for storage, similar to the work of Barbour et al., (2012). However, as an approach to investigating realisable value, such foresight is unrealistic since such knowledge of prices ahead of time is unlikely, forming the basis for the storage value study by Mokrian & Stephen (2006). Therefore, this Chapter relaxes the assumption of perfect foresight and investigates simple strategies to capture storage value under imperfect foresight.

## 6.2. Firm Frequency Response under co-optimisation

The allocation of storage power and energy capacity to Firm Frequency Response was assumed to be flexible; this allows for the optimal allocation of FFR windows. Subsequently, based on the findings, a fixed FFR window can be allocated (rather than arbitrarily). Figure 6.1 shows the number of occasions in 2013 whereby the co-optimisation model chose to allocate a half hourly window to the provision of FFR. The maximum number of possible allocation for each window is 365, which represents an allocation for the chosen window on every single day of the year.

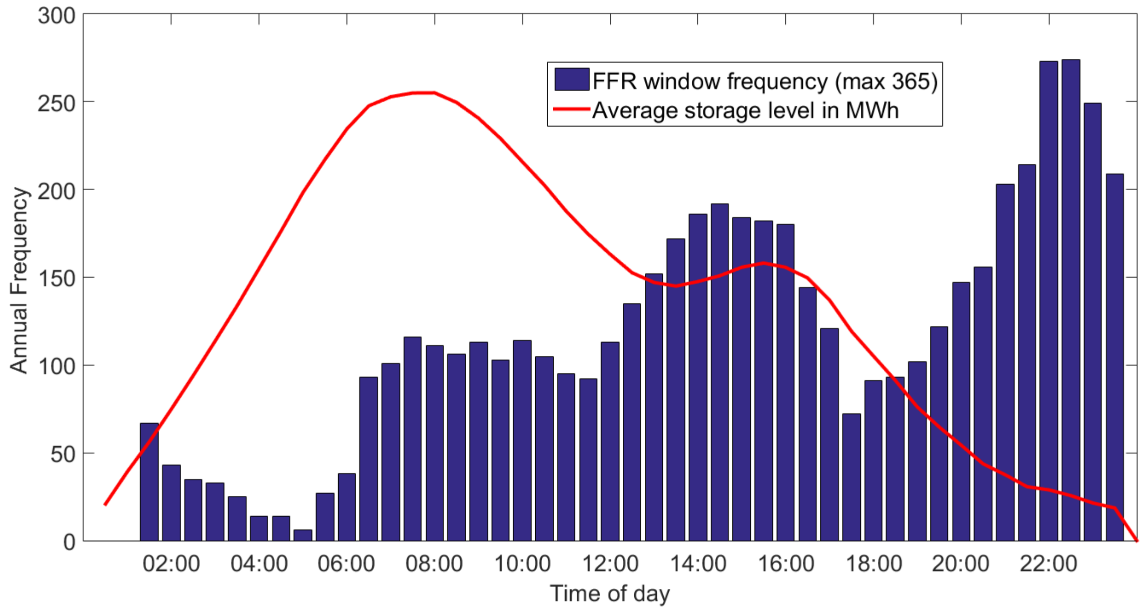


***Figure 6.1**: A histogram of FFR allocated windows under co-optimisation in 2013.*

From the diagram, the most frequent FFR windows during 2013 were from the 41st to 47th settlement period that is from 20:00 to 23:30. Such an allocation can be explained as follows; as the system is nearing the end of the optimisation horizon, arbitrage opportunities in the APX market or BM become more scarce. A non-zero SOC at the end of the optimisation horizon means that the system has residual amounts of energy and this situation is sub-optimal as this energy has a market value. Therefore, the storage system would need to discharge the remainder of its energy before the end of the period. Furthermore, if there is a possibility to provide FFR before the final discharge is undertaken, then the system could generate even more revenues. This trend is actually observed frequently, up to 291 times out of 365, and the last settlement period of the day almost always represents a discharge into either the BM or APX market, finalising the total revenues for the day.

The second most frequently allocated windows relate to periods from 13:00 to 16:00. This allocation, however, arises due to a different reason; APX and BM prices tend to rise sharply in the morning then fall during midday and later rise again during peak time. During the periods where the prices are rising but significantly less than their peaks, the storage system is essentially idle while waiting to discharge at peak prices.

The third set of FFR allocated windows are between 7:30 and 10 am. Similar to the second set the system which has charged on the low early morning prices is waiting for the morning prices to spike and therefore remains idle during that time. This observation is supported by the average SOC which clearly reaches its highest levels during the same period.

These periods represent ideal windows to offer FFR whereby the SOC are sufficiently high. However, the co-optimisation model accounts for availability payments only and actual utilisation of the FFR service may change the allocated windows depending on how extensively the service is called on. For example, if FFR is called on to such an extent that the service severely reduces SOC, ahead of peak prices, the model may either allocate a different window for FFR or not choose to allocate FFR at all. The actual utilisation frequency and volume is not considered in the co-optimisation model due to the unavailability of data.

## 6.3. The impact of market volume constraints on storage value

Thus far it was assumed that storage operation was unconstrained by market parameters, particularly market volumes in the APX and BM. Furthermore, the prevailing assumption was that storage could operate in the BM solely based on the system prices, irrespective of whether the system was long or short. These assumptions have now been relaxed; storage charge or discharge cannot exceed the traded volume in the APX market. In the BM, charge and discharge behaviour is constrained by the system status; when the electricity system is short and requires power, the storage system is only allowed to discharge and the discharge volume is limited by the actual imbalance volume. Similarly, when the electricity system is long, the storage system can only charge to absorb up to the excess volume. Under these new assumptions, the likelihood of a bid/offer being accepted by the system operator is higher. When the model is constrained by the assumptions above, its respective charges and discharges for each market is altered with a lower charge and discharge in the BM as shown in the lower graph of figure 6.2.

Comparing the upper part of figure 6.2 to the lower part shows a change in allocation between the APX spot market and the BM. In the unconstrained version, BM charge and discharge was higher than those in the APX market which, as shown in Chapter 5, was due to more extreme prices which in turn meant higher revenues. Under the new assumptions, this proportion changes to the extent that most of the charging and discharging now happens in the APX market.

Total revenues and total volumes are not significantly altered, however, with the constraints reducing total revenues by 3% and total charge and discharge volumes by about 6%. However, the shift in market participation is substantial; the constraints cause charging in the BM to drop by 30% and discharge by 23%, shown in figure 6.3. This fall is compensated by a greater participation in the APX spot market whereby charging increases by 29% and discharging increases by 20%. Capacity allocation to FFR increases by 12%.

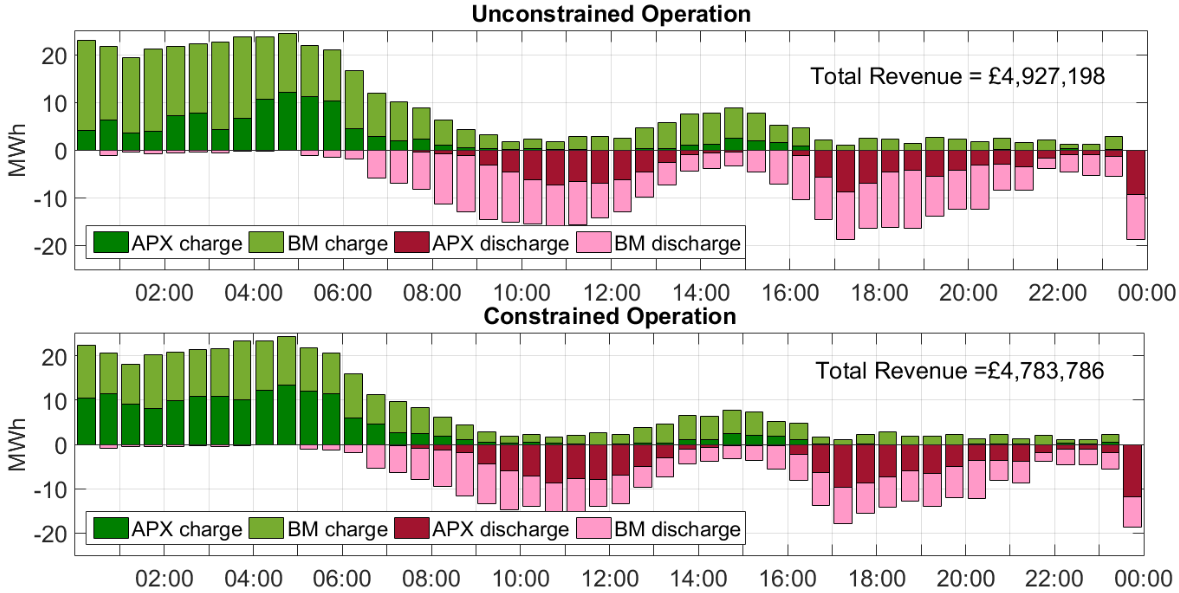


***Figure 6.2:*** *The change in total and relative volumes when storage operation is constrained by the market volumes.*

This result can be explained by the fact that the APX spot market trades in higher volumes compared to the imbalance volumes in the BM. Therefore, any restrictions in the latter can be more easily accommodated by the spot market at the expense of less attractive prices, therefore resulting in a decrease in total revenue. However, this decrease is not very significant implying that at the time the storage system was constrained in the BM, the APX prices were very similar which, usually happens under small imbalance volumes. Conversely, large imbalance volumes drive the imbalance prices to the extremes which are attractive to the storage system. In such cases, these large volumes can easily accommodate the storage capacity and hence also explain why the constraints do not affect the total revenues significantly, under co-optimisation.

The other constraint in the BM is storage operation that is consistent with actions to relieve a system imbalance. In Chapter 3, it was explained that imbalance volumes drive the imbalance price which is the price of interest, as the other price (calculated using the reverse pricing method) is equivalent to the APX market price. Therefore, in a co-optimisation model, where the APX market price is already accessible, this new assumption makes little difference in terms of revenues. In terms of operation, however, the cross-system price arbitrage mechanism (that is unrestricted buying and selling on SSP and SBP prices) found earlier in Chapter 5 is limited; the storage system can no longer perform unrestricted arbitrage between the system prices as storage operations have to take into account the state of imbalance. This means the reverse price (equivalent to the APX price) is not accessible under the BM alone. Instead, the same trades can still happen but only by participating in the APX market, effectively bypassing this restriction. In effect, part of the cross system price arbitrage is now replaced by arbitrage across the APX market and BM.

In other words, small imbalance volumes which constrain storage operation in the BM do not matter in a co-optimisation model because trading can shift into the APX market. Additionally, since the imbalance volume is low, the imbalance price is unlikely to be much different from the market price. Therefore, the volume constraints in the BM do not strongly impact the co-optimisation model. Restricting storage operation to align with the state of imbalance has little effect; the restriction usually has the effect of preventing access to the wholesale price but in the co-optimisation model the storage system can already do so through the APX market.

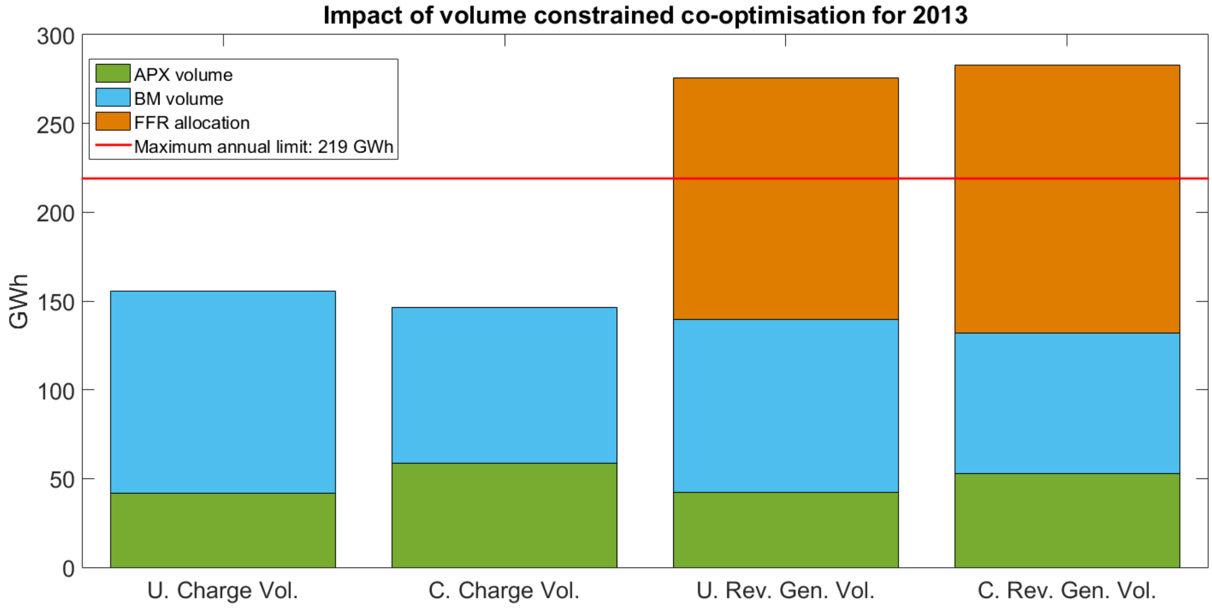


***Figure 6.3:*** *The aggregate charging and revenue generating volume with and without volume constraints. U and C refer to Unconstrained and Constraned (conditions) whereas Rev. Gen. refers to Revenue Generating respectively. For example, C. Rev. Gen. Vol, represents the Constrained Revenue Generating Volume.*

Figure 6.3 also shows that to some extent the constrained model compensates for the reduction in revenues by increasing the volume of storage operation allocated to FFR provision. It also points to an effect that is achieved only by co-optimisation; the total combined revenue generating volume exceed the maximum limit a 50 MW system is able to physically discharge (at 219 GWh). This arises due to the difference between an ancillary service that generates most of its revenue from power capacity and arbitrage revenues which are dependent on the energy stored (and hence energy capacity). For example, if the system has an FFR window during which the service has not been utilised, the stored energy can still be discharged later for arbitrage profits. While this can be deemed as 'double counting', the purpose is to illustrate how in effect, revenues can be derived for a total energy volume that exceeds the storage system's maximum capacity.

Not counting energy volume allocated to the provision of FFR, total energy physically discharged by the system was approximately 150 GWh, representing 68% of the 219 GWh maximum potential. Henceforth, the results presented in this thesis will take into account the trading volume constraints in the APX and the NIV constraints in the BM. Furthermore, storage operations in the BM will be confined to those actions that reduce the NIV, in aligning with one of the System Operator's objectives.

## 6.4. Storage operation as a product of price interactions

A greater understanding of intra-day storage operation under co-optimisation can be achieved by looking at the trend in average prices. Figure 6.4 shows the average prices for the APX spot market, SBP, SSP and aggregate demand for 2013. On average SSP is lower than the APX price and significantly lower than SBP, clearly showing a greater potential for arbitrage revenues. Since the BM price differentials, on average, seem to be greater than the APX prices, one would expect the co-optimisation model to participate more in the BM than the APX spot market.

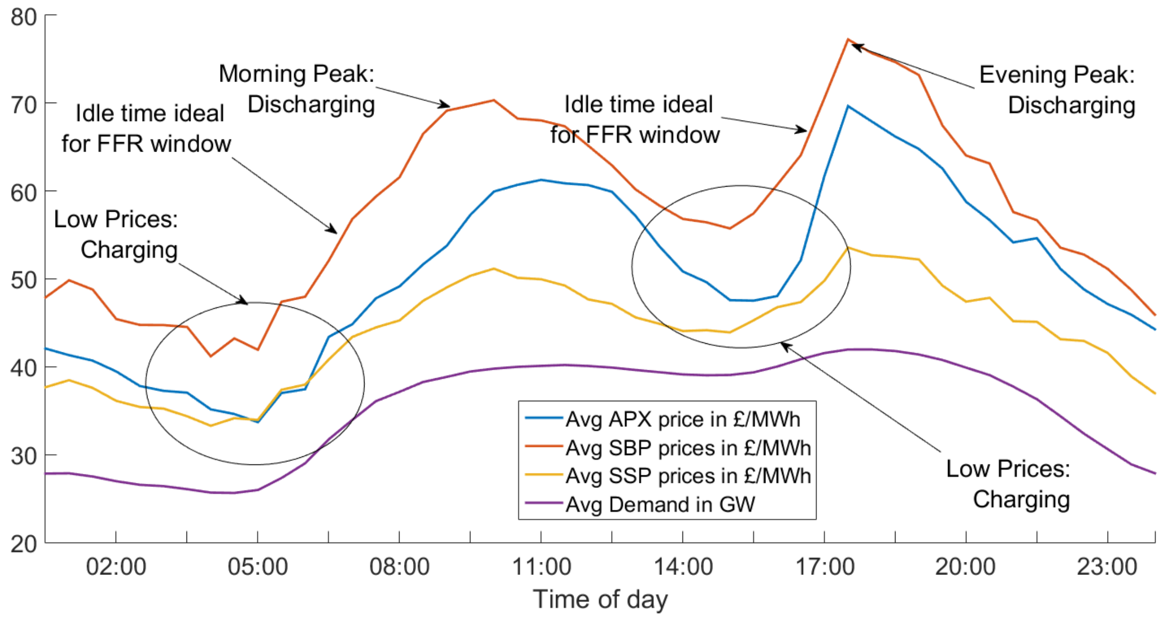


***Figure 6.4:*** *Average prices in the APX spot market and BM across the day in 2013.*

The co-optimised schedule shows that on average, charging takes place during the first 6 hours (see figure 6.2) due to the low prices seen here in figure 6.4. The schedule also shows that, on average, a two-hour FFR window is allocated after the 6-hour morning charge, followed by a discharge period of approximately 3 hours, taking advantage of the morning peak prices. Some charging may occur in the afternoon as prices fall. The greatest discharge volume occurs during the early evening peak from 17:00 to 20:00 due to the highest prices of the day. Following this discharge any residual energy is offered for a short frequency response window before a final discharge which brings the SOC back to zero at the end of the day.

## 6.5. Seasonal impacts on co-optimised operation

Seasonal influences in the co-optimisation model are very similar to the single market models; the transitionary effect between seasons resulting in later peak discharges is also seen here in figure 6.5. Similarly, the sparse pattern of discharge during the morning peak and dense pattern at peak time in winter is also present in the co-optimised results.

The existence of two discharge cycles is attributed to the nature of the optimisation problem whereby discharge volumes are limited by the system's power capacity. When this limitation is combined with a short time window during which the evening peak occurs, the system is unable to discharge all of its stored power to maximise its revenue. Therefore, the next best feasible strategy is to discharge power during the morning price spikes in addition to the evening peak.

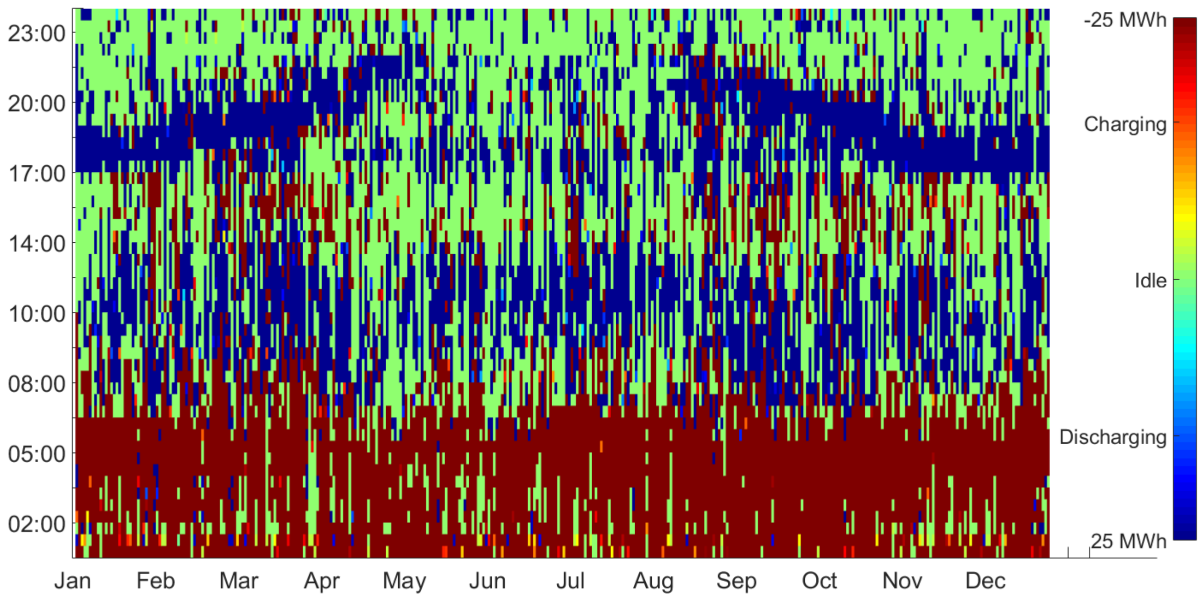


***Figure 6.5:*** *Seasonal influences on the constrained operation of storage in the presence of three revenue streams; APX, BM and FFR.*

Figure 6.5 also highlights the challenging task a storage owner faces in the absence of perfect foresight. In Chapter 5, it was shown that the trends in prices matter more than small differences in price accuracy. This is also true with the co-optimisation model; however, with the presence of seasonal influences, the trend in prices shifts implying an operation schedule on a day in January is different from that in July. Thus there is a risk of storage charging or discharging at the wrong times, which in turn could negatively impact revenues. Realistic simple strategies to capture this value are presented at the end of this Chapter.

## 6.6. Relative profitability of revenue streams

Apart from charging and discharging in the APX spot market and BM, the system is idle for a substantial amount of time, shown by the shaded green part of figure 6.5. Some idle states of the system represent FFR allocated windows and therefore explains the substantial allocation of the system's capacity to FFR.

Figure 6.6 shows the revenues, discharge volumes and FFR allocations in 2013. In terms of revenues, the BM revenue stream shows the highest value at £ 2,969,657 representing more than twice the revenues from the APX spot market at £1,057,503 and more than three times that from FFR payments which totalled £756,625.

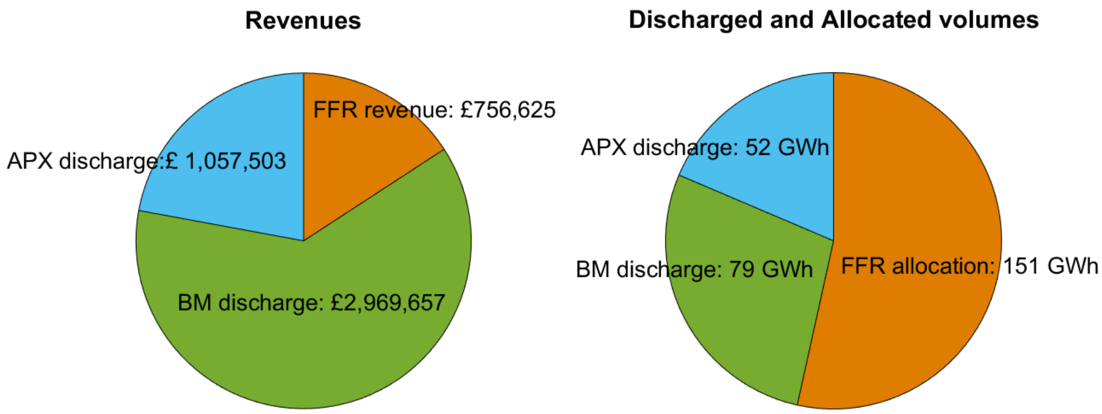


***Figure 6.6:*** *Pie charts of revenues and discharge volumes in 2013.*

Figure 6.6 also shows a stark contrast in terms of profitability based on how much volume was allocated to the respective mechanisms; The BM which generated the most revenue required 79 GWh of energy discharge whereas the FFR revenues required 151 GWh of volume allocation to yield significantly less revenues. When average revenues are considered, the BM revenue stream thus yields the highest value at £37.57/MWh followed by the APX at £20.09 and lastly the FFR availability payment fixed at £5/MW/h. So far the revenues generated in 2013 may not be typical and therefore merits an investigation into the variability of revenues.

## 6.7. Monthly variability in revenues

In Chapter 5, it was shown that revenues vary from year to year, sometimes substantially. While seasonal effects are expected to be present strongly on a month to month basis, it is not known whether the magnitude of the seasonality effects is constant throughout the years.

Figure 6.7 shows the monthly[7] co-optimisation revenues from 2011-2014. The monthly co-optimisation values shown here uses a daily horizon. Under a daily optimisation horizon, changes in monthly aggregate revenue can only mean that daily revenues persistently differ rather than average out over a 30-day period. This confirms the presence of seasonality effects on storage revenues. However, these seasonal effects do vary in magnitude from year to year.

In 2011, there was relatively less variation in the monthly revenues, to the point where summer revenues were not much lower than winter revenues. Monthly revenues in 2012,2013 and 2014 show a stronger seasonal impact; during these three years the revenues from June to August are low and tend to be the highest during early autumn and late winter. The highest revenue was in March 2013 whereby a monthly revenue of £ 572,590 was generated while the lowest value occurred in July 2011 at of £259,885.

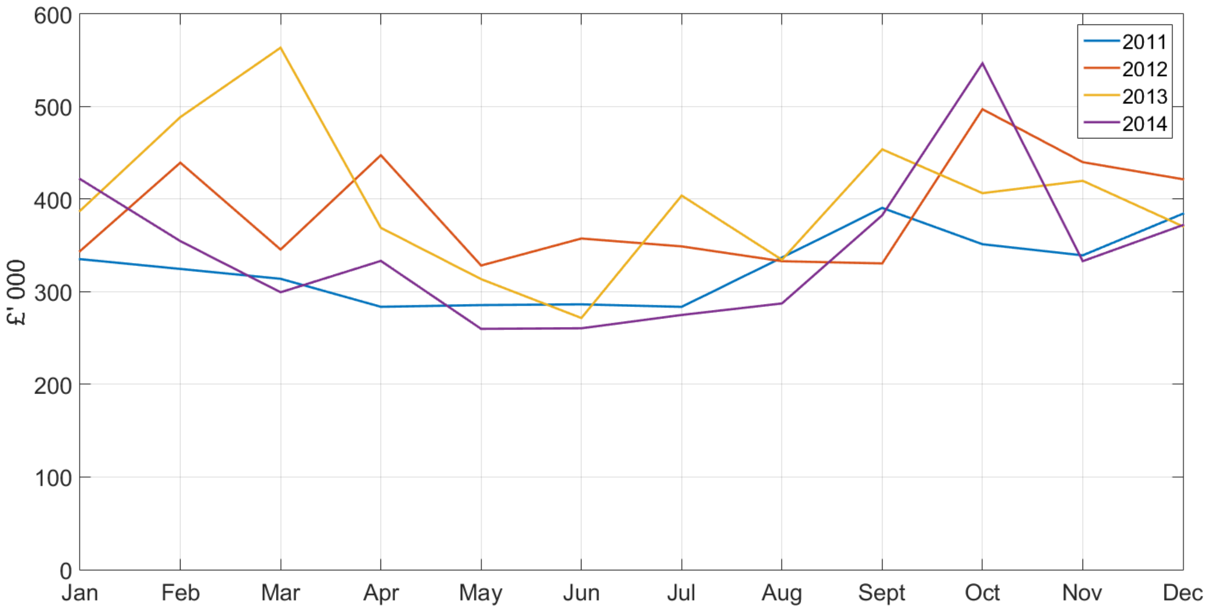


***Figure 6.7:*** *Monthly variability of co-optimised revenues from 2011-2014.*

## 6.8. Annual variability in co-optimised revenues

Table 6.1 shows the revenues when the co-optimisation model uses data from 2011-2014. The total revenues over the four years show moderate changes with 2012 and 2013 yielding the highest revenues.

The proportional allocation of storage operation to each mechanism also changes annually, shown in figure 6.8. BM participation was slightly higher in 2012 and 2013 whereas FFR allocation was higher in 2011 and 2014. Unlike FFR revenues, the BM revenues were much higher. Comparing BM and APX

[7] A month is assumed to be 1460 half hourly periods corresponding to approximately 30.42 days.

discharge volumes to their total revenues indicates that imbalance prices and the spot market price volatility can shift large proportions of revenues from one mechanism to the other.

| **Annual Co-optimisation revenue variability** | | |
|---|---|---|
| Year | Total Revenue | Change from 2013 |
| 2011 | £3,708,403 | -19.64% |
| 2012 | £4,426,239 | -4.08% |
| 2013 | £4,614,706 | 0.00% |
| 2014 | £3,961,674 | -14.15% |

***Table 6.1:*** *The annual variability in total co-optimised revenues from 2011-2014.*

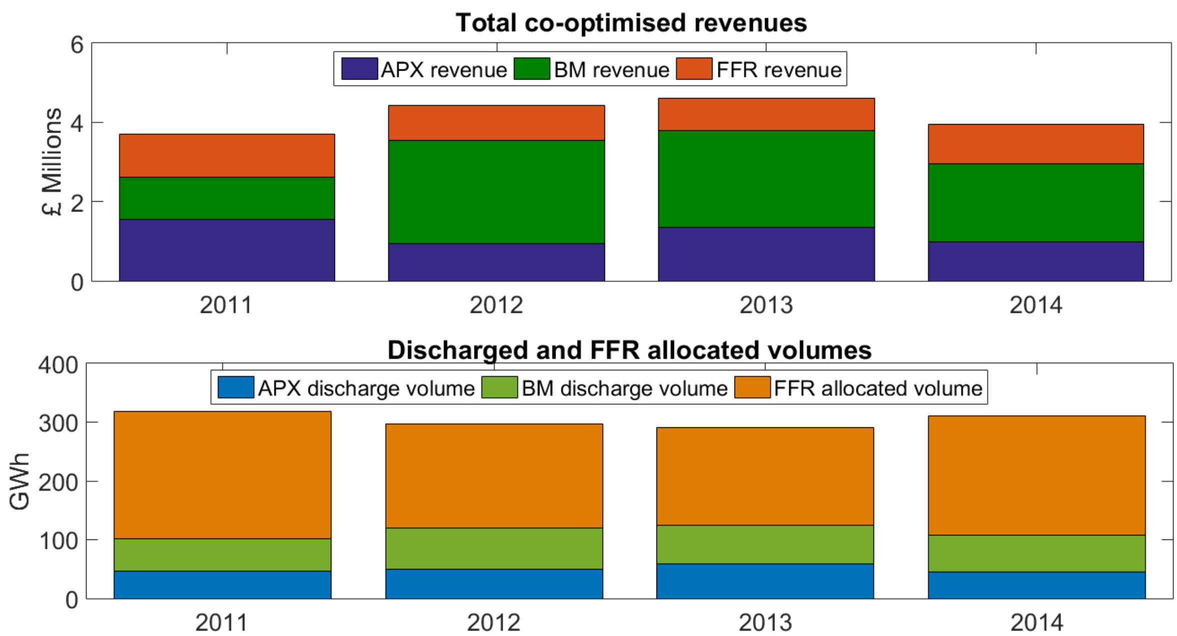


***Figure 6.8:*** *Annual variability in revenues and discharged/allocated volumes for each market under a co-optimised operation from 2011-2014.*

A closer look at 2011 revenues illustrates this effect, whereby APX revenues are the highest in spite of a lower discharge volume. In the following year, APX discharge volume was slightly higher but its revenue was substantially lower, whereas the BM discharge volume and revenues increased. This points towards the greater resilience of the co-optimised revenue model; by being able to allocate optimal capacity to different mechanisms, the storage system reduces its exposure to each individual revenue mechanism's vulnerability to annual variability.

## 6.9. The comparative performance of single vs multiple revenue streams

With revenue streams determined under a single and multiple mechanisms, it is possible to compare how they fare. In addition, since market volume constraints have been applied, their impacts on both cases can be analysed.

Figure 6.9 shows the effect of market volume constraints. FFR revenues particularly are shown for two cases; one where the system generates revenues from availability payments only, labelled as '*Constrained*' and the other where utilisation payments are included to simulate a situation whereby the service is called for by the SO, labelled as '*Unconstrained*'. Figure 6.9 shows that when the revenue mechanisms are unconstrained the BM yields the highest revenues in single markets. However, volume constraints reduce the total BM revenues dramatically by about 42%. In contrast, APX revenues, due to less restrictive constraints, are almost unaffected with a decrease of 0.4%.

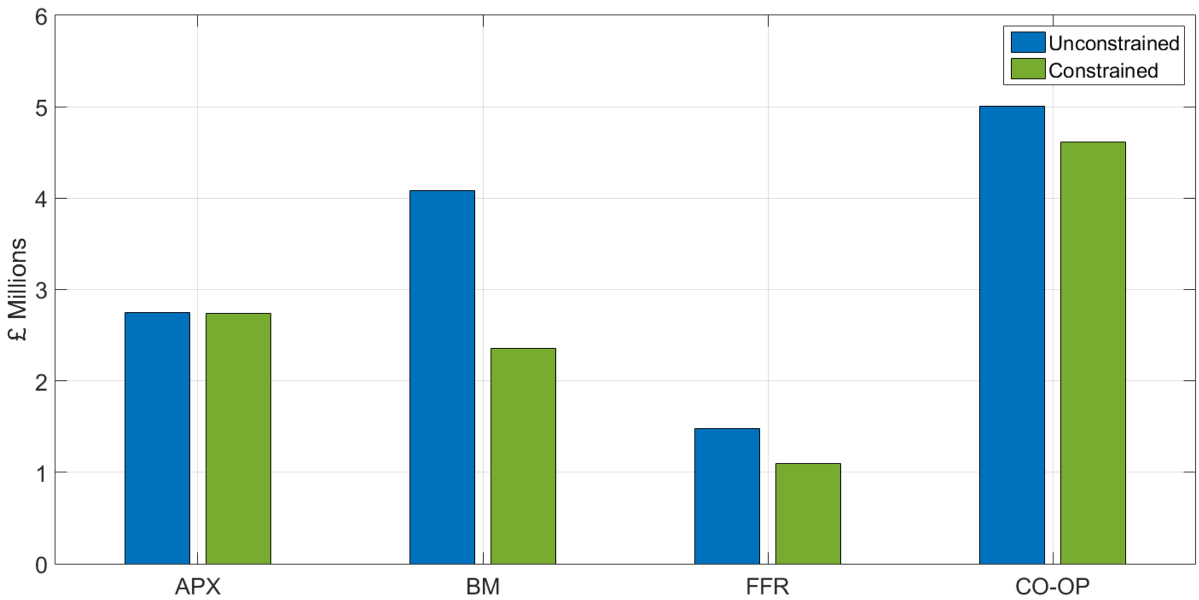


***Figure 6.9:*** *The impact of market constraints on the APX, BM, FFR and co-optimised (CO-OP) revenues.*

Comparing the constrained and unconstrained FFR revenues, relative to availability payments, utilisation payments do not bring substantial increases in revenues. Overall, co-optimised revenues are by far the highest and also lightly affected by market constraints. This arises, similar to the annual variability analysis, revenues from the other mechanisms compensate for the loss of revenues caused by constraints affecting one mechanism.

Thus, a co-optimisation model capturing multiple revenue streams is superior not only because of its higher revenues but also due to the stability of such revenues; the latter is more resilient to annual variations than single revenue mechanisms and such revenues are also more resilient to constraints that affect each of the mechanisms individually.

Conceptually, co-optimisation offers additional benefits compared to three dedicated systems providing these services separately. Under the co-optimised approach, the storage system can perform arbitrage trades across mechanisms, such as between the APX and BM, to take advantage of greater price differentials. Similarly, energy stored for the provision of FFR can be discharged for arbitrage profits under the co-optimisation approach but not if operated separately. The co-optimisation model also optimally allocates power and energy to each type of revenue mechanism taking into account market and time constraints. For example, the model may fully allocate discharging capacity to the APX in one period, fully allocate the same capacity to the BM in the next period and offer a FFR window for the period after. In doing so, the storage system's power and energy capacities are utilised to a greater extent. This is visible from the heat maps from figure 5.2 compared to figure 6.5; in the latter, periods whereby storage operation is shown as idle includes of FFR windows whereas in the former, the storage system does not generate any revenues when idle. By making greater use of the storage system's capacities, additional capital costs are avoided whilst increasing revenues, improving the economic prospects for energy storage. In 2013, three individual storage systems of 50 MW (150 MW total), each dedicated to APX arbitrage, BM arbitrage and FFR service provision generated £2.7 million, £2.4 million and £1.5 million respectively, totalling £6.6 million in revenues. By comparison, a 150 MW co-optimised system generated £14.1 million.

## 6.10. Sensitivity analysis: the co-optimisation model

Total storage revenues are strongly dependent on model parameters, such as efficiency, variable costs, power and energy capacity. A sensitivity analysis was carried out with respect to these parameters to investigate how their changes influence co-optimised revenues shown in figure 6.10

In the top left of figure 6.10, the impact of round-trip efficiencies is shown in 5% increments, on total revenue, discharge volume, average revenue and the average SOC. Total revenues are approximately a linear function of efficiency only showing slight disproportionate relationships at very low or very high efficiencies. The average revenue function, calculated as total revenues divided by the volume of energy discharged, rises then falls, reaching its maximum around 25% efficiency. This situation arises as two parameters interact: discharge volume and discharge prices. At low discharge volumes due to low round-trip efficiencies, only large price differentials are of interest to the co-optimisation model. At those low efficiency levels, the storage system can only generate arbitrage revenues from extreme price swings. These swings are rare occurrences, hence resulting in a low discharge volume. However, every MWh of energy discharged in this situation yields a high revenue, over £150/MWh at its maximum. Nevertheless, it should be pointed out that because these events are rare, total revenues still remain relatively low at approximately £1.6 million for a 25% round-trip efficiency system. By comparison, at a 95% round-trip efficiency, the storage system generated about £6.3 million.

The peaking shape of the average revenue function can be explained through the efficiency gain concept stated in section: 5.7.2; as the round-trip efficiency rises, large price differentials yield more revenues due to the higher efficiencies. In this case, the efficiency gain effect is driving the average revenues upwards in the 0-25% efficiency range; at the lowest efficiency level, the storage system can only generate revenues from the highest prices. Further trades (as efficiency rises) occur at lower prices, yet, the average revenue rises due to this efficiency gain effect. For example, an increase in efficiency from 10% to 20% doubles the revenues of existing trades, whereas discharge volume does not increase significantly. As a result, average revenue rises sharply.

The other effect through which efficiency causes revenues to rise, also described previously in section 5.7.2, is the feasibility gain effect whereby smaller price differentials become feasible opportunities for arbitrage, therefore resulting in greater discharge volume. Thus, as efficiency keeps rising, the number of feasible trades increases and therefore discharge volume rises substantially. These feasibility gains, however, are relatively smaller price differentials and therefore as a combined effect causes the average revenue to fall.

In other words, in the low efficiency ranges from 0-30%, the efficiency gain effect dominates the average revenues, however at higher efficiency levels the feasibility gains effect become the dominant driver of revenues. This is evidenced by the orange line in the upper left corner of figure 6.10, representing discharge volume; the latter rises substantially beyond a round-trip efficiency of 35%.

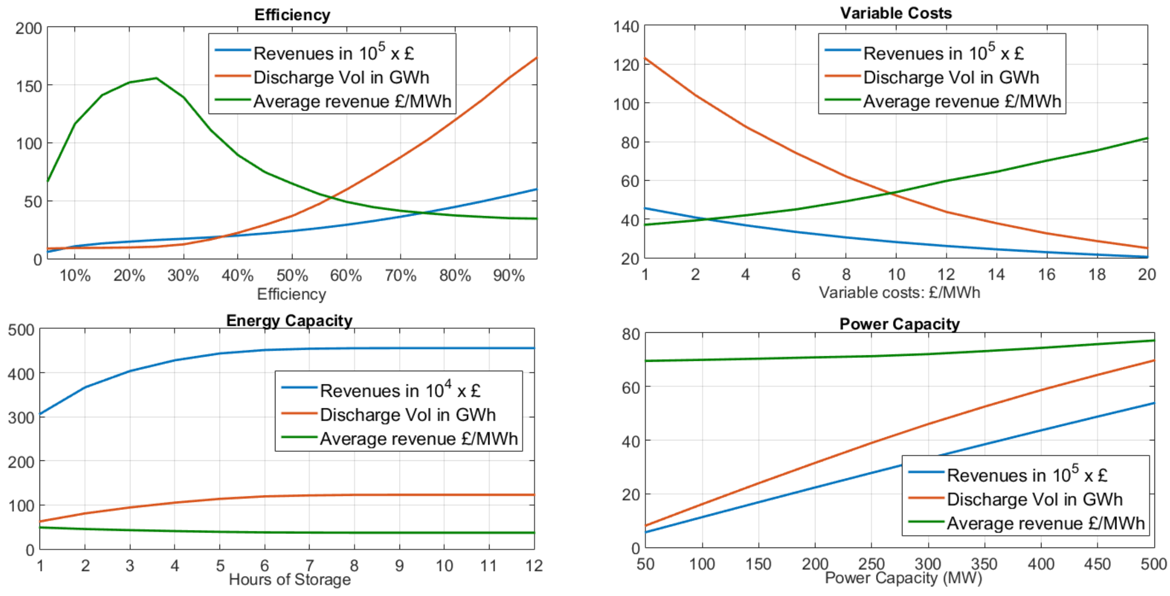


***Figure 6.10:*** *Changes in total revenues, discharge volume and average revenue relative to changes in efficiency, variable costs, energy and power capacity.*

The top right of figure 6.10 shows the sensitivity of the same output parameters with respect to variable costs. These costs which are incurred both on charging and discharging can be seen to reduce revenues, total discharge volume and average revenues more than proportionately. Revenues are sensitive to variable cost changes though to a lesser extent than efficiency; at a variable cost of zero, total revenues were £4.8 million and at a variable cost of £10/MWh total revenues were £2.9 million. At a variable cost of £20/MWh revenues fell to £2.1 million. On the other hand, average revenue increases as trades from increasingly high price differentials become the only viable source of revenues.

One of the main considerations in evaluating storage's economic feasibility is its energy capacity since it represents a significant proportion of capital expenditures. Therefore, an appropriate sizing of storage technology is essential and has been investigated with respect to several markets worldwide (Hessami & Bowly 2011; Drury et al. 2011; Kloess & Zach 2014; Sioshansi et al. 2009). The bottom left of figure 6.10 shows the effect of increasing the energy capacity of the storage system expressed in the number of hours of output; at 1 hour of output, 68% of maximum revenues is captured, rising to 81%, 89% and 94% at 2, 3 and 4 hours' output. By 8 hours, the maximum revenues within a 1-day optimisation horizon are captured, the same effect is observed for total discharge volumes. This implies that on a 1-day optimisation horizon, most of the energy stored is released within 4 hours. Average revenue is very weakly affected as it shows a barely noticeable decrease as energy capacity rises. It is worth pointing out that energy capacity which is sometimes expressed in energy to power ratio is effectively constrained by market liquidity (trading volume or imbalance volume). In this energy capacity analysis, the power capacity was fixed at 50 MW.

As opposed to efficiency, variable costs and energy capacity sensitivities, which all show elements of non-linearity in the form of diminishing returns, power capacity changes bring about almost linear changes in revenues and other parameters. Energy capacity is in this case fixed at 12 hours of output. These occur due to the assumptions; under co-optimisation, power capacity is actually limited by the APX market and BM imbalance volumes. However, additional FFR windows can still generate additional revenues. Average revenues in this case rise since larger power capacities are able to utilise large price variations, increasing their charging and discharging volumes, generating greater profitability.

It is assumed that discharge capacity in the range of 50-500MW is not limited from an FFR perspective. This power capacity sensitivity range lies within the primary frequency response reserve requirement of up to 1800 MW (National Grid. 2015). Further considerations on the probability of FFR tenders being accepted is beyond the scope of this study but become increasingly important the higher the capacity.

## 6.11. System impacts

Generally, markets project the requirements of the system, as to whether more or less power is needed. Nevertheless, a market driven objective function is different from one that seeks to optimise system benefits and therefore storage operation and system benefits may not always align. Strbac et al., (2012) showed that conflicts can arise in the operation of storage; under a cost minimisation objective storage at transmission level generally charges during high wind output and discharges during low wind output. However, at the distribution level, the system discharges even during high wind, in order to reduce peak demand on local networks. The extent to which a profit maximising storage system achieves system benefits which, in this case, is confined to peak shaving and imbalance volume reduction is investigated below.

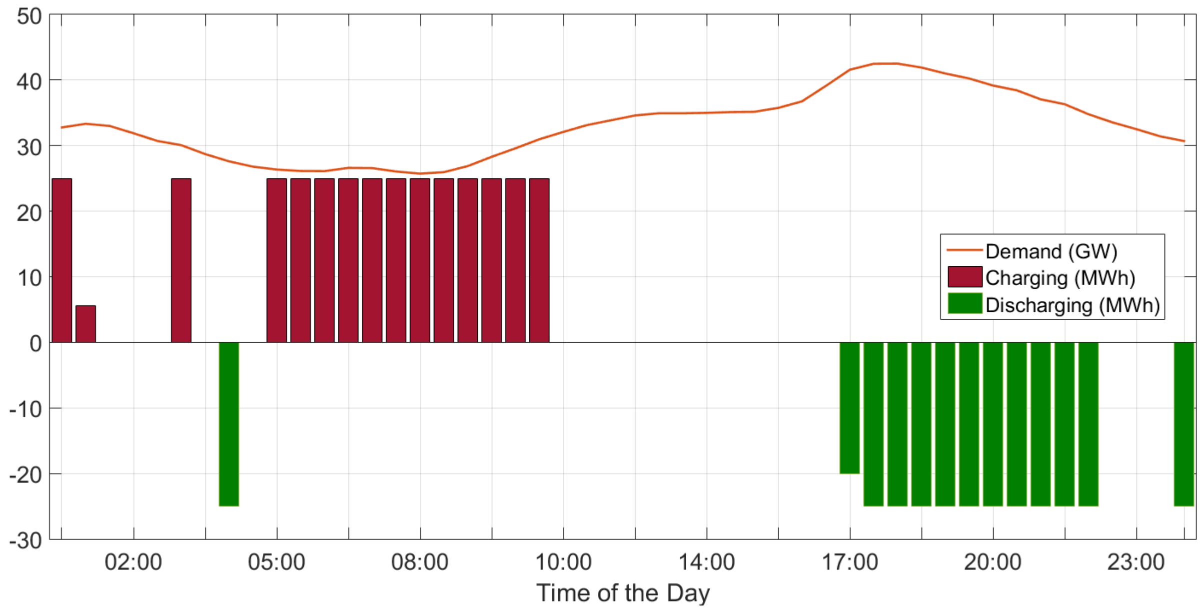

***Figure 6.11:*** *Storage operation and total demand on 1 Jan 2013.*

Since demand generally drives prices, the storage operations driven by the maximisation of arbitrage revenues generally achieve peak shaving as well, shown in figure 6.11. Thus, to a certain extent, it can be argued that the spot market helps to drive investment towards peak demand reduction, by providing sufficient financial incentives. This peak demand reduction is driven by price differentials which essentially reflect the interaction of demand and the cost of electricity generated. Other benefits such as network investment deferral are also achieved but not specifically rewarded by the wholesale market.

In 2013, storage participation raised the level of total electricity consumed by 22.85 GWh. This effect is attributed to round-trip efficiency losses and also observed by Foley & Díaz Lobera (2013); in their study, the authors used gross pool pricing models to show that energy storage causes wholesale electricity prices to rise due to additional energy lost through charging and discharging.

In the Balancing Mechanism, the relationship between storage operation and imbalance volume is investigated. The Net Imbalance Volume (NIV) is calculated after accounting for the impact of storage participation. In 2013, storage system operation under co-optimisation reduced NIV by a total of 141 GWh, demonstrating that system benefits do arise from market operations.

Under co-optimisation of multiple revenues, actions in the APX market may not be conducive to reducing system imbalances in the BM. An example of this is shown in figure 6.12 whereby storage operation is illustrated on the 1st of Jan 2013. The figure shows that the storage system on that day was set to reduce the shortage of power occurring around peak time but not reduce the excess power occurring from 11am-5pm because electricity prices are usually high and therefore would not be favourable for charging. The charging and discharging volumes shown, include those occurring in the APX market as well as in the BM, implying that neither the short term wholesale market nor the balancing mechanism are providing an economic incentive for the storage system to reduce the excess power occurring between 11am-5pm on that day.

This highlight possible situations whereby co-optimisation models do not have sufficient incentives to help with secondary objectives. Since the only objective of the models is to maximise revenues, they do so irrespective of the energy system's requirements.

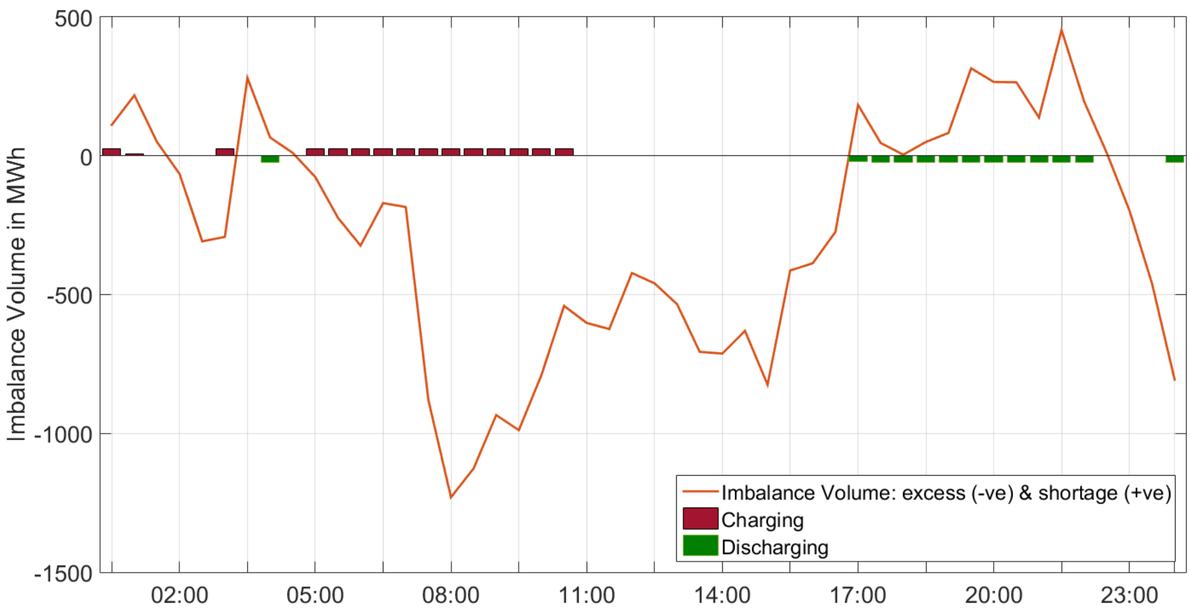


***Figure 6.12:*** *Storage charge and discharge occasions under co-optimisation which conflict with system imbalance.*

Inevitably this is a case of conflicting objective functions; it is not always possible to minimise system imbalances and/or peak demand and maximise storage revenues simultaneously, given the current market framework. Therefore, while in single mechanism models the system impacts of storage operation are generally favourable as private benefits and system benefits align, under co-optimisation this not necessarily true.

## 6.12. Net Present Value of storage based on selected technologies.

Thus far, the models presented were technology neutral with a focus on revenue streams. However, there are significant parameters within the technologies which determine their lifetime economic feasibility such as efficiency, capital costs, O&M costs and lifespan. A Net Present Value (NPV) analysis was undertaken, incorporating these parameters. The chosen technologies were CAES, AACAES, Fe-Cr flow battery, Vanadium redox flow battery, lithium ion battery and PHES. The NPV values are shown in figure 6.13. CAES has a special power configuration due to the compressor-expander ratio, as well as natural gas costs as fuel, detailed in Chapter 4.

As a result of the findings of the sensitivity analysis whereby most of the revenues were captured with 6 hours of energy capacity, all storage technologies were assumed to have an energy capacity equivalent to 6 hours of output, reduced from 12 hours assumed in previous analysis.

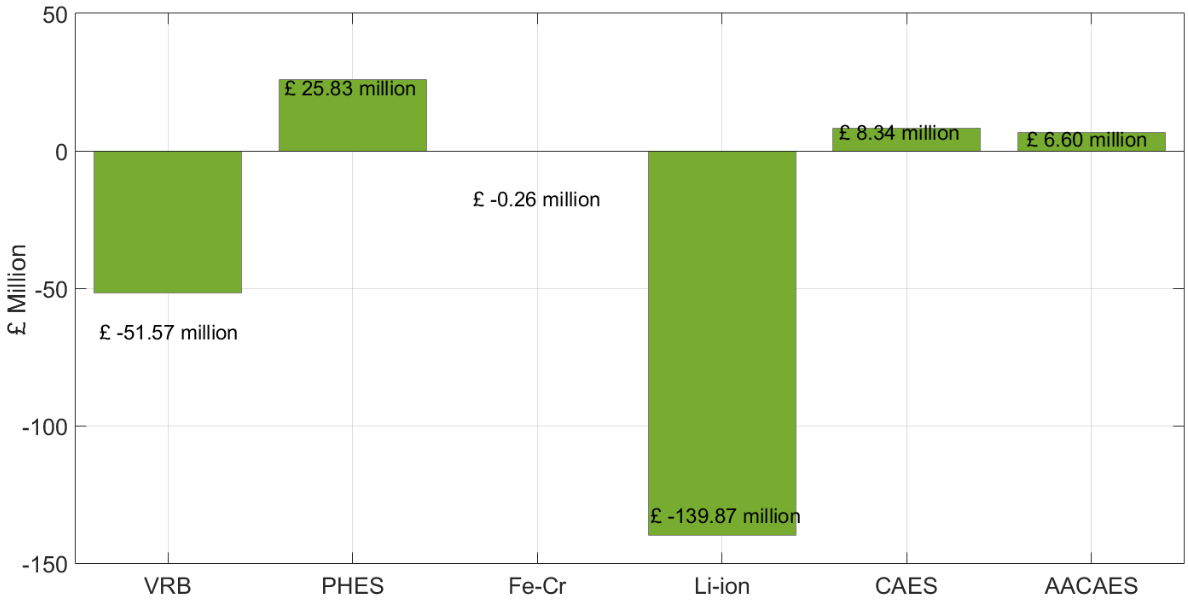


***Figure 6.13:*** *The NPV of selected storage technologies over their lifespan based on co-optimised revenues from 2011-2014.*

For all the technologies explored, PHES remains the most economically viable storage technology yielding a positive NPV at £25,825,530. It is important to point out that one of the major contributing factors to the positive NPV results is the lifespan of the system which in this case is 60 years, equal to three times that of a VRB system for example and approximately 6 times that of lithium-ion batteries.

CAES, the second most profitable technology, showed a positive NPV at £8,336,998 benefitting from a high output to input ratio due to the use of natural gas. The NPV result however is strongly dependent on future gas prices which were assumed as fixed; a rise in natural gas prices would be detrimental to CAES' NPV.

AACAES, despite being less profitable than CAES due to additional capital costs of thermal energy storage, still yields a positive NPV of £ 6,595,176. On the other hand, Lithium-ion batteries showed the worst performance of all, with a negative NPV at £139,873,017 despite having the highest efficiency at 94%. Equivalent full cycles were calculated at 521, 591, 614 and 550 for 2011-2014 respectively, averaging 569 cycles annually. This average translates into a lifespan of approximately 10 years assuming a 6000 full cycle life. The high capital cost of £613/kWh as well as the short lifespan are largely responsible for the negative NPV; media reports of lithium costs in the range of £267-400/kWh and projected future costs of £107/kWh (Russel et al. 2012) could potentially change the economics of lithium-ion battery storage.

VRB was found to be unprofitable under the current market revenues with a negative NPV of £51,567,530 similar to lithium-ion suffering from high capital costs and additional O&M costs. A similar configuration with less than half capital costs, representing Fe-Cr flow batteries, yields a negative NPV of £ 260,930 making the project almost feasible.

An alternative measure of economic feasibility is shown in figure 6.14 in terms of nominal annualised rate of return and lifetime return on investment. Compared to NPV figure, the results show that Fe-Cr flow batteries can be a feasible project under a lower discount rate than initially assumed. At present however, VRB and Lithium Ion batteries do not generate sufficient revenues over their lifetime to cover their costs.

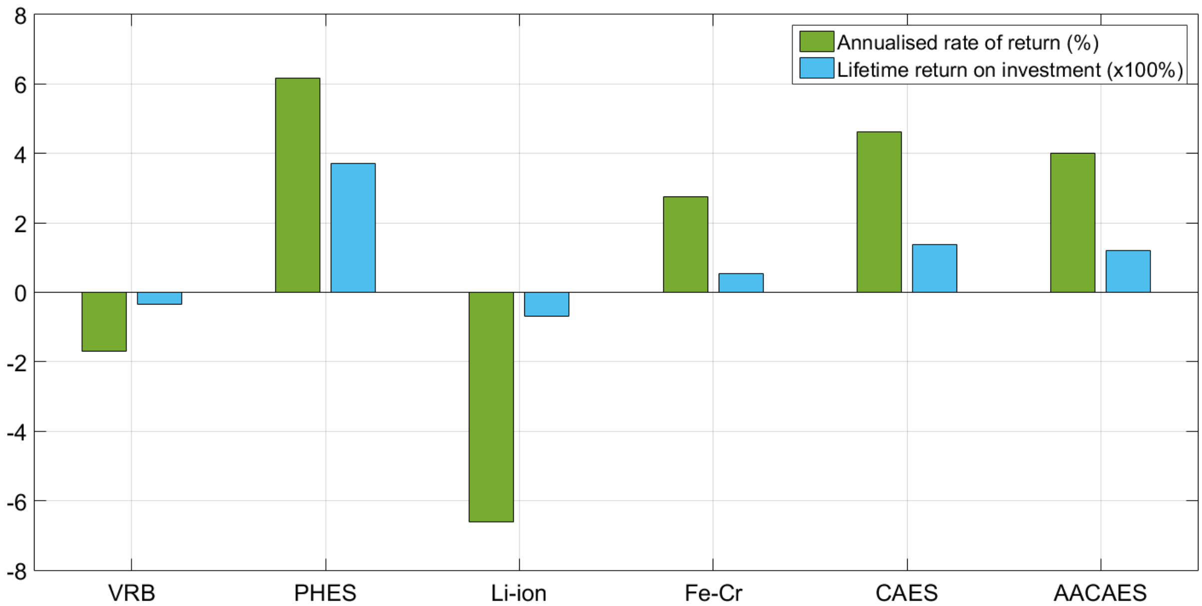


***Figure 6.14:*** *The return on investment of several storage technologies under a co-optimised schedule over their lifetimes.*

Besides round-trip efficiency, one of the major factors which dramatically affects the economic feasibility of energy storage systems is the capital costs. These, in turn, are strongly dependent on the type of technology. As a simplification, capital costs can be broken down into power capacity costs and energy capacity costs.

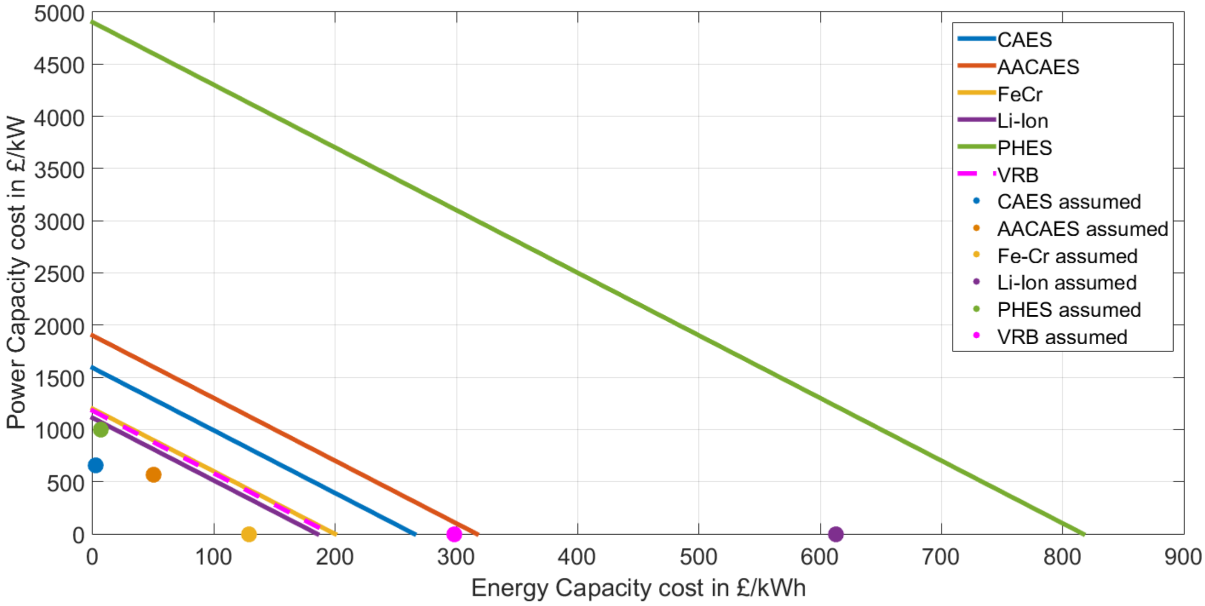


***Figure 6.15:*** *The disparity between feasible power and energy capacity cost combinations, displayed as solid coloured lines, and the assumed power and energy capacity costs in this thesis, shown as coloured dots.*

Figure 6.15 shows the levels of power and energy capacity costs at which the selected technologies become feasible, shown as lines, as well as their current costs shown as dots. The area below (or to the left of) the line shows profitability and similarly the area above (or to the right of) the line indicates losses. The perpendicular distance between the respective dots and lines is a measure of actual profitability.

The analysis assumes an average annual revenue equal to the average co-optimised revenues from 2011-2014. Furthermore, discount rates are ignored in this particular analysis but include O&M costs. The most noticeable feature of figure 6.15 is the disparity in terms of profitability between PHES and the other technologies explored. This result is driven by the specific parameters playing in favour of PHES; this mature technology has a moderately high round-trip efficiency at 81%, low energy capacity cost at £7/kWh, moderate capacity costs of £1000/kW and very long lifespan of over 60 years. The current costs parameters for PHES, shown as a green dot is well below the economic feasibility threshold line, shown in green.

By contrast, Li-ion batteries generate the lowest total revenues from co-optimisation due to their short lifespan. Consequently, it has the highest threshold for profitability and combined with the fact that it is the most expensive of the selected technologies leads to the conclusion that it is not economically feasible under the three revenue mechanisms explored.

CAES has been shown to be profitable at appropriate discount rates, with a substantial difference between the actual capital costs and feasibility threshold costs. Similar to CAES, AACAES also shows profitability potential. AACAES considered a novel technology, as least in part, benefits from further possible cost reduction. Several thermal storage mechanisms/mediums have been put forward within AACAES systems with varying costs (Pimm et al. 2015; Drury et al. 2011; Kloess & Zach 2014; Pickard et al. 2009)

Figure 6.15 also shows a stark difference in feasibility between two types of flow batteries; VRBs are substantially more expensive than Fe-Cr flow batteries, unlike VRBs, which have a lower capital costs than their profitability thresholds. The efficiencies between the two systems are very similar, however Fe-Cr electrolyte is significantly less costly than conventional vanadium redox electrolytes (Zeng et al. 2015; Viswanathan et al. 2014).

From figure 6.15, two major forces can change the economics of the storage systems; firstly, manufacturing and technological advances which lower capital costs, increase efficiency and the lifespan of the system would increase lifetime revenues, shifting the profitability threshold lines to the right. These advances would also reduce the capital costs, moving the dots to the left.

The other force is market and regulatory changes leading to the increase in existing or additional revenue streams. Aggregation of benefits is a well-known issue for storage value (Grunewald et al. 2012; Anuta et al. 2014), and policy which addresses these issues could have a dramatic effect on the economics of energy storage, considering there is significant value in network investment deferral for example, especially at distribution level (Strbac et al. 2012).

## 6.13. Feasible strategies under imperfect foresight

In the absence of perfect foresight, a co-optimised based scheduling was derived; the average of the charging and discharging volumes was calculated for each half-hour of the day, using the co-optimisation results in 2013. Thus each half-hourly period represents the average charge or discharge for that same period throughout the year, shown in figure 6.16.

Based on this method, the first 7 hours of the day are allocated to charging followed by a fixed 2-hour window dedicated to the provision of FFR. During the next 4 hours from 09:00 to 13:00, the system discharges into the APX and BM markets in the same averaged proportions to those derived by the co-optimisation model. From 13:30 to 16:30 the system offers FFR. The remainder of the daily schedule consists of discharging except for a 1-hour window from 21:30 to 22:30 dedicated to FFR.

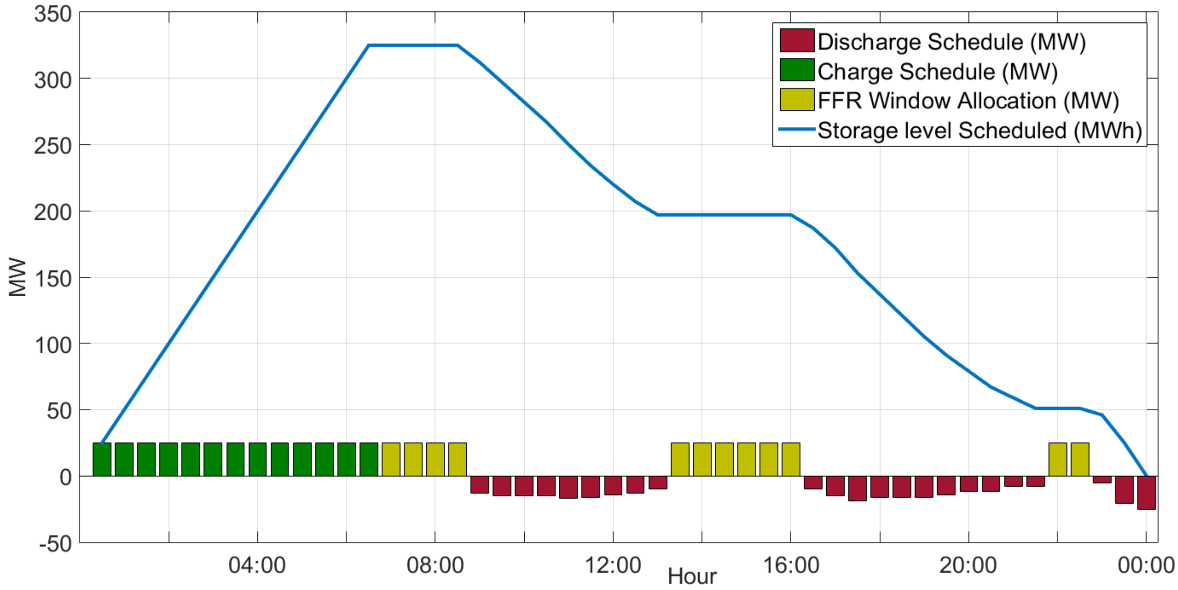


***Figure 6.16:*** *A fixed dispatch schedule derived from the co-optimisation results.*

This dispatch schedule's effect on SOC is also displayed; it rises sharply in the morning, peaking at 06:30 before falling relatively slowly during the rest of the day and on a 1-day horizon, implies that the state of charge drops to zero by the end of the 24-hour period.

The dispatch schedule shown in figure 6.16 is by no means an optimal one but rather gives an example of a simplified strategy to capture potential values. It is conceivable that tweaks to this schedule could increase total revenue; this was not tested. For example, charging from 00:00-06:30 was assumed to be at full capacity, which was very similar to, but not exactly the daily average co-optimised output; however, this adjustment was required for energy balance. Therefore, considering these figures are based on averages, there is room for adjustments to capture additional revenues and represents an area for future work.

In addition to the fixed scheduled operation, a backcasting strategy is explored whereby the model is optimised on past data but revenues are calculated using current data. Sioshansi et al., (2009) proposed this simple strategy to show that they could capture over 85% of perfect foresight revenues in the PJM market.

A comparison of storage value captured under backcasting techniques is shown in figure 6.17 with different lags, namely 1-month, 2-weeks, 1-week and 1-day lags. Additionally, the co-optimised fixed dispatch schedule is shown for comparison. Under the 1 month backcasting method, about 62% of co-optimised value, or £2.85 million, was captured. Reducing the backcasting lags to 2 weeks and 1 week does not significantly change the results; at 2 weeks, 61% of potential revenues was captured and at 1 week, this figure was 59%. A slightly more noticeable change occurred on a 1-day lag, reducing revenues to 52% of the maximum, or £2.39 million. Finally, the fixed 12-hour operation strategy generated 53% of potential revenues. The fixed dispatch strategy performs slightly less well than many of the backcasting techniques since the latter is able to capture seasonal and weekly-weekend differences.

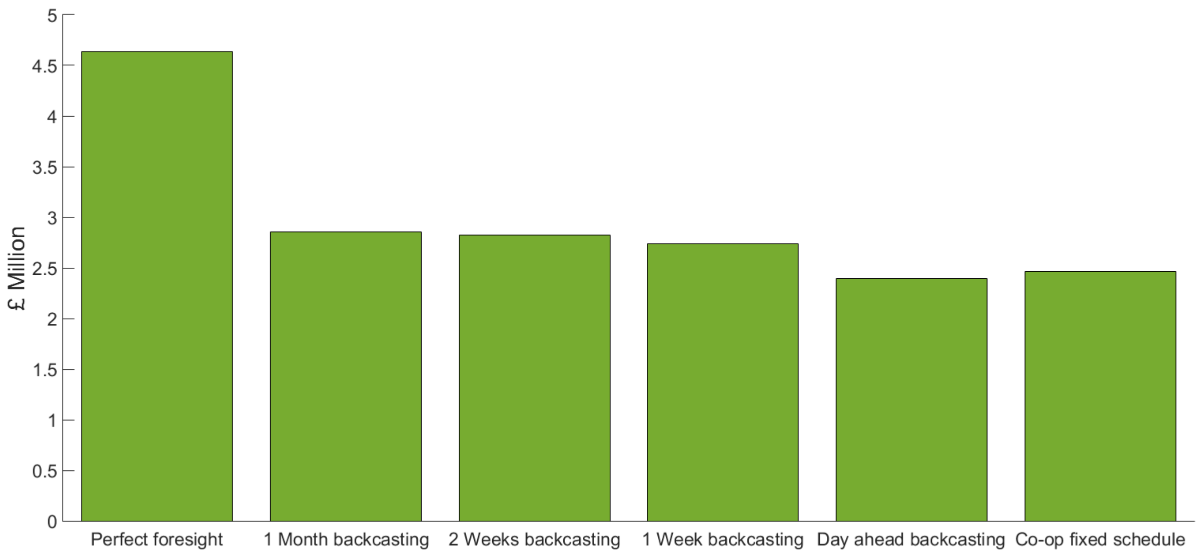


***Figure 6.17:*** *The performance of strategies to capture storage value, benchmarked against the perfect foresight case.*

The results also show the tendency for revenues to fall slightly as backcasting lags get shorter, with the exception of the 1-day lag. It is not known whether this fall in revenues is an actual effect or whether it can be disregarded as insignificant, occurring merely as a result of random noise in the dataset. If there were a genuine effect that would enable longer term backcasting to generate additional revenues, it would imply that there is a time and day of the month effect, which together affect prices - for example, a $5^{th}$ of March price profile would resemble a $5^{th}$ of April trend but not the $6^{th}$ of April. There does not seem to be enough evidence to support such a cyclical trend on such a long horizon. Furthermore, the effects themselves are very small in magnitude and hence can be disregarded.

However, a genuine effect which explains a decrease in the 1-day lag backcasting revenue compared to the other backcasting lags is the weekday-weekend effect. When the past 24 hours of data is used, there is an inherent assumption that the previous day resembles the current day, which causes some discrepancies. As an example, using a 1-day backcasting technique, one could derive a storage operation profile for Friday using the data for Thursday; the closer the price profile of Friday resembles that of Thursday, the closer the revenues will be to the maximum potential. This principle breaks down at the weekends, however, whereby a Saturday price profile is substantially different from that of a Friday price profile.

Sioshansi et al., (2009) point out that using a two-week backcasting lag, weekday-weekend effects are captured and the horizon is sufficiently small to capture seasonal effects but not short enough to capture short term persistence such as disturbances which persist on a daily-weekly scale.

In this case, it is clear that weekday-weekend effects dominate any short term persistence effects. The key result shown here is that with the most basic strategies, at least 50% of maximum value can be achieved. While these are far from the 85-90% levels Sioshansi et al., (2009) found, the markets are markedly different and this technique was applied to a co-optimised model as opposed to the authors' single market model. In fact, considering the complexities in co-optimisation, the backcasting method provides an arguably simple technique to capture 62% of maximum value.

Apart from the co-optimised fixed dispatch schedule, another fixed dispatch strategy is also investigated; one that charges for 12 hours and discharges for 12 hours. This fixed 12-on/12-off schedule has been used by Nyamdash et al., (2010) who investigate wind penetration and storage in Ireland; such strategy has the advantage of being far easier to implement with scheduled operation planned well in advance.

In this case, the charging schedule was fixed between 00:00-07:30 and 20:30-00:00 whereas discharging was fixed from 08:00-20:00. The simple strategy is however best suited for operation in single markets as figure 6.18 demonstrates; the strategy captures 56% of revenues. The schedule can also be adapted to operate within both the BM and the APX market whereby if charging and discharging is not possible in the former, due to BM constraints, the latter becomes an alternative option, i.e. the possibility of operating in the APX market.

Under perfect foresight in the BM, £2.35 million was generated in revenues. Using the 12-on/off schedule in the BM with APX as a backup enables the system to generate £2.30 million, about 98% of the maximum in the BM alone. Compared to co-optimisation across the three revenue mechanisms, the 12-on/off strategy captures 53% of maximum potential revenues.

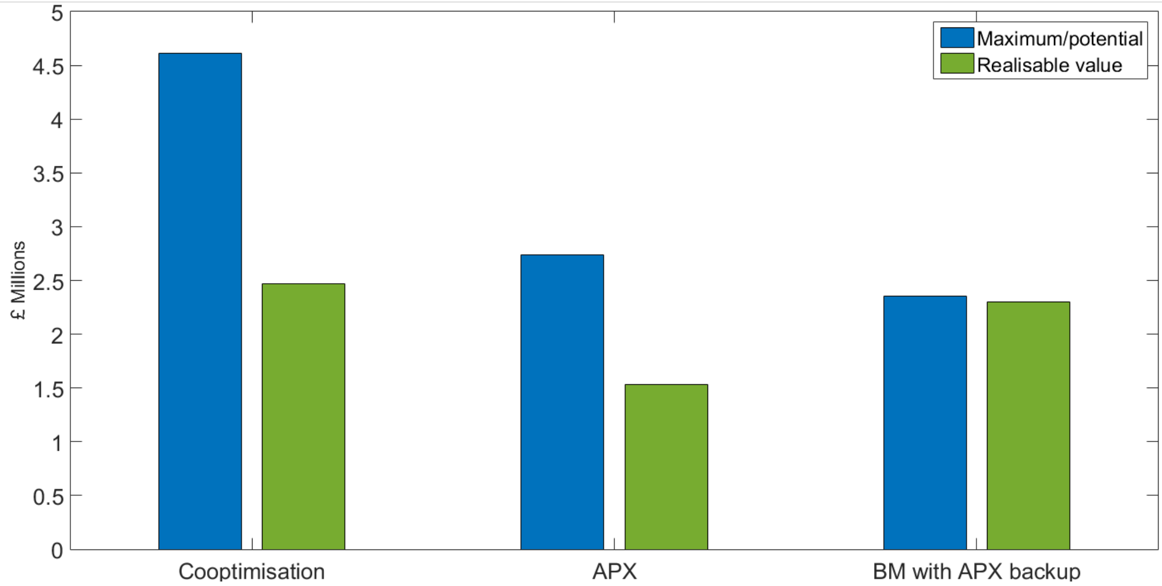


***Figure 6.18:*** *The realisable value of storage operation using simple fixed dispatch strategies.*

Energy capacity under imperfect foresight has been investigated by Sioshansi et al., (2009) and McConnell et al., (2015) with conflicting results; the former study advocates that under imperfect foresight, larger energy capacities are detrimental to capturing additional value, as each additional trades are low-value arbitrage trades which are harder to predict or captured by the backcasting technique. McConnell et al., (2015) on the other hand show that larger energy capacities reduce the disparity between perfect foresight revenues and imperfect foresight revenues. The authors do not fully explain this result but hypothesise that storage inflexibility at shorter capacities could account for this result.

In order to investigate the impact of energy capacities on realisable revenues, the APX revenue model was run with a 1-week backcasting lag, with energy capacities ranging from 1 to 12 hours. The results show that as the energy capacity increases, the gap between maximum potential revenue (under perfect foresight) and the realisable revenue (using a backcasting technique) increases. This gap widens until 6 hours' energy capacity, beyond which revenues stagnate. These are visually depicted in figure 6.19. Therefore this finding confirms the result of (Sioshansi et al. 2009) and also confirms their explanation of why this situation occurs.

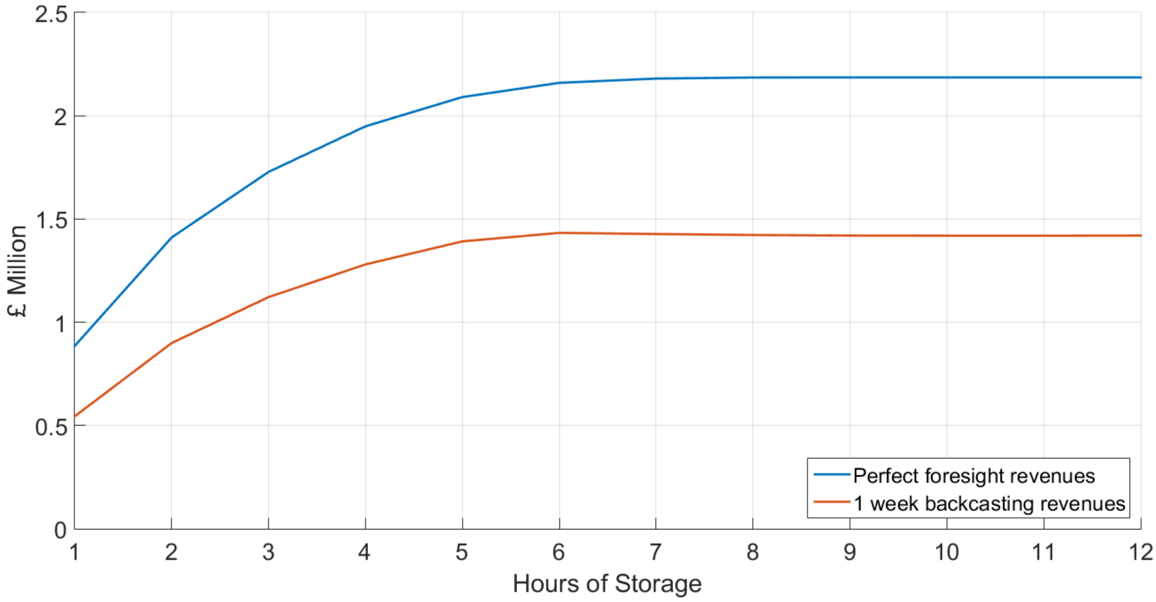


***Figure 6.19:*** *Larger energy capacities increase the gap between perfect and imperfect foresight revenues.*

## 6.14. Conclusion

This Chapter set out to investigate the core difference between the case whereby storage operates under a single versus multiple market mechanism. The most common choice of windows for the provision of FFR was found to be between 08:00-10:00, 13:00-16:00 and 21:00-23:30. These corresponded to times where the storage system was idle while waiting for the morning peak price, evening peak prices and the residual energy discharge at the end of the day.

In the single revenue mechanism mode, the imposition of market constraints reduced the APX market revenues by 0.4%, due to sufficient liquidity. In the BM, again under single market revenue mode, market constraints negatively affect revenues, resulting in a decrease of 42%. These occur due as storage operations are confined to actions that alleviate system imbalances, rather than the imbalance volume not being sufficiently high to absorb the storage system's charges and/or discharges.

On the other hand, co-optimised total revenues and discharge volumes are not significantly affected by market constraints with revenues and total discharge volumes falling by 3% and 6 % respectively. This is due to the ability of storage to compensate by participating more or less in another revenue mechanism.

Due to the more restrictive constraints in the BM and the greater liquidity in the APX market, the imposition of market constraints shifts a substantial proportion of storage charging and discharging from the BM into the APX market. The allocated volume to the FFR service also increased under those market constraints. These are the compensating mechanism contributing to the resilience of co-optimised revenues.

A further benefit of the co-optimisation model is shown whereby the storage system gets remunerated on a total energy volume that exceeds its maximum capacity; this arises with the special case of FFR whereby energy stored for these purposes, if not used, can later be discharged in the APX market or BM for arbitrage revenues.

Similar to the single markets case, co-optimised revenues are influenced by both the seasons and annual variability; peak price discharging tends to occur later during the day as summer approaches. Charging is confined to the early hours of the day and occasionally mid-day charging preceding peak prices.

Annual variations affect the proportion of storage capacity allocated to each revenue mechanism; in 2011, for example, the co-optimised revenues allocated a larger proportion of storage capacity to FFR provision whereas in 2012 the proportion of storage capacity allocation to the BM increased substantially. Similarly, in 2013, capacity allocation to the APX market increased noticeably. In the presence of inter-annual variability, the total (co-optimised) revenues show greater resilience to annual variability than single market revenues.

A sensitivity analysis of co-optimised revenues to power capacity, energy capacity, round-trip efficiency and variable costs was carried out: power capacity scales almost linearly with revenues in the 50-500 MW range explored whereas the energy capacity showed strong diminishing returns beyond the 4-hour level. Changes in efficiency lead to more than proportionate changes in revenues, similar to the single market case. Variable costs are strongly influential on revenues, however, less so than efficiency changes.

In terms of system impacts, peak shaving and arbitrage revenue maximisation are generally aligned objectives in the APX market. Similarly, system balancing objectives and arbitrage maximisation objectives are aligned in the BM, imposed by the market constraints. However, under co-optimisation, conflicting objectives occur and therefore the maximisation of revenues and system benefits are not always aligned.

Through an NPV analysis, it was shown that the most profitable energy storage technologies were PHES and CAES; PHES due to its long lifespan, relatively low capital cost and relatively high efficiency remained the most economically feasible technology. The least profitable technology was lithium-ion which due to the very limited lifespan and high capital cost yielded a highly negative NPV. There is potential feasibility for Fe-Cr flow batteries and AACAES which can be viable at low discount rates since annualised net (of capital costs) returns show positive values.

Lifetime revenues can be used to generate capital cost thresholds at which each type of technology becomes profitable; currently, the economic feasibility gap for lithium-ion is shown to be the greatest amongst all technologies. From this analysis, two major forces can change the economics of energy storage – one of them is the manufacturing and technological advances which raise efficiency, reduce variable costs, prolong the lifespans and reduce capital costs. The other is regulatory and policy changes which allow for the aggregation of benefits.

In the absence of perfect foresight, a simple strategy was derived from co-optimisation; the average charge, discharge and FFR volume allocation for each half hour of the day were calculated. A fixed strategy using these values was then run throughout the year to show that it captured about 53% of maximum value under perfect foresight. Backcasting techniques were also applied for 1 month, 2 weeks, 1 week and 1-day lags. The results showed that the backcasting techniques managed to capture 62%, 61%, 59% and 52% respectively. Thus, as a worst-case scenario, at least 50% of revenues can be captured using simple strategies.

Fixed dispatch strategies can perform better with the addition of another revenue mechanism. For example, when the storage system is allowed to participate in an additional market mechanism besides the BM, such as the APX market, the total revenues are almost equal to the revenues achieved under perfect foresight in the BM. Thus to a certain extent, combining revenue streams can compensate for the lack of perfect foresight. Lastly the impact of energy capacity under imperfect foresight in capturing arbitrage revenues was investigated to show that in the absence of accurate price forecasts, storage systems with large energy capacities (relative to their power capacity) perform worse than their smaller counterparts. This arises due to the fact that large price differentials which usually form the basis for off-peak and peak price arbitrage, are predictable whereas smaller price differentials are much less predictable. A large energy capacity would also need to derive arbitrage revenues from those smaller price differentials and this is inherently more challenging under imperfect foresight, a conclusion Sioshansi et al., (2011) support but not McConnell et al., (2015). Besides the knowledge of prices in the short run, the viability of energy storage projects depends on the understanding of future changes in the energy landscape and how they affect market revenues. One of these changes, renewable energy penetration level, particularly wind energy has grown rapidly over the past few years and its impact is investigated in the next chapter.

# Chapter 7. Storage value under a high wind penetration scenario.

## 7.1. Introduction

The findings of the previous Chapter, have shown how co-optimised revenues differ from single market operation revenues and their implication for storage technologies. Together with Chapter 5, they complete the understanding of overall value the markets can offer. This value, however, is uncertain in the long run, with forthcoming changes in the energy landscape. The Chapter compares how storage value differs under uncertainty with a focus on increased wind penetration; it is exploratory in nature and seeks to deepen the understanding of how wind can affect the economic feasibility of energy storage.

Storage projects are usually long-term projects; the lifespan of a pumped hydro energy storage system lasts over 50 years whereas other technologies have lifespans in the 15-30 years' range. During the lifetime of storage systems, revenues are unlikely to remain the same, especially considering the dynamic nature of the energy landscape. The increase in renewable energy penetration is an ongoing process in order to tackle climate change. This, in turn, increases the need for system balancing services both in the short and long term. An increase in embedded generation can cause constraints on local networks. On the other hand, demand is becoming increasingly flexible as more services become available to demand side response. The phasing out of large fossil fuel plant by the large combustion plant directive brings further impacts on the energy mix.

These changes ultimately affect the markets; with increased variability in both demand and supply. While the impact of all these changes is beyond the scope of this research, it is possible to investigate the impact of wind on the APX price and imbalance price in the BM. These, in turn, would indicate the value of storage under high wind penetration. This Chapter adopts this approach using econometric techniques to derive the relationship between wind and prices.

A 20 GW scenario of wind penetration is simulated during the years 2011-2014 and their impact estimated under the econometric models. Further to this, the co-optimisation model is run under the new prices, and the results are compared to evaluate wind impact on storage value. Additionally, an analysis of the effect of the increase in wind penetration during 2011-2015, on optimisation horizons, is carried out. Finally, a brief comment on how storage value is expected to change under the recent changes in the BM is included at the end of the Chapter.

## 7.2. The impact of increasing wind penetration on storage value

For a storage owner, there are additional concerns for storage's economic feasibility besides realisable value and operating strategies; energy storage projects usually span decades in lifespan, in addition to construction time. Thus to better understand the value of storage, long term changes should be taken into account. There is currently a lot of uncertainty over how the value of storage can change in the near future. In recent years, from 2010 to 2014, installed wind capacity increased at an average rate of 2.2 GW annually. (National Grid 2015d) anticipate an installed wind capacity of at least 19 GW in 2020 under their most conservative scenario known as '*No Progression*' whereby conventional forms of generation dominate the generation mix due to their low cost and decarbonisation targets are not prioritised.

The impact of wind penetration on storage value is of particular significance, given the number of studies investigating combined storage operation in the presence of wind (Black & Strbac 2006; Denholm & Sioshansi 2009; Denholm & Hand 2011; Mason & Archer 2012; Nyamdash et al. 2010). While these studies investigate how storage can be used to effectively and economically reduce wind curtailment or smoothing output, little is known about how wind itself will affect the market value of storage.

This section investigates the influence of wind on prices using econometric analysis in addition to the co-optimisation models developed earlier in Chapter 6. A scenario of 20 GW of wind penetration is simulated using conditions as experienced throughout 2011-2014. Data from these four years are thus scaled to a 2020 scenario of 20 GW of wind penetration level. Subsequently, an econometric model is run to determine the impact of variables, especially wind, on the APX market price and the BM prices. Using the scaled data of a 20 GW wind penetration and assuming similar conditions prevailing from 2011-2014, price forecasts can be generated. These prices thus reflect the specific impact of an increased wind generation; they do not reflect future prices as many other changes have not been accounted for such as future changes in demand, solar power generation and other forms of power generation by 2020.

### 7.2.1. The APX econometric model

A regression model consisting mainly of generation variables and interconnector power flow was run for the four years from 2011-2014. The full model specification was described earlier in equation 4.25 from section 4.11.2. The results of the regression are shown, in part, in table 7.1. The full results are displayed in Appendix D. It should be pointed out that the generation data is at transmission level and does not take into consideration generation at distribution level (embedded generation).

By conventional, the intercept signifies the value of the dependent variable, APX price, in this case, takes when all other independent variables are equal to zero. Intercepts may or may not have meaningful results depending on the application of theory and its interpretation (Dougherty 2011). In this case, the negative coefficient equivalent to £10.2 pounds is statistically significant. However, a zero generation scenario is unrealistic and in practice such a scenario would occur in extreme circumstances of a nationwide blackout. This scenario is well beyond the range of data used to derive the regression model and therefore is of limited value. Instead, the results are more useful when interpreted for data within the current range of total generation, namely 20 GW-60 GW range.

Although such a situation whereby all variables are equal to zero is very unlikely to arise, prices can be negative for various reasons; for large conventional plants, it is sometimes more desirable to maintain operation rather than switch off production completely, as additional start-up costs may be incurred and operational readiness for a particular time frame may be jeopardised. In such cases these generators are likely to bid at a lower price than their marginal cost, and in some cases willing to pay to remain operational, hence resulting in negative prices.

Similarly, wind power generators, having low marginal costs may be willing to sell power at a negative price as long as compensation/incentives from other mechanisms such as Renewable Obligation Certificate, EU-ETS…etc., outweigh those marginal costs and hence make trading at those negative prices economically viable. Negative prices are rare in both the APX market and the Balancing Mechanism.

Table 7.1 shows that the half-hourly APX spot market price is strongly influenced by flexible plants and weakly affected by inflexible generation, in line with a merit order of generation. Peaking plants, for example, have a strong positive effect on the APX prices; one MW of power from OCGT generation is associated with an increase in the APX price by 4.4 pence. Similarly, one MW of Oil generation is associated with a 2.1 pence increase in the APX price.

Mid-merit plants, on the other hand, have lesser flexibility and show a weaker positive effect on the prices; CCGT shows a coefficient of 0.0015, implying a one MW increase in CCGT power is associated with a 0.15 pence increase in the APX price. One MW of Coal power is associated with a price increase of 0.07 pence.

| APX static Model - OLS/FGLS | | | | |
|---|---|---|---|---|
| **Variable Name** | **OLS Coefficient** | **FGLS Coefficient** | **OLS Std Error** | **FGLS Std Error** |
| '(Intercept)' | -10.1998 | -10.1900 | 0.972 | 0.016 |
| 'OIL' | 0.0216 | 0.0214 | 0.001 | 0.000 |
| 'OCGT' | 0.0442 | 0.0441 | 0.002 | 0.000 |
| 'CCGT' | 0.0015 | 0.0015 | 0.000 | 0.000 |
| 'COAL' | 0.0007 | 0.0007 | 0.000 | 0.000 |
| 'NUCLEAR' | 0.0002 | 0.0002 | 0.000 | 0.000 |
| 'NPSHYD' | 0.0060 | 0.0060 | 0.000 | 0.000 |
| 'WIND' | -0.0007 | -0.0007 | 0.000 | 0.000 |
| 'NIV' | 0.0037 | 0.0037 | 0.000 | 0.000 |
| 'pumping' | -0.0003 | -0.0003 | 0.000 | 0.000 |
| 'britnedimport' | 0.0011 | 0.0011 | 0.000 | 0.000 |
| 'eastwestimport' | 0.0000 | 0.0000 | 0.000 | 0.000 |
| 'frenchimport' | 0.0006 | 0.0006 | 0.000 | 0.000 |
| 'moyleimport' | 0.0008 | 0.0008 | 0.000 | 0.000 |
| 'APXV' | 0.0011 | 0.0011 | 0.000 | 0.000 |

***Table 7.1:*** *An extract of Autoregressive model results, highlighting the impact of the generation types and interconnectors in the APX market. All generation coefficients relate to a change per MW.*

Non Pumped Storage Hydro (NPSHYD) is also associated with a positive increase in prices at 0.6 pence per MW. PHES in pumping mode, shown as '*pumping*', is associated with an increase in APX price by 0.03 pence for every MW produced. It should be noted that '*pumping*' is shown as negative value, representing a load (National Grid 2015b) and hence a negative regression coefficient implies an increase. The result that the pumping stage of a PHES increases prices is supported by other studies; Foley & Díaz Lobera., (2013) showed that CAES can cause wholesale electricity prices (System Marginal Price) to increase in the Irish market under a high wind penetration scenario. In the same market, Nyamdash & Denny., (2013) showed that while energy storage displaces peaking plant generation and reduces the cost of production; however due to the gross pool pricing mechanism and some plant inflexibility, the electricity price, in effect, rises. The authors also investigate the impact of storage on prices through econometric analysis and found that both pumping and generating mode of a PHES increase the wholesale electricity price, corroborating the findings from their gross pool pricing model.

Nuclear power, as baseload generation, has a very small but positive effect on the APX price; a 1 MW increase in generation is associated with a 0.02 pence increase in price. Wind has a relatively weak but statistically significant effect on prices; a 1 MW increase in wind power reduces prices by 0.07 pence.

The strong influence of flexible generation and conversely the weak impact of inflexible generation on the spot market price can be explained by the fact that the spot market reflects last minute adjustments to parties’ position prior to gate closure. Therefore, the spot market not only shows not more volatility but also higher prices than would normally occur in trades well ahead of delivery, such as a forward bilateral contract taking place a year in advance. Thus, one might expect that the APX market prices to be inflated by flexible generation whereas increases in baseload generation would tend to have weak effects on prices.

The Net imbalance volume refers to persistent imbalances between demand and supply in the balancing mechanism, conventionally shown as positive for a deficit and negative for a surplus. A positive coefficient in the regression results, therefore, implies that each MWh of deficit is associated with a price increase of 0.37 pence and the converse is true in the case of a surplus. It is worth noting that even though the actual imbalance is not known ahead of time, namely in the APX half hourly spot market, trends in imbalances should to some extent be correlated with the APX market price; the APX market offers opportunities to rectify an imbalance between contracted generation and demand and therefore it is reasonable to assume that large imbalances in demand and supply will have an impact on both the APX market price and Balancing Mechanism prices. The use of the Net Imbalance Volume from the BM in the APX regression model would not be appropriate for ordinary forecasting purposes as these are not know in real time. However, since the purpose of the regression models is to isolate the impact of wind power generation, the use of NIV is acceptable and in this case provides additional insights on the state of balance of the system.

Looking at the other independent variables, the coefficients for all interconnection power flows are positive except for east-west interconnector referring to Ireland-Great Britain interconnector; interconnector power flows are conventionally shown (by National Grid) as a positive value for a power import into GB and as a negative value for power export. Thus from the coefficients, it can be said that interconnectors usage is generally associated with an increase in prices.

In addition to the above variables, dummy variables or indicator variables were added to investigate the effect of time of day on the APX price, as described earlier in section 4.11.1. Since prices are determined by demand and supply, they are likely to reflect a certain extent bidding behaviour, relating to aspects other than the type of generation on the system. For example, a generator who is trying to sell excess power at peak time is likely to put an offer at a higher price than if the same situation were to occur during an off-peak time, even if its marginal cost of production is the same for both periods.

The coefficients of the dummy variables are shown in figure 7.1, using 00:30 as the reference period. Since the model already accounts for the types of generation on the system, the cost of generation should not account for these price influences (and hence the marginal cost of production element should be of little influence). The most likely explanation, therefore, is that these premiums are due to bidding behaviour or reactions by market participants, especially at predictable periods such as morning and evening peaks.

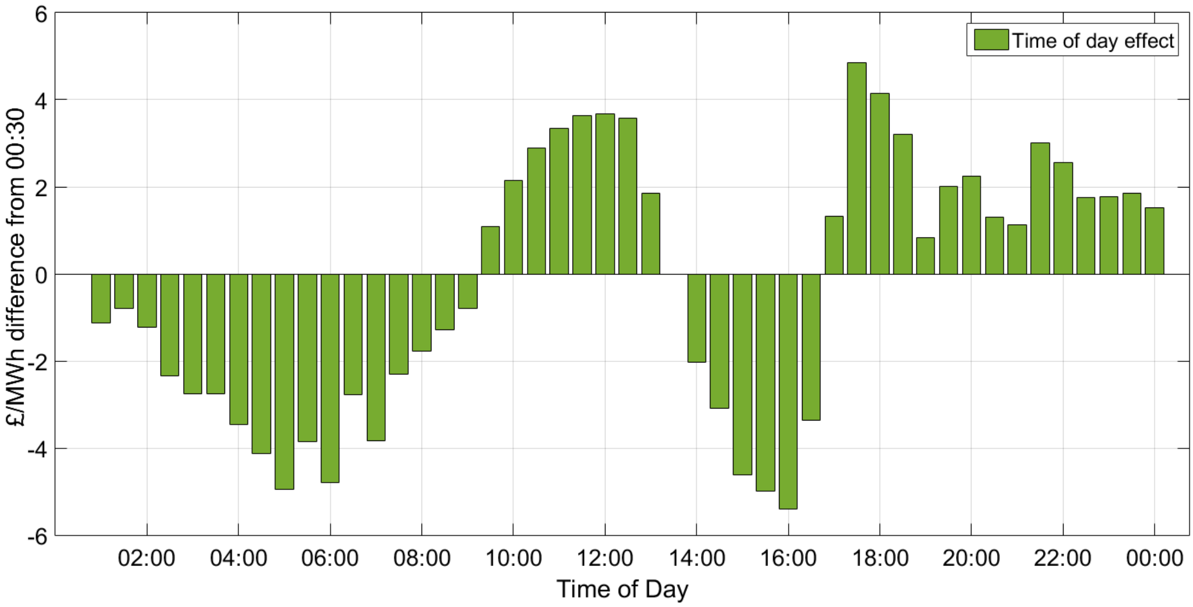


***Figure 7.1:*** *The impact of time of day on the APX price using dummy variables and 00:00-00:30 as the reference half-hourly period.*

Bidding behaviour also explains why the early afternoon fall in prices occurred when demand and generation were relatively constant during that period (shown earlier in figure 6.4). As mentioned previously, generators are willing to bid at prices lower than their marginal costs due to additional start-up costs and operational readiness. Therefore, it is unlikely that generators would, ahead of peak demand and peak prices, switch off any units and are willing to bid at lower prices to maintain generation level.

### 7.2.2. An autoregressive versus static modelling approach

The APX econometric model provides some explanatory power of the effect of the independent variables on the price; however, the presence of heteroscedasticity, autocorrelation, combined with an R-squared value of 0.54, indicate the likelihood of missing variables. Such missing variables, relevant to the model, are forecast errors, transmission constraints and embedded generation, each of which can have significant impacts on the APX market. System constraints influence the market prices and yet can be almost invisible from aggregate data; for example, a peaking plant which is constrained due to transmission operational requirements is unable to provide its power to the market. This, in turn, would have the effect of raising prices as available supply is reduced and in a highly volatile short-term wholesale power market, this rise in prices can be substantial. Due to the unavailability of data, these elements could not be factored in, and hence they suggest that the accuracy of the model is limited, especially at price extremes.

Working with short time resolution results in a high degree of autocorrelation. Using 2 lags of the dependent variable, an autoregressive model, AR (2), the R-squared value rises to 0.84, indicating a significant improvement of fit. However, under this model, the contribution of the other variables in explaining changes in the dependent variable is substantially reduced. In table 7.2, the coefficient for the lagged dependent variable is approximately 0.99 with a p-value of 0; this leads to the interpretation that at any price at any given point is on average 0.99 times that of the previous price.

The autoregressive model also significantly reduces the explanatory power of the independent variables compared to the static model. In fact, different types of generation should have a strong and significant effect on the wholesale price, even on the short-term markets. Yet clearly the autoregressive model shows a statistically better fit.

This paradox is the focus of Achen (2000) who looks at this problem from a general perspective; the author takes econometric examples to show that models which appear superior statistically due to lagged dependent variables can, under special circumstances, be wrong and have interpretations inconsistent with fundamental principles of the model. They investigate this effect to show that in such cases, the addition of a lagged dependent variable can diminish the explanatory power of the independent variables, especially if the dependent variable is trended. According to statistical theory, the additional of a variable under normal circumstances should not cause bias towards other variables and if relevant should be included to specifically to avoid omitted variable bias (Achen 2000; Dougherty 2011). However in the presence of very high autocorrelation in both the error terms and the independent variables themselves, as is the case in the APX market and BM models, Achen (2000) shows that the coefficients of the independent variables are biased downwards i.e. the greater the correlation the greater the underestimation of the other coefficients. In fact, when both correlation coefficients are equal to 1, the coefficients of the independent variables tend to zero.

Implementing Achen (2000)'s findings, the Static (ST) model should provide consistent estimates of the coefficients and standard errors, when estimated using feasible generalised least squares. However, omitted variable bias can still persist, which means that the impact of wind can be overestimated. On the other hand, the Autoregressive model (AR) shows downward bias on the independent variables, which means that the impact of wind is underestimated. Therefore, in this thesis, both the Autoregressive (AR) and Static (ST) model results are presented, as the most likely effect of wind lies in between the two approaches.

| APX AR (2) Model - OLS | | | | |
|---|---|---|---|---|
| **Variable Name** | **Coefficient** | **Std Error** | **t-statistic** | **p-value** |
| '(Intercept)' | -2.5826 | 0.571 | -4.526 | 0.000 |
| 'OIL' | 0.0104 | 0.001 | 13.284 | 0.000 |
| 'OCGT' | 0.0074 | 0.001 | 6.276 | 0.000 |
| 'CCGT' | 0.0004 | 0.000 | 33.984 | 0.000 |
| 'COAL' | 0.0001 | 0.000 | 12.925 | 0.000 |
| 'NUCLEAR' | 0.0000 | 0.000 | 0.986 | 0.324 |
| 'NPSHYD' | 0.0024 | 0.000 | 17.046 | 0.000 |
| 'WIND' | -0.0003 | 0.000 | -11.851 | 0.000 |
| 'NETIMBALANCEVOL' | 0.0011 | 0.000 | 15.189 | 0.000 |
| 'pumping' | 0.0001 | 0.000 | 0.675 | 0.499 |
| 'britnedimport' | 0.0000 | 0.000 | 0.681 | 0.496 |
| 'eastwestimport' | 0.0000 | 0.000 | 0.273 | 0.785 |
| 'frenchimport' | 0.0001 | 0.000 | 2.706 | 0.007 |
| 'moyleimport' | -0.0001 | 0.000 | -0.337 | 0.736 |
| 'APXV' | 0.0007 | 0.000 | 10.049 | 0.000 |
| 'APXPLAG1' | 0.9888 | 0.004 | 272.812 | 0.000 |
| 'APXPLAG2' | -0.2893 | 0.004 | -81.573 | 0.000 |
| 'imbapricelag2' | 0.0373 | 0.001 | 27.608 | 0.000 |

***Table 7.2****: An extract of the autoregressive model results.*

A comparative predictive performance between the static model and autoregressive model is shown in figure 7.2; it shows the ability to predict the APX market price based on out-of-sample data. More precisely, both models were regressed on 2011-2014 data and their predictive ability evaluated using 2015 data as input. Figure 7.2 shows that the static model performs less well than the autoregressive model; in particular, during the first week of January some peaks are captured by the model while others are exaggerated as seen 138$^{th}$ hour for example. Similarly, some troughs are captured while others greatly underestimated shown in the figure at the 26$^{th}$ hour. It is clear that the model fails to capture aspects of the price mechanism, as mentioned earlier possibly due to omitted variables.

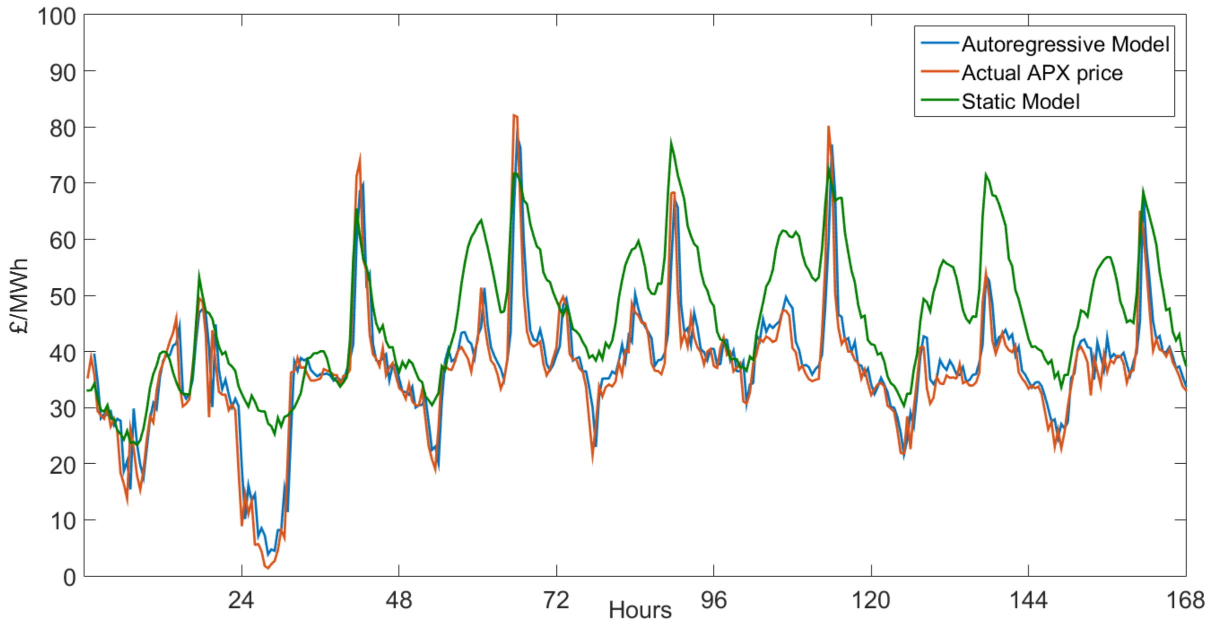


***Figure 7.2:*** *A comparison of the autoregressive model prediction to the static model prediction through out-of-sample testing.*

Although the autoregressive model appears to present a very good fit, the fact that it uses the APX price lagged by 30 mins, raises questions about the usefulness of the model in identifying the relationship between the dependent and independent variables, especially taking into account Achen (2000)'s earlier findings. Thus although statistically, the AR model is relatively accurate, its usefulness is limited by the fact that the large predictive ability of the model is driven by strong autocorrelation.

### 7.2.3. The BM regression model results and out-of-sample testing.

The BM regression model specification is very similar to the APX regression model except that it lacks dummy variables, as stated in equation 4.26 from section 4.11.2. As in the case with the APX regression model, two approaches were investigated: an autoregressive approach and a static approach.

The most influential variables on the imbalance price in the BM are OCGT representing power from Open Cycle Gas Turbine (OCGT) power Generation, net imbalance volume (NETIMBALANCEVOL), APX price (APXPHH) and Oil power generation (OIL), shown in table 7.3. The strong influence of peaking plants OCGT and OIL on the BM is not surprising as they are flexible plants which by nature are designed to operate rapidly to meet peak demand or imbalances. The strong influence of the APX price on the imbalance price is expected as well since Chapters 3 and 5 have shown that they are correlated to some extent.

NIV is one of the most significant explanatory variables, as it also directly determines the calculation method of the imbalance price. From the model, for every MWh of imbalance volume increase, the imbalance price rises by 3.7 pence.

| BM Static Model | | | | |
|---|---|---|---|---|
| **Variable Name** | **Coefficient: OLS** | **Coefficient: FGLS** | **OLS Std Error** | **FGLS Std error** |
| 'Intercept' | 4.4509 | 4.4538 | 1.099 | 0.010 |
| 'OIL' | 0.0197 | 0.0192 | 0.002 | 0.000 |
| 'OCGT' | 0.0937 | 0.0932 | 0.003 | 0.000 |
| 'CCGT' | 0.0010 | 0.0010 | 0.000 | 0.000 |
| 'COAL' | 0.0002 | 0.0002 | 0.000 | 0.000 |
| 'NUCLEAR' | 0.0001 | 0.0001 | 0.000 | 0.000 |
| 'NPSHYD' | 0.0011 | 0.0011 | 0.000 | 0.000 |
| 'WIND' | -0.0001 | -0.0001 | 0.000 | 0.000 |
| 'NIV' | 0.0370 | 0.0370 | 0.000 | 0.000 |
| 'pumping' | 0.0014 | 0.0014 | 0.000 | 0.000 |
| 'britnedimport' | 0.0000 | 0.0000 | 0.000 | 0.000 |
| 'eastwestimport' | 0.0013 | 0.0013 | 0.000 | 0.000 |
| 'frenchimport' | 0.0007 | 0.0007 | 0.000 | 0.000 |
| 'moyleimport' | -0.0047 | -0.0047 | 0.000 | 0.000 |
| '$P_{APX}$' | 0.2218 | 0.2218 | 0.009 | 0.000 |
| 'APXV' | 0.0004 | 0.0004 | 0.000 | 0.000 |
| 'APXPLAG1' | -0.0921 | -0.0920 | 0.012 | 0.000 |
| 'APXPLAG2' | -0.0194 | -0.0195 | 0.008 | 0.000 |
| 'quarterlyfuelpriceCOAL' | 0.0003 | 0.0000 | 0.069 | 0.000 |
| 'quarterlyfuelpriceGAS' | 1.3806 | 1.3808 | 0.034 | 0.000 |
| 'quarterlyfuelpriceOIL' | -0.0336 | -0.0336 | 0.018 | 0.000 |

***Table 7.3:*** *An extract of the results from the static model regression in the BM*

Every MW of CCGT and COAL power increase is associated with an imbalance price increase of 0.1 pence and 0.02 pence per MWh respectively. The fact that mid-merit generation such as CCGT and COAL are partly influential on the imbalance price determination can be explained by the fact that these forms of generation are largely part of participating BMUs; the BM itself relies on existing generation to adjust their output according to their bid/offer they submitted (should they be accepted).

Wind has a very small impact (-0.01p/MWh increase for each MW generated), in fact, a smaller impact in the BM than in the APX market. This is likely due to the fact that wind forecast errors within the hour preceding delivery is much smaller than errors in day-ahead wind forecast, for example as Hodge et al., (2012) have shown. Therefore, the APX half-hourly spot market which closes just ahead of the BM can accommodate trading to correct imbalances whereas the BM deals with imbalances within the hour preceding actual delivery. Thus on such a short timescale, wind forecast errors are small and therefore their direct impact on the BM is limited.

Finally, as an alternative to BM participation and reflective of electricity costs, the wholesale market price, APXPHH, was correlated with imbalance prices. In this case, every £1 increase in the half hourly spot market price was associated with a £0.22 increase in the imbalance price.

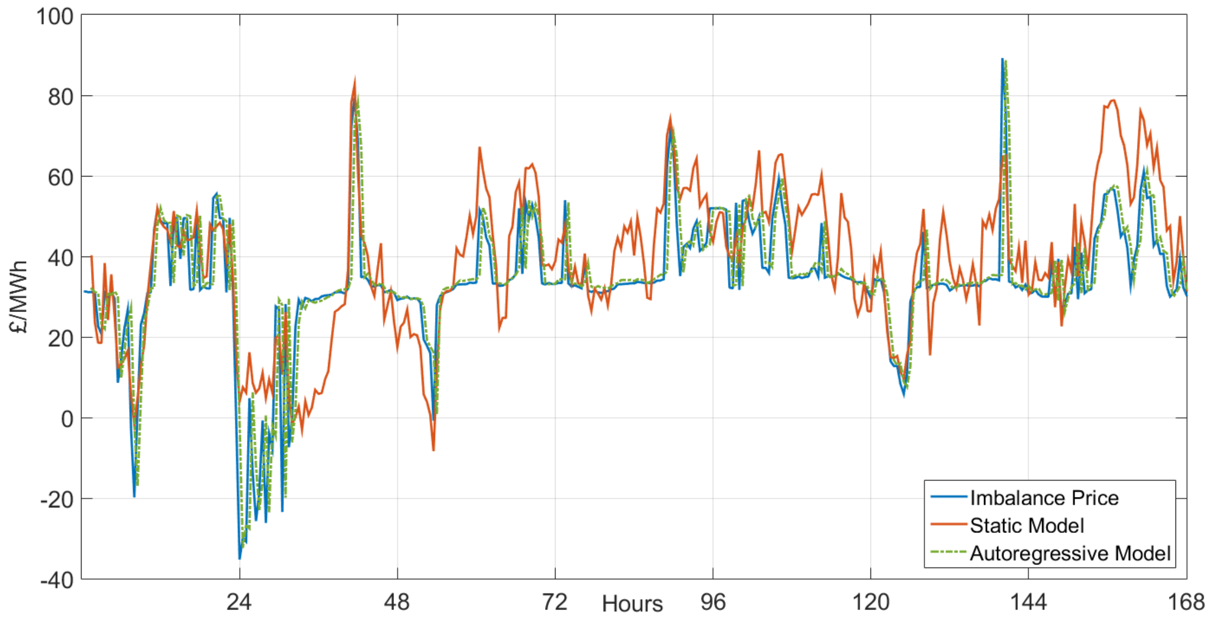


***Figure 7.3:*** *The predictive performance of the static BM model through out-of-sample testing.*

Compared to the APX price, the imbalance price is harder to predict due to the random nature of the imbalance volume. However, with imbalance volume included as an independent variable, a better fit is achieved. Figure 7.3 shows that the regression model over the interval of a particular week is able to capture some of the changes in the actual BM price, however, there tends to be an overestimation predicted imbalance price under the ST model.

### 7.2.4. Wind impact in the APX market and storage value

A scenario of high wind penetration was adopted to investigate the impact it would have on market prices; a 20 GW wind penetration level was simulated, roughly representative of expected wind penetration levels in 2020. Under both a static or autoregressive model, it is clear that wind has a depressing effect on prices. The static model, however, showed a greater impact of wind on prices. By assumption, additional wind power displaces generation according to the merit order stack. Thus at peak times, power plants such as OIL and OCGT are displaced. Therefore, wind generation in the model not reduces prices directly but also indirectly, by displacing peak power plant generation.

In figure 7.4, peak prices do not appear to be significantly reduced during the first week of 2014. In effect, the actual load factor for each period determines the impact that a 20 GW wind penetration would have. On days 1, 3, 5, 6 and 7 of Jan 2014, in figure 7.4, wind power was at a high load factor at peak time and thus a high wind penetration scenario caused a visible fall in peak prices. On days 3 and 4 on the other hand wind load factor was low and hence the scenario did not achieve a noticeable decrease in peak prices. In figure 7.5, this inverse relationship between wind generation and simulated prices is shown.

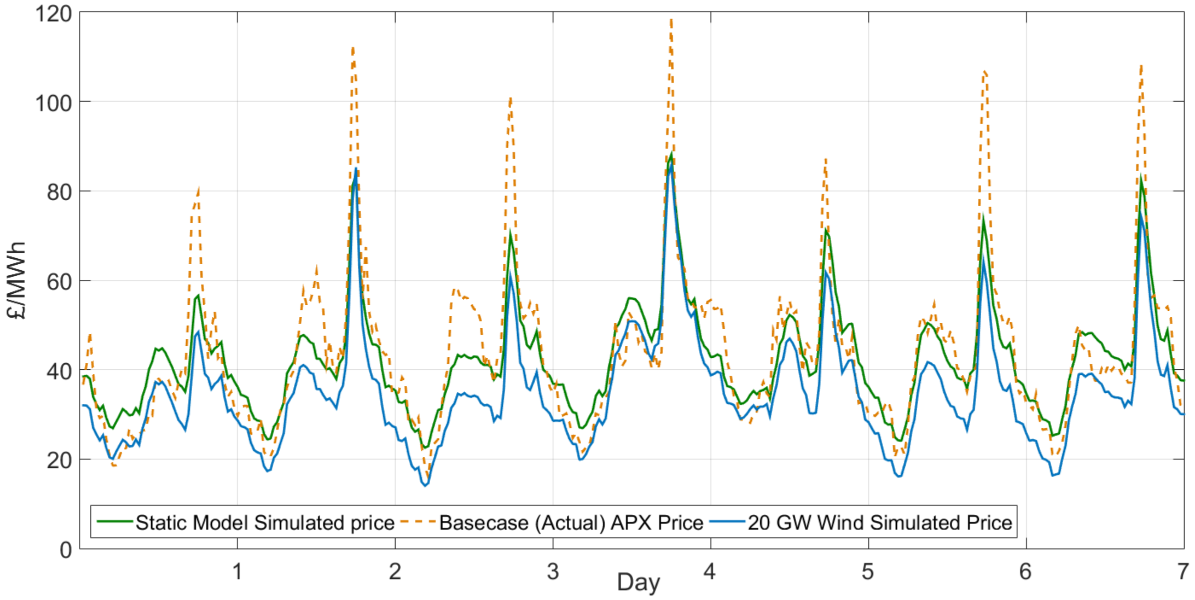


***Figure 7.4:** The impact of a 20 GW wind generation on the APX price for the first week of 2014.*

Assuming wind power reduces prices, storage value varies depending on when prices are reduced; if peak prices are reduced while off-peak prices are relatively unaffected, this reduces arbitrage profits. However, if peak prices are relatively unaffected and off-peak prices are reduced, greater arbitrage profits can be made. The net effect of wind on storage value depends on when wind power is generated, the magnitude and its frequency across the year.

While figure 7.4 shows the case when wind reduces off-peak APX prices more compared to peak prices (hence beneficial for arbitrage values), figure 7.5 shows the case where peak prices are reduced while off-peak prices are relatively lightly reduced. These are due to the wind generation at that time coinciding with peak prices as shown by the dotted line.

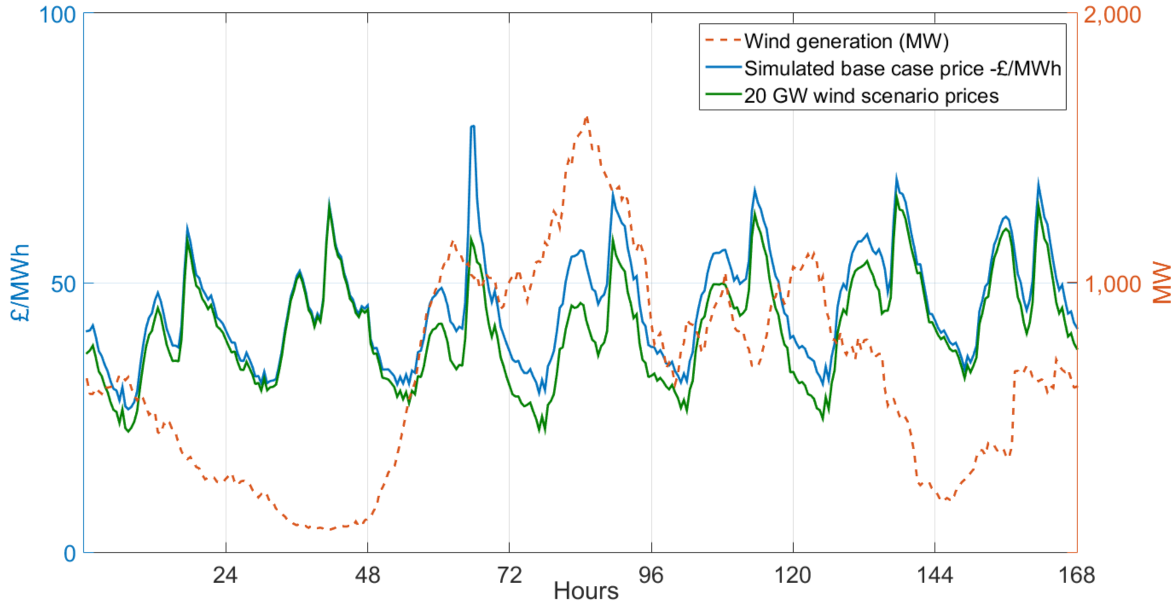


***Figure 7.5:*** *The relationship between wind generation, simulated (base case) APX prices and simulated prices under a 20 GW wind penetration scenario, for the first week of January 2011.*

In order to understand the impact of high wind penetration on wholesale market arbitrage revenues, the optimisation model was re-run from 2011-2014 under simulated prices. In addition, both the AR and ST model simulations are used to derive arbitrage price.

Base case simulations of prices are undertaken for both the AR and ST models; their purpose is to isolate errors which arise due to the limited ability of the respective models in predicting prices. The next step is to compare the effect of scaling wind to 20 GW and investigate any difference from the base case prices predicted by each model. Hence the pure wind effect can be isolated instead of misleadingly comparing a 20 GW wind scenario against actual prices. This basis of comparison is essential to separate model error and the true wind effect.

The results of the co-optimisation model, under this high wind penetration scenario are shown in figure 7.6.in all cases, i.e. under both models for all years, there was an increase in arbitrage value compared to their base case prices. Figure 7.6 also shows that in 2013 the static model performs less well in predicting prices and a large share of arbitrage value is lost due to the difference between the actual prices and the simulated price under the ST model.

The increase in arbitrage value under 20 GW of wind penetration could arise in the case whereby wind depresses off-peak prices more than peak prices consistently; however, this would appear unlikely since wind is uncorrelated with the APX price (correlation coefficient = -0.099). However, figure 7.7 shows the averaged wind output throughout the day, which in fact shows a slight pickup during daylight hours. Intriguingly, it points towards the opposite trend, that peak prices during the day should be depressed slightly more than off-peak hours (since the 20 GW scenario utilises historic wind output profiles between 2011-2014). Therefore, based on the trend in figure 7.7, storage value should be expected to fall under a high wind penetration scenario, in contrast with the results of the co-optimised results.

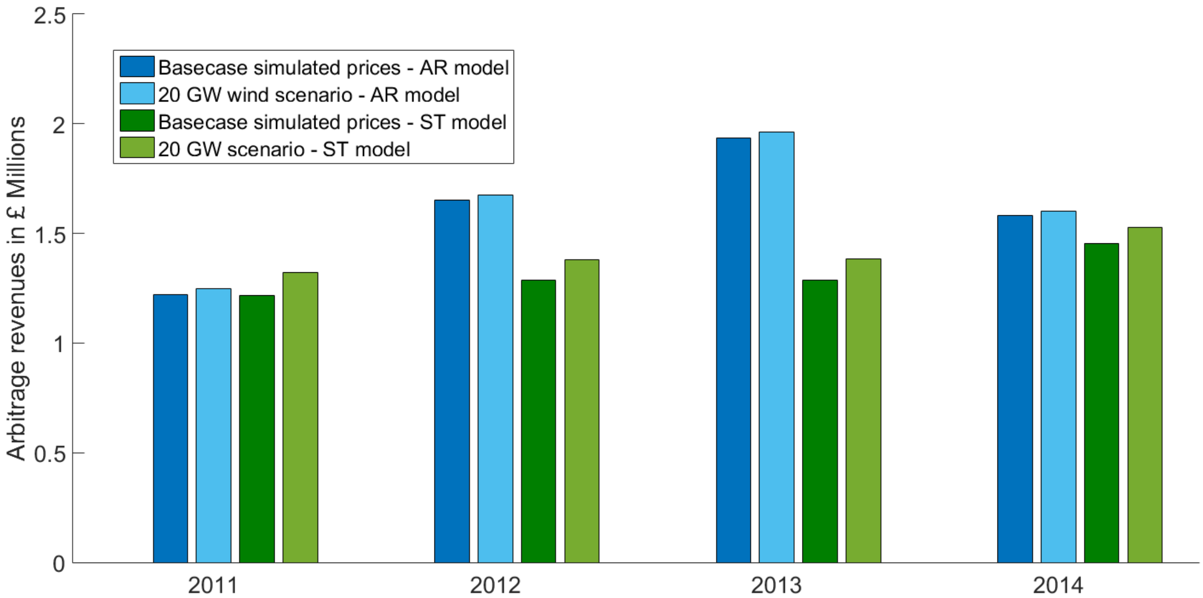


***Figure 7.6:*** *The impact of a 20 GW wind penetration on arbitrage revenues in the APX market under 2 regression models.*

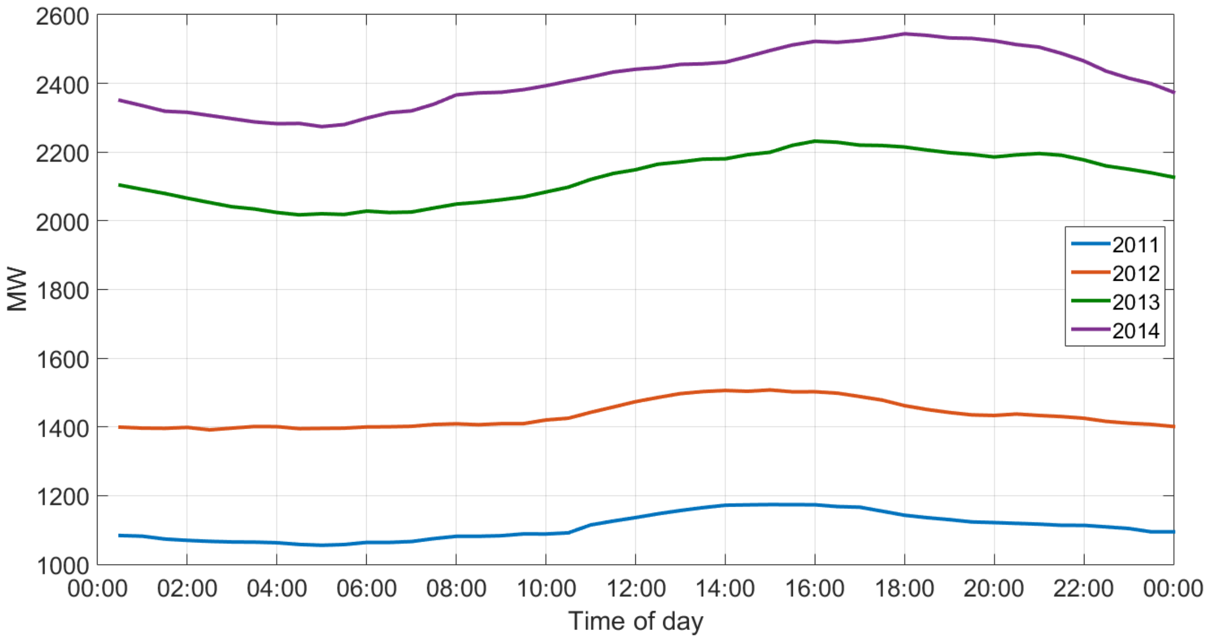


***Figure 7.7:*** *The average wind output by time of day from 2011-2014 showing a slight diurnal wind pickup effect.*

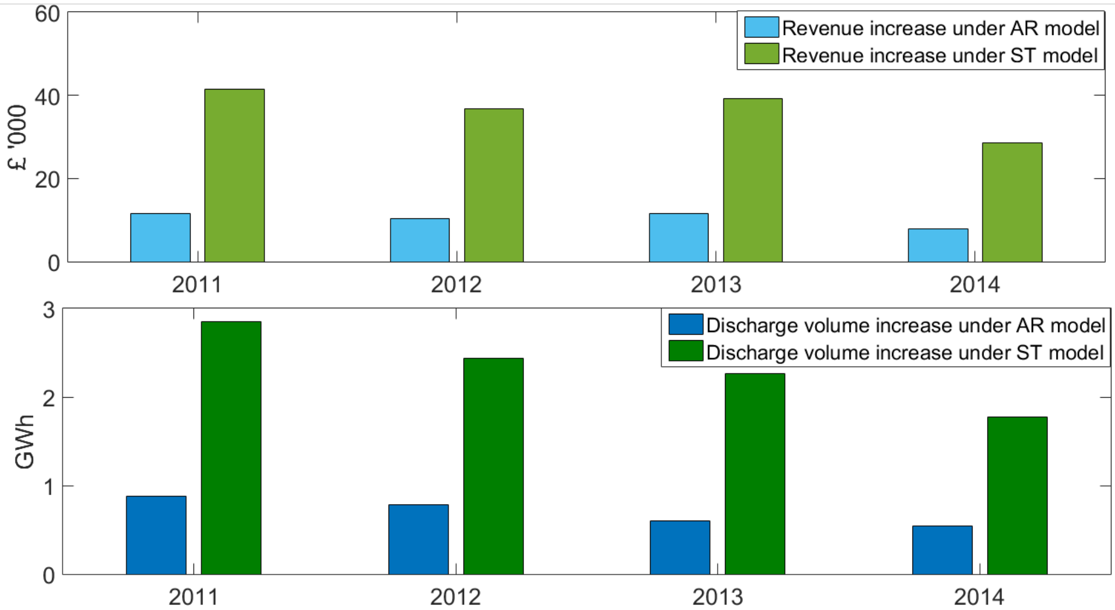

***Figure 7.8:*** *Changes in revenues and discharge volume from storage operation in the APX market under a high wind penetration scenario.*

Figure 7.8 helps to shed some light on this paradox; the rise in discharge volume and revenues occurs for all years under both models. A rise in discharge volume implies that under increased wind penetration, a greater number of arbitrage trades became possible. This increase in feasible trades occurs as the reduced prices create sufficiently large price differentials to compensate for round-trip efficiency losses and hence new trades become economically feasible. For example, the storage system can now charge at times where the prices are even lower (when wind generation is high) and discharge at almost the same price (when wind generation is low), generating higher or additional revenues.

On the other hand, the average diurnal wind pick-up effect seen earlier in figure 7.11 shows a rather a relatively small increase in wind generation, less than 200 MW or 10% of actual wind generation. In the econometric analysis, the impact of wind was relatively small; a 1 MW increase in wind generation was associated with a 0.07p/MWh decrease in the APX spot market price. Even when the conventional generation displacement effect of wind is factored in, the overall effect is relatively small. Consequently, the new arbitrage opportunities arising from the high wind penetration compensates for the loss of revenues occurring when peak prices are reduced. Hence storage revenues overall could rise under a high wind penetration scenario provided that wind and its associated price forecast is accurate, discussed further in Chapter 8.

### 7.2.5. Wind influence on the balancing mechanism and storage revenues

So far, the analysis which shows the depressing effect of wind power on prices relies heavily on siting assumptions and use historic data re-adjustment. In all likelihood, the imbalance prices in the future are likely to be subject to a variety of influences from demand side response, increased renewable energy penetration including solar and distributed generation amongst others. The evolution of the distribution of net imbalance volumes from 2011-2015 does not point towards any emerging tendencies, shown in figure 7.9.

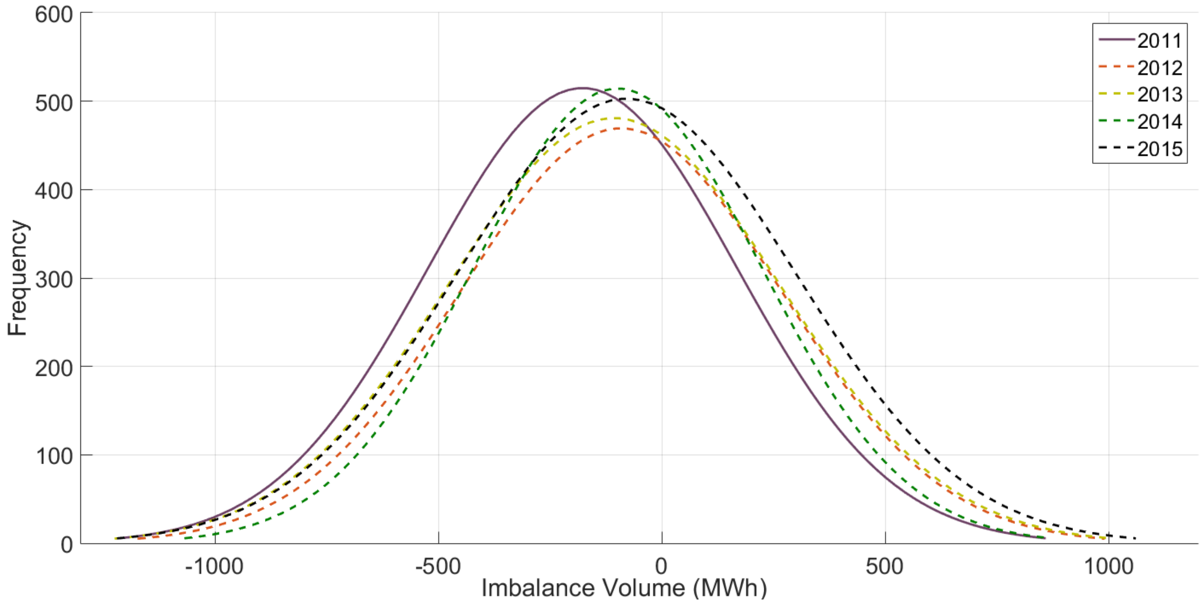


***Figure 7.9:*** *The distribution of net imbalance volumes from 2011-2015.*

The almost normally distributed imbalance volume is apparent throughout the years, with a persistent negative mean. This implies the persistent tendency for generation to exceed supply, perhaps as a precautionary measure as deficits are more detrimental to parties than excesses. Under the November 2015 amendment to the BM, a single price now prevails - the imbalance price. This symmetry means that the BM now offers a greater incentive for parties which help balance the system. Section 7.6 discusses the impact of this amendment and its implications.

Despite the strong increase in intermittent renewable energy, the magnitude of the imbalance volumes does not show an increase but instead display a narrower spread. Furthermore, for renewable energy sources to generate an extreme imbalance on their own is rare since mitigation effects occur at large scale, with distributed wind farms for example or the addition of other sources of renewable energy such as solar. Mitigation effects occurring at higher levels of different sources of renewable energy has been shown in GB by Coker (2011). Thus large imbalance volume swings while possible are not expected to be a frequent event and not visible from the graph. Increases in forecasting accuracy could also account for a slightly narrower spread in imbalance volume observed from 2012-2015.

The impact of a 20 GW wind penetration was simulated in the BM. Similar to the fall in APX simulated prices, a reduction in BM simulated prices occurs and is shown in figure 7.10. The fall in the imbalance prices are driven by three effects; first, the average cost of electricity during that period itself is likely to be lower as the APX price is lower. This effect is shown in Appendix E

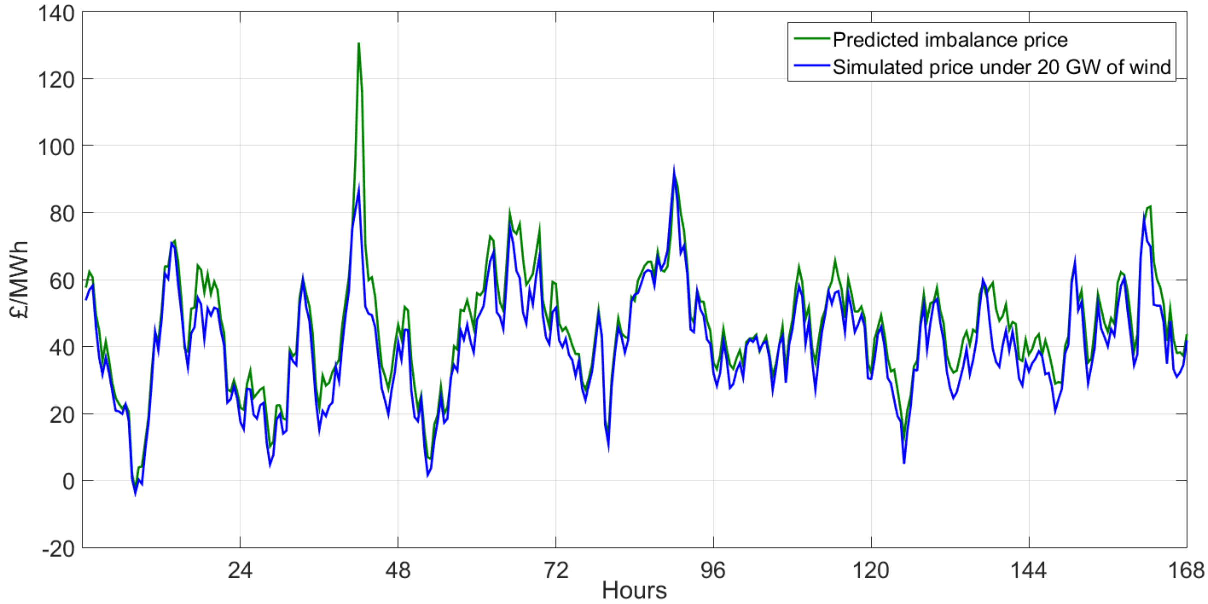


***Figure 7.10:*** *The total effect of wind on the imbalance price in the BM for the 1st week of Jan 2014.*

The second effect arises due to changes in the imbalance volume which could completely change in sign (between shortage and excess) and thus could affect the price calculation method itself. The third effect consists of the impact displaced generation has on the BM; the econometric analysis shows that the peaking plants have a strong impact in the BM, and therefore wind, by displacing these forms of generation, lowers prices, shown in Appendix E. Thus, one might expect a large fall in imbalance prices under a high wind penetration scenario; however, the magnitude of each of these effects are small but, when combined, are sufficient to cause a noticeable decrease.

The BM optimisation model was re-run from 2011-2014 under the simulated prices, under both the AR and ST models. The results are shown in figure 7.11; unlike the APX case whereby storage arbitrage value increased unequivocally, the BM arbitrage revenues show a very small decrease in 2011 and 2013 under the AR model. Prices calculated under the ST model on the other hand favourably predict a positive increase in arbitrage revenues for all four years.

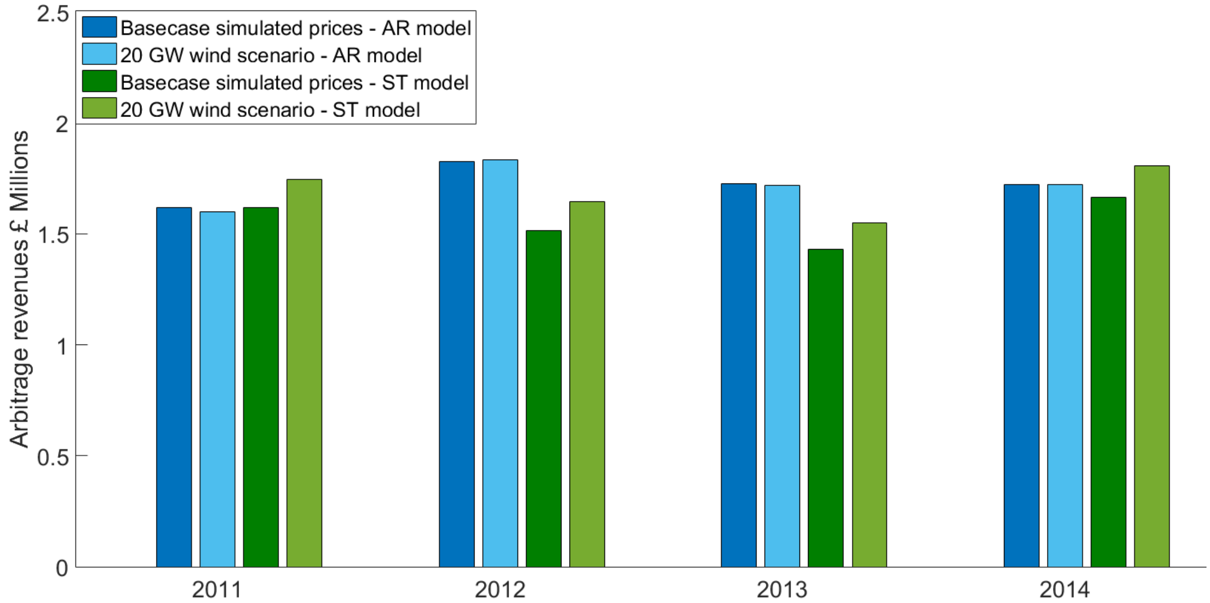


***Figure 7.11:*** *The arbitrage revenues in the BM under a 20 GW of wind penetration simulation from 2011-2014.*

In order to better understand these changes, the change in revenues and discharge volumes is shown in figure 7.12. It shows an increase in discharge volume in all years and under both models, implying that new arbitrage opportunities were created under higher wind penetration. Nevertheless, revenues fell under the AR model for 2011 and 2013. Very small decreases in prices, which occur under the AR model, are detrimental to arbitrage revenues since these decreases reduce both peak prices and off-peak prices by such a small amount that the price differential still remains too small for new opportunities to become viable.

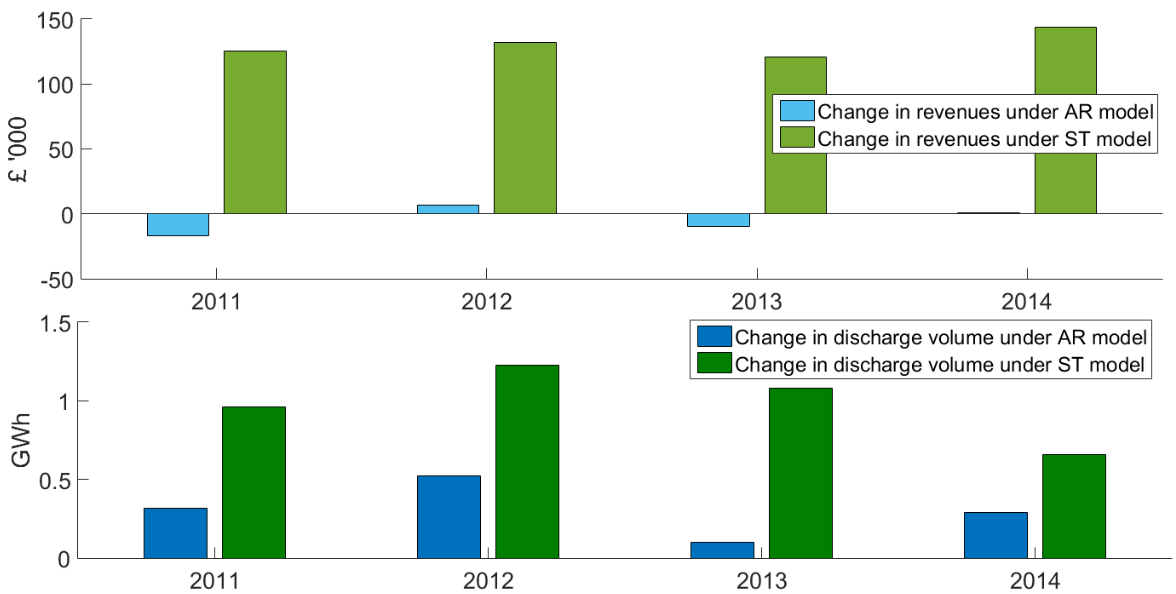


***Figure 7.12:*** *Changes in revenues and discharge volume under a high wind penetration scenario in the BM.*

The AR model compared to the ST model shows that wind has a relatively smaller effect on prices. Small price changes do not create arbitrage opportunities due to the round-trip efficiency losses from the storage system. In this situation, prices are lower and arbitrage opportunities fewer, resulting in a net loss.

Thus far, the impact of a high wind penetration scenario based on prevailing conditions of 2011-2014 results in a rather small change in storage revenues in the APX market and the BM. The small magnitude of this increase or decrease in revenues is supported by the findings of Coker et al., (2013) who show that wind power in the UK is uncorrelated (p=0.09) with demand, one of the main drivers of prices. Similarly, a Spearman correlation formula was applied, the correlation coefficient was -0.099 between wind generation and the APX market price, and -0.073 between wind generation and the imbalance price.

## 7.3. Co-optimised value of storage under increasing wind penetration

Unlike in the APX market and BM where prices are likely to fall, the reserve requirements are likely to increase under increasing wind penetration. Das et al., (2015) have explored the requirement for increased frequency regulation under increasing wind penetration; they impose a criterion for regulating reserve is to meet 99% of 1 minute (standard) deviations for every 5-minute period. Using this criterion, reserves requirement is likely to be higher. Furthermore, National Grid (2015f) anticipates the increased wind penetration to increase the rate of change of frequency as system inertia falls and thus require an increase in even faster-acting frequency response; the recently created Enhanced Frequency Response service seeks to address this issue. Previously, the impact of high wind was shown on individual market mechanisms. In this section, the combined impact of wind and hence value of storage is evaluated and the results are shown in Figure 7.13.

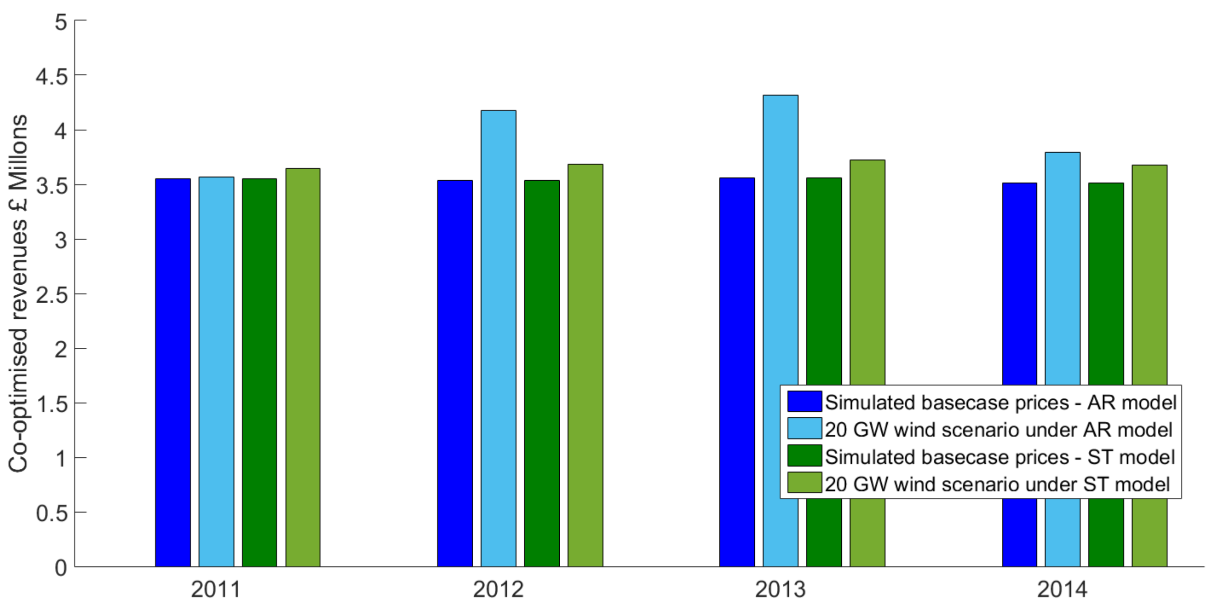


***Figure 7.13:*** *The co-optimised value of storage under a 20 GW wind penetration scenario*

Figure 7.13 shows the co-optimised revenues of simulated APX, BM and FFR revenues from 2011-2014. In all cases, there is an increase in revenues. This occurs primarily due to the increase in FFR availability payment which in turn increases FFR revenues. In 2012 and 2013 the AR revenues under a 20 GW wind was significantly higher compared to its base case scenario and in fact, this increase is higher than that predicted by the ST model revenues.

The drivers behind the changes are more complex in the co-optimisation case; even though all cases show an increase in revenue, the allocations are markedly different between the AR model and ST models; figure 7.14 breaks down the revenues and discharges for all three revenue mechanisms.

In 2011, under AR prices, the co-optimisation model derived a greater proportion of revenues from FFR seen by both an increase in revenues and allocated (shown as discharge) volumes for FFR. Conversely, there was a fall in participation in the BM, with both revenues and discharge volumes falling. In the APX market, a reduced participation is seen with discharge volumes falling, however, revenues increase. This means that while many trades were unfavourably affected by wind in 2011, causing a fall in discharge volume as seen in light and dark blue in the lower part of figure 7.14, some high-value arbitrage trades were created resulting is a net gain as shown in light and dark blue in the upper part of the figure.

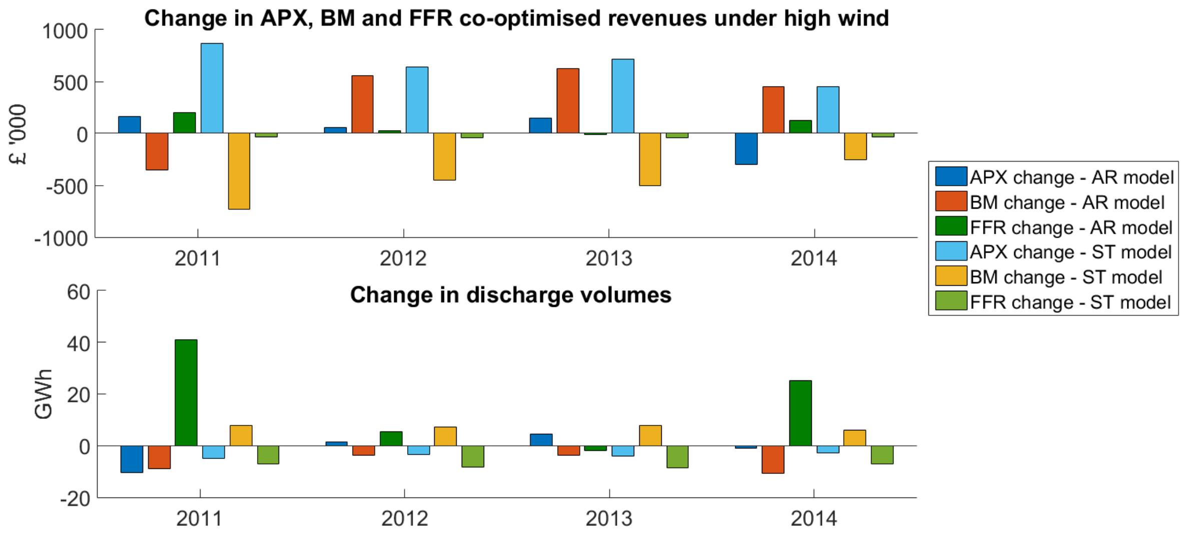


***Figure 7.14:*** *Changes in each type of revenue and discharge volumes under a high wind penetration; the changes are more complex than in the single market case.*

For the same year, under the ST prices, APX revenue increased while discharge volume decreased slightly, implying the arbitrage trades were more profitable in value but some trades were no longer feasible. In the BM, discharge revenues fell but discharge volume increased; this can be explained by wind changes affecting the high-value arbitrage trades but providing a slightly greater volume of small value arbitrage trade, such that overall total revenues are reduced. Table 7.5 explains the 4 possible changes affecting revenues and discharge volumes.

**The relationship between revenue and discharge volume changes**

| | | **Change in Revenues** | |
|---|---|---|---|
| | | **Increase** | **Decrease** |
| **Change in Discharge Volume** | **Increase** | Greater volume of arbitrage trades, at higher or lower values | Greater volume of arbitrage trades but at lower values. |
| | **Decrease** | Smaller volume of arbitrage trades but at higher values. | Smaller volume of arbitrage trades at higher or lower values. |

***Table 7.4**: The underlying conditions determining the relationship between discharge volume and arbitrage revenues.*

Using figure 7.14 and table 7.4, it is possible to see why the increases in revenues under the AR model in 2012 and 2013 were so substantial; in 2012 revenues from all 3 mechanisms increased either due to higher value arbitrage trades or a greater volume of trades. Figure 7.14 also highlights the difference in AR and ST model on the BM; BM revenues fell for all 4 years under the ST model. By contrast, figure 7.12 showed that when the storage system operates in the BM alone, revenues do not fall. Hence, the only explanation towards this fall in BM revenues under co-optimisation is that cross-market trades occur, such that revenues from other mechanisms increase; for the same four years APX market revenues increased by substantially more than sole participation in the APX market. For example, in 2011, sole participation in the APX market generated an additional £41,000 whereas under co-optimisation, APX revenues rose to £868,000.

## 7.4. The impact of optimisation horizons under increasing renewable energy penetration and other changes.

So far the impact of increasing wind penetration was evaluated on a 1-day optimisation horizon, guided by the findings of Chapter 5, which showed that the bulk of value of storage lies in the 1-day horizon. It is not known whether higher levels of wind penetration could potentially shift the value of storage from the 1-day horizon to longer horizons. This could happen, for example, if consistently there are periods of very high wind output followed by periods of very low wind output, spread out over a few days or perhaps longer. Under these circumstances, especially if these situations occur regularly, longer optimisation horizons might be preferable.

Recurrent patterns of sustained high wind periods and low wind periods were not observed from the wind data gathered. While on several occasions, periods of high wind generation followed by low wind generation was observed, this pattern was not regular to the extent that might result in substantially larger revenues under longer horizons; rather these were unusual occurrences.

This can be observed by running the optimisation using longer horizons to show whether longer horizons increase value under wind penetration. Figure 7.15 shows that under the 5 horizons investigated in the APX market, namely the 1-day, 2-days, 3-days, 5-days and 7-days horizon, there is no discernible difference to support the idea that longer horizons are preferred under higher renewable energy penetration and other changes in the current market structure.

In the BM, longer horizons do appear to be of greater benefit to storage, as shown in figure 7.15, but there is no indication that the benefit for longer horizons is increasing over the five-year period. Market constraints in the BM clearly justify longer horizons, as compared to figure 5.16 from Chapter 5 which showed small differences under no market restrictions. For example, in figure 7.16, the difference between a 1-day horizon and a 1-week horizon was over £1 Million in 2012, or over a 40% increase in revenues.

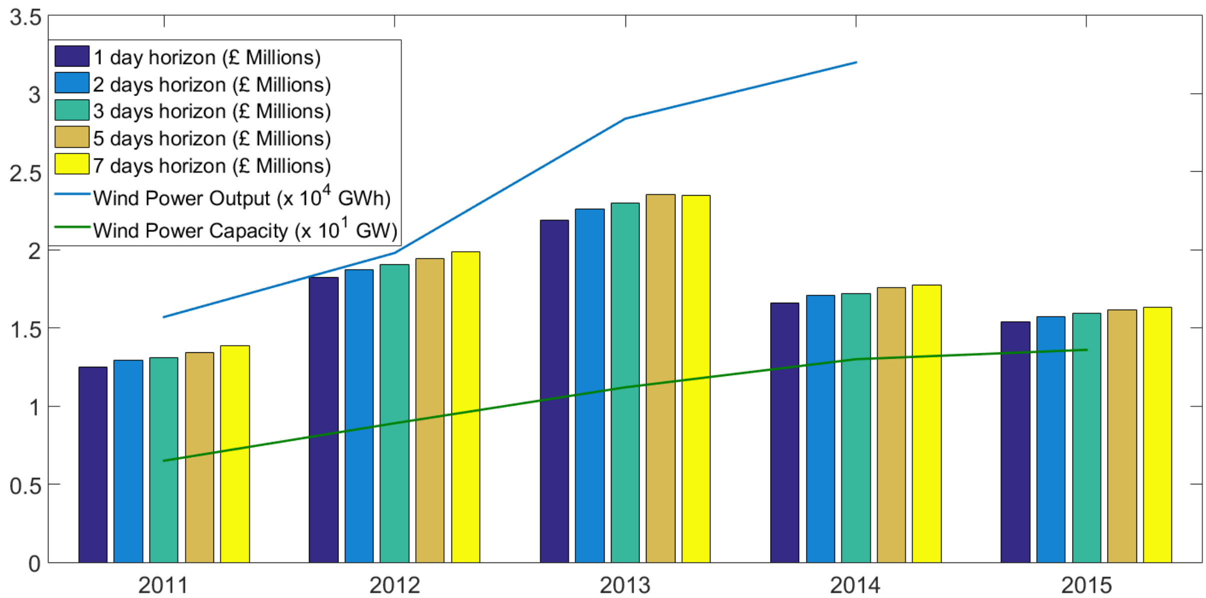


***Figure 7.15:*** *Revenues under different optimisation horizons in the APX market as wind penetration increased from 2011-2015.*

Over the five years from 2011 to 2015 wind capacity and output has more than doubled while solar power rose from almost 1 GW to 5.3 GW by the end of 2014; yet there is no clear evidence of their impact on optimisation horizons. It is essential to distinguish between two aspects of wind power, and generally renewable energy, that justify longer horizons; first the magnitude of wind output and second the timing of the variations, more specifically the gap between highs and lows. Only if both occur together, that is, large swings in wind power over a long period spanning days, then longer horizons can be beneficial.

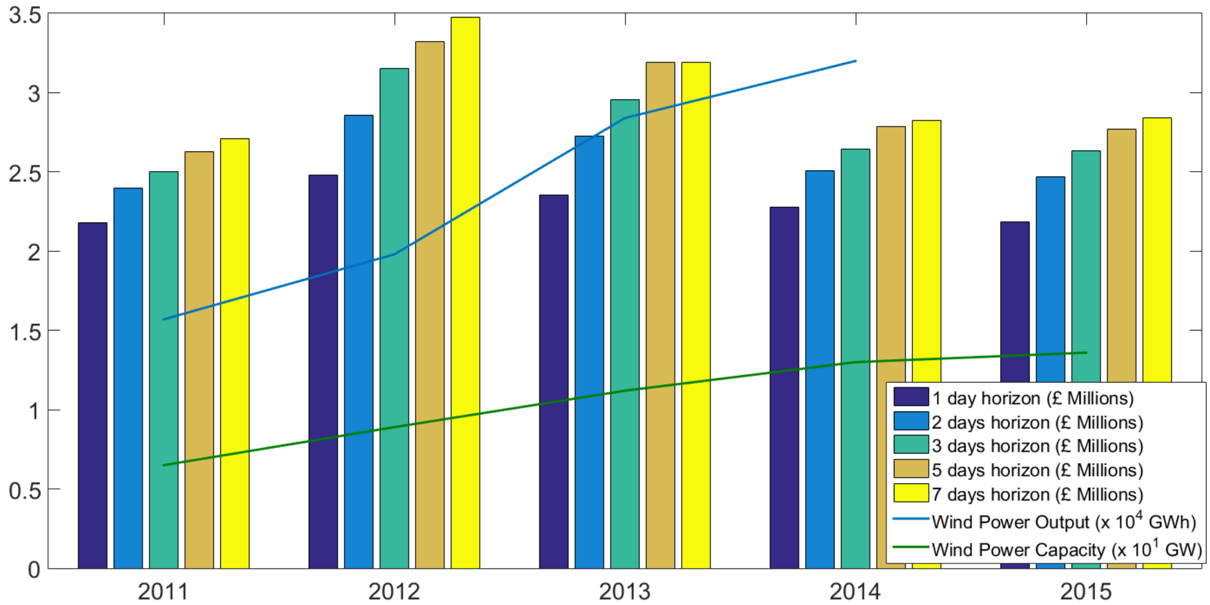


***Figure 7.16:*** *Revenues in the BM under different horizons under increasing wind penetration.*

There is a great deal of complexity surrounding the impact of wind on optimisation horizons; large wind power swings over longer periods need to be aligned with the market prices to favour longer horizons. Furthermore, this trend needs to be sustained continuously to generate a consistent preference for longer horizons, otherwise, gains at times are neutralised by losses at others.

Therefore, changes over the 5-year period, predominantly consisting of an increase in renewable energy penetration, do not drive the need for a longer optimisation horizon. On the contrary figures 7.15 and 7.16 support the argument that the intra-day variability in prices remains the dominant source of arbitrage revenues.

## 7.5. A note on the new pricing system in the Balancing Mechanism

One of the amendments to the BM in November 2015, briefly mentioned in Chapter 3, has special implications for values; a reduction in the price average reference volume from 500 MWh to 50 MWh increases the penalising effect of not meeting contracted demand or generation. According to the imbalance pricing method, an average of the most expensive 50 MWh of accepted offers will constitute the imbalance price (previously SBP) during periods of energy shortage on the system. Similarly, during periods of excess energy, the average the cheapest 50 MWh of accepted bids will constitute the imbalance price (SSP previously).

The amendment to the BM also included the addition of a function to reflect the impact of potential power loss to consumers (Ofgem 2015); this function is derived from the value of loss load and the loss of load probability. A value of loss load of £3000/MWh is initially implemented, rising to £6000/MWh on 1st of November 2018. It is conceivable that during periods of high system stress, whereby the loss of load probability rises, the imbalance price could be affected.

The elimination of dual prices (reverse price and imbalance price) for a single imbalance price has no impact on the co-optimised value of storage for several reasons; the reverse price which is almost identical to the half hourly APX market price is already accessible to the model under co-optimisation. Even in the case when storage operates in the BM only, market constraints mean that the storage system can only take actions that help the system and aligns operation to those of interest of the system operator. In this case, too the reverse price which applies to opposite actions, is irrelevant. The co-optimisation and BM model was re-run under the single price and confirmed that there was no difference in revenues from this change. However, with a greater incentive to help balance the system, parties may behave differently and this potential change in behaviour following this amendment is unknown at present.

## 7.6. Conclusion

This aim of this Chapter was to investigate the value of storage under increasing wind penetration levels. In order to do so, the impact of wind penetration on both the APX and BM prices was evaluated. The results of the econometric analysis show that the most influential variables on the APX price were a reflection of the merit order of generation; peaking plants have stronger effects, followed by mid-merit plants while nuclear plants as baseload generation have a very weak but positive impact on the spot markets.

These findings corroborate the economic theory of power dispatch whereby the least expensive generations are dispatched first followed the next least expensive. Furthermore, being a very short-term market, influences of the variables appear to be directly related to their level of flexibility, hence one of the reasons peaking plants have a stronger impact on the half-hourly spot market price.

Wind generation is shown to have a negative impact on the APX price, under both the autoregressive model and the static models. Lower prices, as a result of increased wind penetration, however, do not necessarily mean a fall in storage arbitrage value; this depends on the extent off-peak prices are reduced relative to peak prices.

Using the APX price under a 20 GW wind penetration level scenario, the co-optimisation model was run, with special precautions to isolate model error and wind impact. The results show that a slight increase in storage value arises as wind penetration level increases for all four years from 2011-2014. This increase in storage value occurs under both AR and ST simulated prices. The econometric regression in the BM shows that the most influential variables on the imbalance prices, in descending order of magnitude are OCGT, NIV, the APX price and Oil. Thus, similar to the APX, peaking plants with greater flexibility have a strong influence in the BM.

Similar to the case in the APX market, a 20 GW wind penetration scenario is simulated in the BM, whilst adjusting for additional effects; the BM which opens after the APX market closes is influenced by the latter and therefore this effect has to be accounted for. The NIV which cannot be assumed to remain fixed under such a scenario is adjusted by generating wind forecast errors from known distributions of wind error forecasts, one hour ahead. The third adjustment is derived from the econometric result and assumes that wind displaces generation in descending order of the merit order stack i.e. peaking plants, followed by mid-merit plants…and so on.

The results of the econometric models, both AR and ST show a fall in prices as with the APX market case. However, when the co-optimisation model is run, the impact in storage value is not clear; in some cases, under the AR model storage revenue falls slightly whereas prices generated under the ST model lead to a small increase in value, for all years.

Thus, there is a stronger tendency for storage value to increase slightly under higher wind penetration. This result, which may at first appear counter-intuitive occurs due to the fact that wind generation is uncorrelated with demand (Coker et al. 2013) as well as both the APX and imbalance price. A lack of correlation between the prices and wind generation implies that the falls in peak and off-peak prices, translate into gains and losses which cancel each other out, although not completely. This explains the small magnitude of the increase in storage value under the 20 GW wind scenario.

The slight increase in storage value could arise because consistently, there could be a slight tendency for wind to depress prices further during an off-peak period than during a peak period. The other, more likely explanation, is that the additional wind power causes prices to fall further such that new arbitrage opportunities become feasible (as price differentials are now larger).

Large swings in wind power can change the case for a short optimisation horizon, shown earlier in Chapter 5, in favour of a longer one. An investigation on how the value of optimisation horizons changed from 2011-2015, under changing market conditions, was carried out. No discernible difference was found either in the APX markets or BM. Mitigation effects of different types of renewable energy Coker (2011) and the low wind-price correlation coefficients explain the existence of weak effects of higher wind penetration for storage value in the markets.

This Chapter has thus shown that the absence of perfect foresight is detrimental to storage value whereas an increase in wind penetration level, although detrimental to prices can be beneficial to storage arbitrage value. The findings of Chapters 5,6 and 7 are further discussed in the following Chapter, including the implication and significance of these results.

# Chapter 8. Discussion

## 8.1. Introduction

This thesis introduced the research problem in Chapter 1. In Chapter 2, it was shown that despite a number of studies investigating storage value, these findings could not be extended to GB due to the market difference as well as unknown questions surrounding storage value. These market differences were described in Chapter 3 and based on these, suitable models were derived in Chapter 4. Chapter 5,6 and 7 presented the results of the models explaining why they arose. This Chapter discusses the implication and significance of these findings in the context of what previous studies have shown. In this respect, our understanding of specific aspects of storage value is advanced. The limitations of this study are discussed as well as areas that remain unknown and hence require further work.

## 8.2. Storage value in single vs multiple markets

The results in Chapter 5 have shown that there are potentially substantial arbitrage revenues in the APX market and BM. These were equivalent to £55/kW-yr and £82/kW-yr for the APX market and BM respectively in 2013. Across the 10 years from 2005-2015, APX arbitrage revenues ranged from £33/kW-yr to £102/kW-yr. These substantial variations, across mechanisms and across the years, imply that storage projects should factor these in building an economic case, otherwise an overestimation or underestimation of revenues may occur when these results are extrapolated over long timescales.

Although not directly comparable due to design and parameter differences, Sioshansi et al., (2009) found wholesale arbitrage revenues in the PJM market to range from approximately £40/kW-yr to £75/kW-yr from 2002-2007[8]. Connolly et al., (2011) showed the large variations of revenues across several markets worldwide but did not specifically investigate whether volatility was the reason behind the large variations. They found the arbitrage revenues in Alberta, Canada to be the highest of all 13 markets they explored. Safaei & Keith (2014) argued that the large price differential is due to the large proportion of electricity being from baseload generation and uses a real time gross pool (as opposed to common day ahead pools). As a result, they explain, the low load factor peaking plants recover their costs through high bidding prices, which under a gross pool becomes the MCP. Subsequently, Safaei & Keith (2014) showed a strong correlation between the standard deviation of electricity prices and CAES profit.

In the Australian markets, McConnell et al., (2015) show the arbitrage value of storage to range between £26/kW-yr to £184/kW-yr[9]. They point out that the price volatility in the Australian market is one of the highest in the world. Chapter 3 showed that the BM has more volatility than the APX market

[8] Using £1=$1.5 (USD) exchange rate
[9] Using £1= $1.9 (AUD) exchange rate

and consequently, in Chapter 5, it was shown that the BM revenues were substantially higher than those from the APX market. In Chapter 7, part, the reason why an increased wind penetration increases storage value, despite its clear depressing effect on prices, is that the additional wind generation increases price volatility thereby creating opportunities for storage. Therefore, the strong link between price volatility and storage revenues has been shown in this thesis; furthermore, the findings from previous studies also support this finding.

In evaluating and comparing the revenues in each market mechanism, identical storage parameters were used in each of these markets. While this allowed for a basis of comparison in terms of revenues, these parameters have not been optimised for these markets. Thus the energy to power ratio is initially chosen as 12 hours' equivalent to avoid restrictions as mentioned in section 4.2. However optimal energy to power sizing in the APX and BM market would likely be less than 5-6 hours of equivalent as the sensitivity analyses in Chapter 5 and 6 have shown. For the sole provision of FFR however this ratio is likely to be even smaller since the requirements for the provision of FFR is a minimum ratio of 0.5 hours. In Chapter 5 where a revenue comparison was made across mechanisms, smaller ratios would not substantially change the revenues considering the minimum requirements were met and that most of the revenues were derived from available capacity. Furthermore, it is unlikely that disturbances are consecutive and even so, in reality, recovery periods would be active, an aspect not explored in this thesis. However, for the calculation of NPV from FFR related revenues, smaller energy to power ratios are one of the key determinants of economic feasibility. Large power and energy capacities result in higher capital costs and since FFR revenues are mostly power capacity focused much smaller power capacities would likely be preferred.

In Chapter 6, when market constraints were imposed, revenues were reduced, some to a greater extent than others; the APX market showed great liquidity being almost completely unaffected. In the BM, although prices are higher, opportunities for arbitrage trades are limited by the state of imbalance on the system as well as the magnitude of the imbalance volume. As a result, the cross-system price arbitrage, or arbitrage between the system prices, is severely affected. Firm frequency response is not strongly affected in the absence of a utilisation profile since these have low utilisation rates; in fact, most of the revenue is derived from availability payments. FFR and STOR provision have special implications: they are niches for storage technologies that are highly sensitive to cycle life but with low self-discharge rates, for example, Lithium-Ion batteries.

These results highlight the need for caution when operating in the Balancing Mechanism alone whereas wholesale market arbitrage and FFR revenues are more easily accessible. Under a co-optimisation model, there is a synergy between the three mechanisms, being able to generate a high revenue which is lightly affected by market constraints. This occurs because constrained operation in one mechanism can be compensated by operating in another. More specifically, the constrained BM operation is compensated by participation in the APX market, thus benefitting from the high-value arbitrage trades in the BM and the increased liquidity in the APX market, essentially getting the best of both. Idle times whereby storage energy capacity is non-zero can be offered for the provision of FFR. Furthermore, because the FFR service is not called on all the time, residual energy can be sold in the other markets, generating additional revenues for the same energy volumes. Therefore, a co-optimisation of revenues is more resilient to market constraints and also generates additional revenues due to the synergy of operations. This mode of operation is thus of particular significance to a private investor who is risk averse.

Storage operation and system benefits were shown to align when the system operates in a single revenue mechanism. However, Co-optimised storage operation does not always align with system benefits, as the model chooses trades that increase revenues at the expense of those that could bring about a system benefit. For example, if there is an underestimation of demand at the early hours of the morning when demand is the lowest, a shortage of energy in the Balancing Mechanism arises. Usually, storage would be charging at that time and thus, under co-optimisation may not participate in alleviating the imbalance. Imbalances at low levels of demand can bring about rapid changes in the system frequency, which highlights the need for FFR during those periods. Thus a situation arises whereby storage operation is desirable in the BM or for the provision of FFR but financially there is greater value in maintaining a status quo by charging (and purchasing power from the APX market). This conflict can be mitigated by providing aligned financial incentives, a finding that is of particular relevance to policy makers.

## 8.3. The impact of efficiency and variable costs on revenues.

The sensitivity analysis from Chapter 5 and 6 strongly confirm Sioshansi et al., (2009)'s findings on efficiency against those of McConnell et al., (2015) in the Australian market; in fact, a deeper analysis was undertaken to explain why efficiencies strongly affect revenues. Two separate effects were shown to contribute to the increase in revenues under an efficiency increase; firstly, the direct efficiency gain whereby existing trades benefit from reduced losses under higher efficiency and secondly the feasibility gain effect whereby new trading opportunities become economically viable as losses are reduced. Under the structures of the APX and BM, these two effects when combined increase revenues in a more than proportionate fashion.

Since revenues are very sensitive to efficiency changes, special implications arise in the choice of storage technology; generally high-efficiency technologies should be preferred. RTE below 50% is ineffective for capturing revenues and RTE above 70% is preferred as 50% of maximum revenues are captured at that point.

A slightly smaller energy capacity is preferred under co-optimisation, at approximately 4-hour energy capacity 94% of maximum revenues was captured versus 89% and 91% for the APX market and BM respectively, as single revenue mechanisms. This conforms to the principle whereby large energy capacities are not desirable in the presence of multiple short-term arbitrage trades.

Variable costs have a strong influence on arbitrage values, as they directly affect each trade. It was shown that although their effects are not as strong as efficiency, within the £1/MWh-£20/MWh range, variable costs strongly impact revenues, almost halving revenues at £20/MWh. This study assumes that variable costs are directly proportional to output, in the sense, they scale up per every MWh of energy, similar to those shown earlier in table 4.1. While some costs scale directly with output such as natural gas prices in a CAES model, for many other technologies it is not clear whether the costs are linearly proportional to electricity output. Since arbitrage optimisation models are highly sensitive to variable costs, the accuracy of the variable cost estimates and the nature of these costs, that is, whether they increase linearly with every unit of output, are important considerations. Otherwise, revenues may be understated as a consequence.

## 8.4. Power and energy capacity impacts on revenues

The sizing of the energy capacity of a storage system is a crucial aspect; oversizing results in excessive capital costs which lead to losses whereas under-sizing leads to a loss of potential revenues. Appropriate sizing depends on the market structure; long gaps between peak and off-peak prices mean a longer storage capacity is preferred. Similarly, Chapter 5 showed that under long optimisation horizons, diminishing returns occur and since additional energy capacities result in higher capital costs, smaller energy capacities are preferred. The application of storage systems also determines the energy capacity sizing requirements; a storage system with a commercial focus or profit maximisation would be designed ideally with 4-5 hours of energy storage capacity.

Wind farm sited storage systems, on the other hand, require larger energy capacities; Denholm & Sioshansi (2009) have shown, in a US context, that when storage is sited with wind farms to reduce capital investment in transmission costs and reduce curtailment, capacities in the order of 20 hours or more is required. In the UK Grünewald et al., (2011) showed that under the same purpose of minimising wind curtailment, NPV is maximised at 14 hours of flow battery energy capacity whereas for CAES this figure was about 81 hours. Hessami & Bowly (2011) estimate the economically optimal energy capacity for wind farm sited storage to vary from 9.5 hours for a seawater-based PHES to 23 hours for a thermal energy storage system. Thus there appears to be a need for larger energy capacities when storage operation is confined to reducing wind curtailment. However, this study did not specifically explore storage operation and wind curtailment; Coker (2011) has shown that large energy capacities in the days-week range are preferred for the purpose of energy import reduction when storage operation and a wide array of renewable energy resources are combined. This is especially true as the penetration level of renewable energy increases.

For a purely revenue maximising purpose, Sioshansi et al., (2009) show that 85% of arbitrage revenues in the PJM market are captured at 8 hours of energy capacity, rising to 95% at 20 hours. McConnell et al., (2015) find that 90% of arbitrage revenues is captured under a 4-hour energy capacity. In Chapter 5 of this thesis, a 4-hour energy capacity was shown to capture 89% market and 91% of revenues in the APX and BM respectively. While these results are not directly comparable due to differences in markets and optimisation horizons, they do point towards a preference for shorter energy capacity for revenue maximising purposes. Hence small energy capacities are preferred for revenue maximisation, which compared to the wind sited storage optimal storage capacities, is substantially smaller.

The results from Chapter 6, show that under co-optimisation 94% of maximum revenues were captured at 4 hours of storage output, slightly more than the 89% in the APX market alone or the 91% figure in the BM; this is attributable to the presence of additional arbitrage opportunities within any given period. A storage system faced with more arbitrage opportunities in a short period of time does not need large energy capacities as the system can charge and discharge rapidly, and thus does not need to store energy for long periods. Co-optimisation provides additional opportunities for arbitrage trades as the storage system can buy/sell from/into each market mechanism. Thus a co-optimisation mode of operation may justify downsizing energy capacity which is particularly useful as this results in lower capital costs.

Revenues were shown, in section 6.10, to scale almost linearly with power capacity under a co-optimisation model. Under increasing power capacity and when market constraints are applied in the APX market and BM, storage discharge cannot exceed the market volumes. However, as a compensating mechanism, extra power capacity is offered as FFR provision. Larger power capacities are also able to take a greater advantage of large price differentials by charging and discharging more during those times. This results in an increase in average revenues. This is also supported by the fact that peak prices are relatively short time windows, lasting 2-3 hours. Ideally, most of the energy charged would be discharged during the narrow peak time window. However, power capacity limits prevent this and as a result, the system also discharges on the next best option - morning peak prices. Thus the increase in power capacity yields additional benefits, which overpower the reduction in revenues that market constraints bring. From these findings, a storage owner would prefer a storage system which favours power capacity over energy capacity as long as the energy capacity is around the 4-hour mark.

## 8.5. Perfect foresight relaxation – feasible operating strategies

Storage optimisation models often assume perfect foresight for the calculation of arbitrage profits (Safaei & Keith 2014; Drury et al. 2011). Other models forecast prices using linear regression (Sioshansi et al. 2009), Monte Carlo simulations (Yucekaya 2013) and cost functions that are broadly representative of a merit order of generation (Grünewald et al. 2011; Foley & Díaz Lobera 2013; Das et al. 2015). While the relaxation of the perfect foresight assumption achieves a more realistic estimation of storage value, for the investigation of potential value in a market, this is justified (Barbour et al. 2012).

The relaxation of perfect foresight in Chapter 7 showed that under a backcasting technique used by Sioshansi et al., (2009), 62% of maximum revenues under co-optimisation were captured, much lower than the 85% figure Sioshansi et al., (2009) found in the wholesale market. However Sioshansi et al., (2011) have also shown that arbitrage trades arising from small price differentials are harder to capture and using the backcasting technique under such circumstances reduce revenues to 45% of maximum revenues. Given the complexities of co-optimising across three fundamentally different revenue mechanisms, the backcasting technique captures 62% of maximum revenues. Therefore, as a worst case scenario, at least 62% of maximum revenues can realistically be achieved.

Using different backcasting lags, one might expect that shorter lags are able to capture short-term persistence effects and therefore demonstrate a higher revenue. However, no such trend was found; the only clear difference in backcasting lags was the 1-day lag compared to the other three lags, namely the 1-week, 2-weeks and 1-month lags; the 1-day lag showed a marked decrease in revenues. A 1-day backcasting lag, by definition, assumes that the previous day price profile resembles the next day price profile. This is not necessarily the case as weekend prices differ from those during weekdays; for example, a Saturday storage operation schedule would be derived from the day before, Friday, under a 1-day backcasting technique. Nevertheless, in principle, short term persistence effects should favour the 1-day backcasting technique, as long as those effects last for at least 2 days (to cover both the previous and current day). Therefore, this leads to the conclusion that the persistence effects are very weak and/or disturbances are not frequent in such timescales, to such an extent that the weekday-weekend effect overshadows any positive benefits a 1-day backcasting lag may have. It is quite possible that on backcasting lags, shorter than 1 day would capture stronger persistence effects, however, in doing so, the daily price would be lost (on any lags shorter than 24 hours). Considering that Chapter 5 showed that most of the arbitrage value lies within the 1-day horizon, shorter backcasting lags do not have a rationale, at present. In fact, a dramatic fall in revenues was shown for backcasting lags shorter than 24 hours but not included in the results as the choice of such a short lag is irrational and thus the large reduction of revenues found, is of trivial importance.

Besides the backcasting technique, a fixed dispatch strategy was explored; a daily average of storage operation was calculated from the co-optimised results. This technique captured 53% of maximum revenues under co-optimisation; generally, any fixed dispatch strategy would suffer from low revenues as seasonal effects cannot be captured. However, this technique was shown to derive similar revenues to the backcasting technique and provides greater simplicity – since the optimisation is only performed once as opposed to multiple times for backcasting techniques.

Alternative operating strategies have also been proposed to capture maximum value; Connolly et al., (2011) investigate arbitrage value across several countries including GB and propose strategies for capturing value. Their strategies capture between 81%- 97% of maximum arbitrage revenues. However, these strategies are not completely devoid of perfect foresight; for example, their '*24Prognostic*' strategy dispatches electricity based on the knowledge of the future 24-hour prices. The authors rightly point out that this strategy does not perform as well in markets whereby the exact prices are not known ahead of real time, citing the example of the Irish electricity market. Similarly Kanakasabapathy & Shanti Swarup (2010) present a bidding strategy that requires knowledge of prices ahead of time. While strategies proposed by Connolly et al., (2012) and Kanakasabapathy & Shanti Swarup (2010) have merits in markets whereby prices are known in advance such as Nordpool Connolly et al., (2011), the half hourly spot market prices are exposed to demand and supply forces up to 1-hour ahead of real time electricity delivery and therefore their findings cannot be applied in this study, under truly imperfect foresight.

The impact of imperfect foresight on storage energy capacity was also investigated, in order to shed light on the conflicting results found by Sioshansi et al. (2011) and McConnell et al., (2015). In this thesis, it was shown that the disparity between perfect foresight and imperfect foresight revenues increased as energy capacity increased. The results thus supported the findings of Sioshansi et al., (2009), showing that increasing energy capacities under imperfect horizons increase the disparity between perfect foresight revenues and realisable revenues under a backcasting technique. McConnell et al., (2015) used forecasted prices by the Australian Energy Market Operator, which is a different approach to backcasting techniques and thus in principle could account for different values. However the trend should be the same irrespective of the approach, because as Sioshansi et al., (2011) explained, smaller energy capacities derive arbitrage profits from large price differentials which consist mainly of the peak and off-peak arbitrage. Larger capacities need to derive value from small price differentials which are less cyclical or trend related, and hence harder to predict.

The difference between total revenues generated under perfect foresight and imperfect foresight for a given storage system, represents a measure of forecasting accuracy; a high forecasting accuracy implies that the difference between perfect and imperfect foresight revenues should be small. Equation 8.1 shows this relationship in absolute terms; if the forecasting accuracy = 100% then $TR_{PF} -$

$TR_{IF}$ is equal to 0. Equation 8.2 shows the partial differential equation of changes in this accuracy measure with respect to changes in the energy capacity, and this expression simplifies into equation 8.3.

The difference between total revenues generated under perfect foresight and imperfect foresight for a given storage system, represents a measure of forecasting accuracy; a high forecasting accuracy implies that the difference between perfect and imperfect foresight revenues should be small. Equation 8.1 shows this relationship in absolute terms; if the forecasting accuracy = 100% then $TR_{PF} - TR_{IF}$ is equal to 0. Equation 8.2 shows the partial differential equation of changes in this accuracy measure, with respect to changes in the energy capacity. This expression simplifies into the difference in rate of change of both types of revenues.

In other words, the trend in this accuracy measure depends on the relative increase in perfect and imperfect foresight revenues as energy capacity increases. If, relatively, perfect foresight revenues increase faster than imperfect foresight revenues with an increase in energy capacity, then it is expected that larger energy storage systems would fare worse than smaller ones (under imperfect foresight). Sioshansi et al. (2009) proposed a corroborating argument that in the absence of perfect foresight, larger energy capacity storage systems need to capture smaller price differentials (for arbitrage purposes) and this becomes increasingly harder, especially as arbitrage trades shift from the conventional off-peak to peak buying and selling of energy.

$$ACC = TR_{PF} - TR_{IF} \tag{8.1}$$

$$\frac{\partial(ACC)}{\partial(EC)} = \frac{\partial(TR_{PF} - TR_{IF})}{\partial(EC)} = \frac{\partial(TR_{PF})}{\partial(EC)} - \frac{\partial(TR_{IF})}{\partial(EC)} \tag{8.2}$$

*Whereby*

$ACC$: Accuracy of imperfect foresight
$EC$: Energy Capacity
$TR$: Total Revenue
*PF*: Subscript referring to Perfect Foresight
*IF:* Subscript referring to Imperfect Foresight

The following example is given to illustrate why with larger capacities under imperfect foresight is detrimental to revenues; given a storage system with a 1-hour energy capacity, one might choose to charge at 04:00 and discharge at 18:30 without the need for foresight but based on the likelihood of highest and lowest demand levels and the resulting prices. This would likely be close to the value generated by a perfect foresight arbitrage trade.

By contrast, an 8-hour energy storage system would require additional charging and discharging outside of these hours to maximise revenues. These additional trades are less predictable and usually yield less revenues, making the margin of error smaller. Thus, to a storage owner with perfect foresight, a larger energy capacity would not be problematic since he/she could capture these smaller unpredictable price differentials. For a storage owner with imperfect foresight however, this would prove to be difficult. This can be seen analytically from equation 8.3 that if $\frac{\partial(TR_{PF})}{\partial(EC)} > \frac{\partial(TR_{IF})}{\partial(EC)}$, ACC would increase implying the gap between potential revenues and actual revenues widens as the energy capacity increases.

## 8.6. Seasonal variations

The optimisation results, when capturing both single and multiple revenue streams, show that there is a pattern in charging and discharging, driven by prices (and demand). Charging tends to be confined to the early hours of the day, and this does not change for different season nor different years. Discharging, on the other hand, tends to be confined to two windows; the morning and evening peak price windows. From winter to summer the peak time window slowly shifts to later periods. Prices also fall and as a result discharging during that peak period in summer is reduced. Relatively the morning peak prices become more appealing in the summer and hence discharging during that window increases. These seasonal effects were shown in figures 5.6 and 6.5; as an increased discharge density during the morning peak price window and a decreased density in evening peak discharge window, from winter to summer.

Thus, seasonal storage operation partly reflects seasonal demand changes but not fully. The morning peak prices occur as demand increases while generation ramping rates on the system are stressed; in absolute levels however, demand is well below mid-day levels. At mid-day, prices tend to drop ahead of the peak price, whilst demand remains high and fairly constant. A storage operator should be aware of these price trends which are different to demand trends; storage operation determined by aggregate demand alone will underestimate storage revenues. Understanding seasonal revenues allow the storage operator to schedule maintenance, for example.

## 8.7. Annual variations

Annual variations in storage value have been explored previously for other markets (Sioshansi et al. 2009; Moreno et al. 2015; Connolly et al. 2011). APX market revenues were estimated for the period 2005-2015, showing that revenues do vary substantially; the difference between the lowest (in 2011) and highest revenues (in 2008) were over £4.5 million. It should be noted that prices in 2008 were exceptionally high. Connolly et al., (2011) looked at the variation in annual wholesale market arbitrage revenues between 2005-2009 in several countries including GB. Using operational strategies, they find similar results to those presented in figure 5.3; there are substantial variations in annual revenues and that 2008 yielded abnormally high revenues.

Under co-optimisation, annual variations bring about different changes with a reduced impact on revenues; allocations between different mechanisms change in the presence of annual variability. Moreno et al., (2015) found this effect using a similar MILP co-optimisation model, however operating within distribution networks. Since their revenue streams consisted of reserves payments, frequency response payments and wholesale arbitrage revenues, they showed how, under annual variability, allocation of storage capacity shifts between mechanisms over the years. Chapter 6 results confirmed that these changes occurred even when the balancing mechanism is considered.

These results also showed that the revenues, as a consequence of compensation effects, are not severely affected by annual variability; from 2011-2014, annual co-optimised revenues showed variations of up to 20%. Hence these results demonstrate the superior resilience of co-optimised revenues. Considering the additional resilience of co-optimised revenues to market constraints, these are further advantages of using co-optimisation as an approach to capturing storage revenues.

## 8.8. The choice of optimisation horizons for energy storage

Optimisation horizons define the interval over which storage operation takes place; it is also equivalent to the minimum foresight horizon required to schedule operations. The choice of optimisation horizons have been mostly arbitrary in studies Sioshansi et al., (2009) use a 2-week optimisation horizon, Sioshansi et al., (2011) use a 1-week horizon, Safaei & Keith (2014) used an eight-day horizon whereas Yucekaya (2013), Lund et al., (2009), Lund & Salgi (2009), Connolly et al., (2011) and Kloess & Zach (2014) use a full year horizon. There are benefits to choosing longer horizons, as more trade opportunities become available over a longer period. On the other hand, longer horizons require a greater number of variables, which in turn necessitates exponentially more computer processing power. Therefore, there is a trade-off between a horizon that is sufficiently long to capture the majority of revenues and one that is short enough to be solvable within a reasonable amount of time.

The results from Chapter 5 confirmed this; more precisely the majority of revenues lie in the 1-day horizon which manages to capture 93% of maximum revenues. The 2-day, 1 week and 1-month horizons capture some additional storage revenues but show diminishing returns. This occurs as the additional high-value trades over longer horizons come at the cost of a large number of smaller trades in between; for example, a 1-week horizon is able to capture inter-day arbitrage trades, but this would mean forgoing some intra-day trades. Therefore, in order to compensate for this loss, the gain from the inter-day trade needs to be of sufficiently high value, implying a larger price differential.

The fact that the majority of storage value lies in the 1-day horizon is also indirectly supported by the energy capacity sensitivity analysis in this thesis; in a highly volatile market, large energy capacities tend to be underutilised, as long and sustained periods of low and high prices (or vice-versa) are uncommon. Consequently, charges and discharges occur frequently, which as a result causes the SOC to remain low. Therefore, in a volatile market, there are greater intra-day arbitrage opportunities wich, in turn, favours shorter optimisation horizons. The preference for a 1-day optimisation horizon implies that the accuracy of price forecasts is most valuable on the day ahead.

Nevertheless, a longer horizon increases energy capacity utilisation by charging as much energy as possible on the lowest price and discharging as much energy as possible at the high price. Since longer horizons offer larger price differentials, the optimisation model prioritises these prices. Thus under longer horizons, capacity is better utilised and however, caution should be exercised so as not to oversize the storage system if it is to operate under short optimisation horizons.

An investigation was carried out on whether an increased wind penetration could change this result, that is, whether scaled wind output would make a stronger case for having longer optimisation horizons. The results showed no significant impact of wind output on the trend in optimisation horizons; most of the arbitrage value still lies largely within the 1-day horizon. In order to shift value from the 1-day optimisation to a longer one, wind output should be persistently high and low, and these should occur on a regular basis. Furthermore, those high and low wind periods should be separated by a least 1-day. While high and low wind persistence do occur occasionally, these do not occur on a consistent basis to warrant longer optimisation horizons. In fact, scaling wind increases price volatility which is as explained earlier justifies using shorter energy capacities (in addition to generating more revenues).

## 8.9. Impact of revenues on the choice of storage technologies

Revenues ultimately determine the economic feasibility of storage systems. An investment appraisal was carried out for six storage technologies; these differed in terms of capital cost of power and energy capacities, operation and maintenance costs, round-trip efficiencies and lifespan. Comparatively, PHES was shown to be the most profitable of the technologies, arising due to much longer lifespan than the rest. Conversely lithium-ion batteries, despite having a very high round-trip efficiency were shown to have the lowest negative NPV of all, arising due to a combination of high capital costs and short lifespan. Under co-optimised operation, lithium-ion batteries had a lifespan of approximately 10 years. The result thus highlighted the importance of lifespan on economic feasibility; it is critical that the storage system lasts for a sufficient length of time to recover its costs. Like Lithium-ion batteries, VRB was not profitable; the economic feasibility of storage by technology echoes the findings of Bradbury et al., (2014). They showed that PHES and CAES are they most profitable technologies, across several US markets whereas Lithium-Ion and VRB are the worst performers with negative NPVs in almost all cases.

The profitability of CAES and AACAES was due to their relatively lower capital costs; these technologies evolved from gas power plants which decouple compression and expansion. The addition of thermal energy storage for AACAES renders the latter less profitable than CAES. However, CAES requires natural gas costs as input; an increase in gas prices should reduce profits, however Sioshansi et al., (2011) showed that these are usually attributed to higher electricity prices and hence also generate higher arbitrage revenues in the PJM market.

While the choice of setting energy capacity at 6 hours' equivalent stems from the results in Chapter 5 in figure 5.12, which shows that the maximum revenues are reached around the 6-hour mark, it is important to stress this does not represent the optimal size for overall profitability as capital costs have not been taken into account in optimising revenues but rather included post-optimisation for the NPV calculation. Therefore, a revenue maximising approach rather than an NPV maximising approach was undertaken. This approach is consistent with the focus of this thesis which is on the market revenue potential rather than the feasibility of specific technologies. However, this distinction highlights the fact that a revenue-maximising storage configuration (in terms of power and energy capacity) is not necessarily equivalent to an NPV maximising one.

This difference arises because revenues show a diminishing return trend with increases in energy capacity, seen earlier from figures 5.12 and 6.10 and thus, the difference in capital costs of storage technologies means that the optimal profit maximising size will differ accordingly. For example, for storage technologies with energy capacity capital costs a smaller energy capacity is preferable. The NPV results in this thesis cannot be used to determine absolute profitability of a technology for the reasons above. However, precisely because the power to energy ratios have been kept the same across technologies, the results rather show relative profitability instead.

Finding the NPV-maximising size of energy storage would change an MILP problem to an MINLP problem and require a change in the co-optimisation model. The model would no longer be linear as changes in power and energy capacities affect not only the decision variables (charging and discharging) but also the revenues and costs. Additionally, the NPV results are critically sensitive to the cost inputs, especially capital costs. Therefore, high quality cost data would be such as accurate costs relating power capacity, energy capacity as well as variable and fixed operating costs. The cost values found in the literature show substantial variations as shown in table 4.1, and therefore an investigation into the optimal sizing of energy storage would be more meaningful in the presence of more robust cost values.

The profitability of each storage technology can be expressed as the gap between current capital costs and break-even capital costs. Break-even capital costs are calculated as the level capital costs at which the project recovers all of its investment. At present, the technology with the largest gap between the current cost and break-even capital costs is lithium-ion batteries. These findings highlight the fact that current market revenues still largely favour the conventional PHES and CAES technologies. However, the aggregation of further benefits such as network investment deferral could change the economics since there is a large potential for additional value in GB, especially in the future Strbac et al., (2012). However, there are restrictions on ownership of generation class assets by network operators Anuta et al., (2014).

From a break-even capital cost perspective, two major forces can improve the economics of energy storage. Firstly, manufacturing and technological advances can improve the performance parameters of the system, such as efficiency, lower maintenance costs and longer lifespan. Mass production where possible could also reduce capital costs. Secondly, the market themselves may provide additional revenues, whether arising from restructuring to allow for the aggregation of benefits or the changes that are likely to come on the system (increased demand, wind, uncertainty…etc.).

Locatelli et al., (2015) found that under arbitrage revenues and revenues from the provision of STOR, none of the three technologies investigated, namely PHES, CAES and AACAES were profitable. These losses arose, in the presence of significant limitations in the model design. Chapter 7 findings show to the contrary that PHES, CAES and AACAES can be profitable.

## 8.10. The impact of wind on storage value

An investigation of the effect of wind on revenues required an econometric analysis of the APX and BM prices. In the APX market, the most influential variables on price are reflective of the merit order of generation; peaking plants have stronger effects, followed by mid-merit plants while nuclear power generation have a very weak but positive impact on the spot markets. Wind on the other hand showed a negative but statistically significant coefficient, implying wind generation tends to reduce prices. The econometric regression in the BM shows that the most influential variables on the imbalance prices are OCGT, NIV, APX price and OIL.

The negative effect of wind power on APX market prices conforms to economic dispatch; wind turbines are generally capital investment heavy and have low variable costs. As a result, they are dispatched first and if they have further financial incentives to generate, they can even bid at negative prices.

Two model results are presented, the Autoregressive(AR) and the Static(ST) model; the AR model downplays the role of wind whereas the ST model possibly overestimates its impact. However, under both models, the effect of wind on prices is negative. While the effect of wind on prices is clear, the impact for storage is not; revenues could increase or decrease. A 20 GW wind penetration scenario was simulated from 2011-2014 using scaled wind data and the results show that in the APX market, revenues increase under both models. In the BM, however, the picture is not as clear; under the AR model, revenues fall for 2011 and 2013 whereas under the ST model, revenues increase for all years. The fall in storage revenues in the Balancing Mechanism occurs due to the additional pathways for wind to affect imbalance prices such as the net imbalance volume. Hence wind has a more pronounced negative effect on prices in the BM compared to the APX market, as sections 7.3.4 and 7.3.5 showed.

Under a 20 GW wind penetration discharge volumes increase throughout the four years, across both the APX market and BM, and across both price models. Hence there is clear evidence that scaling the wind output makes new arbitrage trades possible as previously infeasible trades now become feasible due to a larger price differential. These are low-value arbitrage trades. High-value arbitrage trades which consist mainly of the difference between peak and off-peak prices can increase or decrease. Thus the true impact of wind depends on the interaction of two effects; the net impact of wind on low-value arbitrage trades and the net impact of wind on high-value arbitrage trades.

Under co-optimisation, revenues increase slightly under both the AR and ST model, with FFR revenues increasing due to the increase in availability payment assumed. Much larger changes are seen in storage operation in each mechanism in practice, it means that businesses are able to adapt to more easily to increasing wind penetration under a multi-market business model than the single market business model. While these findings are confined to GB markets, these are likely to hold true in other geographical regions due to the fact that a single market business case is a subset of a multi-market one.

Kloess & Zach (2014) showed a declining storage revenue from 2007-2011 from Austrian and German markets; they put forward the hypothesis that increased solar power reduces the prices during the day and hence likely affect peak prices to a certain extent. Meanwhile, the GB system has experienced remarkable solar power growth over the past few years. While this thesis showed that the impact of wind on storage revenues is positive, the impact of solar may be very different and thus represents an avenue for future work.

## 8.11. The identification of specific drivers of storage value

A number of specific mechanisms driving storage value have been identified; generally, some arbitrage trades can be identified as high-value trades which depend on the time of day trend, such as peak and off-peak prices. On the other hand, low-value trades can occur at any time, as long as there is a sufficient price differential; these have the characteristic of being more frequent in a volatile market. High-value trades also have the characteristic of being generally more predictable (off-peak to evening peak arbitrage, off-peak to morning peak arbitrage) and this is precisely why Sioshansi et al., (2011) found that smaller energy capacity storage systems perform better in the absence of perfect foresight.

As they explain, larger energy capacities need to capture the low-value arbitrage trades, which are much harder to predict.

When the impact of efficiency on revenues was analysed, it was these high and low-value trades which were affected; a pure efficiency gain affected all existing arbitrage trades (both high and low-value trades) but a feasibility gain created a number of new low-value trades. The creation of low-value trades proved to be a major driver of revenues. A similar sensitivity to low-value trades was found in Chapter 7 when exploring the impact of wind on storage revenues; the creation of new low-value trades and their associated revenues mostly exceeded the reduction (if any) of high-value trade revenues.

The difficulty in predicting those low-value trades raises further questions as to the extent to which these additional low-value arbitrage trades can be captured. Thus, while the results show that additional value is present under increased wind penetration, the ability to capture such value is uncertain and likely to depend on forecasting accuracy. These, together with other limitations are discussed further in the next section.

## 8.12. Limitations and scope for further work

In investigating the operation of energy storage in the markets, for the most part, a technology neutral approach has been adopted. A more elaborate model could capture omitted complexities such as the non-linearity in self-discharge, round-trip efficiency and optimal cycling depth for batteries for example. These would have a particular influence on the results of Chapter 6, whereby an NPV analysis for each technology was carried out. Lithium-ion batteries were assumed to have a lifespan equivalent to 5000 full cycles; in reality, it is unlikely that they would be cycled to such depths. Since this thesis has shed light on the market mechanisms and the effects driving storage value, further work could thus merge ongoing research on the optimal storage system control with market revenue optimisation.

Similarly, some aspects relating to the construction and deployment of these technologies have not been considered; while the results show that the traditional PHES and mature CAES systems are the most viable economically, the technical feasibility of building such systems is drawn into question and additional costs such as transmission and/or distribution connections should be factored in the end result. An aggregation of smaller storage devices, such as domestic behind the meter lithium-ion batteries, could provide the 50 MW of capacity assumed in the model, however, their economic feasibility could be different when additional values are taken into consideration such as the network investment deferral.

Earlier in section 4.13, one of the limitations of this thesis is the fact that the indirect impact of additional wind power on other forms of generation is not considered. Another limitation relates to the price taker assumption, due to the small scale of the storage system relative to the market mechanism volumes. On one hand, storage discharge during peak time could reduce prices (Denholm & Sioshansi 2009; Nyamdash & Denny 2013) while on the other hand low wind conditions during the same period are likely to lead to higher prices as peaking plant generators submit higher bids (unless displaced). It is not known to what extent these effects mitigate each other and therefore highlight the need for further work in this area.

National Grid offers a wide array of services, and the criteria for choosing FFR and STOR as ancillary services was based on the mostly highly utilised services. It is acknowledged that there is potential for a slightly higher revenue for the FFR revenues in the single market model as the provision of high-frequency response was not considered in this study. The provision of high-frequency response usually generates slightly higher availability payments and may thus generate additional revenues. However, the high-frequency response service has a lower utilisation payment compared to the low-frequency response service. Therefore, it is not considered that the inclusion of the high-frequency response service in the co-optimisation model would bring about significant changes in the total revenues.

Throughout much of this thesis, a best-case scenario approach was used to evaluate the maximum value energy storage could derive. Thus, in order to investigate the maximum revenue potential in the markets, simplifications were required such as a perfect foresight assumption in the APX market and BM, and the ability to choose any FFR window of any length under co-optimisation. In reality, the knowledge of prices ahead would be limited whereas FFR windows would have to be agreed in advance; the relaxation of these assumptions was explored in Chapter 6 with backcasting strategies and a fixed dispatch schedule of storage operations. It should be stressed, however, that these strategies are examples of more realistic strategies and not optimal ones. Therefore, there could be potential for higher revenues than those derived under these strategies and represents an avenue of further research.

Additional avenues for storage value are emerging; National Grid is currently procuring frequency response with faster response time, known as Enhanced Frequency Response (National Grid 2015c). The recent Energy Market Reforms created a market mechanism for the procurement of system capacity for the purpose of raising system margin. Thus there is potential for storage to provide other ancillary services, however, these are unlikely to bring dramatic changes– the addition of more ancillary services to the co-optimisation model becomes limiting as these revenue mechanisms are very similar to each other and hence a choice between them has to be made, effectively running into diminishing returns.

An important consideration in the BM is the acceptance of bids/offers; National Grid accepts these in order to reduce the imbalance volume. However, there is no guarantee that a bid/offer will be accepted; the likelihood of having a bid/offer accepted depends on the bid/offer prices as National Grid will choose to balance the system at the lowest cost. The BM model assumed that the storage would charge on SSP and sell at SBP. These system prices are calculated from the average of accepted bids/offers, however since bids/offers are usually placed ahead of the BM opening, strategic bid/offer placement is required, akin to forecasting in the APX market. Similarly, securing a long term FFR contract with National Grid is not guaranteed; monthly tender round results have shown that some tenders have been accepted/rejected based on the frequency response requirement of National Grid. Furthermore, the awarded tenders range from 1-18 months, an uncertainty not considered in this research. Hence there is scope investigating business cases for storage in the presence of uncertainty associated with short-term contracts together with the recent creation of additional ancillary services.

In this thesis, many of the results have been derived under limitations in data access; for example, wind and other types of generation have been obtained from National Grid and Elexon and represent power flows at transmission scale. It is important to recognise that as generation at the distribution level, known as embedded generation, grows the approach taken to produce some of the results would not be appropriate. Obtaining embedded generation data can be more challenging for reasons such as confidentiality. Similarly, the lack of data on transmission constraints and other aspects of power flows limited the ability of the regression models to fully depict the relationship between prices and other variables.

The econometric approach undertaken to investigate the impact of an increased wind penetration scenario on storage revenues showed that despite several different model specifications, there was evidence that the chosen variables still generated substantial residual errors. The results highlighted the possibility of some missing variables as mentioned in the previous paragraph. It is speculated that data on system constraints and embedded generation, which were not available, could improve the model fit. The true effect of wind lies in between the results found by the AR and ST models presented and more sophisticated techniques in the field of econometrics could be applied. Alternatively, data mining techniques could be applied to the current data as well as future data to reveal further patterns.

In order to investigate the impact of a 20 GW wind penetration on the system, existing wind generation was scaled according to installed wind capacity for each of the years from 2011-2014. Conceptually this would imply that the additional wind turbines were installed at existing wind farms during those years such that the same weather conditions are experienced. If these wind farms are geographically spread, a wind scaling to the expected wind capacity in 2020, as a simplification may not cause substantial distortion of results. However, using existing wind generation data to extrapolate a 20 GW wind penetration scenario implies that the ratio of onshore to offshore wind farms remains unchanged, which may not be true as offshore wind power is expected to increase more than onshore wind power. If they are characteristically different, the results can only be extended to onshore wind generation. The location of the additional wind farms thus determines the extent the wind profile output is changed and represents an area for further improvement. Additionally, wind forecast errors were assumed to follow a distribution similar to those in Germany and Spain as they reached a 20 GW wind penetration level approximately. While the tendency for lower forecast errors in relative (%) terms have been shown by Hodge et al., (2012) for these two countries, the distribution of wind forecast errors in GB as wind reaches 20 GW is unknown and will dependent on a large number of factors such as location.

Finally, the extent to which the findings in this thesis can be generalised depends on their dependence on the GB market structure. The impact of a higher wind penetration on storage value depends heavily on actual GB market characteristics; the relationship between wind and price was derived statistically from GB market data then using GB wind output, scaled accordingly. Nevertheless, the mechanism behind the impact of wind on storage value can be generalised; namely, the impact of wind on low and high-value arbitrage trades determines the net effect on storage revenues. Similarly, other results such as the resilience of co-optimisation models compared to single mechanisms, are universal because they are grounded mathematically and do not depend on GB markets.

# Chapter 9. Conclusion

## 9.1. Storage value in single revenue mechanisms

This thesis aimed at quantifying the value of electricity storage under a 'best case scenario' across three types of mechanisms; a wholesale market, balancing mechanism and an ancillary service. The investigation of storage revenues across three types of market mechanisms showed that in the APX market, roughly £55/kW-yr was earned in 2013. In the BM, this was substantially higher at £82/kW-yr. The BM thus showed greater potential for arbitrage due to its penalising method of imbalance price calculation. Revenues associated with the provision of ancillary services, in this case, FFR and STOR, generate most of their revenues from availability payments due to their low utilisation rate. However, the provision of FFR generated slightly more revenues than the provision of STOR. While the ancillary services revenue is substantially less than the arbitrage revenues, they could be appropriate for storage technologies with limited cycling life.

## 9.2. Operational characteristics of a storage system within each mechanism.

Charge and discharge patterns in the APX market were identified; broadly two periods of discharge are of interest – the morning and evening peak periods (corresponding to prices spiking). The relative magnitude of those peaks were shown to vary seasonally with the evening peak generally being greater in the colder months whereas in the warmer months, the morning peaks tends to be greater instead. In turn, these have implications for the operation of storage under optimisation; while charging patterns are not substantially affected by seasonal changes, discharging patterns are – morning discharge pattern is spread in winter and dense in summer.

Compared to the APX market, energy storage operations in the BM share some similarities as prices in both mechanisms are correlated. During peak demand, prices tend to be higher in the APX and BM irrespective of system imbalance. A clear difference, however, is the volatility of prices in the BM which was much higher in the latter than in the APX market, arising for reasons explained earlier in Chapter 3. Another similarity which both mechanisms share is a transitionary effect occurring as the seasons change; it was shown, in sections 5.2 and 5.4, that evening peak prices tend to occur later in the day from winter to spring by the summer months they are very much smaller in magnitude and spread during the early evening hours. Additionally, by comparing the charging and discharging frequency across the APX market and BM, it was evident that the storage system is idle for a greater proportion of time in the former than in the latter. As a result, there is better utilisation of the storage system's energy capacity in the BM.

Unlike in the APX market whereby arbitrage occurs across a single price, in the BM, due to the presence of 2 system prices, cross system price arbitrage was shown to be an additional pathway to generate revenues, which substantially increased the total revenues. This distinct form of arbitrage however is dependent on the System Operator's acceptance of bids/offers and furthermore as of November 2015, this is no longer possible as dual prices have been abolished in favour of a single imbalance price.

The third avenue of revenues explored was ancillary services, in particular, 2 services – FFR and STOR. Due to the nature of these ancillary services, the storage system was on standby for most of the time and its services were called on occasionally. The revenues generated therefore were largely from availability payments rather than utilisation payments. For the provision of FFR, the choice of windows is essential to maximising revenues; The choice of a 12 hour fixed FFR window was shown to be optimal when the system is allocated to charge from 3am-3pm and provide FFR from 3pm-3am taking into account electricity costs and a utilisation payment scaling factor. Otherwise, revenues could fall by over 60%, highlighting the importance of choosing the best windows to offer FFR. Comparatively, although the utilisation payment for STOR is much higher than that for FFR, the total revenues are very similar due to the fact that the services are not frequently called on.

## 9.3. The impact of round-trip efficiency, power and energy capacity on revenues in single markets.

A sensitivity analysis of revenues to efficiency was carried out in the APX market and the BM; both showed a more than proportionate change resulting from an efficiency change. Two mechanisms driving this relationship were identified; an efficiency gain effect affecting all existing trades and a feasibility gain effect arising from the creation of new low-value arbitrage trades. These low-value trades occur frequently and drive a large proportion of total revenues. Energy capacities above 6 hours were not justified (assuming a 1-day optimisation horizon), since, by that point, 98%-99% of maximum revenues were captured in both the APX market and BM. This conformed to the findings in other studies for other countries (Sioshansi et al. 2009; McConnell et al. 2015).

## 9.4. The choice of optimisation horizons and its impact on arbitrage revenues.

As opposed to the arbitrary choice of the optimisation horizon length in previous studies, in section 5.9, a 1-day, 2-day, 1-week and 1-month optimisation horizon were investigated, showing that a 1-day optimisation horizon earned over 93% of maximum revenues and diminishing returns occurred with longer optimisation horizons.  Diminishing returns occurred because although longer optimisation horizons offer potentially greater price differentials between the charging price and the discharging price, the fact that the storage system has to store energy during longer periods comes at the cost of the other arbitrage opportunities sacrificed in the process. Eventually, it would be more profitable to perform a number of short-term arbitrage trades rather than wait for a long period for a high value arbitrage trade. There is a further argument against longer optimisation horizons; a longer period of price foresight, which is required under longer optimisation horizons, is improbable and also computationally more intensive for an MILP model. There is, however, some merit for longer optimisation horizons; they enable a greater utilisation of power and energy capacities.

## 9.5. Storage operation under co-optimisation: benefits and synergies.

This thesis also investigated the difference in both storage operation and revenues when participation is confined to a single revenue mechanism or extended to multiple revenue mechanisms simultaneously. In Chapter 6, an integration of the revenue streams was carried out through a co-optimisation model. Further to this, market constraints were imposed in terms of trading volume and imbalance volume for the APX market and BM respectively. The constraints had a negligible effect on APX revenues but substantially reduced BM revenues, by over 42%. Under a co-optimisation model, however, many of these constraints were overcome through cross-market arbitrage as well as allocating capacity to FFR provision. With market constraints, co-optimised revenues only fell by 6% but participation in the APX market increased by 20% while FFR participation increased by 12%. This highlighted the flexibility of the co-optimisation model to adapt to restrictions in particular markets and compensating by increasing participation in others. The resilience of the co-optimisation model is not only confined to market constraints but also annual variability; in a similar fashion, the co-optimisation model compensates for substantial revenue losses in on mechanism by allocating more operations in another, thereby limiting the reduction in total revenues.

Scheduled operations under the co-optimisation model were shown to have further benefits; FFR windows are allocated to periods where storage is idle, usually waiting for the morning or evening peak prices. Furthermore, any residual energy not used for the provision of FFR can be discharged later for additional revenues. Thus, under co-optimisation of revenues, the windows which are been consistently for the provision of FFR corresponded to 21:00-23:30. Additionally, mid-day periods between 13:00-16:00 show potential for FFR windows. In the morning, windows between 8-10 were frequently allocated as well. The synergies between FFR and the other revenue mechanisms do not stop there; energy stored for the provision of FFR, if not utilised, can be further discharged, generating revenues.

## 9.6. A comparison between the impact of storage parameters in single vs multiple markets.

Similar to the case whereby storage operations are confined to single revenue mechanisms, a sensitivity analysis was carried out for the co-optimisation results. Revenues were highly responsive to changes in efficiency. Compared to single market operations, a slightly smaller energy capacity of approximately 4 hours is preferred under co-optimisation, as more trade opportunities become available and hence storing energy for longer periods becomes less necessary. There are clear arguments for favouring power capacity over energy capacity; revenues increase almost linearly with power capacity increases under co-optimisation. Within the 50-500 MW range explored, this almost linear relationship occurs as additional capacity is offered for the provision of FFR and also provides the storage system with the ability to utilise this extra power capacity to charge and discharge at price extremes. Energy capacity, on the other hand, shows diminishing returns and energy capacities over 6 hours are hard to justify. The preference of shorter optimisation horizons also reinforces the notion that small energy capacities are preferred as most of the value lies in the intra-day arbitrage. Under market constraints and under a co-optimisation model, power capacity is more easily accommodated than energy capacity; power capacity takes a greater advantage of large price differential and excess capacity arising from market constraints can be offered to the provision of FFR.

## 9.7. Alignment of system benefits under a revenue maximising regime

The market mechanisms are effective at generating signals for storage operation to align with system benefits; in the APX market, storage was shown to alleviate peak demand whereas in the BM imbalance volume is always reduced (when market constraints are imposed). Under co-optimisation, however, these do not always occur and conflicts occur. For example, given an imbalance in the BM, the storage system may be faced with a situation whereby aggravating the imbalance may be financially beneficial as long as the APX market can provide sufficient compensation. These have potential implications for policy makers.

## 9.8. Lifetime economic feasibility of energy storage technologies

Under the revenues generated under co-optimisation, four out of six storage technologies were found to be potentially feasible (under assumed parameters), using an annualised rate of return approach. PHES, CAES, AACAES and Fe-Cr flow batteries were shown to generate total revenues which exceed total costs, over their lifespan. Lithium-ion batteries and VRB on the other hand did not. PHES was shown to be the most profitable due to the long lifespan, relatively high efficiency and low capital costs. Lithium-ion batteries on the other hand, despite having the highest efficiency, had the shortest lifespan and high capital cost, and as a result was the least profitable. At a 5% discount rate, Fe-Cr flow battery was no longer economically feasible. Two major forces can change the economics of energy storage – one of them is the manufacturing and technological advances which raise efficiency, reduces variable costs, prolongs the lifespans and reduces capital costs. The other is regulatory and policy changes which allow the aggregation of benefits.

The revenues generated by the storage models should be regarded as the theoretical maximum as in practice conditions would be less favourable. For example, the participation of storage may have further impacts on the prices which in turn affect these revenues. Furthermore, the results from the NPV analysis show the disparity between technologies in terms of relative profitability and these values should not be interpreted indicative or representative of actual absolute profitability. This is because the power to energy ratio were not optimised for each specific technology which is compounded by the fact that a '*best-case scenario'* approach was taken to evaluate revenues.

## 9.9. The relaxation of the perfect foresight assumption and the performance of simple strategies in capturing revenues.

Using the results from the co-optimisation model, and in the absence of perfect foresight, a fixed dispatch schedule was derived based on averages. Under this approach, the storage system is set to operate as follows: Charging occurs during the first 7 hours of the day, followed by a 2-hour FFR window. Over the remaining 15 hours, the system discharges for 4.5 hours, offers a 3-hour FFR window, discharges again for 5.5 hours, offers a 1-hour FFR window before finally discharging all residual energy over the last hour. Such an allocation takes into account the low prices in the early hours of the morning, morning peak prices, idle periods for storage operation whereby FFR service can be offered and the evening peak prices. This co-optimisation derived strategy and backcasting technique captured 52%-62% of maximum revenues under perfect foresight. Fixed dispatch strategies based on co-optimisation have a similar performance, in terms of revenues, to backcasting techniques. Using different backcasting lags, it was shown that short-term persistence effects are not sufficiently strong to warrant a 1-day backcasting lag since at this point weekday-weekend discrepancies reduce revenues to a greater extent.

In Chapter 6, the contradictory findings of Sioshansi et al., (2011) and McConnell et al., (2015) on the effect of imperfect foresight on the choice of storage energy capacity were also investigated. It was shown that there is a negative relationship between energy capacity and realisable revenues under imperfect foresight, further supporting the findings of (Sioshansi et al. 2011). Optimisation models are particularly sensitive to extreme prices and hence a distortion of results can occur in their presence.

## 9.10. The impact of a high wind penetration scenario and other variables on the markets.

This thesis also investigated how storage value changes under high wind penetration. In order to do so, an econometric analysis was carried out to isolate the wind impact on the market prices. Econometric analysis shows that the most influential variables on the APX half hourly spot market price are reflective of the merit order of generation; peaking plants have stronger effects, followed by mid merit plants while nuclear plants as baseload generation have a very weak but positive impact on the spot markets. Wind generation is associated with a negative but statistically significant coefficient, implying wind generation tends to reduce prices.

Besides the independent variables, the time of day itself was shown to have a direct effect on the prices due to the bidding behaviour of parties, as the types of generation have already been accounted for. This time of day effect, strongly reflects the average price curve along the day; the effect is strong and positive at peak time, weak at off peak times and strong and negative during mid-day, reflective of bidding behaviour of parties.

## 9.11. Storage revenues under a high wind penetration scenario.

Two econometric model results are presented, the AR and the ST model; the AR model downplays the role of wind due to strong autocorrelation whereas the ST model possibly overestimates its impact due to omitted variable bias. While the results from both econometric models show a clear depression of prices under a 20 GW wind penetration scenario, storage value under higher wind penetration is unclear and relies on the timing of wind generation. Thus, a greater depression of peak prices relative to off-peak prices would reduce storage value and vice-versa. Average wind data shows a wind pick-up effect during the day effectively reducing peak prices to a greater extent than off-peak prices, implying that storage value, under a high wind penetration scenario, should, in principle, fall. However, from the co-optimisation results derived under the same scenario, storage revenues increased. Under a high wind penetration scenario, an increased volatility was shown to prevail due to the direct impact of wind on the prices. However, further volatility could occur as market participants adjust their behaviour to both storage operations and the increase in wind generation. Hence it is worth pointing that the values found in this thesis are subject to this complex interaction.

## 9.12. Identifying positive and negative impacts of wind generation on storage value.

An investigation revealed that a higher wind penetration was generating higher volatility to such an extent that new arbitrage opportunities were created and on the whole compensated for the slight depression of peak prices during the day. The increase in total revenues were relatively small due to the small impact of wind on prices. This is particularly true for the APX market but in the BM, where other pathways affecting the imbalance prices: wind has a direct effect on the APX price which is correlated with imbalance price. Furthermore, an increase in wind forecast errors affects the imbalance volume which in turn affect the imbalance price. Additionally, the displacement effect of wind on the peak generation reduces imbalance prices. Under these additional pathways, the impact of wind power is stronger and a scenario of increased wind penetration does not always increase revenue in the BM, falling for 2 of the 4 years explored under the AR model.

In the co-optimisation mode, due to the cross-market arbitrage ability, new arbitrage opportunities are created. Much larger changes are seen in storage participation in each mechanism; the co-optimisation nature of the model means that, depending on the annual variation and the wind impact scaling, participation in some mechanisms is reduced in favour of others. However, increases in revenues do not always occur as a result of increases in discharge volumes; in some market mechanism, a decrease in discharge volume sometimes arises but nevertheless revenues overall increase. In those cases, the wind impact had a stronger effect on the high value arbitrage trades but many low value trades became infeasible. Thus the true impact of wind depends on the interaction of two effects; the net impact of wind on low value, but large volume arbitrage trades and the net impact of wind on high value but small volume arbitrage trades. Since the assumption of perfect foresight was maintained for the high wind penetration scenario analysis, it is important to point out that forecasting prices under such a scenario may be more challenging. This implies that while the potential for increased revenue exists the ability to capture these additional revenues may be reduced and hence in practice realisable revenue may fall. Furthermore, indirect impacts of an increase wind penetration on other forms of power generation could result in an increased price volatility as explained earlier in section 4.13 – these are not considered within the scope of this thesis but nevertheless represents an important aspect.

## 9.13. Concluding remarks

This section describes how the findings represent important advances in our state of knowledge. At the beginning of this thesis, the potential value for energy storage in GB was relatively unknown, despite a number of studies in international markets. Three types of market mechanisms were investigated; The Balancing Mechanism showed the potential for greatest revenues followed by the short-term wholesale market and the ancillary services, FFR and STOR. While network investment deferral is a substantial benefit of storage, due to its lack of monetization, the above finding is of particular relevance to private firms, looking towards to the market to generate revenues. Therefore, the scale of potential revenues in these market mechanisms has been presented.

In order to capture these revenues, the required storage operations were identified through optimisation models, highlighting some important cyclical patterns. Simple strategies (in the absence of perfect foresight) were evaluated to investigate the extent to which the revenues could be more realistically captured. This approach is of particular significance as the knowledge of how to operate a storage system based on price signals and payment schemes is a vital component of the revenue generating process. This thesis has thus shown the maximum potential for revenues across several market mechanisms in GB as well as the extent to which these can be captured using simple strategies.

In recent years, there has been a great emphasis on aggregating storage revenues, sometimes referred to as '*revenue stacking*'. Apart from the potential for higher revenues, previous work have placed little focus on the other benefits of co-optimising revenues across mechanisms. In fact, in this thesis, it has been shown that, besides maximising revenues, there are important benefits for choosing a co-optimisation model; The latter is more resilient to annual variability and volatility from additional wind generation. A co-optimisation model also reduces the need for greater capacities in a storage system and creates synergies across mechanisms. Nevertheless, this model has some drawbacks such as its computational complexity and the requirement for more accurate forecasts.

The relative importance of some storage parameters in GB markets was also explored, such as round-trip efficiency and energy capacity. An understanding of how these parameters affect market revenues is essential when choosing the storage technology. Furthermore, since their relative performance of in the markets determine the high-value parameters, storage technology manufacturers may choose to focus their efforts on these parameters.

Recently, there has been a substantial amount of work exploring the role of storage under a high renewable energy penetration future scenario and this includes the aspect of storage value. However, these works have mostly taken either a whole-system approach or a configuration whereby storage is coupled with wind rather than explored how the market themselves will be affected, and how these in turn affect storage value, particularly in GB. Chapter 7 addressed this issue and described the interaction between the positive and negative impacts of wind generation on storage value. Hence, the findings above provide a useful basis in assessing the potential viability of a storage system in Great Britain, both at present and in a near future of high wind penetration.

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# Appendices

## Appendix A.1 – The Balancing Mechanism bids and offer acceptance

Bids have a corresponding bid price representing the price at the party is willing to pay in order to decrease its generation or increase demand and similarly offer prices reflect the price the party would like to be paid for an increase in generation or decrease in demand; negative bid prices are possible, that is, a party would rather want to be paid to reduce its generation or increase demand(Elexon 2013b, p.10).

BMUs usually submit bid-offer pairs as "*an undo mechanism*" for acceptances(Elexon 2013b, p.10) . Figure A1 shows an example of bid-offer pairs of a fictitious BMU.

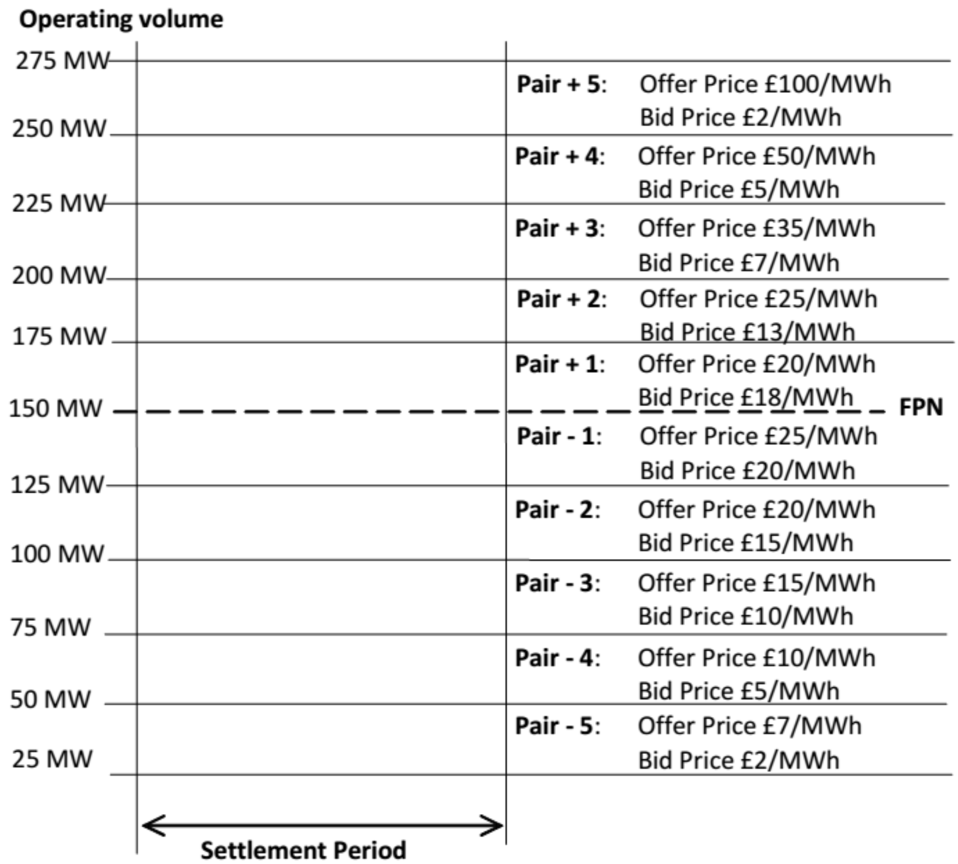


***Figure A.1*** *shows the bid-offer pairs from a BMU to follow an instruction to deviate from its FPN.*
*Source:* (Elexon 2013b)

For example, in figure A1, an instruction to the BMU to reduce output from its FPN level at 150 MW to 125 MW would cost the party (owning the BMU) £20/MWh. If this bid is accepted by the SO who later decides to reverse this decision, the offer price of £25/MWh will be paid to the party. In general parties submit 5 pairs of bids and offers in the balancing mechanism. Accepted bids and offers are known as Bid Offer Acceptances (BOAs) (Elexon 2013b, p.11).

### Energy Balancing, System Balancing & Flagging

In order to balance the system, the SO can utilise BOAs or take action outside of the BM, known as balancing services adjustment data (BSAD). BSAD consists of two components: Balancing Services Adjustment Actions (BSAA) which consists of(Elexon 2013b, p.11):

- Forward Contracts such as:
    - Energy Related Products
    - Pre-Gate Closure Balancing Transactions (PGBTs)
    - System-to-System services
- Maximum Generation
- System to Generator Operational Inter-tripping
- Emergency de-energisation instructions

The other component of BSAD is Buy Price Adjustment (BPA) or Sell Price Adjustment (SPA) which consists of long term contracts for services at the disposal of the SO such as Short Term Operating Reserve (STOR) and Balancing Mechanism start-up. BPA and SPA are also added to the net imbalance volume depending on the state of the system, i.e. long or short.

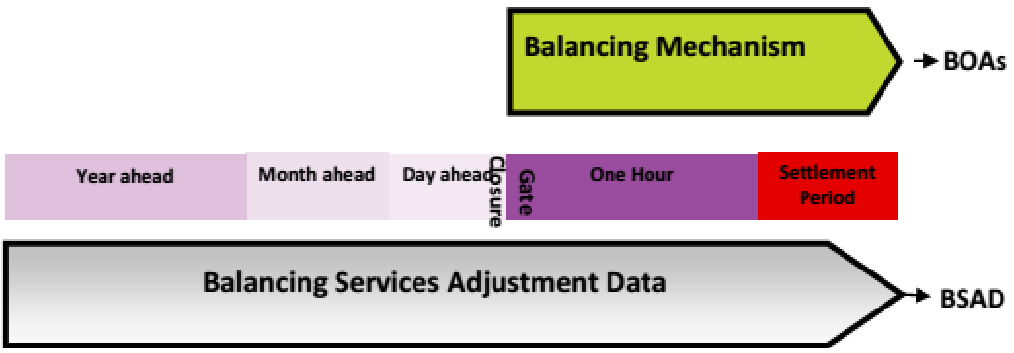


***Figure A.2*** *shows the timescales for BOAs and BSAD; BOA's are undertaken within an hour preceding delivery whereas BSAD actions can be undertaken at any time. Source:* (Elexon 2013b)

The purpose of the BM is to resolve energy imbalances primarily due to the difference between half hourly demand and supply under a business as usual scenario. Occasionally however the SO may be required to take action to protect the physical system, this irrespective of the parties' positions. These actions taken are distinct from energy balancing actions and termed system balancing actions.

Potential system balancing actions are flagged, examined and if confirmed to be system balancing, their prices but not their volume are removed (or tagged) from imbalance calculations.

Actions are flagged and tagged as system balancing for several reasons:

- De-Minimis flagging whereby volumes smaller than 1 MWh are removed.
- Arbitrage tagging whereby the SO can make a profit from accepting bids and offers but does not change the overall energy imbalance.
- SO-Flagging whereby actions are taken by the system operator to maintain system security.
- Continuous Acceptance Duration Limit (CADL) flagging whereby short duration actions usually less than 15 minutes are flagged as system balancing.

**Net Imbalance Volume**

At any given period, the SO can accept both bids and offers but generally it will accept more offers than bids when the system is short and the reverse is true when the system is long.

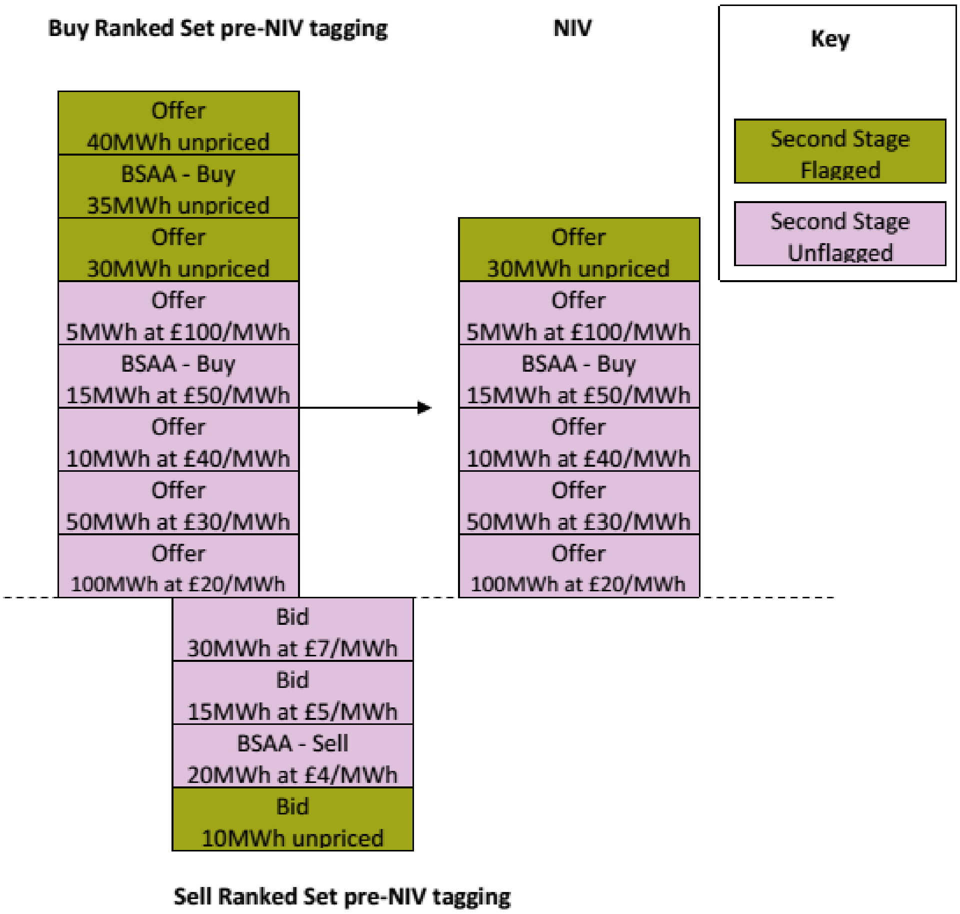


***Figure A.3*** *shows how NIV is calculated after the flagging and tagging process has taken place.*
*Source:* (Elexon 2013b, p.38)

In the example shown in figure A.3, the NIV is equal to 210 MWh which means the cost and the volume of all the net offers will be used to calculate the system prices, in the case the System Buy Price.

# Appendix A.2 Distribution of NIV

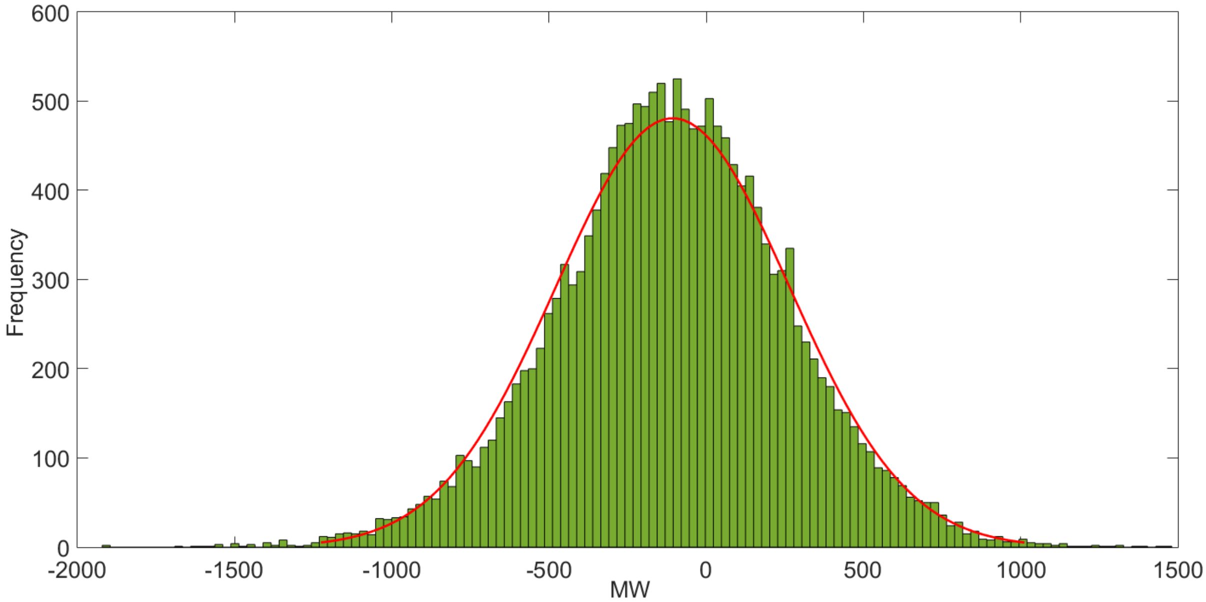


***Figure A.4** shows that NIV almost follows a normal distribution in 2013.*

The half hourly distribution of Net Imbalance Volume in the Balancing Mechanism is shown in figure A.4. The distribution appears to be normal with a tendency to have a greater proportion of negative NIV, representing system excesses. Under the imbalance pricing method, it is preferable to contribute to a system excess rather than a system shortage as the in the former, the party gets paid at a price below market price whereas in the latter case the party will be charged at a price above market price.

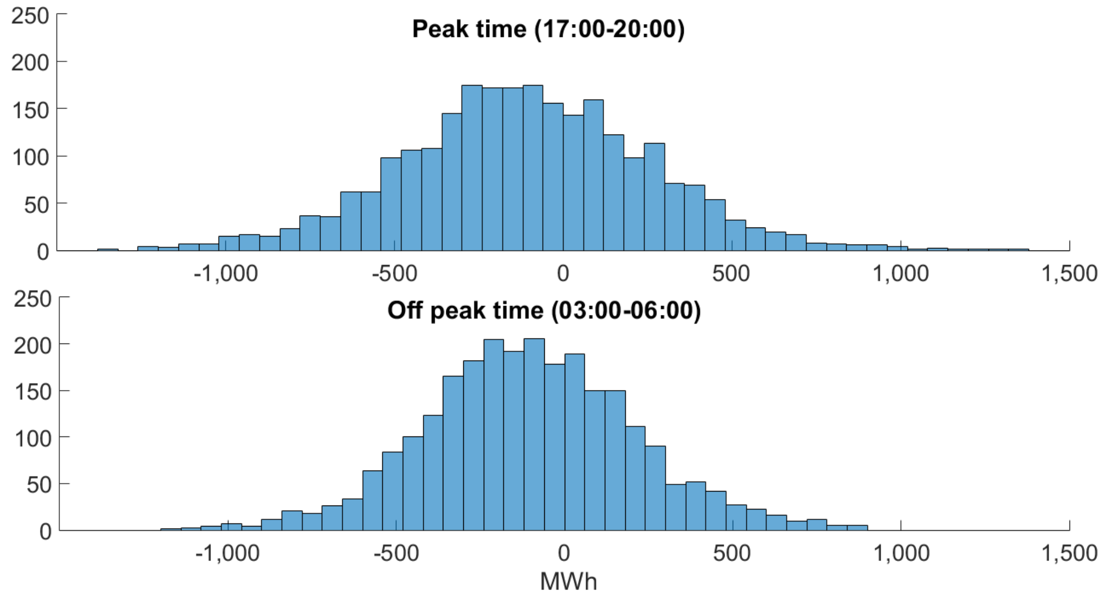


***Figure A.5** compares the NIV distribution between peak and off peak periods in 2013, showing no significant differences in imbalance volumes for the 2 time periods.*

Overall, the NIV appear to be normally distributed, however the possibility exists that particular biases tip NIV in one direction during peak or off peak period. A closer look at NIV distribution is undertaken during peak and off peak with peak period defined as the hours between 17:00 and 20:00 whereas off peak period is chosen for the hours between 03:00 and 06:00. The distributions are shown in figure A.4

From figure A.5 it is clear that the tendency for negative NIV persists during both peak and off peak periods. Of particular interest is the fact that both distributions are remarkably similar despite occurring at the opposite ends of the demand spectrum. As the nature of NIV is unpredictable, as a simplification, it can be thought of as a randomly drawn observation from a normally distributed population with mean -106.97 and a standard deviation of 371.76.

# Appendix B.1 – Ancillary services characteristics

| Ancillary Service | Power Requirement (Min) | Duration Requirement (minimum) | Response Time (maximum) | Market Procurement | Availability Payment (£/h) | Utilisation Payment (£/MWh) | Additional Payment | Participation: Demand or Generation | Source: |
|---|---|---|---|---|---|---|---|---|---|
| Mandatory Frequency Response | All large generation (1) | N/A | 10 for primary; 30 secs for secondary | Mandatory for large generators(1) | See note (2) | See note (3) | No | Generation Only | a |
| Firm Frequency Response | 10 MW | 30 mins | 10 for primary; 30 secs for secondary | Monthly Tender Rounds | £3-4.9/MW/h See note (4) | Market price x adjustment factor See note (3) | See note (4) | Generation Only | b |
| Frequency Control by Demand Management | 3 MW | 30 mins | 2 seconds | Bilateral Agreement | bilateral basis (5) | Not applicable | No | Demand Only | c |
| Black Start Capability | 100 MW | 3-7 days | n/a | Bilateral Agreement | bilateral basis | Yes | No | Generation Only | d |
| Obligatory Reactive Power Service | 50 MW | N/A | N/A | Mandatory for units>50MW | N/A | £2.69/Mvarh for April 2015 | No | Generation Only | e |
| Enhanced Reactive Power Service | over 50 MW (6) | N/A | N/A | 6 months Tender Rounds | see note (7) | see note (7) | Yes | Generation Only | f |
| Short Term Operating Reserve | 3 MW (By Aggreg) | 120 mins | 240 mins (typically less than 15 mins) | Tender Rounds | £1-0.5/MWh see note (8) | £168-170/MWh see note (8) | No | Both | g |
| Fast Reserve | 50 MW see note (9) | 15 mins | 2 mins | Monthly tender | £2.97-3.88/MW/h | £140-325/MWh see note (10) | No | Both | h |
| Balancing Mechanism Start Up | N/A | 89 mins from instruction | N/A | Bilateral Agreement | per agreement | | | Generation Only | i |
| Maximum Generation | N/A | 120 mins | N/A | Bilateral Agreement | No | per agreement | No | Generation Only | j |
| Demand Management | 25 MW | 60 mins | N/A | Bilateral Agreement | per agreement | | | Demand Only | k |
| Intertrips | N/A | N/A | N/A | Bilateral Agreement | See note (11) | | | Both | l |
| Supplemantary Balancing Reserve (SBR) | No Min | tender dependent | bid/offer acceptance post gate closure (BM) but potentially | Tender and bilateral agreement | £12.73-15.83/kW see note (12) | £200-250/MWh see note (12) | Hot Standy & BM start up fee £4.4/MW/h see note | Generation Only | m |
| Demand Side Balancing Reserve | 1 MW | 1 hour (3 preferably) | 2 hours notice given by NG | Tender Rounds | No | £250-12500/MWh | Optional Admin fee: £5000-9000/MW | Demand Only | n |
| Capacity Mechanism - Generation & DSR | 2MW but less than 50MW for DSR | N/A<br>N/A | 4 hours from Capacity Mechanism Warning Issued | Auction rounds | £19.40/kW/yr see note (14) | unclear | | Both | o<br>p |

***Table B.1** displays the wide variety of ancillary services procured by National Grid; in addition, the recently introduced Capacity Mechanism is shown.*

*Notes:*

1. Large is defined as greater than 100 MW for National Grid
2. As of March 2015, Dinorwig generators had availability payments equivalent to £4.9/MWh for Primary, £3/MWh for Secondary and £9/MWh for High response. Generally, rates vary between £1-8/MWh
3. Utilisation payment is usually 1.25 x Market Price of electricity for primary & secondary response and 0.75 times the Market Price for high response.
4. Availability Payment, Window initiation fee and Nomination fee are agreed on a bilateral basis. In March 2015, the accepted tenders had an availability price equating to £3-6/MWh

5. Payment rates are unavailable for FCDM due to the highly bespoke nature of the service provision and therefore negotiated on a bilateral basis.
6. ERPS is a service aimed at units that can provide reactive power above ORPS.
7. No tenders have been offered by BM units since Oct 2009. Availability and Utilisation payments rates are usually requested in the tender
8. These are typical values based on March 2014 accepted STOR tenders.
9. Additionally ramping rates of at least 25MW/min is required.
10. Values are averages of price bands of bids & offers for the month of February 2015
11. In April 2005 the capability and trip payments were specified at 1.72 £/settlement period and 400,000 £/trip. These prices are subject to indexation to account for current value.
12. Rates are based on latest tender results - see SBR Winter 2015-16 Market Report.
13. In capacity adjusted value for 1 accepted tender (£1000/h for both Hot standby and BM start up for Barry CCGT unit at 227 MW capacity)
14. Provisional results can be found at: (DECC 2014)

Sources:
a:(National Grid 2014a)
b:(National Grid 2016h)
c:(National Grid 2016i)
d:(National Grid 2016a)
e:(National Grid 2016l)
f:(National Grid 2016f)
g:(National Grid 2016m)
h:(National Grid 2016g)
i:(National Grid 2016b)
k:(National Grid 2016c)
l:(National Grid 2016j)
m:(National Grid 2016n)
n:(National Grid 2016d)
o:(DECC 2013)
p:(National Grid 2016k)

# Appendix B.2: An example of a FFR tender

## Firm Frequency Response Tender Report - January 2013

This report summarises the Firm Frequency Response tenders received this month. In addition all tenders which have previously been accepted and have yet to expire are included at the bottom of the report.

| Tendered Unit | Tender Status | Tendered Service Term and Period | Tendered Frame | Tendered Prices | | | | | Dynamic Provider Volume of Response Tendered | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Window Initiation Fee (£/window) | Window Revision Fee (£/h) | Availability Fee (£/h) | Nomination Fee (£/h) | Response Energy Fee (Non-BM only) (£/MW/h) | Primary Response (max.) @ 0.2Hz (MW) | Primary Response (max.) @ 0.5Hz (MW) | Primary Response (max.) @ 0.8Hz (MW) | Secondary Response (max.) @ 0.2/0.2Hz (MW) | Secondary Response (max.) @ 0.5/0.5Hz (MW) | High Frequency Response (max.) @ 0.2Hz (MW) | High Frequency Response (max.) @ 0.5Hz (MW) |
| **Tenders Received in December** | | | | | | | | | | | | | | | |
| FIDL-02Z | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 2300 All days | 0 | 0 | 932 | 2174 | - | 13 | 20 | 22 | 25 | 35 | 30 | 50 |
| FIDL-04Z | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 2300 All days | 0 | 0 | 905 | 2111 | - | 13 | 20 | 22 | 25 | 35 | 30 | 50 |
| FERR-3 | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 0700 All days | 0 | 0 | 1187 | 2769 | - | 7 | 19 | 32 | 20 | 30 | 6 | 18 |
| FIDL-04Z | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 0700 All days | 0 | 0 | 1013 | 2363 | - | 13 | 20 | 22 | 25 | 35 | 30 | 50 |
| FIDL-02Z | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 0700 All days | 0 | 0 | 1037 | 2419 | - | 13 | 20 | 22 | 25 | 35 | 30 | 50 |
| FERR-3 | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 2300 All days | 0 | 0 | 1001 | 2335 | - | 7 | 19 | 32 | 20 | 30 | 6 | 18 |
| DAMC-1 | Reject | 01/01/13 - 31/03/13 (three month) | 2300 - 2300 All days | N/A | N/A | 2750 | 795 | - | 52 | 52 | 52 | 60 | 76 | 60 | 190 |
| DAMC-1 | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 2300 All days | N/A | N/A | 2850 | 995 | - | 52 | 52 | 52 | 60 | 76 | 60 | 190 |
| RATS-2 | Accept | 01/01/13 - 31/01/13 (single month) | 2300 - 2300 All days | N/A | N/A | 1227 | 318 | | 22 | 39 | 46 | 25 | 44 | 42 | 90 |
| RATS-2 | Reject | 01/01/13 - 31/01/13 (single month) | 2300 - 2300 All days | N/A | N/A | 3465 | 426 | - | 39 | 84 | 90 | 39 | 54 | 40 | 40 |
| RLTEC-1 | Accept | 01/01/13 - 31/01/13 (single month) | 0600 - 1200 Weekdays & Saturdays | 0 | N/A | 15.72 | 0 | - | - | 3 | - | - | 3 | - | - |
| RLTEC-1 | Accept | 01/01/13 - 31/01/13 (single month) | 2200 - 0300 All days | 0 | N/A | 18.48 | 0 | - | - | - | - | - | - | - | 3 |
| **Previously Accepted Tenders** | | | | | | | | | | | | | | | |
| DINO-1 | Accepted | 01/11/2010 - 30/09/2012 (23 months) | 07:00-23:00 Weekdays 07:30-2300 Saturdays 08:30-2300 Sundays | 0 | 0 | 1875 | 1875 | N/A | 68 | 170 | 170 | 107 | 170 | 0 | 0 |
| DINO-5 | Accepted | 01/11/2011 - 30/09/13 (23 Months) | 07:00-23:00 Weekdays 07:30-2300 Saturdays 08:30-2300 Sundays | 0 | 0 | 1725 | 1725 | N/A | 68 | 170 | 170 | 107 | 170 | 0 | 0 |

***Figure B.2*** *shows an example of a FFR tender (National Grid 2013a)*

# Appendix C – Raw and transformed data inputs

| | 23.00 - 23.30 | 23.30 - 24.00 | 00.00 - 00.30 | 00.30 - 01.00 | 01.00 - 01.30 | 01.30 - 02.00 | 02.00 - 02.30 | 02.30 - 03.00 |
|---|---|---|---|---|---|---|---|---|
| Date | HH- 47 | HH- 48 | HH- 01 | HH- 02 | HH- 03 | HH- 04 | HH- 05 | HH- 06 |
| 01-Jan-12 | 36.41 | 36.91 | 45.46 | 47.19 | 43.17 | 38.64 | 36.31 | 34.80 |
| 02-Jan-12 | 35.96 | 35.69 | 35.20 | 35.38 | 35.90 | 33.25 | 30.56 | 30.86 |
| 03-Jan-12 | 36.01 | 35.27 | 33.72 | 33.71 | 32.83 | 32.33 | 30.00 | 31.12 |
| 04-Jan-12 | 35.46 | 34.14 | 35.39 | 35.05 | 34.54 | 31.39 | 30.06 | 30.46 |
| 05-Jan-12 | 36.25 | 36.68 | 36.38 | 36.50 | 36.25 | 35.31 | 33.43 | 33.66 |
| 06-Jan-12 | 32.93 | 32.55 | 33.15 | 33.09 | 34.25 | 33.67 | 34.08 | 33.35 |
| 07-Jan-12 | 35.15 | 35.23 | 36.82 | 35.99 | 34.75 | 34.68 | 32.71 | 33.09 |
| 08-Jan-12 | 36.07 | 34.03 | 35.33 | 34.85 | 35.34 | 34.37 | 33.02 | 34.04 |

***Table C.1.*** *Raw data extract for the half-hourly APX spot market price*

| Settlement Date | Settlement Period | System Sell Price (£/MWh) | System Buy Price (£/MWh) | Net Imbalance Volume(MWh) |
|---|---|---|---|---|
| 21/04/2010 | 1 | 24.77042 | 28.3 | -457.8509 |
| 21/04/2010 | 2 | 24.0266 | 28.07 | -688.1913 |
| 21/04/2010 | 3 | 24.58013 | 28.23 | -472.6239 |
| 21/04/2010 | 4 | 24.59852 | 29.1 | -346.2756 |
| 21/04/2010 | 5 | 24.28999 | 29.03 | -296.95 |
| 21/04/2010 | 6 | 24.5833 | 29.24 | -357.5999 |

***Table C.2.*** *Raw data extract for the Balancing Mechanism*

| settlement date | stlmt period | indo | england wales | embed wind | embed solar | non bm stor | i014 demand | i014 TGSD | pumping | french import | britned import | moyle import | east west import |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 01/04/2005 | 1 | 32926 | 29566 | 0 | 0 | 0 | 33274.31 | 34544.15 | -1099.84 | 1968.89 | | -170.3 | |
| 01/04/2005 | 2 | 32154 | 28871 | 0 | 0 | 0 | 32531.73 | 34330.95 | -1615.12 | 1968.59 | | -170.4 | |
| 01/04/2005 | 3 | 33633 | 30340 | 0 | 0 | 0 | 33994.82 | 35598.66 | -1335.14 | 1968.89 | | -170.3 | |
| 01/04/2005 | 4 | 34574 | 31253 | 0 | 0 | 0 | 34960.08 | 36322.46 | -1192.38 | 1968.59 | | -170.3 | |
| 01/04/2005 | 5 | 34720 | 31325 | 0 | 0 | 0 | 35141.18 | 36508.08 | -1196.9 | 1968.79 | | -170.3 | |
| 01/04/2005 | 6 | 34452 | 31094 | 0 | 0 | 0 | 34846.89 | 36231.33 | -1214.44 | 1968.49 | | -170.4 | |

***Table C.3.*** *Raw data extract for transmission level electricity demand*

| #Settlement Date | Settlement Period | CCGT | OIL | COAL | NUCLEAR | WIND | PS | NPSHYD | OCGT | OTHER | INTFR | INTIRL | INTNED | INTEW |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 06/11/2008 | 1 | 12563 | 0 | 16532 | 5659 | 29 | 0 | 238 | 0 | 0 | 1844 | 0 | | |
| 06/11/2008 | 2 | 12302 | 0 | 16479 | 5657 | 31 | 0 | 238 | 0 | 0 | 1846 | 0 | | |
| 06/11/2008 | 3 | 12070 | 0 | 16612 | 5658 | 27 | 0 | 227 | 0 | 0 | 1844 | 0 | | |
| 06/11/2008 | 4 | 11699 | 0 | 16349 | 5656 | 26 | 0 | 227 | 0 | 0 | 1846 | 0 | | |
| 06/11/2008 | 5 | 11465 | 0 | 16041 | 5658 | 20 | 0 | 227 | 0 | 0 | 1844 | 0 | | |
| 06/11/2008 | 6 | 11411 | 0 | 15848 | 5658 | 33 | 0 | 226 | 0 | 0 | 1846 | 0 | | |

***Table C.4.*** *Raw data extract for generation of different types at transmission level*

| | | Coal | | Oil | | Natural gas |
|---|---|---|---|---|---|---|
| | | £ per tonne | pence per kWh | £ per tonne | pence per kWh | pence per kWh |
| 2011 | 1st quarter | 78.78 | 1.091 | 493.68 | 4.104 | 1.873 |
| 2011 | 2nd quarter | 82.75 | 1.146 | 525.65 | 4.370 | 1.926 |
| 2011 | 3rd quarter | 80.06 | 1.108 | 565.14 | 4.698 | 1.825 |
| 2011 | 4th quarter | 79.24 | 1.097 | 544.62 | 4.528 | 2.057 |
| 2012 | 1st quarter | 72.05 | 0.990 | 607.19 | 5.048 | 2.122 |
| 2012 | 2nd quarter | 66.06 | 0.908 | 562.87 | 4.679 | 2.067 |

***Table C.5.*** *Raw data extract for quarterly fuel prices*

Table C.6 describes the variables in the raw demand data from National Grid.

| Data Item | Description |
|---|---|
| **indo** | *Initial National Demand Outturn (INDO) - as published on BM Reports. It is equivalent to the Great Britain generation requirement and is comparable to the National Demand forecast. The figures exclude station load, pump storage pumping and interconnector exports.*<br>*INDO is calculated as a sum of generation based on National Grid operational generation metering. The list of generators that are included in the sum is published separately in the accompanying BMU List.xls file.* |
| **england_wales** | *England and Wales Demand - as INDO above but on an England and Wales basis.* |
| **embedded_wind** | *Embedded Wind Generation - an estimate of the UK's wind generation from wind farms which do not have Transmission System metering installed. These wind farms are embedded in the distribution network and invisible to National Grid. Their effect is to suppress the electricity demand during periods of high wind. The true output of these generators is not known but is modelled based on actual weather and capacity data.*<br><br>*Note that embedded wind farms which do have Transmission System metering are not included in this total.*<br><br>*For future dates a forecast value is shown. This is equivalent to the data that feeds into the National Demand forecast published on BM Reports. This is updated daily.* |
| **embedded_solar** | *Embedded Solar Generation – as embedded wind generation above, but for solar generation.* |
| **non_bm_stor** | *Non-BM Short-Term Operating Reserve – operating reserve for units that are not included in the INDO generator definition. This can be in the form of generation or demand reduction.* |
| **i014_demand** | *I014 Demand - the demand as derived from Settlement data. This is done using metered generation from the I014 file. The list of generators used is identical to that used for INDO above. Note that the demand includes station load and is therefore higher than INDO. Station load is 500MW in BST and 600MW in GMT.* |
| **i014_tgsd** | *Total Gross System Demand (TGSD) - the total demand on the Transmission System; it includes station load, pump storage pumping and interconnector exports. The data is derived from Settlement data similarly to the I014 Demand above.* |
| **pumping** | *Pump Storage Pumping – the demand due to pumping at hydro pump storage units; the -ve signifies pumping load.* |
| **french_import, britned_import, moyle_import, east_west_import** | *Interconnector Flow – the flow on the respective interconnector. -ve signifies export power out from GB; +ve signifies import power into GB.* |

***Table C.6.*** *Raw demand data variables from National Grid. Source:* (National Grid 2015b)

| Settlement Date | Settlement Period | CCGT | OIL | COAL | NUCLEAR | WIND | PS | NPSHYD |
|---|---|---|---|---|---|---|---|---|
| 08/06/2011 | 1 | 11096 | 0 | 6034 | 8722 | 847 | 0 | 250 |
| 08/06/2011 | 2 | 10876 | 0 | 5758 | 8481 | 825 | 0 | 250 |
| 08/06/2011 | 3 | 10980 | 0 | 5537 | 8339 | 807 | 0 | 233 |
| 08/06/2011 | 4 | 11047 | 0 | 5459 | 8282 | 770 | 0 | 232 |
| 08/06/2011 | 5 | 10885 | 0 | 5207 | 8158 | 853 | 0 | 217 |
| 08/06/2011 | 6 | 10810 | 0 | 4970 | 8211 | 720 | 0 | 174 |


| Settlement Date | Settlement Period | CCGT | OIL | COAL | NUCLEAR | WIND | PS | NPSHYD |
|---|---|---|---|---|---|---|---|---|
| 08/06/2011 | 1 | 11096 | 0 | 6034 | 8722 | 847 | 0 | 250 |
| 08/06/2011 | 2 | 10876 | 0 | 5758 | 8481 | 825 | 0 | 250 |
| 08/06/2011 | 3 | 10980 | 0 | 5537 | 8339 | 807 | 0 | 233 |
| 08/06/2011 | 4 | 11047 | 0 | 5459 | 8282 | 770 | 0 | 232 |
| 08/06/2011 | 5 | 10885 | 0 | 5207 | 8158 | 853 | 0 | 217 |
| 08/06/2011 | 6 | 10810 | 0 | 4970 | 8211 | 720 | 0 | 174 |


| non bm stor | i014 demand | i014 TGSD | pumping | french import | britned import | moyle import | east west import |
|---|---|---|---|---|---|---|---|
| 0 | 26728.5 | 28133.53 | -1020.56 | 986.81 | -0.4 | -386 | 0 |
| 0 | 25662.51 | 27278.44 | -1231.46 | 986.71 | -0.8 | -386 | 0 |
| 0 | 25369.08 | 26982.91 | -1222.16 | 985.92 | -0.4 | -383.4 | 0 |
| 0 | 25148.6 | 26826.29 | -1337.08 | 985.92 | -0.8 | -332.3 | 0 |
| 0 | 24788.82 | 26524.52 | -1487.04 | 986.81 | -0.4 | -250.1 | 0 |
| 0 | 24315.65 | 26077.16 | -1570.14 | 986.52 | -0.8 | -192.4 | 0 |

| SSP | SBP | NETIMBALANCE VOL | APX RPD price HH 2H 4HB | APX RPD volumes HH 2H | APXPHH | APXVHH |
|---|---|---|---|---|---|---|
| 39.27204 | 46.03 | -145.8025 | 46.89 | 1915 | 47.11 | 1716 |
| 38.8617 | 43.99 | -213.7651 | 46.93 | 1040 | 47.39 | 841 |
| 45.24 | 45.88 | 43.0157 | 46.03 | 965 | 46.31 | 766 |
| 43.81 | 45.88 | 104.8547 | 43.99 | 825 | 43.68 | 626 |
| 42.37 | 42.37 | 162.005 | 45.24 | 638 | 45.72 | 508 |
| 42.37 | 42.37 | 86.3643 | 43.81 | 314 | 44.14 | 184 |

***Table C.7.*** *An extract of the Master dataset used for all quantitative analysis in this thesis.*

# Appendix D: Residual plots for the AR model

Error plots can provide a good indication of the deficiencies of a regression model; a plot of residuals versus lagged residuals show the extent of autocorrelation. Typically, econometric models use data on an annual resolution whereas in this thesis half-hourly resolution of data was used. As a result, autocorrelation tends to be very strong, as a period separation is so short that the variable is not likely to change by much over that period. Conceptually, change require time and the shorter the time, the smaller the change is likely to be; this is true for many real world events. In the AR model, two lagged dependent variables were added, similar to the approach (Nyamdash & Denny 2013) used in their econometric model, and this model specification was found to be a good fit. As shown in the top left part of figure D.1, the plot of residuals vs lagged residuals are fairly well distributed around the origin with the exception of a small number of observations.

In the top right part of figure D.1, the error plot of fitted vs actual residuals shows the accuracy of the model at different ranges of the dependent variable, in this case the APX price. As the price range increases, errors tend to be more spread, indicating heteroscedasticity. As mentioned previously, it is hypothesised that this is likely due to missing variables which, if included, would provide a more accurate fit of the model. Such missing variables could potentially be transmission constraints, embedded generation data…etc.

In the bottom left part of the figure, the chronological residual plots show that over the four years, the residual spread were fairly similar, however with some tendency for the residuals to be greater over the winter months. Since the model includes dummy variables for each month, the seasonal effect seen here is hypothesised to be related to the omitted variables mentioned earlier. In the bottom right of the figure, the distribution of the residuals shows a narrow spread, with the exception of extreme outliers.

Besides the graphical methods, more formal tests were implemented. A Breusch-Pagan test for heteroscedasticity, a Ramsey reset test for non-linearity, an augmented Dickey-Fuller test for non-stationarity and a Breusch-Godfrey test for autocorrelation were carried out to refine and improve the model. (Dougherty 2011) provides a good explanation of these tests.

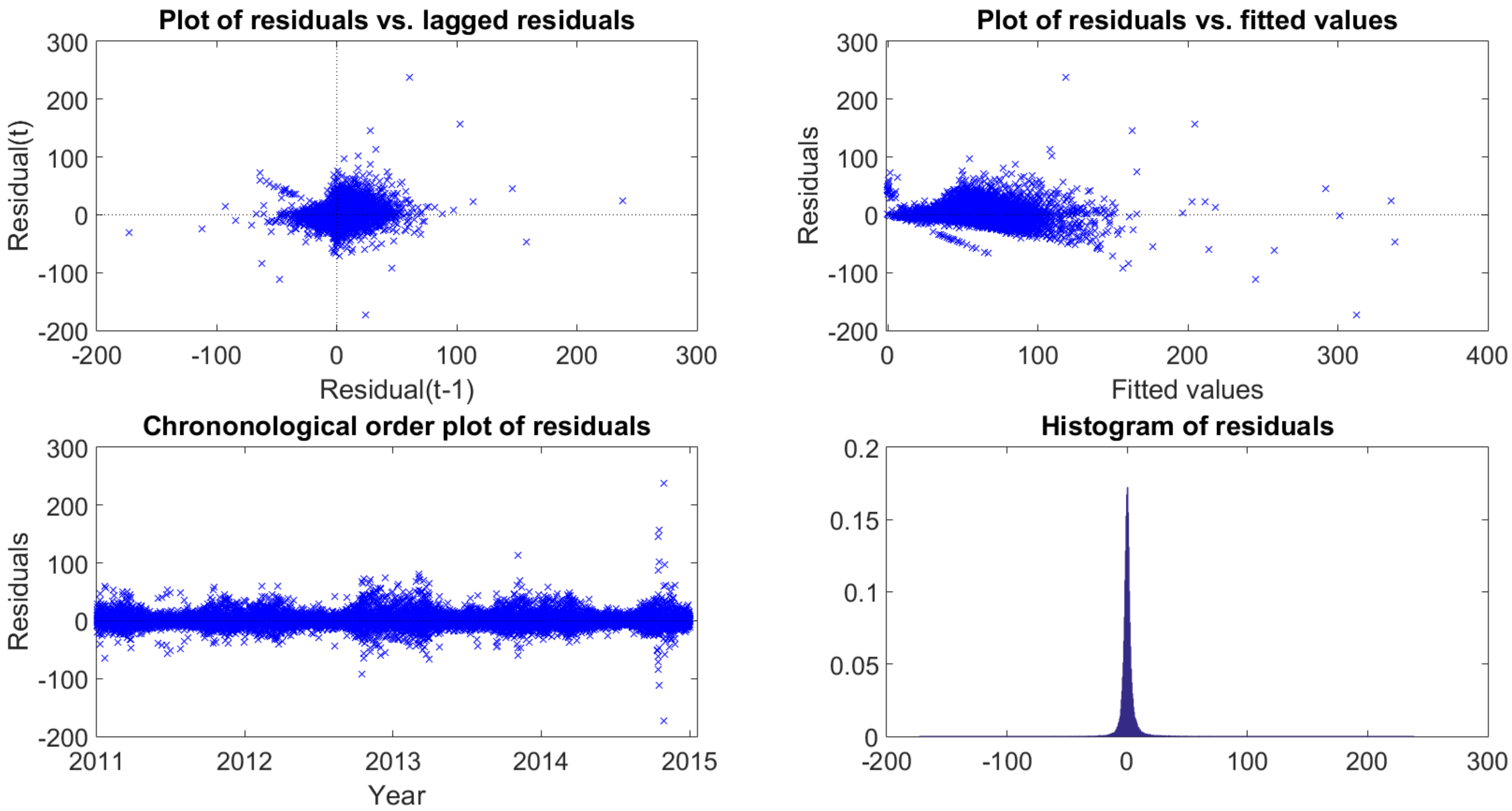


***Figure D1.*** *The residual plots of the AR model; no strong presence of autocorrelation however with a presence of heteroscedasticity. Residual plots also indicate the possible omission of variables*

# Appendix E: Econometric model results: APX static Model

| APX static Model - OLS/FGLS | | | | | |
|---|---|---|---|---|---|
| Variable Name | OLS Coefficient | OLS Std Error | FGLS Coefficient | FGLS Std Error | OLS t-statistic |
| '(Intercept)' | -10.1998 | 0.972 | -10.1900 | 0.016 | -10.499 |
| 'OIL' | 0.0216 | 0.001 | 0.0214 | 0.000 | 16.119 |
| 'OCGT' | 0.0442 | 0.002 | 0.0441 | 0.000 | 22.121 |
| 'CCGT' | 0.0015 | 0.000 | 0.0015 | 0.000 | 86.970 |
| 'COAL' | 0.0007 | 0.000 | 0.0007 | 0.000 | 39.779 |
| 'NUCLEAR' | 0.0002 | 0.000 | 0.0002 | 0.000 | 4.064 |
| 'NPSHYD' | 0.0060 | 0.000 | 0.0060 | 0.000 | 25.381 |
| 'WIND' | -0.0007 | 0.000 | -0.0007 | 0.000 | -17.985 |
| 'NETIMBALANCEVOL' | 0.0037 | 0.000 | 0.0037 | 0.000 | 33.585 |
| 'pumping' | -0.0003 | 0.000 | -0.0003 | 0.000 | -2.407 |
| 'britnedimport' | 0.0011 | 0.000 | 0.0011 | 0.000 | 10.075 |
| 'eastwestimport' | 0.0000 | 0.000 | 0.0000 | 0.000 | -0.118 |
| 'frenchimport' | 0.0006 | 0.000 | 0.0006 | 0.000 | 9.698 |
| 'moyleimport' | 0.0008 | 0.000 | 0.0008 | 0.000 | 2.334 |
| 'APXVHH' | 0.0011 | 0.000 | 0.0011 | 0.000 | 9.633 |
| 'quarterlyfuelpriceCOAL' | 0.2524 | 0.052 | 0.2541 | 0.001 | 4.880 |
| 'quarterlyfuelpriceGAS' | 2.4353 | 0.028 | 2.4353 | 0.000 | 87.859 |
| 'quarterlyfuelpriceOIL' | -0.6521 | 0.019 | -0.6521 | 0.000 | -35.092 |
| 'SPintdummy2' | -1.1116 | 0.348 | -1.1069 | 0.004 | -3.197 |
| 'SPintdummy3' | -0.7661 | 0.350 | -0.7699 | 0.005 | -2.192 |
| 'SPintdummy4' | -1.1254 | 0.351 | -1.1268 | 0.002 | -3.204 |
| 'SPintdummy5' | -2.1064 | 0.353 | -2.1050 | 0.004 | -5.967 |
| 'SPintdummy6' | -2.5726 | 0.353 | -2.5744 | 0.003 | -7.281 |
| 'SPintdummy7' | -2.5099 | 0.356 | -2.5118 | 0.004 | -7.042 |
| 'SPintdummy8' | -3.1423 | 0.358 | -3.1490 | 0.005 | -8.776 |
| 'SPintdummy9' | -3.7055 | 0.357 | -3.7083 | 0.004 | -10.378 |
| 'SPintdummy10' | -4.5755 | 0.356 | -4.5759 | 0.004 | -12.868 |
| 'SPintdummy11' | -3.7327 | 0.353 | -3.7343 | 0.003 | -10.564 |
| 'SPintdummy12' | -4.9734 | 0.355 | -4.9726 | 0.010 | -14.000 |
| 'SPintdummy13' | -3.8011 | 0.367 | -3.8042 | 0.004 | -10.351 |
| 'SPintdummy14' | -6.0945 | 0.389 | -6.0987 | 0.006 | -15.681 |
| 'SPintdummy15' | -5.1198 | 0.390 | -5.1168 | 0.004 | -13.124 |
| 'SPintdummy16' | -4.4477 | 0.388 | -4.4496 | 0.004 | -11.458 |
| 'SPintdummy17' | -4.0548 | 0.393 | -4.0523 | 0.004 | -10.312 |
| 'SPintdummy18' | -3.3946 | 0.396 | -3.3964 | 0.005 | -8.570 |

| | | | | | |
|---|---|---|---|---|---|
| 'SPintdummy19' | -1.2316 | 0.400 | -1.2223 | 0.011 | -3.076 |
| 'SPintdummy20' | 0.5409 | 0.402 | 0.5477 | 0.007 | 1.347 |
| 'SPintdummy21' | 1.1785 | 0.403 | 1.1828 | 0.005 | 2.926 |
| 'SPintdummy22' | 1.6120 | 0.403 | 1.6161 | 0.004 | 3.996 |
| 'SPintdummy23' | 1.8620 | 0.406 | 1.8649 | 0.004 | 4.587 |
| 'SPintdummy24' | 2.3691 | 0.406 | 2.3716 | 0.005 | 5.841 |
| 'SPintdummy25' | 2.2975 | 0.403 | 2.2907 | 0.005 | 5.700 |
| 'SPintdummy26' | 0.6028 | 0.402 | 0.5929 | 0.012 | 1.499 |
| 'SPintdummy27' | -1.3751 | 0.402 | -1.3657 | 0.009 | -3.422 |
| 'SPintdummy28' | -3.8787 | 0.401 | -3.8751 | 0.005 | -9.668 |
| 'SPintdummy29' | -5.1791 | 0.400 | -5.1939 | 0.013 | -12.955 |
| 'SPintdummy30' | -7.1058 | 0.400 | -7.1055 | 0.007 | -17.783 |
| 'SPintdummy31' | -8.0573 | 0.400 | -8.0641 | 0.007 | -20.134 |
| 'SPintdummy32' | -8.6269 | 0.402 | -8.6240 | 0.005 | -21.440 |
| 'SPintdummy33' | -6.3212 | 0.408 | -6.3218 | 0.006 | -15.487 |
| 'SPintdummy34' | 1.1399 | 0.412 | 1.1515 | 0.006 | 2.768 |
| 'SPintdummy35' | 8.5150 | 0.415 | 8.5159 | 0.015 | 20.494 |
| 'SPintdummy36' | 6.6007 | 0.416 | 6.6159 | 0.007 | 15.883 |
| 'SPintdummy37' | 4.5942 | 0.414 | 4.5929 | 0.005 | 11.095 |
| 'SPintdummy38' | 3.9212 | 0.412 | 3.9198 | 0.010 | 9.524 |
| 'SPintdummy39' | 2.9935 | 0.408 | 2.9799 | 0.013 | 7.341 |
| 'SPintdummy40' | 1.2467 | 0.404 | 1.2441 | 0.004 | 3.088 |
| 'SPintdummy41' | 0.2009 | 0.398 | 0.2006 | 0.005 | 0.505 |
| 'SPintdummy42' | -0.1782 | 0.394 | -0.1824 | 0.006 | -0.453 |
| 'SPintdummy43' | 1.6065 | 0.388 | 1.6078 | 0.005 | 4.144 |
| 'SPintdummy44' | 1.3384 | 0.383 | 1.3408 | 0.004 | 3.492 |
| 'SPintdummy45' | 0.6915 | 0.376 | 0.6919 | 0.003 | 1.841 |
| 'SPintdummy46' | 0.8302 | 0.377 | 0.8315 | 0.004 | 2.199 |
| 'SPintdummy47' | 1.1697 | 0.361 | 1.1714 | 0.004 | 3.237 |
| 'SPintdummy48' | 1.4933 | 0.349 | 1.4909 | 0.002 | 4.279 |
| 'monthintdummyfeb' | 1.6023 | 0.181 | 1.5976 | 0.003 | 8.840 |
| 'monthintdummymar' | 6.9691 | 0.187 | 6.9623 | 0.004 | 37.246 |
| 'monthintdummyapr' | 12.0616 | 0.208 | 12.0574 | 0.004 | 58.085 |
| 'monthintdummymay' | 10.4304 | 0.229 | 10.4281 | 0.004 | 45.646 |
| 'monthintdummyjune' | 8.8317 | 0.250 | 8.8280 | 0.004 | 35.307 |
| 'monthintdummyjuly' | 10.9484 | 0.264 | 10.9419 | 0.004 | 41.475 |
| 'monthintdummyaug' | 11.5569 | 0.254 | 11.5500 | 0.005 | 45.554 |
| 'monthintdummysept' | 12.8026 | 0.233 | 12.7961 | 0.004 | 54.883 |
| 'monthintdummyoct' | 2.5495 | 0.228 | 2.5404 | 0.004 | 11.180 |
| 'monthintdummynov' | 0.7544 | 0.209 | 0.7432 | 0.003 | 3.606 |
| 'monthintdummydec' | 0.8721 | 0.195 | 0.8699 | 0.003 | 4.480 |
| 'weekeffdummyweekday' | -3.4370 | 0.102 | -3.4355 | 0.001 | -33.644 |

***Table E.1.*** *Full list of the coefficients of the APX Static Model*

In the presence of autocorrelation and heteroscedasticity, the Feasible Generalised Least Squares (FGLS) method is a better estimator of the standard errors as Ordinary Least Squares (OLS) tends to be biased. As Table E.1 shows, the coefficients from the OLS and FGLS are almost identical, however the standard error is biased. Table E.2 shows the full results of the AR regression model for the APX market. In addition to the types of generation on the system the quarterly fuel prices were included in the model. Given the strong influence of the time of day on the prices, dummy variables for each half-hourly period were included with the reference period being from 00:00-00:30. These dummy variables are shown as '*SPdummy'* with the corresponding number relating to the settlement period; for example, '*SPdummy46*' corresponds to the settlement period 46 which refers to the time period between 22:30-23:00. Similarly, dummy variables for each month is added, with the reference month being January.

***Table E.2*** *The coefficients of the APX Autoregressive Model*

**APX autoregressive model**

| Variable Name | Coefficient | Standard Error | t-statistic | p-value |
|---|---|---|---|---|
| '(Intercept)' | 0.649201 | 0.329 | 1.973 | 0.049 |
| 'OIL' | 0.000516 | 0.000 | 1.139 | 0.255 |
| 'OCGT' | 0.002079 | 0.001 | 3.057 | 0.002 |
| 'CCGT' | 0.000076 | 0.000 | 12.354 | 0.000 |
| 'COAL' | 0.000035 | 0.000 | 5.460 | 0.000 |
| 'NUCLEAR' | -0.000057 | 0.000 | -3.602 | 0.000 |
| 'NPSHYD' | 0.000539 | 0.000 | 6.771 | 0.000 |
| 'WIND' | -0.000165 | 0.000 | -12.697 | 0.000 |
| 'NETIMBALANCEVOL' | 0.000674 | 0.000 | 16.339 | 0.000 |
| 'pumping' | 0.000303 | 0.000 | 7.084 | 0.000 |
| 'britnedimport' | -0.000072 | 0.000 | -1.929 | 0.054 |
| 'eastwestimport' | -0.000191 | 0.000 | -2.288 | 0.022 |
| 'frenchimport' | -0.000069 | 0.000 | -3.241 | 0.001 |
| 'moyleimport' | -0.000008 | 0.000 | -0.064 | 0.949 |
| 'APXVHH' | 0.000369 | 0.000 | 9.443 | 0.000 |
| 'APXPHHLAG1' | 0.959487 | 0.002 | 459.064 | 0.000 |
| 'APXPHHLAG2' | -0.110072 | 0.002 | -53.828 | 0.000 |
| 'imbapricelag2' | 0.020972 | 0.001 | 26.935 | 0.000 |
| 'quarterlyfuelpriceCOAL' | 0.178178 | 0.018 | 10.172 | 0.000 |
| 'quarterlyfuelpriceGAS' | 0.264837 | 0.010 | 26.688 | 0.000 |
| 'quarterlyfuelpriceOIL' | -0.092673 | 0.006 | -14.584 | 0.000 |
| 'SPintdummy2' | 0.156922 | 0.118 | 1.332 | 0.183 |
| 'SPintdummy3' | 1.042474 | 0.118 | 8.808 | 0.000 |
| 'SPintdummy4' | -0.012768 | 0.119 | -0.107 | 0.915 |
| 'SPintdummy5' | -0.345778 | 0.120 | -2.890 | 0.004 |
| 'SPintdummy6' | 0.401767 | 0.120 | 3.355 | 0.001 |
| 'SPintdummy7' | 0.631136 | 0.121 | 5.224 | 0.000 |
| 'SPintdummy8' | -0.303292 | 0.121 | -2.497 | 0.013 |
| 'SPintdummy9' | 0.177754 | 0.121 | 1.468 | 0.142 |

*Table E2 continued*

| | | | | |
|---|---|---|---|---|
| 'SPintdummy10' | -0.203518 | 0.121 | -1.686 | 0.092 |
| 'SPintdummy11' | 1.985497 | 0.120 | 16.537 | 0.000 |
| 'SPintdummy12' | 0.074323 | 0.121 | 0.614 | 0.539 |
| 'SPintdummy13' | 3.250583 | 0.125 | 26.012 | 0.000 |
| 'SPintdummy14' | 0.385753 | 0.133 | 2.910 | 0.004 |
| 'SPintdummy15' | 2.467215 | 0.133 | 18.594 | 0.000 |
| 'SPintdummy16' | 0.926103 | 0.132 | 7.015 | 0.000 |
| 'SPintdummy17' | 1.563862 | 0.133 | 11.715 | 0.000 |
| 'SPintdummy18' | 1.384964 | 0.134 | 10.305 | 0.000 |
| 'SPintdummy19' | 2.563819 | 0.136 | 18.885 | 0.000 |
| 'SPintdummy20' | 2.293939 | 0.136 | 16.847 | 0.000 |
| 'SPintdummy21' | 1.656638 | 0.136 | 12.144 | 0.000 |
| 'SPintdummy22' | 1.841008 | 0.137 | 13.478 | 0.000 |
| 'SPintdummy23' | 1.451207 | 0.137 | 10.559 | 0.000 |
| 'SPintdummy24' | 1.685167 | 0.137 | 12.271 | 0.000 |
| 'SPintdummy25' | 1.349529 | 0.136 | 9.888 | 0.000 |
| 'SPintdummy26' | -0.225408 | 0.136 | -1.655 | 0.098 |
| 'SPintdummy27' | -0.028715 | 0.136 | -0.211 | 0.833 |
| 'SPintdummy28' | -1.003700 | 0.136 | -7.385 | 0.000 |
| 'SPintdummy29' | 0.026350 | 0.136 | 0.194 | 0.846 |
| 'SPintdummy30' | -0.656138 | 0.136 | -4.841 | 0.000 |
| 'SPintdummy31' | 0.463455 | 0.136 | 3.409 | 0.001 |
| 'SPintdummy32' | 0.669891 | 0.137 | 4.894 | 0.000 |
| 'SPintdummy33' | 2.408364 | 0.139 | 17.335 | 0.000 |
| 'SPintdummy34' | 3.440896 | 0.140 | 24.556 | 0.000 |
| 'SPintdummy35' | 3.983059 | 0.142 | 28.104 | 0.000 |
| 'SPintdummy36' | -0.627045 | 0.142 | -4.429 | 0.000 |
| 'SPintdummy37' | -0.328267 | 0.141 | -2.335 | 0.020 |
| 'SPintdummy38' | -0.521233 | 0.140 | -3.732 | 0.000 |
| 'SPintdummy39' | 2.046843 | 0.138 | 14.809 | 0.000 |
| 'SPintdummy40' | 0.411671 | 0.137 | 3.008 | 0.003 |
| 'SPintdummy41' | -0.253936 | 0.135 | -1.881 | 0.060 |
| 'SPintdummy42' | -0.082295 | 0.133 | -0.617 | 0.537 |
| 'SPintdummy43' | 1.673281 | 0.131 | 12.741 | 0.000 |
| 'SPintdummy44' | -0.631905 | 0.130 | -4.867 | 0.000 |
| 'SPintdummy45' | -0.546794 | 0.127 | -4.296 | 0.000 |
| 'SPintdummy46' | 0.011713 | 0.128 | 0.092 | 0.927 |
| 'SPintdummy47' | 0.027593 | 0.122 | 0.225 | 0.822 |
| 'SPintdummy48' | 0.104158 | 0.118 | 0.881 | 0.378 |

| | | | | |
|---|---|---|---|---|
| 'monthintdummyfeb' | 0.064508 | 0.061 | 1.051 | 0.293 |
| 'monthintdummymar' | 0.592497 | 0.064 | 9.263 | 0.000 |
| 'monthintdummyapr' | 1.155211 | 0.072 | 16.038 | 0.000 |
| 'monthintdummymay' | 1.021880 | 0.078 | 13.019 | 0.000 |
| 'monthintdummyjune' | 0.844284 | 0.085 | 9.887 | 0.000 |
| 'monthintdummyjuly' | 1.128811 | 0.090 | 12.482 | 0.000 |
| 'monthintdummyaug' | 1.111144 | 0.087 | 12.748 | 0.000 |
| 'monthintdummysept' | 1.128348 | 0.081 | 13.977 | 0.000 |
| 'monthintdummyoct' | -0.254644 | 0.077 | -3.296 | 0.001 |
| 'monthintdummynov' | -0.140436 | 0.071 | -1.982 | 0.047 |
| 'monthintdummydec' | -0.031688 | 0.066 | -0.481 | 0.631 |
| 'weekeffdummyweekday' | 0.036618 | 0.035 | 1.049 | 0.294 |

Unlike the APX regression models, in the BM model, the addition of dummy variables was found to be of little significance due to the fact that the APX price is included as an independent variable and the latter already conveys the strong seasonal effects.

*Table E3 below shows the coefficients of the BM Static Model*

| **BM Static Model** | | | | |
|---|---|---|---|---|
| **Variable Name** | **Coefficient** | **Standard Error** | **t-statistic** | **p-value** |
| 'Intercept' | 14.462626 | 0.753 | 19.210 | 0.000 |
| 'OIL' | -0.003804 | 0.001 | -2.880 | 0.004 |
| 'OCGT' | 0.043387 | 0.002 | 21.961 | 0.000 |
| 'CCGT' | 0.000400 | 0.000 | 31.664 | 0.000 |
| 'COAL' | 0.000291 | 0.000 | 24.263 | 0.000 |
| 'NUCLEAR' | 0.000230 | 0.000 | 6.241 | 0.000 |
| 'NPSHYD' | -0.003167 | 0.000 | -15.786 | 0.000 |
| 'WIND' | 0.000186 | 0.000 | 5.487 | 0.000 |
| 'NETIMBALANCEVOL' | 0.030200 | 0.000 | 289.645 | 0.000 |
| 'pumping' | 0.001942 | 0.000 | 27.483 | 0.000 |
| 'britnedimport' | -0.000582 | 0.000 | -5.796 | 0.000 |
| 'eastwestimport' | -0.001835 | 0.000 | -7.881 | 0.000 |
| 'frenchimport' | 0.000470 | 0.000 | 8.229 | 0.000 |
| 'moyleimport' | -0.001278 | 0.000 | -4.164 | 0.000 |
| 'APXPHH' | 0.125664 | 0.006 | 21.063 | 0.000 |
| 'APXVHH' | -0.000361 | 0.000 | -4.395 | 0.000 |
| 'APXPHHLAG1' | -0.037910 | 0.008 | -4.464 | 0.000 |
| 'APXPHHLAG2' | 0.018220 | 0.006 | 3.169 | 0.002 |
| 'quarterlyfuelpriceCOAL' | 1.116901 | 0.047 | 23.795 | 0.000 |
| 'quarterlyfuelpriceGAS' | 0.973135 | 0.023 | 41.537 | 0.000 |
| 'quarterlyfuelpriceOIL' | -0.225115 | 0.012 | -18.507 | 0.000 |

# Appendix F: Additional pathways for wind to affect the BM prices

The negative impact of wind generation on prices were shown in the regression results. Under a 20 GW wind penetration scenario, further pathways through which additional wind generation could affect the BM prices were considered; the increase in wind penetration would affect wholesale prices which in turn would have an impact on the BM as the latter partly reflects the short-term wholesale market price. In figure F.1, the impact of the new APX price, under a 20 GW wind penetration scenario, on the imbalance price. These changes are generally small but have stronger impacts at specific times for example during peak times.

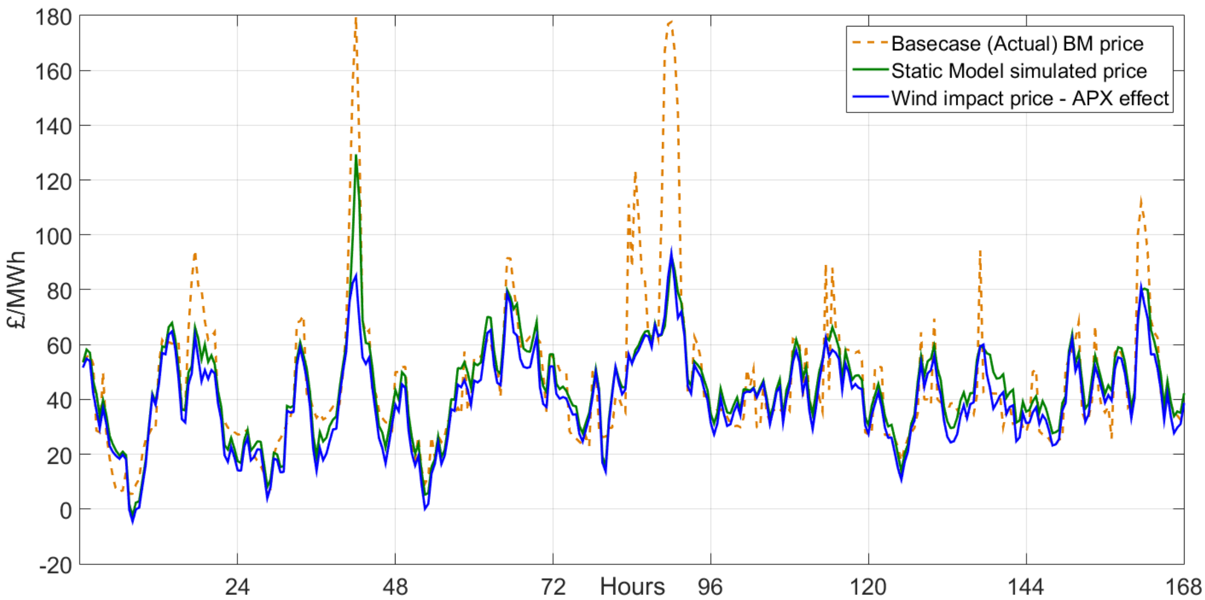


***Figure F.1***. *one of the pathways wind can indirectly affect the BM - the APX price. Data for the 1st week of Jan 2014 is used.*

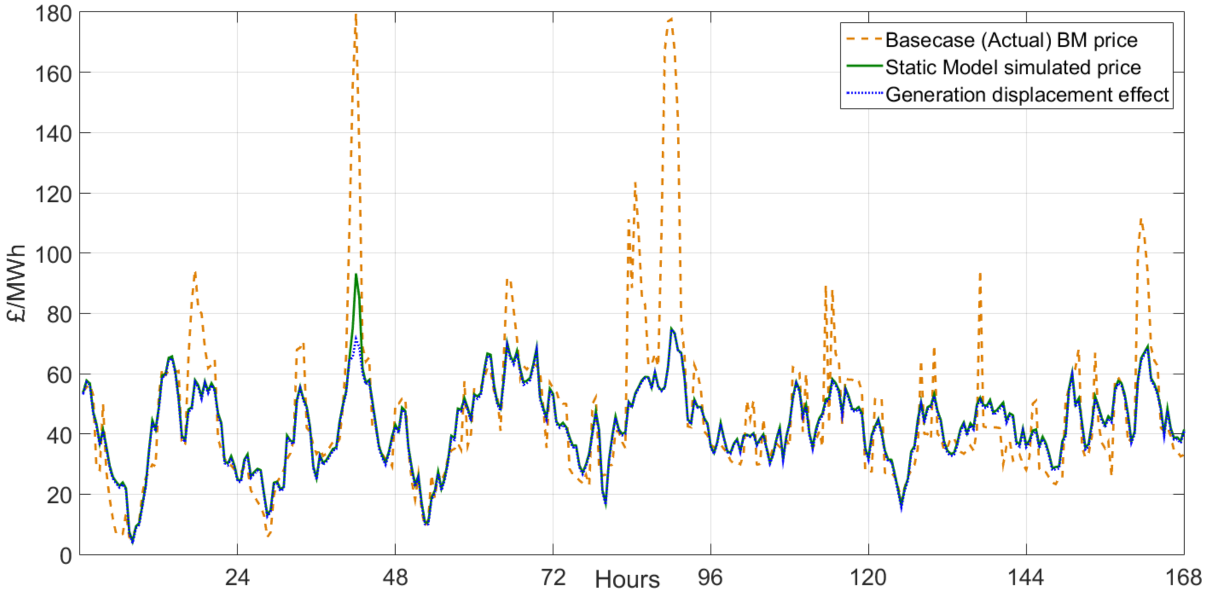


***Figure F.2.*** *A different pathway whereby wind affects the BM, through the displacement of generation by merit order. This is shown using data from the 1st week of Jan 2014.*

Besides the APX price pathway, an increased wind generation can affect the imbalance price through generation displacement. It was shown earlier through the regression results that the peaking plants have a stronger effect in the BM than in the APX market. Using a merit order of generation, it is assumed that wind generation displaces peaking plants and under such an assumption, the negative impact of wind on prices is greater. Figure F2 shows this pathway through which wind generation reduces the imbalance price. The results show that this displacement effect is very small. However cumulatively, the effects through all the pathways add up.