Business Models for Energy Storage Systems

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Declaration of Originality

I hereby declare that:

- 1. The material contained within this thesis is the result of my own work.
- 2. Other work is appropriately referenced.
- 3. No part of the work presented herein has been used in support for another degree or qualification in this on any other academic institution.

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Abstract

Recent commitments to reduce greenhouse gas emissions in the electricity industry associated with the electrification of segments of heat and transport sectors pose significant challenges of unprecedented proportions. The unique features of Energy Storage Systems (ESS) coupled with the flexibility of providing services to multiple sectors of the electricity industry, make it a key technology to tackle current and upcoming challenges in the electricity industry.

Although ESS have the potential to support future system integration with large amounts of renewable generation, the potential value that ESS brings to stakeholders and its associated economics are not well understood to date. In addition, further research is needed on its business model in various markets and system conditions, in particular in the value associated with each service or set of services.

In this context, the conducted research has addressed ESS operational aspects when considering a multiple services portfolio provided to various stakeholders and sensitive to market and system conditions. New ESS operational frameworks together with a computationally efficient modelling framework are proposed for a better understanding of ESS business models.

The novelty introduced with this work is associated with a multiple service business model for ESS which considers services to distribution network operators, system operators, low capacity value generation and participation in the energy market. In addition, the economic aspects of ESS considering various operating policies for maximum revenue is also investigated and enhances the understanding of ESS to develop appropriate market mechanisms and allow efficient deployment of ESS in the electricity industry.

Contents

Abstra	ıct		7
List of	Fig	ures	13
List of	Tal	oles	17
Abbre	viati	ons	19
Ackno	owle	dgements	21
List of	Pu	olications	23
1. Int	rodu	action	25
1.1	M	otivation	
1.2	Sc	ope and Research Questions	
1.3	Su	mmary of Research Findings	
1.4	Th	esis Structure	
2. A N	Mult	i Service Business Model for Energy Storage Systems	
2.1	No	omenclature	
2.2	In	troduction	
2.3	Re	lated Work	
2.4	Ma	athematical Formulation	
2.4	4.1	Objective Function	
2.4	1.2	ESS Capacity Constraints	
2.4	4.3	Balancing Services Deliverability Constraints	
2.4	1.4	DNO Constraints	
2.4	1.5	Additional Modelling Constraints	
2.5	Bu	siness Models for Distributed ESS	
2.5	5.1	Input Data for GB Studies	
2.5	5.2	ESS Operation with Single Services	
2.5	5.3	Multiple Services Portfolio	
2.6	Sy	nergies and Conflicts Between Services	

2.7	Conclusion	56
3. Co:	mmercial Strategies for Distributed Energy Storage Systems	59
3.1	Nomenclature	60
3.2	Introduction	61
3.3	Related Work	
3.4	Benders Decomposition	
3.5	Mathematical Formulation	
3.5		
3.5		
3.5	5.3 Sub-problems	72
3.5	5.4 Convergence Criterion	75
3.6	ESS Commercial Strategies in GB Markets	75
3.0		
3.0	5.2 Impact of Markets and System Conditions on Commercial Strategies	77
3.6	5.3 Value of Reactive Power Coordination	78
3.6	5.4 Value of ESS Roundtrip Efficiency	
3.0	5.5 Impact of Utilisation of Balancing Services on ESS Revenues	
3.6	5.6 Economics of ESS in a Low-Flexibility Power System	
3.7	ESS Commercial Strategies with Support to Intermittent Generation	
3.7	7.1 Modelling Considerations and Input Data	
3.7	7.2 Value of ESS in Support of Wind Imbalances	
3.7	7.3 Impact of ESS Sizing Characteristics on its Economics	
3.8	Conclusion	91
4. Val	lue of Network Support with Distributed Energy Storage Systems	93
4.1	Nomenclature	
4.2	Introduction	
4.3	Related Work	
4.4	Mathematical Formulation	
4.4	1.1 Objective Function	
4.4	1.2 DNO Service Constraints with Corrective Security	
4.4		
4.4	4.4 Further Modelling Constraints	
4.5	Input Data	
4.6	ESS Operation with Corrective Network Security in a Day	
4.0		

4.6	2 Deliverability of DNO Service and Security of Supply	
4.6	3 Increased Energy Arbitrage Revenue through Corrective Security	
4.6	4 Increased Balancing Services Revenues through Corrective Security	105
4.7	Business Case in Support of Corrective Security: Yearly Impact Assessment	106
4.7	1 Yearly Revenues in Energy and Balancing Services Markets	
4.7	2 Yearly Revenues of DNO Rervice	
4.8	Conclusion	107
5. Ene	ergy Storage Systems Business Models with Oversell Operating Polici	es109
5.1	Nomenclature	110
5.2	Introduction	111
5.3	Related work	112
5.4	Mathematical Formulation	113
5.4	1 Objective Function	114
5.4	2 DNO Capacity Constraints with Overselling Policies	115
5.4	3 Balancing Services Constraints with Overselling Policies	115
5.5	Input Data and Modelling Considerations for GB Studies	117
5.6	Oversell Opportunities in a Day	119
5.7	Business Case in Support of Oversell Operating Policies	121
5.8	Impact of System Conditions on Oversell Operating Policies	123
5.9	Conclusion	124
6. Cor	ncluding Remarks and Further Work	125
6.1	Research Achievements and Contributions	126
6.2	Suggestions of Future Work	128
6.2	.1 Implications of Energy Storage Systems Operating Strategies on Services Value	
6.2	2 Market Mechanisms for Energy Storage Systems Efficient Remunerability	
6.2	.3 Energy Storage Systems Operating Strategies Considering Market Power	
6.3	Concluding Remarks	129
Referen	nces	131
Appen	dix A : Performance of Benders Decomposition	137
Appen	dix B : Value of Uncertainty	141
Appen	dix C : Definitions of ESS Services	143

List of Figures

Figure 2.1: Diagram of modelled ESS with local demand and distribution network
infrastructure
Figure 2.2: Linearization of Eqs. (2.4) and (2.29) with a set of lines
Figure 2.3: (a) Time series of local demand and (b) energy prices in two typical days in summer and winter
Figure 2.4: Season averages of UK maximum temperatures (1981-2010) [24] and primary substation secured capacity
Figure 2.5: (a) ESS output and energy price and (b) ESS energy levels, when optimised for energy arbitrage
Figure 2.6: (a) ESS output and committed volumes for reserve services in prescribed reserve window and (b) ESS energy levels, when optimised for up reserve provision
Figure 2.7: (a) ESS output and (b) energy levels for scheduled operation and a possible real time operation
Figure 2.8: (a) ESS output and committed volumes for response services in prescribed response window and (b) ESS energy levels, when optimised for up response provision
Figure 2.9: ESS operation, local demand and net demand (a) active power profiles and (b) reactive power profiles when optimised for DNO service
Figure 2.10: ESS output and (a) energy prices and (b) volumes committed for balancing services
Figure 2.11: ESS energy levels managed for maximum revenue
Figure 2.12: (a) Active and (b) reactive power profiles for ESS operation, local and net demand
Figure 2.13: (a) ESS active power output and (b) energy levels for scheduled operation and a possible real time utilisation of up reserve service
Figure 2.14: Revenue streams associated with the provision of multiple services

Figure 2.15: Interactions between energy arbitrage and other services over one year of operation.	54
Figure 2.16: Interactions between DNO service and other services over one year of operation.	56
Figure 3.1: Diagram showing the general form of stochastic Benders decomposition algorithm.	69
Figure 3.2: Diagram of Benders decomposition with additional step for proposed heuristic	71
Figure 3.3: Histogram of energy prices in (a) summer and winter and (b) spring and autumn, used as input data	76
Figure 3.4: ESS monthly average revenue on different seasons and respective portfolio of services	.77
Figure 3.5: Comparison of probability distribution functions of ESS revenues with different commercial strategies and associated expected revenues	78
Figure 3.6: Monthly average ESS revenues when considering operation with active and reactive power coordination or active power only	.79
Figure 3.7: ESS operation for the same day with active power only (a) and (b), and with active and reactive power coordination (c) and (d)	80
Figure 3.8: ESS monthly revenue for maximum and minimum revenue scenarios when operating at different roundtrip efficiencies.	80
Figure 3.9: ESS monthly average revenues and portfolio of services with (a) 100% and (b) 80% roundtrip efficiency.	
Figure 3.10: ESS revenues with different levels of utilisation of (a) down reserve – Case A – and (b) up reserve – Case B	82
Figure 3.11: Additional ESS revenue in £/MWh exercised for Case A (profit) and Case B (loss)	83
Figure 3.12: ESS monthly average revenue when operating in power systems with different levels of flexibility.	84
Figure 3.13: Wind imbalance for a single day with positive imbalances representing power excess and negative imbalances representing power shortage.	86

Figure 3.14: Observed and fitted distribution functions of wind imbalance data from (a) [52] and (b) [53]
Figure 3.15: Cost for wind balancing service with three different strategies
Figure 3.16: ESS monthly average revenues for individual services when including provision of wind balancing services
Figure 3.17: (a) Opportunity cost of wind service for ESS with different power and energy capacities and (b) service value when provided by a PPA contract or an ESS & Imbalance market for various sized wind plants
Figure 3.18: ESS revenue with various power and energy capacities
Figure 4.1 Schematic of electricity system and services provided by the ESS
Figure 4.2: (a) Local demand and demand excess or surplus in a day (in white and blue, respectively), and (b) energy required (at every period t) to exercise DNO service in post-fault conditions
Figure 4.3: Energy price and local demand profiles during a typical week in (a) winter and (b) summer
Figure 4.4: (a) Histogram of energy prices in a month during summer and winter and (b) load duration curve in a month for summer and winter
Figure 4.5: Local demand, substation installed and N-1 secured capacity
Figure 4.6: ESS scheduled operation, local and net demand with (a) preventive and (b) corrective network security
Figure 4.7: ESS energy levels and levels of energy required to deliver DNO service in post- contingency conditions
Figure 4.8: ESS scheduled and real-time (a) power output and (b) energy level for a contingency at 10:00 h, and (c) power output and (d) energy level for a contingency at 14:00 h
Figure 4.9: (a) ESS output with preventive and corrective security and energy prices, and (b) revenue associated with energy arbitrage actions under preventive and corrective security mode
Figure 4.10: ESS power output and balancing services provided under (a) preventive and (b) corrective security modes

Figure 4.11: Revenues under preventive and corrective control strategies by (a) services and	
(b) month	106
Figure 4.12: Opportunity cost of providing DNO service under different security modes	107
Figure 5.1. Aggregated local demand and peak demand occuring during reserve window	117
Figure 5.2. Duration of exercise of reserve services and associated probabilities in (a) real	
GB data for 2014 and (b) inputa data for the proposed model	118
Figure 5.3. ESS operation and energy prices considering robust and oversell operating policies.	119
Figure 5.4. ESS energy levels and headroom required for delivery of down reserve considering (a) robust and (b) oversell operating policies.	120
Figure 5.5. Scheduled and real time net demand considering (a) robust and (b) oversell operating policies.	120
Figure 5.6. ESS revenue on single services for (a) oversold capacity to reserve services and (c) oversold capacity for DNO, including associated revenue, and expected penalties and profit (b) and (d) respectively	. 121
Figure 5.7. (a) Average increase in ESS revenue due to oversell operating policies differentiated by yearly seasons and (b) frequency of occurrence differentiated by oversold service.	. 122
Figure 5.8. (a) Change in ESS revenue due to change in penalty fees and (b) probability of services exercise	123
Figure A.1: Comparison of value of objective functions between original and decomposed problems for different number of scenarios of energy prices	137
Figure A.2: Comparison of optimisation time between original and decomposed problems with different number of scenarios of energy prices	138
Figure A.3: Comparison of optimisation times and objective function values with different sets of scenarios using a decomposed formulation	138
Figure B.1. (a) Average monthly ESS revenue considering uncertainty (Stochastic) or deterministic energy prices (Deterministic) and (b) different in revenue across different	
scenarios when uncertainty is not considered	141
Figure B.2. Value of uncertainty across different seasons.	142

List of Tables

Table 1.1. Potential ESS services delivered to the four sectors of electricity industry	26
Table 2.1: ESS modelling characteristics used in GB case studies.	. 45
Table 5.1. Probabilities of exercise of reserve and frequency response services used in the	
modelling1	118

Abbreviations

- DNO Distribution Network Operator
- ESS Energy Storage System
- GB Great Britain
- MILP Mixed Integer Linear Programming
- PPA Power Purchase Agreement
- UK United Kingdom

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List of Publications

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- R. Moreira, R. Moreno, G. Strbac; "The value of Corrective Network Security for Distributed Energy Storage Applications", IET Generation Transmission and Distribution, accepted subject to reviews.
- R. Moreno, **R. Moreira**, G. Strbac; "A MILP model for optimising multi-service portfolios of distributed energy storage"; Applied Energy, v. 137, 2015.

Conference papers:

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Technical reports:

 G. Strbac, R. Moreno, R. Moreira, S. Kairudeen, M. Aunedi, P. Djapic; "Conflicts, Synergies and Commercial Strategies for the use of Distribution Network Connected Energy Storage in Multiple Markets"; report for Smarter Network Storage project from UK Power Networks, February 2014

Chapter 1

Introduction

The various aspects that drove this research work and made business models for ESSs the primary focus are detailed in this chapter. The current and upcoming challenges in the electricity system that ESSs can potentially help to tackle are presented herein along with the fundamental features that make ESSs a suitable technology to address them.

Moreover, a comprehensive list of research questions and associated tasks are identified in this chapter to define the scope and objectives of the conducted studies. Fundamentally, this research proposes to identify economically efficient business models for ESSs – either with single or multiple services – that deliver maximum benefits to the various sectors of the electricity industry, by addressing a set of research questions. Following these, are a series of key research findings from the carried out studies.

The chapter ends with an overview of this document structure and the associated research topics addressed in each chapter.

1.1 Motivation

European Union, in particular UK, government's commitment to reduce greenhouse gas emissions poses significant challenges that will require an unprecedented transformation of the electricity system. As part of this effort, markets are expected to deliver and integrate significant amounts of intermittent renewable generation in combination with less flexible nuclear and carbon capture plants while segments of the transport and heat sectors are expected to be electrified, adding further to the system demand.

Integration of low capacity value of intermittent generation, accompanied with possibly important increases in peak demand driven by transport and heating electrification, may lead to significant degradation in the utilisation of generation infrastructure and electricity network assets. As a result, costs associated with system operation and integration are expected to increase considerably. Furthermore, the ability of a system dominated by conventional thermal generation to accommodate significant amounts of renewable generation will be compromised.

In this context, the unique features of ESSs coupled with the flexibility of providing a wide range of services or applications to various sectors of the electricity industry make it a key technology to tackle current and upcoming challenges in the electricity system. ESSs have the potential to support future system integration of low-carbon generation and the electrification of segments of heat and transport, through provision of multiple services to various electricity sectors that facilitate more efficient and secured operation and investment in electricity industry infrastructure.

To exemplify the wide range of services that can be provided by ESSs, Table 1.1 presents a set of services associated with each of the four sectors of the electricity industry (and widely studied in the recent literature). Definition of these services is included in Appendix C.

Generation	Transmission	Distribution	End-Users
Support intermittent generation	Frequency response	Voltage support	Power quality
Arbitrage actions	Reserve	Manage congestions	Reliability
	Black-Start	Reliability	Arbitrage actions
	_		

Table 1.1. Potential ESSs services delivered to the four sectors of electricity industry.

Manage congestions

Although ESSs technologies have the potential to support future system integration, the potential value that ESSs bring to different stakeholders, and therefore its associated revenue streams, are not well understood to date, especially regarding ESSs connected to distribution networks. The

"split benefits" of distributed ESSs across multiple sectors of electricity industry (including generation, provision of services to support real-time balancing of demand and supply, distribution network congestion management and deferring investment in system reinforcement) pose challenges for policy makers to develop appropriate market mechanisms to ensure that investors in ESSs are adequately rewarded for delivering these diverse sources of value.

1.2 Scope and Research Questions

The conducted research focused in addressing the aforementioned challenges and to enhance the understanding of ESSs within the electricity industry. This way, the proposed work will investigate operational aspects of distributed ESSs and its associated economics when connected to distribution networks.

Moreover, with respect to the scale of ESSs connected to a distribution network, the research carried out herein uses typical small scale ESSs characteristics, albeit fundamental conclusions and contribution are still valid for other types of ESSs. In this context, given the scale of the ESS relative to the GB electricity system and the bottom-up single device approach, the modelling framework for the ESS maximum benefits considers a price taker approach, i.e. system prices are neutral to ESS commercial strategies and operational aspects. In addition, the research conducted herein uses a technology agnostic approach and therefore this work can be extended to a wide range of technologies, such as pump-hydro power plants, compressed air energy storage, electric batteries, flywheels and many others.

Among the various existing technologies for ESS – such as hydro pumped storage, flywheels, super-capacitors, batteries, compressed air energy storage and many others – this research was conducted based on a technology agnostic approach. This way flexible modelling techniques were adopted to enable the case studies to be addressed using different ESS technologies.

In terms of services considered for the ESS business model framework, these were modelled according to GB electricity system but adapted to accommodate ESS features. In particular, the services considered were: access to the short term energy market for arbitrage actions, frequency response services (namely firm frequency response service), reserve services (namely short term operating reserve service), balancing service to correct wind forecast imbalances and DNO service defined as peak shaving service for the distribution network operator.

Within this research scope and among the various aspects that will be addressed by the conducted studies, this research work will focus on two objectives:

- I. Given the wide range of services and applications that can be provided by an ESS, which service or set of services should be considered in an ESS business model in order to deliver the most benefits to the various sectors of the electricity industry? In addition, how can ESS capture these benefits if those are split among various stakeholders?
- II. In the context of ESS business models and commercial strategies, how can ESS improve their operational policies in order to maximise utilization of its resources for minimum yield losses and thus improve its economics?

To tackle the proposed objectives, these have been divided in a series of research questions – numbered in relation to each objective – and followed by associated tasks that segment the research problem into a more manageable set of intermediate goals.

- I.i. What are the main features and requirements of ESS operation for delivery of maximum benefits to a particular service?
 - Determine and analyse ESS operation that maximises benefits delivered to single services (addressed in section 2.5.2).
 - Develop a framework to determine and classify interactions among pairs of services when ESS is providing multiple services (addressed in section 2.6).
- I.ii. How can ESS operation coordinate simultaneous provision of multiple services to various stakeholders for maximum revenue?
 - Develop an ESS centric modelling framework for maximum revenue while considering provision of multiple services to various stakeholders (addressed in section 2.4) and identify possible conditions when all considered services are being provided (addressed in section 2.5.3).
- I.iii. Given that services' value is associated with markets and system conditions, how can ESS improve its commercial strategies for maximum revenue?
 - Develop a computationally efficient modelling framework to determine and study ESS commercial strategies, considering a portfolio of services (addressed in section 3.5).
 - Determine the portfolio of services that maximise ESS revenue and analyse the impact that markets and system conditions have on ESS economics (addressed in section 3.6.2).
 - Investigate which portfolio of services can be used to hedge against market volatility and reduce exposure to low revenue scenarios (addressed in section 3.6.2).

- I.iv. How ESS features and parameters affect its economics and selected portfolio of services?
 - Determine the impact that roundtrip efficiency (addressed in section 3.6.4) and sizing characteristics, i.e. power and energy capacities, (addressed in section 3.7.3) have on ESS economics.
 - Study ESS operation with reactive power and its contribution (if any) to ESS business model (addressed in section 3.6.3).
- I.v. How does the value of ESS in the electricity industry change with different levels of flexibility and integration of low capacity value generation?
 - Study the impact of balancing services on ESS economics and how it changes with different balancing services value (addressed in section 3.6.6) and frequency of utilisation (addressed in section 3.6.5).
 - Develop a modelling framework and determine the value of ESS in supporting integration of intermittent generation, such as wind plants (addressed in sections 3.7.1 and 3.7.2).
- I.vi. How can ESS capture the benefits delivered to services/applications which are not market based?
 - Investigate ESS operation for DNO service; analyse the impact that providing the service has on ESS economics and analyse alternative operational policies (addressed in section 4.7).
 - Study reactive power operation for support of DNO service (addressed in section 3.6.3).
- II.i. Redundancy is common practice in electricity networks. How can ESS take advantage of redundant capacity on distribution networks and improve utilization of its resources for maximum revenue?
 - Develop a modelling framework considering new operational policies for provision of DNO service without compromising security of supply (addressed in section 4.4).
 - Analyse and compare ESS operation for DNO service, with different operating policies and associated economics (addressed in sections 4.6 and 4.7).
- II.ii. How can ESS improve the benefits delivered to the various stakeholders by adopting different operating policies?
 - Analyse and compare ESS operation for DNO service, with different operating policies and associated economics (addressed in sections 4.7 and 5.7).

- Develop new modelling framework for minimum ESS yield losses, i.e. allocate ESS resources to the current most valuable service (addressed in section 5.4).
- II.iii. Delivery of balancing services is associated with system conditions and thus probabilities of delivery. How can ESS take advantage of probability of services delivery and maximise utilisation of its resources? What is the impact on ESS economics?
 - Investigate the impact that different levels of balancing services delivery have on: ESS economics (addressed in section 3.6.5 and 5.8) and ESS operational policies (addressed in section 5.6).
- II.iv. With respect to oversell operating policies, when are these most beneficial for ESS economics and with which frequency to they occur?
 - Study ESS operation with oversell policies and their economic viability associated with market and system conditions (addressed in section 5.8).
 - Analyse and determine the frequency that ESS uses such policies for maximum revenue (addressed in section 5.7).

1.3 Summary of Research Findings

The conclusions that emerged from the studies carried out to address the proposed research questions are detailed at the end of each chapter and summarised in the following research key findings:

- Coordinated operation of active and reactive power supports provision of active power only services such as energy arbitrage and system regulation services;
- Provision of reserve or frequency response services may interact differently with energy arbitrage, conflicting or being synergic with each other;
- For maximum remunerability, ESS should provide different portfolios of services throughout a year of operation, e.g. different services should be provided in winter and summer months;
- Provision of downwards balancing services (i.e. increase in ESS charging output) may provide an hedge against volatility and low revenue on energy arbitrage;
- Managing wind imbalances with ESS is more beneficial for wind producers than current practices, e.g. PPAs and imbalance market;

- ESS is capable of delivering network security services (DNO service) either by means of preventive or corrective control actions and still maintain the same level of security of supply;
- Corrective network security actions for DNO service allow a more efficient ESS operation in the energy market and reserve market and thus improved revenues;
- Current market conditions allow cost efficient oversell operating policies to be exercised by ESS for provision of reserve and DNO service;
- Appropriate market mechanisms are required if oversell operating policies by ESS are to be dissuaded.

1.4 Thesis Structure

This research was organised into two parts, each of which addresses one of the objectives defined in section 1.2; specifically, the work in Chapter 2 and Chapter 3 focus to accomplish objective 1 and Chapter 4 and Chapter 5 to accomplish objective 2. This document is structured into five chapters, in which the content is built up so that each chapter refers to previous material, but can also be read in isolation.

Chapter 2 investigates the operational aspects of ESS when providing a portfolio of multiple services to various stakeholders. A novel business model and mathematical modelling is developed to maximise revenue of distributed ESS's by coordinating provision of multiple services.

Chapter 3 expands the work presented in Chapter 2 and develops a computationally efficient mathematical formulation to investigate the fundamentals of ESS commercial strategies on long time scales. The proposed model considers a two stage stochastic optimisation further decomposed using a Benders decomposition approach to determine ESS commercial strategies on long time scales considering provision of energy arbitrage, balancing services, wind balancing services and DNO service.

Chapter 4 proposes a novel ESS operating policy within the multiple services business model framework that considers corrective control actions to manage distribution network congestion and provide services to the DNO. The alternative method uses a corrective control approach to deliver network services while maximising utilisation of ESS resources and further improve its remunerability.

Chapter 5 investigates ESS operational and economic aspects when considering an operating policy derived from other industries. The current practice implemented by airlines and the

hospitality industry for overselling its resources was adapted to the ESS multiple services business model framework for maximum revenue policies.

Chapter 6 presents the main conclusions and the research contributions. In additional, the chapter introduces various aspects and challenges with respect to ESS that can be addressed in potential further work.

Chapter 2

A Multi Service Business Model for Energy Storage Systems

This chapter investigates the economics of ESS's holding a portfolio of multiple services, delivered to various stakeholders. A novel business model and mathematical modelling is thus proposed to maximise revenue of distributed ESS's by coordinating provision of multiple services to various stakeholders. In particular the model includes provision of balancing services – such as reserve and frequency response services -, energy arbitrage and peak demand shaving which supports distribution network operation through both active and reactive power control.

The main features of each individual service are analysed before studying ESS operation with the full set of services. In addition, given the broad range of services and the ability of ESS's to provide multiple services, a framework is developed to assess conflicts and synergies between pairs of services.

The studies demonstrate that an ESS can efficiently coordinate provision of multiple services while maximising its revenue and ensure that distribution network capacity limits are not violated. In addition, the results show that coordination of active and reactive power is key to efficiently support distribution network operation but also support provision of active power services only – such as energy arbitrage and balancing services.

2.1 Nomenclature

Sets

Т	Set of operating periods
Δ	Set of discrete parameters for linearization of $P^2 + Q^2 \leq S^2$

Parameters (in normal font)

\overline{C}^{s}	ESS maximum charging capacity	[MW]
\overline{D}^{S}	ESS maximum discharging capacity	[MW]
d	Duration of standardised period (e.g. 1h or 0.5h)	[h]
Ē	ESS maximum energy capacity	[MWh]
P_t^D	Active power demand from distribution network at period t	[MW]
Q_t^D	Reactive power demand from distribution network at period t	[MVAr]
М	Auxiliary large number used for endogenous constraints	
$\overline{S}{}^{N}$	Secured apparent power capacity of primary substation (N-1 limit)	[MVA]
\overline{S}^{S}	ESS maximum apparent power capacity	[MVA]
β^{Dw}	Parameter to detect provision of simultaneous downwards balancing services $\beta^{Dw} \in [1,2[, e. g. \beta^{Dw} = 1.5]$	
β^{Up}	Parameter to detect provision of simultaneous upwards balancing services $\beta^{Up} \in [1,2[, e.g. \beta^{Up} = 1.5]$	
δ	Parameter used for linearization of nonlinear power constraints	
η	ESS roundtrip efficiency	[%]
π^{E}_{t}	Energy price at period t	[f/MWh]
$\pi_t^{\text{Dw.Rese}}$	Availability price for downwards reserve at period t	[f/MW/h]
$\pi_t^{\text{Dw.Resp}}$	Availability price for downwards frequency response at period t	[f/MW/h]
$\pi_t^{\text{Up.Rese}}$	Availability price for upwards reserve at period t	[f/MW/h]
$\pi_t^{\text{Up.Resp}}$	Availability price for upwards frequency response at period t	[f/MW/h]
τ^{Rese}	Maximum time for utilisation of reserve services	[h]
τ^{Resp}	Maximum time for utilisation of frequency response services	[h]

Variables (in italic font)

C_t^S	ESS charging power output at period t	[MW]
D_t^S	ESS discharging power output at period t	[MW]
E_t	ESS energy at period t	[MWh]
P_t^N	Active power through primary substation at period t	[MW]

34

P_t^S	ESS scheduled active power output at period t	[MW]
Q_t^N	Reactive power through primary substation at period t	[MVAr]
Q_t^S	ESS scheduled reactive power output at period t	[MVAr]
$Rese_t^{Dw}$	Downwards reserve power committed at period t	[MW]
$Rese_t^{Up}$	Upwards reserve power committed at period t	[MW]
$Resp_t^{Dw}$	Downwards frequency response power committed at period t	[MW]
$Resp_t^{Up}$	Upwards frequency response power committed at period t	[MW]
$X_t^{Dw.Rese}$	Downwards reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Dw.Resp}$	Downwards frequency response commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Dw.R\&R}$	Simultaneous downwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Up.Rese}$	Upwards reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Up.Resp}$	Upwards frequency response commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Up.R\&R}$	Simultaneous upwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise	

2.2 Introduction

ESS's can deliver benefits to various stakeholders and thus support activities in the electricity industry associated with generation, network services and support balance demand and supply. Services and applications of ESS on various sectors of the electricity industry have been widely studied in the literature, this study on the other hand will focus on the aggregation of multiple services in a single business model for ESS's and determine the optimum portfolio of services which maximises ESS revenue.

The proposed model analyses and studies an ESS connected to a primary substation that participates on the energy and balancing markets while supporting operation of distribution network infrastructure. The portfolio of services considered in the business model include energy price arbitrage, reserve and frequency response services, and DNO service (peak demand shaving). Figure 2.1 shows a diagram of the considered ESS.

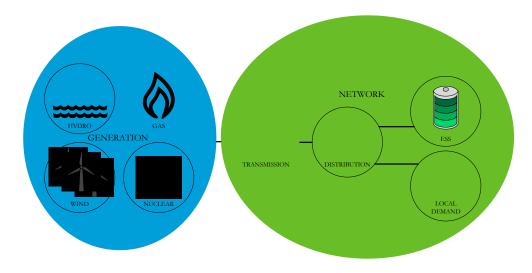


Figure 2.1: Diagram of modelled ESS with local demand and distribution network infrastructure.

The proposed model selects an optimum set of services among a multiple service portfolio and determines ESS operation for maximum revenue while being sensitive to market and system operating conditions. Seasonal fluctuations on energy prices, changes on contractual arrangements for balancing services, variations on system operating conditions such as local demand peaks and distribution network secured capacity, are all factors that drive different set of services to be provided on different conditions. In contrast, business models with fixed set of services in these volatile conditions would be inefficient for maximum benefits to the various stakeholders and thus undermine ESS revenues.

Although, maximum ESS revenues can only be achieved by coordinating operation of ESS active and reactive power outputs. The proposed model determines ESS scheduled operations through coordination of active and reactive power outputs which supports not only DNO service but also active power services only such as energy arbitrage and balancing services.

The rest of this chapter is organised as follows: a review on related work is presented next followed by a detailed mathematical formulation of the proposed model in section 2.4. Section 2.5 presents various studies with single services and a case study comprising the full set of services. Section 2.6 presents a statistical analysis of conflicts and synergies between pairs of services throughout a year of ESS operation. Section 2.7 concludes.

2.3 Related Work

ESS are a valuable source of flexibility for the electricity industry and able to provide a wide range of services and applications to various sectors in the electricity industry, e.g. generation, transmission, distribution and consumption. Decarbonizing the electricity sector and integrate intermittent sources of supply – such as wind and solar plants – is a major challenge to manage system imbalances and which ESS could help to tackle while adding value to the system as reported in [1-6]. For instance, the authors of [3] report that ESS can potentially achieve fuel savings up to 900 f/kW over the ESS life span (assumed 25 years), when integrated with low flexible generation. In a similar study [5] the value of ESS for managing system imbalances in the New York electricity market is estimated between 162,000 and 248,000 \$/MW-year, which clearly demonstrates the benefits that ESS are capable of delivering to system operators in the form of system regulation services.

Likewise, various studies [7-11] have reported the ability of ESS to further support system operation and thus renewables integration through provision of network services, e.g. congestion management. The authors of [8] reported several benefits associated with voltage control and congestion management with a strategic installation of an ESS in an 11-kV distribution network, albeit the benefits of ESS in managing network congestions are not limited to distribution networks; the study of [10] uses ESSs to manage transmission networks congestion and support penetration of wind generation.

In addition the ability of ESSs to support energy market operations by shifting peak demand and thus improving load factors to reduce cost of energy production, has been widely reported in the literature [12-14]. The ability to displace electricity consumption allows ESS to seize arbitrage opportunities in energy markets by buying electricity at low energy prices and selling it back at the market at higher prices; this results in a smoothing effect for peak loads but also on energy prices which can potentially reduce the arbitrage value as [12] reports. In [14] the authors propose a coordinated operation among various distributed ESSs to jointly provide DNO service while minimising the impact that such operating policies have on the joint economics of ESSs operation.

In this context, current studies [5, 10, 15-17] identify the need for combined analysis of multiple services provided to various electricity sectors to adequately assess the value of ESS, including generation, network and renewable energy sources support. The results of [17] show that distributed ESS is capable of achieving savings of circa 60 f/kW.year by deferring distribution network investment, albeit do not quantify benefits and associated revenues to ESS owners, especially for provision of distribution network related services such as congestion management and investment deferral. In contrast, the authors of [18] investigate the value that aggregating provision of various services has for an ESS owner, in particular the study takes into consideration an ESS providing frequency regulation services, correct wind imbalances and support conventional generation with fuel cost minimisation (load shifting).

Hence in contrast to the top-down, whole-system modelling used to demonstrate the value of ESS to the electricity system, a bottom up 'storage centric' modelling framework is developed in this study. The proposed model develops a novel business model for distributed ESS with a multiple service portfolio assuming a price taker methodology which coordinates provision of various ESS services – including managing distribution network operation – for maximum ESS benefits.

2.4 Mathematical Formulation

The proposed model considers an ESS holding a portfolio with multiple services to various stakeholders with a price taker methodology; in particular, the model considers arbitrage actions on energy markets (e.g. day-ahead energy market), balancing services markets and support for distribution network operation - DNO service. The ESS revenues are maximised by coordinating provision of services to various stakeholders and being sensitive to markets and system operating conditions.

Price differentials on energy markets create arbitrage opportunities which are seized by the ESS for maximum revenue. The ESS takes advantage of low prices to buy energy on the day ahead energy market and sell it back at higher energy prices, which allows the ESS to make a profit through arbitrage actions. The proposed model assumes that energy prices are deterministic and known ahead of real time and not influenced by the ESS operation (i.e. price taker approach). In addition to energy arbitrage, the ESS can also provide additional services to other markets – such as balancing services, described next.

The set of services provided to balancing markets by the ESS include: upwards and downwards reserve and frequency response services. Provision of balancing services – such as reserve and frequency response – require commitment of services' volumes ahead of real time and deliverability in real time, which is sensitive to system operator requirements (e.g. system demand-supply imbalances). System imbalances may be of low frequency events (e.g. excess of system demand) thus requiring deliverability of upwards balancing services (e.g. increase ESS discharging power) or of high frequency events (e.g. excess of generation) and thus requiring deliverability of downwards balancing services (e.g. increase ESS charging power). The probabilistic nature of real time deliverability of balancing services is out of the scope of this chapter but investigated in more detail in Chapter 5, nonetheless the proposed model resolves the uncertainty of services utilisation by guaranteeing service deliverability in the worst case scenario (i.e. robust optimisation). This is achieved assuming that reserve and frequency response services have a maximum utilisation time - 2 hours for reserve services [19] and 30 minutes for frequency response services [20].

The ESS can also deliver benefits to DNO's by providing peak demand shaving services and thus support distribution network operation. Peak demand shaving – DNO service – is delivered by managing supply of peak local demand through active and reactive power control. This supports network operation by securing peak demand supply and fundamentally by deferring investment on distribution network infrastructure.

2.4.1 Objective Function

The model is designed to maximise ESS revenues on the energy and balancing services markets by determining scheduled outputs for provision of multiple services - energy arbitrage, reserve and frequency response services. Equation (2.1) shows the model objective function.

$$\operatorname{Max}\left\{\sum_{t\in T} \begin{bmatrix} P_t^S \cdot \pi_t^E + \\ \operatorname{Rese}_t^{Up} \cdot \pi_t^{Up.\operatorname{Rese}} + \operatorname{Rese}_t^{Dw} \cdot \pi_t^{Dw.\operatorname{Rese}} + \\ \operatorname{Resp}_t^{Up} \cdot \pi_t^{Up.\operatorname{Resp}} + \operatorname{Resp}_t^{Dw} \cdot \pi_t^{Dw.\operatorname{Resp}} \end{bmatrix} \cdot d\right\}$$
(2.1)

Energy arbitrage revenue is determined in each period by the bought or sold energy (i.e. ESS charging or discharging power P_t^S times duration, respectively) and multiplied by energy prices π_t^E . Balancing services remunerated based on are their availability price (i.e. $\pi_t^{Up.Rese}, \pi_t^{Dw.Rese}, \pi_t^{Up.Resp}$ and $\pi_t^{Dw.Resp}$) times the committed volume, i.e. upwards or downwards reserve or frequency response services revenues are determined in each period by the power committed to each service ahead of real time and multiplied by the availability price and period duration. Revenues are then summed across all periods (e.g. 24 hours). Note that revenue for DNO service is not included in the objective function; the DNO value is determined as the opportunity cost¹ of allocating energy and power capacity for the service. Robust deliverability of DNO service is ensured by a set of constraints in the model - section 2.4.4. Further details on the value for delivering DNO service are given in Chapter 4.

2.4.2 ESS Capacity Constraints

ESS operation is subject to power constraints – active and apparent power limits – modelled through discharge (D_t^s) and charge (C_t^s) outputs which are combined in a single variable in Eq. (2.2) and respects ESS active power limits in Eq. (2.3). Note that charging actions will be associated with a negative value of P_t^s and bounded by the maximum charging capacity \overline{C}^s , whereas discharging actions are associated with positive values of P_t^s and bounded by the maximum discharging capacity \overline{D}^s .

¹ Opportunity cost is often defined as the loss in revenue (or profit) for pursuing a certain action rather than a more lucrative alternative.

$$P_t^S = D_t^S - C_t^S \quad \forall \ t \in T$$

$$(2.2)$$

$$-\overline{C}^{S} \le P_{t}^{S} \le \overline{D}^{S} \quad \forall \ t \in T$$

$$(2.3)$$

In addition, ESS operation is also bounded by apparent power limits \overline{S}^{S} , through Eq. (2.4).

$$(P_t^S)^2 + (Q_t^S)^2 \le (\bar{S}^S)^2 \quad \forall \ t \in T$$
(2.4)

The flexibility of an ESS allows it to operate either as a typical energy source (e.g. generator) or as an energy demand (e.g. load) albeit, its current state of operation depends on past operational conditions. In particular, previous charge and discharge operations affect its energy reservoir by changing its energy levels² and thus constraining current ESS charging or discharging actions. Therefore, ESS energy balance modelled in Eq. (2.5) takes into account the energy levels in the previous period t (i.e. t-1) and discharge or charging actions in the current period t, which are affected by efficiency losses when charging (following modelling considerations of [17, 21, 22]).

ESS Energy limits are modelled in Eq. (2.6).

$$E_t = E_{t-1} - (D_t^S - C_t^S \cdot \eta) \cdot d \quad \forall \ t \in \mathcal{T}$$

$$(2.5)$$

$$E_t \le \overline{E} \quad \forall \ t \in T \tag{2.6}$$

Due to discretisation of continuous variables, energy levels (E_t) are assumed at the end of each period t. ESS energy balance - Eq. (2.5) - is affected by roundtrip efficiency on charging actions, hence energy reservoir is filled with part of energy withdrawn from the network (e.g. 85% of roundtrip efficiency which is technology dependent). Note that ESS operation is constrained both by power and energy limits, Eqs. (2.3), (2.4) and (2.6); typical generators are often unbundled from past operations and thus do not require such modelling constraints.

2.4.3 Balancing Services Deliverability Constraints

Balancing services are procured by the system operator to balance system demand and generation, and therefore resolve supply shortages or excess in the system. ESS can support and balance demand and supply – through provision of balancing services - with additional discharge or charging actions, respectively for supply shortages or excess.

Provision of reserve and frequency response services (balancing services) should comply with ESS active power limits. In particular, provision of upwards reserve and frequency response is limited

² In this research, energy levels refer to the energy content in terms of MWh in the ESS reservoir and is fundamentally different than state of charge (SOC).

by maximum discharging capacity in Eq. (2.7) and provision of downwards reserve and frequency response limited by maximum charging capacity in Eq. (2.8).

$$Rese_t^{Up} + Resp_t^{Up} \le \overline{D}^S - P_t^S \quad \forall \ t \in T$$

$$(2.7)$$

$$Rese_t^{Dw} + Resp_t^{Dw} \le \overline{C}^S + P_t^S \quad \forall \ t \in T$$

$$(2.8)$$

In Eqs. (2.7) and (2.8) provision of reserve or frequency response services is limited by active power limits however, note that current ESS operation affects the constraints boundaries, for example charging at maximum power capacity ($P_t^s = -\overline{C}^s$) allows to double the volume of upwards reserve or frequency response provided.

The model manages ESS energy levels when providing reserve or frequency response to ensure real time robust delivery of balancing services. Deliverability of upwards reserve service is modelled through Eq. (2.9) which ensures sufficient stored energy to be discharged up to the maximum utilisation time for reserve (τ^{Rese}) and likewise with Eq. (2.11) for upwards frequency response and its maximum utilisation time (τ^{Resp}). On the other hand, when downwards services – reserve or frequency response– are provided, Eqs. (2.10) and (2.12) ensure sufficient headroom in the ESS reservoir for robust deliverability of services. Note that Eqs. (2.9) to (2.12) should not limit ESS operation if balancing services are not provided, and therefore a status commitment variables ($X_t^{Up.Rese}, X_t^{Dw.Rese}, X_t^{Up.Resp}, X_t^{Dw.Resp}$) that control provision of balancing services (i.e. 1 if committed and 0 otherwise) are included to relax constraints modelled through Eqs. (2.9) to (2.12) when services are not committed.

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \le E_{t-1} - \left(P_t^S + Rese_t^{Up}\right) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(2.9)

$$-\mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \le E_{t-1} - (P_t^S - Rese_t^{Dw}) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(2.10)

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \le E_{t-1} - \left(P_t^S + Resp_t^{Up}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \quad \forall \ t \in \mathbf{T}$$
(2.11)

$$-\mathbf{M} \cdot \left(1 - X_t^{Dw.Resp}\right) \le E_{t-1} - \left(P_t^S - Resp_t^{Dw}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Dw.Resp}\right) \quad \forall \ t \in \mathbf{T}$$
(2.12)

Eqs. (2.13) and (2.14) manage ESS energy levels for simultaneous deliverability of upwards or downwards reserve and frequency response respectively.

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \le E_{t-1} - \left(P_t^S + Rese_t^{Up}\right) \cdot \tau^{\operatorname{Rese}} - Resp_t^{Up} \cdot \tau^{\operatorname{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.13)$$

$$-\mathbf{M} \cdot \left(1 - X_t^{Dw.R\&R}\right) \le E_{t-1} - \left(P_t^S - Rese_t^{Dw}\right) \cdot \tau^{\text{Rese}} + Resp_t^{Dw} \cdot \tau^{\text{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Dw.R\&R}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.14)$$

Due to discretisation of continuous variables – such as E_t – Eqs. (2.9) to (2.14) ensure sufficient energy levels if balancing services are instructed to be exercised at the beginning of period t. Hence to increase solution's robustness, an additional set of constraints is included to manage energy levels when balancing services are exercised at any point in time (i.e. from start to end of period t), namely Eqs. (2.15) to (2.26).

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \le E_t - \left(P_t^S + Rese_t^{Up}\right) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(2.15)

$$-\mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \le E_t - (P_t^S - Rese_t^{Dw}) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(2.16)

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \le E_t - \left(P_t^S + Resp_t^{Up}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(2.17)

$$-\mathbf{M} \cdot \left(1 - X_t^{Dw.Resp}\right) \le E_t - \left(P_t^S - Resp_t^{Dw}\right) \cdot \tau^{\text{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Dw.Resp}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(2.18)

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \le E_t - \left(P_t^S + Rese_t^{Up}\right) \cdot \tau^{\text{Rese}} - Resp_t^{Up} \cdot \tau^{\text{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$-\mathbf{M} \cdot \left(1 - X_t^{Dw.R\&R}\right) \le E_t - \left(P_t^S - Rese_t^{Dw}\right) \cdot \tau^{\operatorname{Rese}} + Resp_t^{Dw} \cdot \tau^{\operatorname{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Dw.R\&R}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.20)$$

Commitment of reserve and frequency response services is modelled by Eqs. (2.21) to (2.26) which determine the value of binary variables and hence the commitment status of each service.

$$Rese_t^{Up} \le \mathbf{M} \cdot X_t^{Up,Rese} \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.21)$$

$$Rese_t^{Dw} \le \mathbf{M} \cdot X_t^{Dw.Rese} \quad \forall \ \mathbf{t} \in \mathbf{T}$$
 (2.22)

$$Resp_t^{Up} \le \mathbf{M} \cdot X_t^{Up.Resp} \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.23)$$

$$Resp_t^{Dw} \le \mathbf{M} \cdot X_t^{Dw.Resp} \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.24)$$

$$X_t^{Up.Rese} + X_t^{Up.Resp} - \beta^{Up} \le \mathbf{M} \cdot X_t^{Up.R\&R} \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.25)$$

$$X_t^{Dw.Rese} + X_t^{Dw.Resp} - \beta^{Dw} \le \mathbf{M} \cdot X_t^{Dw.R\&R} \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(2.26)$$

2.4.4 DNO Constraints

Robust deliverability of DNO service is achieved by a set of constraints which ensure ESS operation respects distribution network capacity limits and supports security of supply during congested periods (i.e. peak demand periods). Active power balance between distribution network (P_t^N) , local demand (P_t^D) and ESS operation (P_t^S) is determined through Eq. (2.27) and likewise for reactive power through Eq. (2.28).

$$P_t^N = P_t^D - P_t^S \quad \forall \ t \in T$$

$$(2.27)$$

$$Q_t^N = Q_t^D - Q_t^S \quad \forall \ t \in T$$
(2.28)

Distribution network capacity limits are modelled through Eq. (2.29) by means of apparent power capacity limits which ensures that ESS delivers the DNO service and supports distribution network operation by means of active and reactive power. Note that the model robustness ensures that real time utilisation of balancing services also respects distribution network capacity limits.

$$(P_t^N + Rese_t^{Dw} + Resp_t^{Dw})^2 + (Q_t^N)^2 \le (\bar{S}^N)^2 \quad \forall t \in T$$
(2.29)

2.4.5 Additional Modelling Constraints

The ESS energy levels at the initial and end periods of the optimization horizon were set to have same levels of energy in order to ensure conservation of energy. The initial condition assumption can be suited to adopt different levels of energy, e.g. empty reservoir (0 MWh), full reservoir (\overline{E} MWh) and any value in-between such as previous day's state of charge, which allows implementation of a rolling schedule algorithm.

Eqs. (2.4) and (2.29) model respectively ESS and distribution network apparent power limits, albeit they define a convex region, they are nonlinear. Therefore the nonlinear constraints are approximated by a finite family of linear constraints defined by Eq. (2.30) and illustrated in Figure 2.2, obtained by constructing supporting hyperplanes at sample points in the boundary of the convex region:

$$-\frac{-\delta \cdot \mathbf{P} + \mathbf{S}^2}{\sqrt{\mathbf{S}^2 - \delta^2}} \le \mathbf{Q} \le \frac{-\delta \cdot \mathbf{P} + \mathbf{S}^2}{\sqrt{\mathbf{S}^2 - \delta^2}} \quad \forall \ \delta \in \Delta$$
(2.30)

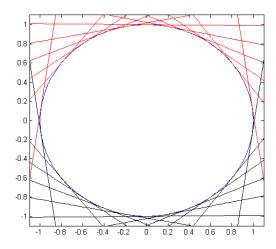


Figure 2.2: Linearization of Eqs. (2.4) and (2.29) with a set of lines.

Reserve services within GB framework are procured within prescribed time windows defined by the system operator needs [20]. Therefore, for GB studies, an additional set of constraints were included to model provision of reserve services only at prescribed time windows and to ensure committed volumes of reserve services to be constant during the windows. For example, if a prescribed window is defined between 16:00 h and 21:00 h the committed volume (e.g. 3 MW) must remain constant during the whole window. In addition, although frequency response services are typically provided at any hour of the day, for the sake of clarity these services were also modelled in prescribed time windows.

In the above formulation $Rese_t^{Dw}$, $Resp_t^{Dw}$, $Rese_t^{Up}$, $Resp_t^{Up}$, D_t^S , C_t^S and E_t are positive decision variables (i.e. greater or equal to zero) and $X_t^{Up.Rese}$, $X_t^{Dw.Rese}$, $X_t^{Up.Resp}$, $X_t^{Dw.Resp}$, $X_t^{Up.R\&R}$ and $X_t^{Dw.R\&R}$ are binary variables (i.e. take 1 or 0 values). The MILP model was implemented in FICO Xpress [23] and solved through the application of standard branch-and-bound and simplex algorithms.

2.5 Business Models for Distributed ESS

The fundamentals of ESS operation when optimised for maximum revenue and considering individual services will be presented next and followed by ESS operation for maximum revenue with a multiple services portfolio. The model was analysed using real data from GB system and markets, albeit fundamental conclusions will still be valid with different system or markets data.

2.5.1 Input Data for GB Studies

Real GB time series data of local distributed demand from DNO metering and prices from energy market were used in the studies presented in this chapter. Time series of local demand was obtained from real DNO metering data at primary substation level with an hourly resolution for the year of 2012 and assumed a constant power factor of 0.96. Energy price time series derives from wholesale electricity prices in the short term³ market – Market Index Price - with an hourly resolution and also for the year of 2012, obtained from ELEXON Portal website [7]. Two profiles of local demand and energy prices are shown in Figure 2.3 (a) and (b) respectively for a typical day in summer and winter.

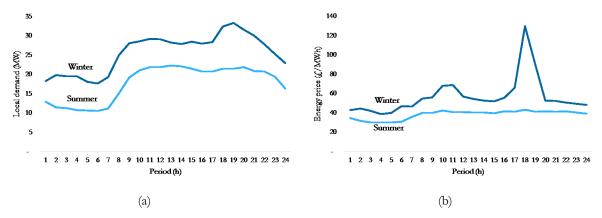


Figure 2.3: (a) Time series of local demand and (b) energy prices in two typical days in summer and winter.

The ESS was modelled considering three fundamental parameters: power capacity, which can be differentiated in charge and discharge active power capacities, energy capacity and roundtrip efficiency. Although the formulation allows different charge and discharge power capacities, for the sake of clarity charge and discharge capacities were assumed equal. Table 2.1 summarises the ESS modelling characteristics.

Maximum charging capacity (\overline{C}^{S})	6 [MW]
Maximum discharging capacity (\overline{D}^{S})	6 [MW]
Apparent power capacity (\overline{S}^{S})	7.5 [MVA]
Energy capacity (E_t)	10 [MWh]
Energy initial condition $(E_{t=0})$	0 [MWh]
Roundtrip efficiency (η)	85 %

Power systems infrastructures are exposed and sensitive to weather conditions - such as temperature and wind - which for example affect network capacity ratings, in particular lines and power transformers ratings. A study on UK monthly maximum temperatures (from 1981 to 2012 and seasonally averaged) was performed to determine secured power capacities of primary substation depending on seasonal maximum temperatures. As shown in Figure 2.4 depending on

³ Short-term is defined as 3 business days before gate closure.

the yearly season, primary substation secured capacity will be affected to account for thermal effects.

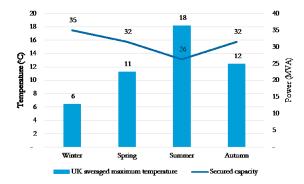


Figure 2.4: Season averages of UK maximum temperatures (1981-2010) [24] and primary substation secured capacity.

Procurement of balancing services in GB framework is achieved in auctions to meet the needs of system operator within prescribed time windows. These are often defined according to seasons in a year and fundamentally cover morning and evening periods; additional detailed information on procurement of balancing services by the GB system operator can be found in [25]. In the studies presented next, frequency response window was defined in the morning between 06:00 h and 09:00 h all year round and reserve window was defined between 19:00 h and 22:00 h in the months of March to August and between 16:00 h and 21:00 h in the remaining months, which follows GB balancing services framework.

Balancing services availability prices are determined through contractual arrangements between system operator and each service provider, which according to [26] in 2014 had an average value of 5.83 \pounds /MW/h for short term operating reserve service and typically lower than 8 \pounds /MW/h for firm frequency response services according to [27]. Availability prices for reserve services were then set at 5 \pounds /MW/h and frequency response services set at 7 \pounds /MW/h. Upwards and downwards reserve or frequency response services were priced equally for the sake of clarity, albeit the model accepts different (and time dependant) values for upwards and downwards.

2.5.2 ESS Operation with Single Services

This section will focus on ESS operational aspects when providing individual services, in particular how ESS operation (i.e. power output and energy levels) is determined for maximum benefits. This will help the reader to understand and identify the fundamental concepts associated with each service and in particular when more services are provided simultaneously.

Energy arbitrage

Arbitrage opportunities in the energy market are seized by taking advantage of price differentials between early morning low energy prices and early evening peak energy prices. Figure 2.5 shows ESS active power output and energy levels on a winter day in 2012, when maximised for energy arbitrage revenue only.

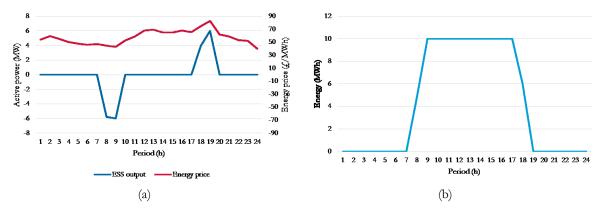


Figure 2.5: (a) ESS output and energy price and (b) ESS energy levels, when optimised for energy arbitrage.

The results show that ESS is buying energy at periods of low energy prices - 8:00 h and 9:00 h – by charging up to its maximum energy capacity – 10 MWh – and selling this energy back to the market at higher energy prices by discharging at 18:00 h and 19:00 h. Note that the ESS discharges less energy than it charges due to wasted energy through losses (i.e. exactly the ESS roundtrip efficiency, 85%). This affects arbitrage actions since its energy losses need to be covered with energy bought at the energy market and therefore arbitrage actions are only performed if price differentials are economically efficient.

Reserve services

Reserve services are committed ahead of real time but only delivered in real time which requires ESS energy levels and power availability to be scheduled in advance for any possible realisation in real time (i.e. robust services deliverability).

When maximised individually, volumes of committed reserve services may exceed ESS energy maximum capacity. Figure 2.6 (a) shows ESS scheduled power output and committed volumes for up reserve during its prescribed window and (b) ESS energy levels.

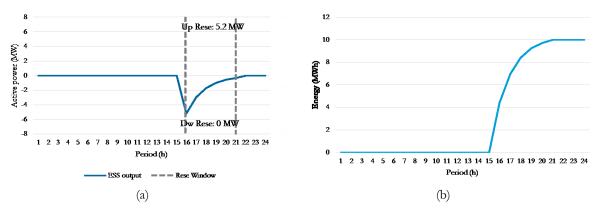


Figure 2.6: (a) ESS output and committed volumes for reserve services in prescribed reserve window and (b) ESS energy levels, when optimised for up reserve provision.

Committed volume for up reserve is 5.2 MW which according to maximum utilisation time (i.e. 2h) would require stored energy equal to 10.4 MWh, although ESS maximum energy capacity is only 10 MWh. The surplus on committed volume for up reserve is achieved through the modelling characteristics of Eq. (2.9); committed volume for up reserve can be maximised by scheduling charge operations during periods of reserve provision. This maximises the volume of committed up reserve service up to twice the maximum power capacity, although charging actions are also limited by maximum energy capacity, i.e. charging for the whole duration of reserve window would violate ESS energy limits (i.e. 10 MWh) and hence the exponential decrease in the charging rate seen between 16:00 h and 21:00 h.

Commitment of up reserve exceeds ESS energy capacity, nevertheless the model's robustness still ensures real time deliverability. Figure 2.7 shows a possible real time output for exercising up reserve and ESS scheduled output. Note that exercise of up reserve endures for 2h (i.e. periods 17:00 h to 18:00 h) although stored energy levels are able to ensure service deliverability.

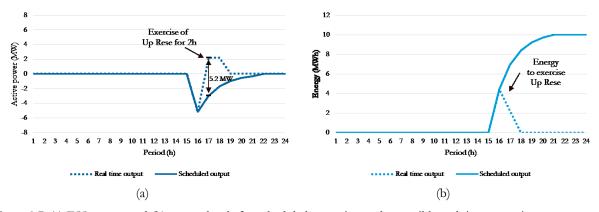


Figure 2.7: (a) ESS output and (b) energy levels for scheduled operation and a possible real time operation. Similar results can be observed for provision of down reserve, in particular commitment of higher volumes than ESS energy capacity.

Response services

Frequency response services have lower energy requirements than reserve services – 30 minutes compared to 2h maximum service utilisation – which enhances the effect of being able to commit higher volumes of balancing services than the allowed ESS capacities. As explained and shown with reserve provision, scheduling charge or discharge operations while simultaneously committing frequency response services allows higher volumes of up or down response to be committed than ESS power capacity. Figure 2.8 (a) shows ESS output and committed volume for up response during the window for response services and (b) shows ESS energy levels.

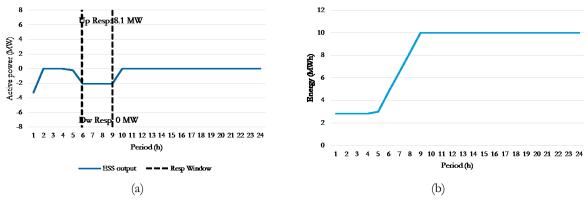


Figure 2.8: (a) ESS output and committed volumes for response services in prescribed response window and (b) ESS energy levels, when optimised for up response provision.

ESS maximises provision of up response service by committing higher volumes than its maximum power capacity, i.e. commitment of 8.1 MW for up response when discharge capacity is limited to 6 MW. Scheduled output is optimised to allow maximum volume of up response by scheduling ESS to charge 2.1 MW during window for response services and thus allowing a change in the output of up to 8.1 MW (from 2.1 MW charging up to 6 MW discharging). Note, however, that ESS energy capacity limits are not violated since maximum utilisation time of response services (30 min) requires 4.05 MWh of stored energy to ensure real time deliverability of committed service.

DNO Service

Maximum provision of DNO service is achieved by minimising power flow through primary substation with coordinated operation of active and reactive power, i.e. minimise peak net demand in terms of apparent power. ESS has the potential of reducing peak net demand up to 7.5 MVA (maximum power capacity), albeit energy constraints may restrict volume of peak shaving.

Figure 2.9 (a) shows active power profiles and (b) shows reactive power profiles of local demand, ESS output and net demand when ESS operation is optimised for maximum DNO service provision.

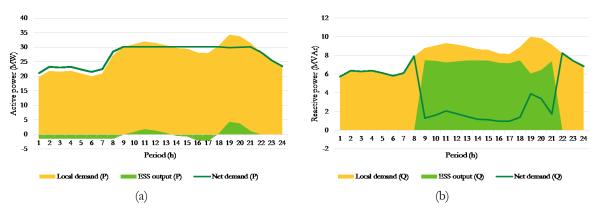


Figure 2.9: ESS operation, local demand and net demand (a) active power profiles and (b) reactive power profiles when optimised for DNO service.

Coordinated operation of active and reactive power is crucial for maximum provision of DNO service, both for discharging and charging operations to manage ESS energy levels, e.g. between periods 19:00 h and 21:00 h ESS is discharging active and reactive power. Likewise, since ESS has to manage its energy levels - charge its reservoir - reactive power can be used to offset increase in active net demand and keep providing DNO service, e.g. between periods 14:00 h to 17:00 h ESS is discharging reactive power to offset increase in active net demand.

2.5.3 Multiple Services Portfolio

The proposed model is able to combine all the aforementioned services in a single business model and efficiently select which portfolio of services should be provided in order to maximise ESS revenues. The model determines ESS scheduled operations – through coordination of active and reactive power - sensitive to markets and system operating conditions.

Figure 2.10 shows a single day where the full set of services is being provided to multiple stakeholders through coordinated operation of active and reactive power.

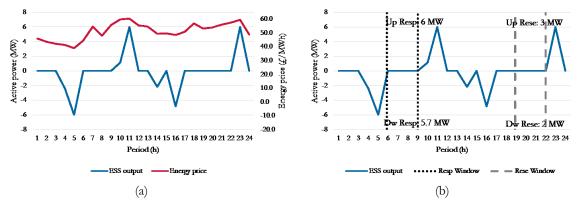


Figure 2.10: ESS output and (a) energy prices and (b) volumes committed for balancing services.

Energy arbitrage is achieved by charging – buying – energy at periods with low energy prices and discharging – selling – it back to the energy market at higher prices. Figure 2.10 (a) shows ESS

active power output and energy prices; it is clear that ESS scheduled operation is seizing arbitrage opportunities at periods 5:00 h and 11:00 h, and at periods 16:00 h and 23:00 h – by charging at low prices and discharging later at higher prices. Note that under these specific conditions, ESS does two charge/discharge cycles which in addition to energy arbitrage actions it also supports the provision of other services as explained next.

Figure 2.10 (b) shows ESS scheduled output and committed volumes for balancing services during their prescribed windows – reserve and response windows. ESS scheduled output is able to coordinate provision of balancing services – both up and down, reserve and response services – in addition to energy arbitrage actions. ESS energy levels required for provision of response and reserve services are being coordinated with energy arbitrage actions by respectively charging the ESS reservoir at periods 4:00 h and 5:00 h for response services and at periods 14:00 h and 16:00 h for reserve services. Robust deliverability of up and down services - if exercised in real time - is achieved by being in stand-by during the services windows which allows the ESS to rapidly change its real time output to discharge or charge if up or down services are instructed to be delivered in real time respectively.

Since up and down services are being simultaneously provided (both for response and reserve) ESS energy levels have to be efficiently managed to accommodate provision of both services by ensuring sufficient stored energy for up services (discharging operations) and sufficient headroom for down services (charging operations), as shown in Figure 2.11.

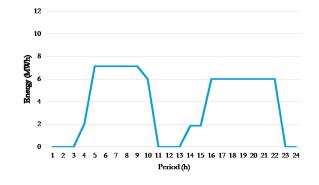


Figure 2.11: ESS energy levels managed for maximum revenue.

ESS operation is able to coordinate energy arbitrage, provision of 6 and 5.7 MW for up and down response services respectively, 3 and 2 MW for up and down reserve services respectively, and it can also provide DNO service by co-ordinating active and reactive power outputs to maintain power flow (net demand) at primary substation within secured capacity limits. Figure 2.12 shows ESS, local and net demand (a) active and (b) reactive power profiles for the same day as Figure 2.10.

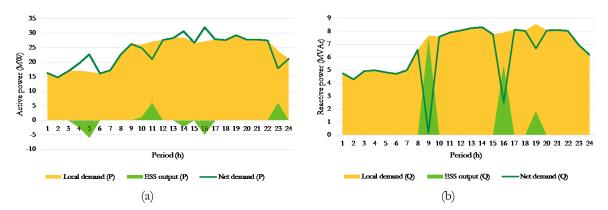


Figure 2.12: (a) Active and (b) reactive power profiles for ESS operation, local and net demand.

Coordinated operation of active and reactive power supports distribution network operation within its secured capacity limits while supporting provision of balancing services – both for scheduled and real time operation. Reactive power output at periods 9:00 h and 19:00 h occur when active power output is in stand-by due to provision of response services (response window between 6:00 h and 9:00 h) and reserve services (reserve window between 19:00 h and 22:00 h), which demonstrates that reactive power is supporting provision of balancing services. Note that although active power output is in stand-by, a possible real time utilisation of down balancing services, could potentially result in a violation of substation secured capacity limits. Thus, reactive power output is scheduled to support provision of balancing services and ensure that real time changes in operation – due to utilisation of balancing services – will not undermine deliverability of DNO service.

In addition to support of provision of balancing services coordinated operation of active and reactive power can also support arbitrage actions on the energy market. ESS charging actions have the potential to aggravate or add further congestions in distribution network, however reactive power output can be used to offset increases in net demand. Note that reactive power output at period 16:00 h is supporting ESS charging actions by offsetting the increase in net demand due to active power charging operation.

The model robustness ensures deliverability of DNO service and balancing services, both for scheduled and real time operation. Provision of balancing services is achieved in a twofold operation: scheduled operation, where volumes for reserve and response services are committed ahead of real time and real time operation which includes multiple possibilities for the utilisation of committed volumes. Figure 2.13 shows ESS active power operation and energy levels for scheduled operation and a possible real time utilisation of up reserve service.

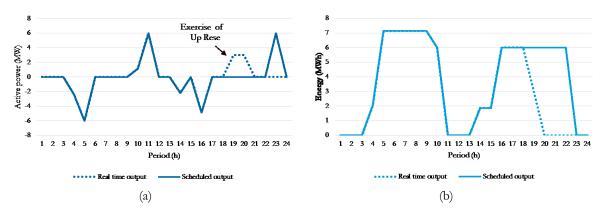


Figure 2.13: (a) ESS active power output and (b) energy levels for scheduled operation and a possible real time utilisation of up reserve service.

To provide up reserve (simulated at period 19:00 h), ESS scheduled output is adjusted from standby to a steady discharge output of 3 MW (i.e. the same volume committed for up reserve) for 2 hours, and therefore ESS energy levels change accordingly. Note that after service delivery ESS needs a recovery period in order to return to its scheduled operation. For the sake of clarity this has been omitted in Figure 2.13 but studied in depth in Chapter 3.

Individual revenues for all provided services are presented in Figure 2.14. In contrast to energy arbitrage and balancing services, DNO service is assumed to be compulsory and if remunerated appropriately it creates an additional revenue stream for the ESS. Revenue from DNO service is calculated as an opportunity cost, i.e. the revenue increase on other services – such as energy arbitrage and balancing services – when no capacity is allocated to provide DNO service.

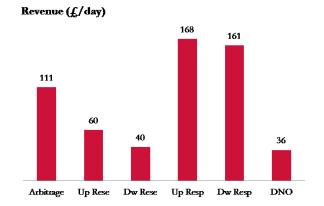


Figure 2.14: Revenue streams associated with the provision of multiple services.

A significant part of ESS total revenue is driven by provision of response services – both up and down response –, due to market value for response services and the fact that energy requirements

are lower than those for reserve (i.e. 30 minutes of maximum utilisation for response compared to 2 hours for reserve services).

As shown in Figure 2.14, ESS on this single day, when optimally coordinating the provision of the aforementioned 6 services, will make a total revenue of 576 f/day. However, note that different market and system operating conditions might change the selected portfolio of services to be provided; services may conflict or be synergic with one another depending on market and system conditions and therefore for maximum ESS revenue, different services have to be selected. The next section will study the conflicts and synergies found between pairs of services over a year of operation.

2.6 Synergies and Conflicts Between Services

A business model with a multi service portfolio is naturally composed of services that share ESS capacity and therefore synergic with each other, and services that will compete with each other for ESS allocated capacity and therefore conflicting with each other. This section will study these synergies and conflicts between pairs of services and quantify the frequency of each interaction on a daily basis over the course of one year operation.

Interactions between pairs of services are influenced by market and system operating conditions, for that reason the same pair of services may interact differently on different days. Figure 2.15 shows the frequency of conflicts (in red) and synergies (in green) over one year of operation between energy arbitrage – driven by daily energy market prices – and all other services, the right most column identifies the recurring interaction (i.e. conflict or synergy).



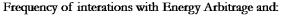


Figure 2.15: Interactions between energy arbitrage and other services over one year of operation.

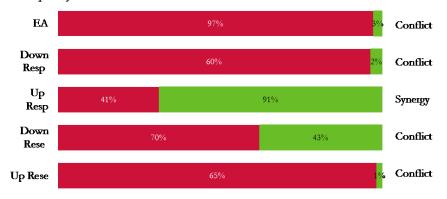
DNO service and energy arbitrage are often conflicting services since peak local demand and peak energy prices are not coincident. Would peak energy prices and peak local demand occur

simultaneously, providing one service would support the other since both services would require discharging actions for maximum benefits, although this is not the case as peak energy price is frequently lagging peak local demand. Therefore, providing DNO service will require discharging actions at inefficient energy prices. In addition, and as shown in Figure 2.12, ESS charging actions at low energy prices increase net demand and aggravate substation congestion, and thus conflicting with DNO service.

Response services can be either synergic or conflicting with energy arbitrage actions, depending whether the window for response services is defined during peak or low energy prices. Response services window was defined in the morning (i.e. between 6:00 h and 9:00 h) which often coincides with low energy prices and thus typical charging periods for energy arbitrage actions. This results in a synergy between energy arbitrage and provision of up response services and a conflict with down response services. This result is supported by Figure 2.8 where provision of up response drives ESS output to charge. Note, however, that if response window was defined during other periods (such as typical discharging periods) these results would invert, as in the case of energy arbitrage and reserve services.

Both reserve services conflict with energy arbitrage, although there is a higher frequency of synergies between energy arbitrage and down reserve. This is due to the period that reserve window is defined which in this study was during late afternoon and early evening (i.e. between 16:00 h and 21:00 h or 19:00 h and 22:00 h) which often coincides with discharging actions for energy arbitrage. However, provision of reserve services – both up and down service – require unique ESS outputs and an efficient management of energy levels which conflicts with energy arbitrage, i.e. since energy levels have to be maintained until the end of reserve window, discharging actions are limited in order to hold energy levels for possible delivery of committed service.

Interactions with DNO service are identical to the ones obtained for energy arbitrage. Figure 2.16 shows the frequency of conflicts (in red) and synergies (in green) over one year of operation between DNO service – driven by daily local demand profiles – and all other services, the right most column identifies the recurring interaction (i.e. conflict or synergy).



Frequency of interations with DNO service and:

Figure 2.16: Interactions between DNO service and other services over one year of operation.

Provision of DNO service is achieved through discharging actions during peak demand periods and preventing that charging actions aggravate net demand. Therefore the type of interactions between DNO service and other services are also explained by the discharge/charge compatibility between services, for example DNO service and up reserve are conflicting since provision of up reserve drives ESS output to charge and this often coincides with peak demand (i.e. evening hours).

The frequency of conflicts between DNO service and up response is higher than those between energy arbitrage and up response. This is due to usual charging actions, driven by up response service, which will add to local demand and thus increase net demand. This conflict is identified in Figure 2.12 when ESS reactive power output is discharging at period 9:00 h to offset increase in net demand due to provision of up response.

2.7 Conclusion

This chapter proposed and studied a novel business model with a multi service portfolio for distributed ESS to various stakeholders in the electricity sector. The model includes coordination of active and reactive power for maximum ESS revenues on the energy market, balancing markets and support operation of distribution network.

The results have shown that distributed ESS is capable to simultaneously deliver benefits to various stakeholders, while maximising its own revenues. Arbitrage on the energy market, provision of reserve, and frequency response services, and peak shaving (DNO service) has been shown in a single day with a total revenue for ESS of 576 f_c /day.

The model robustness ensures real time deliverability of services which were committed ahead of real time. Balancing services – such as reserve and frequency response – are committed ahead of real time although, the model robustness ensures that any possible real time utilisation of

committed volumes is secured by power and energy availability. Moreover, since real time utilisation of balancing services may interfere with substation secured capacity limits, the model robustness still ensures real time deliverability of committed volumes for balancing services – in particular down reserve or frequency response services.

ESS operation is achieved through a coordination between active and reactive power outputs which ensure substation secured capacity limits are not violated in addition to support provision of other services. Results have shown that reactive power output can support provision of energy arbitrage and balancing services, albeit being active power services only.

When provided simultaneously, some services are synergic or conflict with other services. The model was used to analyse the frequency of these conflicts or synergies through a year of operation and under different market and system conditions. The results have shown that services interactions are mainly driven by market and system conditions such as energy prices, distribution network congestion, windows of balancing services, peak demand hours, among many other which differ throughout a year of operation, nevertheless some services have consistent interactions; energy arbitrage, DNO service, up reserve and down response are consistently conflicting with one another.

Fundamentally, this chapter has shown that a single distributed ESS is capable of providing a multi service portfolio sensitive to market and system conditions, all while maximising ESS revenues. Next chapter will investigate how market and system conditions affect the set of services provided and commercial strategies for maximum revenue on longer terms.

Chapter 3

Commercial Strategies for Distributed Energy Storage Systems

This chapter will investigate the fundamentals of ESS commercial strategies on long time scales when considering uncertainty in the energy market and within a multiple service business model framework. The proposed model is an extension of the model from Chapter 2 into a two stage stochastic problem to accommodate uncertainty on energy prices, as well as, a longer time frame – 3 months. ESS scheduled operation will be sensitive to prices of balancing services, contracted 3 months ahead of real time, energy market, with uncertainty in energy prices, and support distribution network operation (DNO service).

A set of studies will determine and analyse the value of reactive power, round trip efficiency and hedging strategies of ESS commercial strategies to contract services 3 months ahead of delivery and in the presence of uncertainty. The results have shown that coordination of active and reactive power is crucial for DNO service – valued up to 2,000 £/month – and that provision of balancing services can be used to hedge against low revenues on energy arbitrage. The economics of round trip efficiency have also been investigated and a revenue increase of up to 4,500 £/month can be achieved with a 10% increase in round trip efficiency. ESS capability to support intermittent renewable generation is also analysed in a case study and its value within the multiple service business model determined along with a comparison with other balancing strategies.

3.1 Nomenclature

Sets

T Set of operating periods

 Ω Set of energy price scenarios

Parameters (in normal font)

\overline{C}^{s}	ESS maximum charging capacity	[MW]
\overline{D}^{S}	ESS maximum discharging capacity	[MW]
d	Duration of standardised period (e.g. 1h or 0.5h)	[h]
Ē	ESS maximum energy capacity	[MWh]
P_t^D	Local active power demand at period t	[MW]
p_{ω}	Probability of realisation of scenario ω	[%]
$Q_{k,\omega}$	Value of Benders decomposition sub-problems at iteration \boldsymbol{k} and scenario $\boldsymbol{\omega}$	[f/3months]
Q_t^D	Local reactive power demand at period t	[MVAr]
$\widehat{Rese}_{k,t}^{Dw}$	Solution of downwards reserve power committed at iteration k and period t	[MW]
$\widehat{Rese}^{Up}_{k,t}$	Solution of upwards reserve power committed at iteration k and period t	[MW]
$\widehat{Resp}_{k,t}^{Dw}$	Solution of downwards frequency response power committed at iteration k and period t	[MW]
$\widehat{Resp}_{k,t}^{Up}$	Solution of upwards frequency response power committed at iteration \boldsymbol{k} and period \boldsymbol{t}	[MW]
\overline{S}^{N}	Secured apparent power capacity of primary substation (N-1 limit)	[MVA]
\overline{S}^{S}	ESS maximum apparent power capacity	[MVA]
М	Auxiliary large number used for endogenous constraints relaxation	
$\widehat{X}_t^{Dw.Rese}$	Downwards reserve commitment status at period t: 1 if committed, 0 otherwise	
$\widehat{X}_t^{Dw.R\&R}$	Simultaneous downwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise	
$\widehat{X}_{t}^{Up.Rese}$		
Λt	Upwards reserve commitment status at period t: 1 if committed, 0 otherwise	
$\hat{X}_{t}^{Up.R\&R}$	•	
-	Upwards reserve commitment status at period t: 1 if committed, 0 otherwise Simultaneous upwards frequency response and reserve commitment status at	[%]
-	Upwards reserve commitment status at period t: 1 if committed, 0 otherwise Simultaneous upwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise	[%]
X ^{Up.R&R} X ^t	Upwards reserve commitment status at period t: 1 if committed, 0 otherwise Simultaneous upwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise Benders decomposition convergence tolerance Dual variable of downwards reserve constraints at iteration k, scenario ω and	[%]

$\lambda^{Up.Resp}_{k,\omega,t}$	Dual variable of upwards frequency response constraints at iteration k, scenario $\boldsymbol{\omega}$ and period t	
η	ESS roundtrip efficiency	[%]
$\pi^E_{\omega,t}$	Energy price at period t and scenario ω	[£/MWh]
$\pi_t^{\text{Dw.Rese}}$	Availability price for downwards reserve at period t	[f/MW/h]
$\pi_t^{\text{Dw.Resp}}$	Availability price for downwards frequency response at period t	[f/MW/h]
$\pi_t^{Up.Rese}$	Availability price for upwards reserve at period t	[f/MW/h]
$\pi_t^{Up.Resp}$	Availability price for upwards frequency response at period t	[f/MW/h]
τ^{Rese}	Maximum time for utilisation of reserve services	[h]
τ^{Resp}	Maximum time for utilisation of frequency response services	[h]

Variables (in italic font)

$C^{S}_{\omega,t}$	ESS charging power output in scenario ω , at period t	[MW]
$D^{S}_{\omega,t}$	ESS discharging power output in scenario ω , at period t	[MW]
$E_{\omega,t}$	ESS energy level in scenario ω , at period t	[MWh]
$P^N_{\omega,t}$	Active power through primary substation in scenario ω , at period t	[MW]
$P^{S}_{\omega,t}$	ESS scheduled active power output in scenario ω , at period t	[MW]
$Q^N_{\omega,t}$	Reactive power through primary substation a in scenario ω , at period t	[MVAr]
$Q^S_{\omega,t}$	ESS scheduled reactive power output in scenario ω , at period t	[MVAr]
$Rese^{Dw}_{\omega,t}$	Downwards reserve power committed in scenario ω , at period t	[MW]
$Rese^{Up}_{\omega,t}$	Upwards reserve power committed in scenario ω , at period t	[MW]
$Resp^{Dw}_{\omega,t}$	Downwards frequency response power committed in scenario ω , at period t	[MW]
$Resp^{Up}_{\omega,t}$	Upwards frequency response power committed in scenario ω , at period t	[MW]
$Rese_t^{Dw}$	Downwards reserve power committed at period t	[MW]
$Rese_t^{Up}$	Upwards reserve power committed at period t	[MW]
$Resp_t^{Dw}$	Downwards frequency response power committed at period t	[MW]
$Resp_t^{Up}$	Upwards frequency response power committed at period t	[MW]
θ	Benders decomposition optimality cut	[£/3months]

3.2 Introduction

ESS are capable of delivering services and applications to multiple stakeholders while maximising its revenues, as demonstrated in Chapter 2. However, different frameworks and contractual arrangements for individual services create a major challenge to efficiently operate ESS for maximum benefits while ensuring deliverability of all services in real time. This chapter will study the fundamentals of ESS commercial strategies on long time scales within a multiple service business model framework.

Contractual arrangements for provision of balancing services within GB framework are achieved through auctions up to 3 months ahead of real time, whereas energy arbitrage actions may be contracted from months ahead to on-the-day trading market. Longer time scales for commercial strategies are associated with higher levels of uncertainty on market prices and system operating conditions which undermine efficient scheduled operation of ESS for maximum revenue. Hence, the proposed model takes into consideration a first stage scheduling for balancing services with perfect knowledge of availability prices (balancing markets prices) and a second stage (stochastic) scheduling for energy arbitrage and provision of DNO service with uncertainty on energy prices, i.e. ESS is scheduled with perfect information on balancing markets prices in contrast to unpredictability of energy market prices.

Formulating a two stage stochastic problem - for multiple services business model framework - while extending the optimization time scale for 3 months featuring scenarios of energy prices creates a major computational challenge as the mathematical model grows in size and complexity. A Benders decomposition technique similar to the one presented in [28] was used to maintain problem tractability and achieve efficient solutions in reasonable computational time with most commercial optimisation solvers while still ensuring effective optimum solutions; a few linearization techniques for quadratic and disjunctive constraints were used to facilitate Benders decomposition.

The impact of markets and system conditions on ESS commercial strategies were analysed on a series of case studies and determined which portfolio of services is the most adequate for maximum benefits. Although constantly changing, markets and system operating conditions are fairly consistent across yearly seasons – summer, autumn, winter and spring – and thus allowing to identify which commercial strategies deliver maximum benefits in each season. Moreover, as the model considers unpredictable energy prices, this research has also investigated hedging strategies against volatility on ESS revenue.

A further set of studies focused on ESS operation in a cost effective manner with regards to roundtrip efficiency and exercise of balancing services committed ahead of real time. Roundtrip efficiency directly affects ESS operation and thus its revenue both on the energy and balancing markets. These results can be used to determine whether or not a more efficient ESS is a cost effective investment when delivering multiple services to various stakeholders. In addition, the studies also analysed the impact that different real time utilisation frequencies of committed balancing services have on ESS revenues, in particular on energy arbitrage revenue.

As demonstrated in Chapter 2, coordination of active and reactive power supports provision of DNO service and can potentially support the economics of other services too. The value of reactive power in supporting provision of other services is determined within ESS long term commercial strategies framework and compared with current reactive power services remunerative policies in the GB electricity market. Furthermore, the fundamentals of supporting distribution network operation (DNO service) by means of coordinated active and reactive power rather than active power only is addressed in this chapter, in particular how coordination of active and reactive power facilitates managing ESS energy levels.

Future power systems are expected to be characterised by decentralised electricity generation with distributed energy resources emerging closer to centres of demand and mainly from renewable energy sources, which is believed to challenge the flexibility of power systems [29]. A technology offering flexibility such as ESS is capable of addressing this with provision of multiple services, albeit understanding how the value of flexibility in future power systems affects its commercial strategies is key for efficient ESS economics. The value of ESS in possible future power systems with different levels of flexibility is thus addressed in this chapter. In addition, ESS can further support integration of intermittent renewable energy sources by correcting imbalances in generation due to forecast errors. The value of using ESS to balance wind forecast errors has been studied as well as compared against alternative strategies, such as resorting to the imbalance market to buy possible energy shortages or using edging contracts – such as power purchase agreements (PPAs).

The rest of this chapter is organized as follows: a review of related work is presented next and followed by a generic description of Benders decomposition in two stage stochastic programs in section 3.4 before presenting the detailed mathematical formulation used in the modelling in section 3.5. Section 3.6 presents a series of case studies on ESS long term commercial strategies, including the model results, and section 3.8 concludes.

3.3 Related Work

Widely studied in the literature presented in section 2.3, ESS are capable of providing various services and applications to several sectors of the electricity industry while maximising its revenues and delivering system benefits. In addition, Chapter 2 has addressed the deficit in research in considering simultaneous provision of multiple services by ESS to various stakeholders of the

electricity industry namely, it was proposed a novel business model for distributed ESS with a portfolio of multiple services to various stakeholders. The model validity was studied taking into account ESS operation in a 24 hour time scale and analysed through a set of case studies that have demonstrated that the proposed business model and ESS scheduling methodology is capable of delivering simultaneous services to various sectors in the electricity industry while maximising its revenue according to market and system conditions; nonetheless, in the particular case of GB markets and given their diverse time scales for contractual arrangements and bidding strategies ranging from 3 months to 1 hour ahead of real time, the model applicability to develop ESS commercial strategies is compromised. As [30] defends, the use of inadequate modelling techniques for ESS may undermine its role in policy discussions.

In this context, several studies have investigated the role of ESS in power systems by considering longer time scales; in [4, 10, 31] the authors consider time scales from days to several weeks and more comprehensive studies such as [2, 5, 12, 14, 32, 33] investigate the economics of ESS in several years of operation. The authors of [31] advocate that the modelling horizon of 1 day (24 hours) is insufficient to develop a new bidding strategy for hydro ESS due its high capability of water storage and therefore the size of the ESS reservoir; this suggests that modelling horizons are not only sensitive to market frameworks and policies but also to ESS characteristics as the particular case of its reservoir size. In contrast, the approach adopted in [32] compares three ESS operational strategies on the energy market for a time scale of 1 year of operation, albeit the ESS scheduling is performed on a 24 hours rolling schedule with energy prices being estimated and updated based either on the past day or forecast of upcoming day. The proposed model in this chapter takes into account the framework in the GB electricity market for procuring balancing services.

Scheduling operation in power systems for long time scales comes with major challenges with regards to markets volatility and problem scalability, i.e. with horizons as long as 3 months - due to energy prices volatility - optimum scheduling operations are difficult to predict and often require stochastic modelling techniques that not only increase the problem size but also its complexity. A large body of literature such as [21, 34, 35] uses two stage stochastic optimization techniques to determine scheduling operations in the presence of stochastic parameters – as the particular case of energy prices. Although different techniques have been employed to determine optimum ESS operation with unpredictability on energy prices, in [35] a rolling scheduling approach is used to determine combined wind and ESS optimum operation in the day-ahead energy market and the authors of [36] use an ESS to provide energy and reserve services with a deterministic approach over a 24 hours horizon. As the authors of [34] discuss, deterministic approaches might give

sufficiently representative results for particular problems and stochastic techniques might not be necessary, therefore the key argument in this discussion is the value of stochastic optimization techniques over deterministic ones, although out of the scope of this research, a short study on the value of uncertainty is included in Appendix B.

Stochastic problems are usually associated with high levels of complexity and large volumes of variables and parameters which increases the problem dimension and raises major challenges with its scalability and convergence time. To overcome the curse of dimensionality, [37] proposes a new methodology based on Benders cuts without the need to enumerate the full set of states and which has been widely used for scheduling problems with pump-hydro ESS. Similarly but with a different method, the authors of [38] propose a Lagrangian Relaxation to decompose the problem and divide it into smaller and more tractable problems. A more recent study presented in [39] uses a rolling schedule method to solve a stochastic economic dispatch problem – in a system with intermittent generation and ESS – and further simplifies the problem with a decomposition method proposed by [40] which redefines the Newtown's optimization method itself by modifying the way the approximations are determined on each iteration. A large and growing body of literature has been investigating decomposition methods and techniques that somehow achieve problem solutions within reasonable amounts of time; as discussed in [41] the contribution in performance time in most methods is the capability to allow parallelization (i.e. parallel computing techniques), which will also be explored in these studies.

Still with a vast selection of decomposition methods with proven efficacy, the most commonly reported in the literature has been the bender decomposition method and its variations, e.g. [21, 41-44]. Studied in more detail in section 3.4, the Benders decomposition method takes advantage of the problem structure and separates it in two smaller problems, allowing this way the method to solve relaxed versions of the original problem and thus reduce convergence time.

Since looking into the future -3 months ahead - in a deterministic way may be far too optimistic, the mathematical model proposed here was formulated as a two stage stochastic problem which was further developed with a Benders decomposition approach to improve its computational efficiency.

3.4 Benders Decomposition

Benders decomposition is a (decomposition) method often used in mathematical programming problems with a complicated nature (often applied in problems with mixed-integer variables) in order to separate the problem in a twofold structure: a Master problem and a sub-problem both with a relaxed set of constraints and thus leading to a more tractable optimization problem. The advantage of the method - proposed by J. F. Benders [42] - is a considerable reduced problem size and relaxed formulation which is computationally simpler and faster to converge and achieve an optimal solution when compared to the original problem. Moreover this method can be extended to other types of problems, such as stochastic programming problems.

When applied to stochastic programming problems, Benders decomposition separates large stochastic problems into smaller deterministic equivalent linear problems that are simpler to solve. For stochastic problems, with a clear structure separable into deterministic and stochastic variables, Benders decomposition has been widely used to improve convergence times and reduce the computational burden. Studies such as [41, 45] demonstrate the method effectiveness in reducing the original problem complexity and convergence time by taking advantage of the problem structure and allow parallel computing techniques to be employed to solve the smaller and more tractable problems.

A two-stage stochastic problem formulated in the form of Eq. (3.1) allows to promptly identify the two block structure required for a stochastic Benders decomposition, i.e. a first stage with "here and now" decisions and a second stage with multiple scenarios for "wait and see" decisions. In Eq. (3.1), x is an array of deterministic decision variables – "here and now" decisions – and y_{ω} the set of stochastic decision variables for each scenario ω – "wait and see" decisions, c and d_{ω} the cost parameters of x and y_{ω} respectively and p_{ω} the probability of each scenario ω .

$$\operatorname{Min}\left\{ \mathbf{c}^{\mathrm{T}} \cdot \mathbf{x} + \sum_{\omega \in \Omega} \mathbf{p}_{\omega} \cdot \mathbf{d}_{\omega}^{\mathrm{T}} \cdot \mathbf{y}_{\omega} \right\}$$
(3.1)

$$\mathbf{A} \cdot \mathbf{x} \ge \mathbf{b} \tag{3.2}$$

 $\mathbf{T}_{\omega} \cdot \mathbf{x} + \mathbf{W}_{\omega} \cdot \mathbf{y}_{\omega} \ge \mathbf{h}_{\omega} \quad \forall \omega \in \Omega$ (3.3)

$$\mathbf{x}, \mathbf{y}_{\omega} \ge 0 \quad \forall \omega \in \Omega \tag{3.4}$$

In the context of ESS operation, "here and now" decisions are associated with commitment of balancing services and "wait and see" decisions associated with energy arbitrage actions. Therefore, x would represent volumes of reserve and frequency response services committed ahead of real time and y_{ω} the various ESS scheduled operations for energy arbitrage actions with respective to each scenario ω of energy prices, although in contrast to the problem presented above, note that the multi service business model should not be formulated as a minimisation problem.

The Benders decomposition framework - adapted here for a two stage stochastic programming model - is a recursive method that solves two problems with a set of linking constraints, which through duality theory allows to generate feasibility and optimality cuts used to reduce the search space and determine a common optimal solution to both master and sub-problems until a convergence criterion is satisfied.

The master problem, in the particular case of stochastic Benders decomposition, is associated with the first stage decisions and therefore to determine trial solutions for the deterministic decision variables. Moreover, an approximation of the sub-problems solutions is included in the objective function modelled through a set of constraints added on each iteration based on information derived from the sub-problems - optimality cuts Eq. (3.7). Note that optimality cuts modelled through Eq. (3.7) are not included in the formulation in the first iteration (i.e. k = 1). The master problem is defined as follows:

$$Z_k = \operatorname{Min}\{\mathbf{c}^{\mathrm{T}} \cdot \mathbf{x} + \mathbf{\theta}\}$$
(3.5)

$$\mathbf{A} \cdot \mathbf{x} \ge \mathbf{b} \tag{3.6}$$

$$\theta \ge \sum_{\omega \in \Omega} p_{\omega} \cdot \left(Q_{k,\omega} - \lambda_{k,\omega} \cdot T_{\omega} \cdot (x - \hat{x}_k) \right) \quad 1 < k \le K$$
(3.7)

$$x \ge 0 \tag{3.8}$$

Once a trial solution \hat{x}_k is determined on iteration k, it is passed as an input parameter to subproblems and a solution for the second stage decisions determined. In the particular case of the multi service business model framework, the trial solutions will be committed volumes of reserve and frequency response. The dual multipliers of the constraints linking the master and subproblems (Eq. (3.10)) are sensitive to trial solutions \hat{x}_k and inform how the sub-problems objective function will change based on new solution \hat{x}_k . Note that the number of sub-problems will depend on the set of scenarios considered on the original problem. A major advantage of Benders decomposition for stochastic problems is the ability to use parallel computing techniques to solve the set of sub-problems simultaneously. The general form of each sub-problem ω is defined as follows:

$$Q_{k,\omega} = \operatorname{Min}\{\mathbf{d}_{\omega}^{\mathrm{T}} \cdot \boldsymbol{y}_{\omega}\}$$
(3.9)

$$W_{\omega} \cdot y_{\omega} \ge h_{\omega} - T_{\omega} \cdot \hat{x}_{k} \quad : \quad \lambda_{k,\omega}$$

$$(3.10)$$

$$y_{\omega} \ge 0 \tag{3.11}$$

With solutions for both master and sub-problems the following step is to test for convergence. Since the master problem is a relaxed version of the original problem until the optimality cuts accurately represent the sub-problems, any solution of Z_k will be a lower bound value of the original problem (Eq. (3.14)). On the other hand, using trial (sub-optimal) solutions \hat{x}_k to solve the sub-problems describes a more constrained version of the original problem and thus the solution is an upper bound value to the original problem (Eq. (3.13)). A convergence criterion for the algorithm can thus be defined as follows:

 $UB - LB \le \varepsilon \cdot |LB| \tag{3.12}$

$$UB = c^{T} \cdot \hat{x}_{k} + \sum_{\omega \in \Omega} p_{\omega} \cdot Q_{k,\omega}$$
(3.13)

$$LB = c^{T} \cdot x + \theta \tag{3.14}$$

A summary of the decomposition algorithm taken from [46] is presented next.

Step 1: Set k = 1, $UB = +\infty$, $LB = -\infty$ and $\theta = 0$.

- **Step 2:** Solve master problem and determine a trial solution for x on iteration k, i.e. determine \hat{x}_k . Note that for k = 1 the master problem is solved without considering optimality cuts ($\theta = 0$). Update value for lower bound, LB.
- **Step 3** Solve all sub-problems with trial solution \hat{x}_k . Determine the dual multipliers from linking constraints and value of objective function for every sub-problem ω . Update value for upper bound, UB.
- **Step 4** Test for convergence. If gap between UB and LB is lower or equal to convergence criterion an optimal solution has been achieved and the algorithm ends, otherwise continue to next step.
- Step 5 Add a new optimality cut to the master problem associated with iteration k. Set k = k+1 and return to step 2

Figure 3.1 shows a representation of stochastic Benders decomposition algorithm. Note that subproblems are completely independent of each other and are therefore able to be solved simultaneously using parallel computing techniques. Though several iterations may be required to satisfy the convergence criterion, the convergence time is significantly lower than for the original problem.

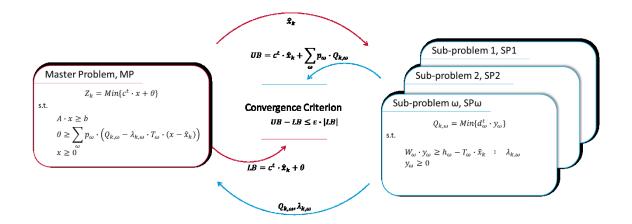


Figure 3.1: Diagram showing the general form of stochastic Benders decomposition algorithm.

The general form of Benders decomposition includes an additional set of constraints designed to keep trial solutions within original problem's feasible region – feasibility cuts. For the sake of simplicity feasibility cuts were not included in the algorithm although, feasibility of solutions is ensured by using a penalisation of slack variables in the sub-problems objective function and passing a feasibility measure to the master problem through the dual multipliers.

3.5 Mathematical Formulation

Considering a longer time scale allows a more accurate representation of contractual arrangements for balancing services - often contracted from 1 to 3 months ahead of real time. Increasing the optimization horizon from 24 hours to 3 months (2160 hours) has a direct impact on the uncertainty of energy prices and therefore considering a deterministic approach is no longer a reasonable assumption. The proposed model addressed the additional uncertainty with a two stage stochastic problem modelling where first stage decisions – contractual arrangements for balancing services 3 months ahead of real time – influence second stage decisions – energy arbitrage in the energy market. Given the larger scale of the model with multiple scenarios for 3 months profiles of energy prices, a stochastic Benders decomposition was used to allow parallel computing techniques and thus reduce convergence time and improve problem tractability. Although Benders decomposition is a recursive method and requires several iterations to solve complex problems, in this particular case convergence time was reduced by more than 240 times (i.e. from 34 hours to 8 minutes) when compared with the original non-decomposed formulation, as shown in Appendix A.

3.5.1 A Benders Decomposition Heuristic for Disjunctive Problems

Benders decomposition on its general form may include binary decision variables on the master problem, albeit the same is not possible in the sub-problems formulation. Duality theory and the strong duality theorem cannot be applied to mixed integer linear programming problems as it is the case of the problem presented in Chapter 2 and used here as the basis for the stochastic Benders decomposition. Therefore, Benders decomposition with the current mixed integer formulation applicable, specific due the binary variables is not in to $X_{\omega,t}^{Up.Rese} X_{\omega,t}^{Dw.Rese} X_{\omega,t}^{Up.Resp} X_{\omega,t}^{Dw.Resp} X_{\omega,t}^{Wp.R\&R}$ and $X_{\omega,t}^{Dw.R\&R}$, which create disjunctive constraints in the formulation.

A novel heuristic has been implemented as an additional step in the Benders decomposition algorithm, along with a constraint relaxation of the original problem which eliminates the need of binary variables in the formulation. The method is used to simplify Eqs. (2.11), (2.12), (2.17) and (2.18) by removing the binary variables and to eliminate Eqs. (2.23) and (2.24) from the formulation. This eliminates the need for variables $X_{\omega,t}^{Up.Resp}$ and $X_{\omega,t}^{Dw.Resp}$, although eliminating the remaining variables using a similar simplification would imply sub-optimal solutions with optimality gaps higher than 10% and thus not a suitable simplification.

A single binary variable is easily eliminated from a given problem formulation by solving the programming mathematical problem twice; by fixing the variable to 0 and then to 1 and then compare and select the optimal solution. However, the combinatorial solutions between two binary variables – namely $X_{\omega,t}^{Up.Rese} X_{\omega,t}^{Dw.Rese}$ – are 4 in total, i.e. (1,1), (1,0), (0,1) and (0,0). Hence, the same technique can be applied by determining the solution for each possibility and comparing the optimal solutions. In particular, since the original problem is a maximum revenue optimization, the solution to be selected should be the one with higher revenues. The remaining binary variables – $X_{\omega,t}^{Up.R\&R}$ and $X_{\omega,t}^{Dw.R\&R}$ – can be derived from the other 4 variables. Figure 3.2 shows a diagram of the stochastic Benders decomposition algorithm, including the additional heuristic.

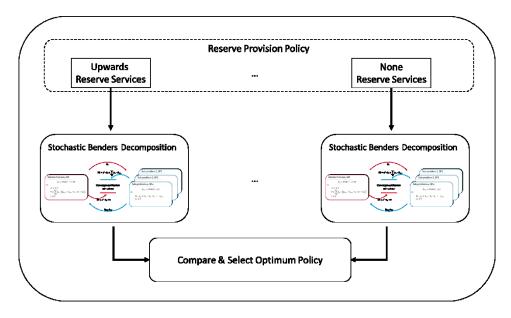


Figure 3.2: Diagram of Benders decomposition with additional step for proposed heuristic.

3.5.2 Master Problem

The master problem determines first stage decisions that maximise its objective function but conditioned to approximations of second stage value (sub-problems objective function). In this particular case, first stage decisions are the committed volumes to balancing services – upwards and downwards reserve and frequency response – 3 months ahead of delivery. The second stage value is the expected revenue from energy arbitrage in real time conditioned to ESS resources (i.e. power and energy capacities) already allocated for balancing services. Eq. (3.15) shows the master problem objective function.

$$Z_{k} = Max \left\{ \sum_{t \in T} \left[Rese_{t}^{Up} \cdot \pi_{t}^{Up.Rese} + Rese_{t}^{Dw} \cdot \pi_{t}^{Dw.Rese} + Resp_{t}^{Up} \cdot \pi_{t}^{Up.Resp} + Resp_{t}^{Dw} \cdot \pi_{t}^{Dw.Resp} \right] \cdot d + \theta \right\}$$

$$(3.15)$$

Committed volumes to reserve or frequency response are still bounded by ESS power capacity through Eqs. (3.16) - (3.21) which limit committed volumes with regards to ESS power capacity. Note that $\hat{X}_t^{Up.Rese}$, $\hat{X}_t^{Dw.Rese}$, $\hat{X}_t^{Up.Rese}$, $\hat{X}_t^{Dw.Rese}$, $\hat{X}_t^{Dw.Rese}$ are no longer decision variables but input parameters.

$$Rese_t^{Up} \le (2 \cdot \overline{D}^S) \cdot \widehat{X}_t^{Up.Rese} \quad \forall \ t \in T$$
(3.16)

$$Rese_t^{Dw} \le (2 \cdot \overline{C}^S) \cdot \widehat{X}_t^{Dw.Rese} \quad \forall t \in T$$

$$(3.17)$$

$$Resp_t^{Up} \le (2 \cdot \overline{D}^S) \quad \forall t \in T$$
(3.18)

$$Resp_t^{Dw} \le (2 \cdot \overline{C}^S) \quad \forall t \in T \tag{3.19}$$

$$\widehat{X}_{t}^{Up.R\&R} = \widehat{X}_{t}^{Up.Rese} \quad \forall t \in T$$
(3.20)

$$\hat{X}_t^{Dw.R\&R} = \hat{X}_t^{Dw.Rese} \quad \forall t \in T$$
(3.21)

Note that Eqs. (3.16) - (3.19) allow committed volumes of reserve and frequency response services to be up to twice the maximum ESS charge/discharge capacity and this is because scheduled ESS operation may allow a change in real time output up to twice its charge/discharge capacity (i.e. a change from maximum charge capacity, 6 MW, to maximum discharge capacity, 6 MW, which accounts for a 12 MW change in output).

Optimality cuts are modelled recursively according to the general form of Benders decomposition to describe the second stage value based on previously determined first stage decisions. Therefore at each new iteration a new optimality cut is added to the master problem to represent second stage values. The cuts are generated from each scenario second stage value and dual variables of constraints that link first and second stage decisions, and weighted by the probability of each scenario (presented in section 3.6.1). Eq. (3.22) shows how to generate an optimality cut in iteration k.

$$\theta \leq \sum_{\omega \in \Omega} p_{\omega} \cdot \left(Q_{k,\omega} - \sum_{t \in T} \left(\lambda_{k,\omega,t}^{Up,Rese} \cdot r_{k,t}^{Up} + \lambda_{k,\omega,t}^{Dw,Rese} \cdot r_{k,t}^{Dw} + \lambda_{k,\omega,t}^{Up,Resp} \cdot f_{k,t}^{Up} + \lambda_{k,\omega,t}^{Dw,Resp} \cdot f_{k,t}^{Dw} \right) \right) \quad 1 < k \leq K$$

$$r_{k,t}^{Up} = \left(Rese_{t}^{Up} - \widehat{\operatorname{Rese}}_{k,t}^{Up} \right) \qquad r_{k,t}^{Dw} = \left(Rese_{t}^{Dw} - \widehat{\operatorname{Rese}}_{k,t}^{Dw} \right) \qquad (3.22)$$

$$f_{k,t}^{Up} = \left(Resp_{t}^{Up} - \widehat{\operatorname{Resp}}_{k,t}^{Up} \right) \qquad f_{k,t}^{Dw} = \left(Resp_{t}^{Dw} - \widehat{\operatorname{Resp}}_{k,t}^{Dw} \right)$$

Note that decision variables ($Rese_t^{Up}, Rese_t^{Dw}, Resp_t^{Up}, Resp_t^{Dw}$) are compared against previous trial decisions ($Rese_t^{Up}, Rese_t^{Dw}, Resp_t^{Up}, Resp_t^{Dw}$) and thus the impact that positive or negative deviations from previously determined solutions have on the second stage value is evaluated on the master problem objective function. In the initial step (i.e. k = 1) the Benders algorithm does not consider optimality cuts.

3.5.3 Sub-problems

A stochastic Benders decomposition will have as many sub-problems as the number of second stage scenarios, and although similar in formulation, they all differ on input parameters. In this particular case, the second stage objective function will be to maximise ESS revenue on the energy market through arbitrage actions. Note that each energy price scenario will generate a different

sub-problem objective function and thus different solutions, i.e. Eq. (3.23) should be repeated Ω times, each one associated with a particular energy price scenario.

$$Q_{k,\omega} = Max \left\{ \sum_{t \in T} \left(P_{\omega,t}^{S} \cdot \pi_{\omega,t}^{E} \right) \cdot d \right\} \quad \forall \omega \in \Omega$$
(3.23)

ESS operation is limited by power capacity – Eqs. (3.24) to (3.26) –, energy balance Eq. (3.27) and maximum energy capacity Eq. (3.28).

$$P_{\omega,t}^{S} = D_{\omega,t}^{S} - C_{\omega,t}^{S} \quad \forall t \in T, \omega \in \Omega$$
(3.24)

$$-\overline{\mathsf{C}}^{\mathsf{S}} \le P_{\omega,t}^{\mathsf{S}} \le \overline{\mathsf{D}}^{\mathsf{S}} \quad \forall \, \mathsf{t} \in \mathsf{T}, \omega \in \Omega \tag{3.25}$$

$$\left(P_{\omega,t}^{s}\right)^{2} + \left(Q_{\omega,t}^{s}\right)^{2} \le (\bar{S}^{s})^{2} \quad \forall t \in T, \omega \in \Omega$$

$$(3.26)$$

$$E_{\omega,t} = E_{\omega,t-1} - \left(D_{\omega,t}^{s} - C_{\omega,t}^{s} \cdot \eta\right) \cdot \mathbf{d} \quad \forall t \in \mathsf{T}, \omega \in \Omega$$

$$(3.27)$$

$$E_{\omega,t} \le \overline{E} \quad \forall t \in T, \omega \in \Omega \tag{3.28}$$

Real time deliverability of committed volumes of reserve or frequency response services ahead of real time is ensured through Eqs. (3.29) to (3.36). ESS charge and discharge power availability for real time delivery of balancing services is ensured through Eqs. (3.29) and (3.30), respectively for discharge and charge capacity.

$$Rese_{\omega,t}^{Up} + Resp_{\omega,t}^{Up} \le \overline{D}^{S} - P_{\omega,t}^{S} \quad \forall t \in T, \omega \in \Omega$$

$$(3.29)$$

$$Rese_{\omega,t}^{Dw} + Resp_{\omega,t}^{Dw} \le \overline{C}^{S} + P_{\omega,t}^{S} \quad \forall t \in T, \omega \in \Omega$$

$$(3.30)$$

The model robustness ensures that ESS energy levels are managed at all times to cope with scheduled output and any possible real time output for utilisation of balancing services. Eqs. (3.31) to (3.36) ensure sufficient energy levels for utilisation of reserve and frequency response services committed ahead of real time.

$$-\mathbf{M} \cdot \left(1 - \hat{\mathbf{X}}_{\omega,t}^{\text{Up,Rese}}\right) \le E_{\omega,t-1} - \left(P_{\omega,t}^{s} + Rese_{\omega,t}^{Up}\right) \cdot \tau^{\text{Rese}} \le \bar{E} + \mathbf{M} \cdot \left(1 - \hat{\mathbf{X}}_{\omega,t}^{\text{Up,Rese}}\right) \quad \forall t \in \mathbf{T}, \omega \in \Omega$$
(3.31)

$$-\mathsf{M} \cdot \left(1 - \hat{\mathsf{X}}^{\mathsf{Dw},\mathsf{Rese}}_{\omega,t}\right) \le E_{\omega,t-1} - \left(P^{\mathsf{S}}_{\omega,t} - \mathsf{Rese}^{\mathsf{Dw}}_{t}\right) \cdot \tau^{\mathsf{Rese}} \le \overline{\mathsf{E}} + \mathsf{M} \cdot \left(1 - \hat{\mathsf{X}}^{\mathsf{Dw},\mathsf{Rese}}_{\omega,t}\right) \quad \forall t \in \mathsf{T}, \omega \in \Omega$$
(3.32)

$$0 \le E_{\omega,t-1} - \left(P_{\omega,t}^{S} + \operatorname{Resp}_{\omega,t}^{Up}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{E} \quad \forall t \in T, \omega \in \Omega$$

$$(3.33)$$

$$0 \le E_{\omega,t-1} - \left(P_{\omega,t}^{S} - \operatorname{Resp}_{\omega,t}^{Dw}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{E} \quad \forall t \in T, \omega \in \Omega$$

$$(3.34)$$

$$-\mathbf{M} \cdot \left(1 - \widehat{\mathbf{X}}_{\omega,t}^{Up,R\&R}\right) \le E_{\omega,t-1} - \left(P_{\omega,t}^{S} + Rese_{\omega,t}^{Up}\right) \cdot \tau^{\text{Rese}} - Resp_{\omega,t}^{Up} \cdot \tau^{\text{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - \widehat{\mathbf{X}}_{\omega,t}^{Up,R\&R}\right) \quad \forall t \in \mathsf{T}, \omega \in \Omega$$

$$(3.35)$$

$$-\mathsf{M} \cdot \left(1 - \widehat{X}_{\omega, t}^{\mathsf{Dw}, \mathsf{R\&R}}\right) \leq E_{\omega, t-1} - \left(P_{\omega, t}^{s} - \operatorname{Rese}_{\omega, t}^{Dw}\right) \cdot \tau^{\mathsf{Rese}} + \operatorname{Resp}_{\omega, t}^{Dw} \cdot \tau^{\mathsf{Resp}} \leq \overline{\mathsf{E}} + \mathsf{M} \cdot \left(1 - \widehat{X}_{\omega, t}^{\mathsf{Dw}, \mathsf{R\&R}}\right) \quad \forall t \in \mathsf{T}, \omega \in \Omega$$

(3.36)

$$-\mathbf{M} \cdot \left(1 - \hat{\mathbf{X}}_{\omega,t}^{\text{Up.Rese}}\right) \le E_{\omega,t} - \left(P_{\omega,t}^{S} + Rese_{\omega,t}^{Up}\right) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - \hat{\mathbf{X}}_{\omega,t}^{\text{Up.Rese}}\right) \quad \forall t \in \mathsf{T}, \omega \in \Omega$$
(3.37)

$$-\mathsf{M} \cdot \left(1 - \widehat{\mathsf{X}}_{\omega,t}^{\mathsf{Dw},\mathsf{Rese}}\right) \le E_{\omega,t} - \left(P_{\omega,t}^{\mathcal{S}} - \mathsf{Rese}_{t}^{\mathcal{D}w}\right) \cdot \tau^{\mathsf{Rese}} \le \overline{\mathsf{E}} + \mathsf{M} \cdot \left(1 - \widehat{\mathsf{X}}_{\omega,t}^{\mathsf{Dw},\mathsf{Rese}}\right) \quad \forall t \in \mathsf{T}, \omega \in \Omega$$

$$(3.38)$$

$$0 \le E_{\omega,t} - \left(P_{\omega,t}^{S} + \operatorname{Resp}_{\omega,t}^{Up}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{E} \quad \forall t \in T, \omega \in \Omega$$

$$(3.39)$$

$$0 \le E_{\omega,t} - \left(P_{\omega,t}^{S} - \operatorname{Resp}_{\omega,t}^{Dw}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{E} \quad \forall t \in T, \omega \in \Omega$$

$$(3.40)$$

$$-\mathbf{M} \cdot \left(1 - \widehat{\mathbf{X}}_{\omega,t}^{\mathrm{Up,R\&R}}\right) \leq E_{\omega,t} - \left(P_{\omega,t}^{S} + Rese_{\omega,t}^{Up}\right) \cdot \tau^{\mathrm{Rese}} - Resp_{\omega,t}^{Up} \cdot \tau^{\mathrm{Resp}} \leq \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - \widehat{\mathbf{X}}_{\omega,t}^{\mathrm{Up,R\&R}}\right) \quad \forall t \in \mathbf{T}, \omega \in \Omega$$

$$-\mathbf{M} \cdot \left(1 - \widehat{\mathbf{X}}_{\omega,t}^{\mathrm{Dw,R\&R}}\right) \le E_{\omega,t} - \left(P_{\omega,t}^{S} - \operatorname{Rese}_{\omega,t}^{Dw}\right) \cdot \tau^{\mathrm{Rese}} + \operatorname{Resp}_{\omega,t}^{Dw} \cdot \tau^{\mathrm{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - \widehat{\mathbf{X}}_{\omega,t}^{\mathrm{Dw,R\&R}}\right) \quad \forall t \in \mathsf{T}, \omega \in \Omega$$

$$(3.42)$$

Active and reactive power balance between net and local demand and ESS – Eqs. (3.43) and (3.44) - depend on the scenario of energy price considered. Note that utilisation of downwards balancing services is also accounted in Eq. (3.45) to ensure that distribution network capacity limits are not violated for both scheduled and real time ESS outputs.

$$P_{\omega,t}^{N} = P_{t}^{D} - P_{\omega,t}^{S} \quad \forall t \in T, \omega \in \Omega$$

$$(3.43)$$

$$Q_{\omega,t}^{N} = Q_{t}^{D} - Q_{\omega,t}^{S} \quad \forall t \in T, \omega \in \Omega$$

$$(3.44)$$

$$\left(P_{\omega,t}^{N} + Rese_{\omega,t}^{DW} + Resp_{\omega,t}^{DW}\right)^{2} + \left(Q_{\omega,t}^{N}\right)^{2} \le (\bar{S}^{N})^{2} \quad \forall t \in T, \omega \in \Omega$$

$$(3.45)$$

In order to determine the dual variables of master and sub-problems linking constraints – Eqs. (3.29) to (3.42) and (3.45) – the model has been formulated with an additional set of constraints to capture the duality value in a single variable. Variables associated with provision of balancing services used in the formulation of the sub-problems ($Rese^{Up}_{\omega,t}, Resp^{Dw}_{\omega,t}, Resp^{Dw}_{\omega,t}, Resp^{Dw}_{\omega,t}$) are first stage decision variables and thus determined in the master problem. However, using Eqs. (3.46) -

$$Rese_{\omega,t}^{Up} = \widehat{\operatorname{Rese}}_{\omega,t}^{Up} \quad : \lambda_{k,\omega,t}^{Up.Rese} \quad \forall t \in T, \omega \in \Omega$$
(3.46)

$$Resp_{\omega,t}^{Up} = \widehat{\operatorname{Resp}}_{\omega,t}^{Up} : \lambda_{k,\omega,t}^{Up.Resp} \quad \forall t \in T, \omega \in \Omega$$
(3.47)

$$Rese_{\omega,t}^{Dw} = \widehat{\operatorname{Rese}}_{\omega,t}^{Dw} : \lambda_{k,\omega,t}^{Dw.Rese} \quad \forall t \in T, \omega \in \Omega$$
(3.48)

$$Resp^{Dw}_{\omega,t} = \widehat{\operatorname{Resp}}^{Dw}_{\omega,t} \quad : \lambda^{Dw.Resp}_{k,\omega,t} \quad \forall t \in T, \omega \in \Omega$$

$$(3.49)$$

3.5.4 Convergence Criterion

The convergence test is set to compare the first stage (master problem) and second stage (subproblems) values and stop the algorithm if values are within a user defined tolerance. The master problem is a relaxed version of the original problem, as the set of constraints responsible for second stage decisions are not included in the formulation, hence its value can be used as an upper bound of the optimal solution (since the problem is formulated as a maximisation problem). On the other hand, the sub-problems describe a constrained version of the original problem and therefore resulting in sub-optimal solutions and therefore representing a lower bound, which associated with the upper bound can be used for optimality test. The difference between upper and lower bound was assumed to be lower or equal to 0.1% of the lower bound, i.e. $\varepsilon = 0.001 \cdot \text{LB}$. Eqs. (3.50) to (3.52) show how the convergence test for this particular problem was formulated.

$$UB - LB \le \varepsilon \cdot |LB| \tag{3.50}$$

$$UB = \sum_{t \in T} \left[\widehat{\text{Rese}}_{t}^{Up} \cdot \pi_{t}^{Up.\text{Rese}} + \widehat{\text{Rese}}_{t}^{Dw} \cdot \pi_{t}^{Dw.\text{Rese}} + \widehat{\text{Resp}}_{t}^{Up} \cdot \pi_{t}^{Up.\text{Resp}} + \widehat{\text{Resp}}_{t}^{Dw} \cdot \pi_{t}^{Dw.\text{Resp}} \right] \cdot d$$

$$+ \sum_{\omega \in \Omega} p_{\omega} \cdot Q_{k,\omega}$$
(3.51)

$$LB = Z_k \tag{3.52}$$

3.6 ESS Commercial Strategies in GB Markets

In the GB electricity market, balancing services are often procured for long terms - up to 3 months - and therefore daily simulations of ESS operation would fail to fully represent viable solutions for longer terms ESS commercial strategies. The aforementioned model was analysed using real data from GB system and with a longer time scale comparatively to the studies of Chapter 2.

3.6.1 Input Data for GB Studies

Energy prices uncertainty was incorporated in the model through scenarios from real GB data for a total of 11 years (from 2004 to 2014). Energy price time series were derived from wholesale electricity prices in the short-term market with hourly resolution, obtained from ELEXON Portal website [7]. This gives a total of 44 scenarios for quarterly energy prices, separated in seasons (summer, autumn, winter and spring). Figure 3.3 shows a histogram of energy prices associated with each season.

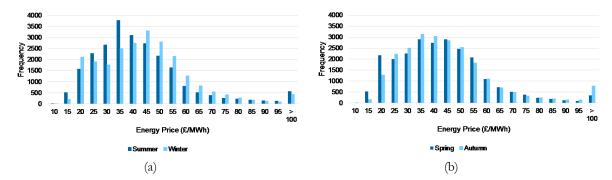


Figure 3.3: Histogram of energy prices in (a) summer and winter and (b) spring and autumn, used as input data.

Note that typically winter energy prices have often higher peaks and are more volatile than summer prices, as indicated in Figure 3.3 (a). In contrast, energy prices in spring and autumn are similar, with only slight differences on extreme prices (peak and lowest) but identical mid-range prices, as shown in Figure 3.3 (b).

Local demand was obtained from real DNO metering data at primary substation level with an hourly resolution and assumed a constant power factor of 0.96.

ESS and distribution network modelling characteristics, and contractual arrangements for balancing services including availability prices used in the studies have been described in section 2.5.1 and therefore for the sake of repetition omitted here. ESS modelling characteristics are described in Table 2.1 and distribution network secured capacity for each season in the year is presented in Figure 2.4. Windows for provision of reserve and frequency response services remain the same as indicated previously in section 2.5.1 as well as an additional constraint ensuring that provision of any of the balancing services is constant in all windows, i.e. for the 3 months horizon provision of balancing services is constant through all windows and days. Availability prices remained as follows: 5 f/MW/h and 7 f/MW/h for reserve and frequency response services response services respectively and according to GB markets [26, 27].

3.6.2 Impact of Markets and System Conditions on Commercial Strategies

System operating conditions and markets economics affect ESS revenues throughout the year but bear a higher impact by changing ESS commercial strategies according to each season in a year. Energy prices differentials directly affect ESS energy arbitrage revenue and thus total revenue. Fundamentally, as in summer energy prices are more constant than in the rest of the year, energy arbitrage revenue is also lower in summer. Hence, since low energy prices differentials undermine ESS total revenue, commercial strategies in summer include provision of down reserve services as a way to improve the business case by allocating ESS resources to a higher remunerating service – in this case down reserve. Figure 3.4 shows ESS expected revenues per average month according to yearly seasons and its commercial strategies with different services volumes being contracted on each season.

In addition, distribution network secured capacity in spring and summer decreases due to higher temperature conditions (input data for distribution network capacity in Figure 2.4) which conflicts with energy arbitrage revenues – as discussed in Chapter 2 in particular in Figure 3.4. This describes the higher value for DNO in spring and summer presented in Figure 3.4, in particular in spring DNO value is the highest as arbitrage actions and provision of down reserve services are constrained due to network secured capacity.

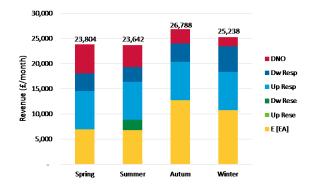


Figure 3.4: ESS monthly average revenue on different seasons and respective portfolio of services.

Commercial strategies with higher volumes of down reserve services can be used to hedge against uncertainty in energy arbitrage revenue due to scenarios of low energy prices. Provision of down reserve services not only ensure ESS higher expected revenues but also reduce the volatility and provide highest minimum revenues than other strategies. This allows ESS to hedge against very low revenues – that may undermine investment and operation decisions – while guaranteeing that ESS resources are being optimally allocated. Figure 3.5 shows how ESS revenues with different commercial strategies perform under energy prices uncertainty.

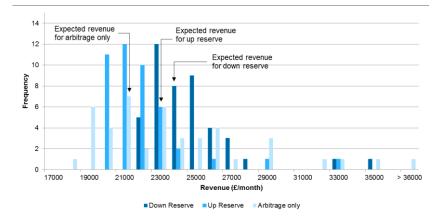


Figure 3.5: Comparison of probability distribution functions of ESS revenues with different commercial strategies and associated expected revenues.

These results also support the fact that summer commercial strategies in Figure 3.5 include provision of reserve services for more efficient ESS economics and that down reserve service is less conflicting with energy arbitrage than up reserve service.

3.6.3 Value of Reactive Power Coordination

Coordination of active and reactive power outputs supports provision of DNO service but also provision of active power services such as energy arbitrage and balancing services and should therefore be remunerated accordingly. The value of reactive power has been studied and determined for specific applications in electricity markets [47, 48]. In particular in the GB electricity market the Obligatory Reactive Power Service (ORPS) is remunerated at circa 3 $f_{c}/MVArh$ – for instance in July 2015 its value was of approximately 2.7 $f_{c}/MVArh$ [49].

Figure 3.6 shows the monthly average value of coordinating active and reactive power by comparing ESS operation with and without active and reactive power coordination. It is clear that an efficient ESS operation with coordinated active and reactive power outputs is more beneficial and increases ESS revenues, in this case, by 2,433 f_{c} /month. Note that if reactive power was remunerated according to the default payment rate of 2.7 f_{c} /MVArh determined according to the ORPS framework, reactive power service would be valued at 74 f_{c} /month.

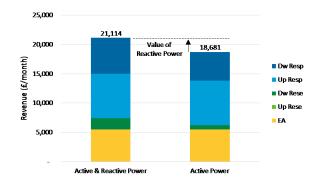
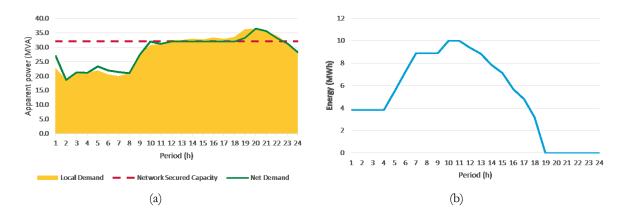


Figure 3.6: Monthly average ESS revenues when considering operation with active and reactive power coordination or active power only.

Active and reactive power coordination is also crucial to support distribution network operation, in particular to ensure security of supply by providing DNO service at critical ESS energy levels. Provision of DNO service is achieved by means of active and reactive power which ensure security of supply at periods of congested distribution network. ESS is able to discharge both within its power capacities, albeit active power discharge (and charge) is also limited by ESS energy capacity, i.e. ESS reactive power outputs are not affected by ESS energy limits (assuming these are provided by power electronics). Therefore, coordination of active and reactive power for DNO service is crucial to ensure that distribution network secured capacity limits are not violated when ESS energy levels are not sufficient to do so by means of active power only. An example of a particular day in autumn when this occurs is presented next; Figure 3.7 shows two operating modes for the same day, (a) and (b) with an active power only operating mode and, (c) and (d) with an active and reactive power coordination mode.



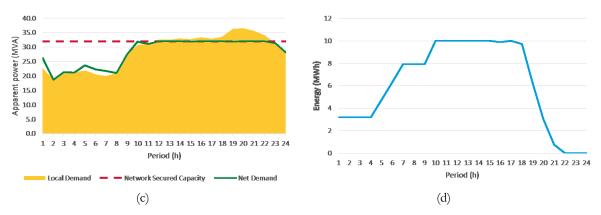


Figure 3.7: ESS operation for the same day with active power only (a) and (b), and with active and reactive power coordination (c) and (d).

Note that with active power only mode, ESS energy reserves are depleted at hour 19 and net demand violates the substation secured capacity limit thereafter in order to supply local demand. On the other hand when active and reactive power are coordinated to deliver DNO service – as in Figure 3.7 (c) and (d) – ESS is able to secure local demand supply by means of active and reactive power. This particular case when local demand is higher than substation secured capacity for long peaks – producing an excess of energy demand higher than ESS energy capacity – reinforces the value of active and reactive power coordination.

3.6.4 Value of ESS Roundtrip Efficiency

Results show that a variation of 10% of ESS roundtrip efficiency may represent a difference of up to 4,000 £/month on revenue and might change the selected portfolio of services. ESS commercial strategies have been compared, over a period of 11 years, at different levels of ESS roundtrip efficiency; over the multiple 3 month scenarios for the whole 11 year data, a drop in 10% roundtrip efficiency reduces revenue on the top remunerable scenarios by approximately 4,000 £/month and 2,000 £/month on the lowest remunerable scenarios. The linear reduction on ESS revenues due to a drop in roundtrip efficiency, both for maximum and minimum remunerable scenarios, is presented in Figure 3.8.

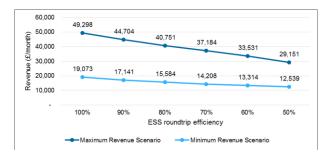


Figure 3.8: ESS monthly revenue for maximum and minimum revenue scenarios when operating at different roundtrip efficiencies.

A change in roundtrip efficiency has a higher impact on energy arbitrage revenues with reductions up to 6,000 £/month, while in contrast frequency response revenues are the least affected by changes in efficiency. Lower roundtrip efficiencies imply higher volumes of energy bought at the energy market to fill the ESS reservoir (to cover losses) and consequently increases charging costs and undermines energy arbitrage revenues. This decrease in energy arbitrage revenue might be so extreme that energy arbitrage may lose its remunerability competitiveness to balancing services and affect the ESS commercial strategies in the long term. Figure 3.9 shows ESS commercial strategies for the same 3 month scenario with two different roundtrip efficiencies, (a) 100% and (b) 80%.

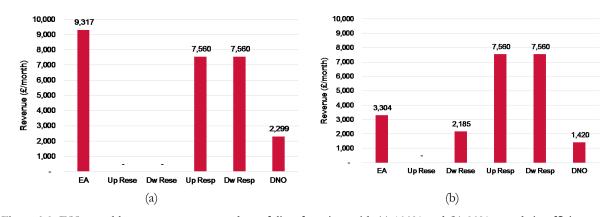


Figure 3.9: ESS monthly average revenues and portfolio of services with (a) 100% and (b) 80% roundtrip efficiency. Note that DNO value is also reduced with a drop in efficiency as higher volumes of energy are bought at the energy market to be able to secure demand supply at periods of peak demand, and therefore increasing net demand.

3.6.5 Impact of Utilisation of Balancing Services on ESS Revenues

Real time deliverability of balancing services is robustly secured through a set of constraints in the model which efficiently manage ESS energy and power resources for scheduled and real time operation. Nevertheless ESS scheduled operation takes into account any possible outcome of balancing services utilisation, the economics of ESS real time operation will be affected by changing its scheduled output.

To investigate the impact that utilisation of balancing services has on ESS revenue, a set of scenarios were used to compare and determine the impact on ESS revenue. Real time operation (i.e. utilisation of balancing services) was modelled based on previously committed volumes of balancing services and divided in 5 scenarios: 0% (base case), 25%, 50%, 75% and 100% of utilisation time, for example exercise of downwards reserve for 2 hours in half of the windows

that it has been committed (50% scenario). A recovery time of 3 hours after delivering the services was assumed to allow the ESS to return to its scheduled operation – recover its energy levels.

Changing ESS output in real time for delivery of balancing services has a twofold effect on energy arbitrage revenues; depending on energy prices during exercise and recovery periods conditions, revenue may increase or decrease in comparison to scheduled operating conditions (i.e. no exercise). For instance, if ESS is required to exercise any downwards balancing service (charge of additional energy) and peak energy prices occur during recovery period (i.e. after service delivery) then energy arbitrage revenue is likely to increase as ESS will be discharging the additional energy (i.e. recover back to schedule status) at high energy prices. In contrast, with exercise of upwards balancing services ESS is required to recovery to its scheduled conditions by charging its reservoir at peak energy prices, and therefore energy arbitrage may decrease and even result in a loss of revenue.

Figure 3.10 (a) shows 5 scenarios of down reserve exercise and (b) 5 scenarios of up reserve exercise and their respective impact on energy arbitrage revenues, (a) Case A shows an increase in energy arbitrage revenue and (b) Case B shows a decrease in energy arbitrage revenue.

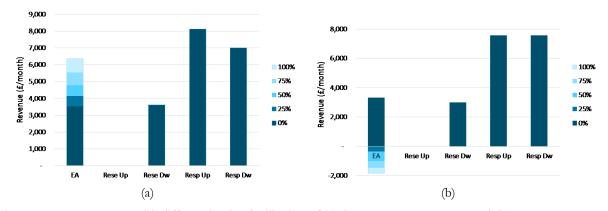


Figure 3.10: ESS revenues with different levels of utilisation of (a) down reserve – Case A – and (b) up reserve – Case B.

Utilisation of down services in winter and autumn is likely to result in an increase in energy arbitrage revenue – as shown in Case A – since peak energy prices in these seasons are likely to occur at the end of window for services delivery (i.e. during recovery periods in the early hours of the evening 19:00 h and 20:00 h). In contrast, utilisation of up reserve services which require ESS to recover to its scheduled conditions by charging/buying energy at the market, will result in a decrease and potential negative revenue for energy arbitrage as shows in Case B.

On average, for each unit of energy exercised for down reserve (case A) ESS revenues increases by 10 \pounds , while in case B, ESS revenue decreases by 6 \pounds for each MWh exercised for up reserve. Hence, ESS may benefit on average up to 10 \pounds /MWh exercised for reserve services or incur in a cost of up to 6 f/MWh as shown in Figure 3.11, depending on energy market conditions and windows of balancing services.

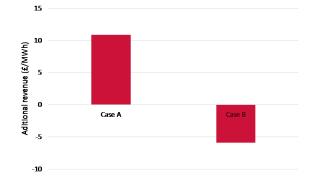


Figure 3.11: Additional ESS revenue in £/MWh exercised for Case A (profit) and Case B (loss).

With a possible loss of up to 6 \pounds /MWh exercised for reserve, the utilisation payments (not modelled in this study) need to cover ESS recovery costs (up to 2,000 \pounds /month in Case B). In 2014 the average utilisation payment for short term operating reserve in GB was approximately 180 \pounds /MWh according to National Grid report [26], which places the ESS as a cheaper technology for short term operating reserve. The economics and framework of utilisation payments for reserve services are out of the scope of this study, albeit the results presented here serve as a possible indicator to the level of remunerability that ESS's need to secure for an efficient provision and utilisation of balancing services.

3.6.6 Economics of ESS in a Low-Flexibility Power System

As the author of [3] defends, a high penetration of renewable energies such as wind and solar power along with deferment of traditional generation compromises power systems flexibility, as volatility of renewable generation adds up. Either the added levels of volatility are passed to endusers by means of demand management policies or flexible services (such as balancing services) will be crucial to support balance between demand and supply.

Highly priced balancing services directly compete with energy arbitrage for ESS power and energy resources and thus affecting its commercial strategies. As frequency response and reserve services become highly valuable in a low flexible power system, ESS optimum strategy is to increase committed volume of down reserve services and maintain provision of frequency response services. As a consequence, energy arbitrage actions are mainly for support of energy levels required for provision of balancing services and thus resulting in lower remunerability.

In contrast, in a high flexible power system it is economically inefficient to contract reserve services but rather to take advantage of higher energy prices and thus allocate ESS power and energy resources for energy arbitrage actions. Since provision (and utilisation) of reserve services requires large amounts of energy stored (or headroom), the lower value of balancing services is not competitive for large amounts of energy (or headroom) to be in stand-by in the ESS reservoir. Note that energy requirements for frequency response services are less constraining than for reserve services and thus, ESS commercial strategies still include provision of frequency response services even when their value decreases. Figure 3.12 shows ESS plant commercial strategies and individual services revenues when considering three levels of power systems flexibility.

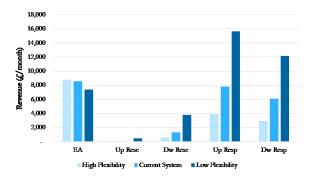


Figure 3.12: ESS monthly average revenue when operating in power systems with different levels of flexibility.

3.7 ESS Commercial Strategies with Support to Intermittent Generation

The capability of ESS to support generation from plants with low capacity value has been widely studied in the literature, in particular integration of renewable generation such as wind and solar - typically characterised by their volatility and unpredictability. Studies such as [3] investigate the value of ESS in supporting system operation by providing reserve services and thus increasing wind penetration and saving generation costs. The authors report a capitalized value for ESS of more than 968 f_{c} /kW with low flexible power systems.

In contrast, there is a large volume of studies which restrict to single wind farms and evaluate the potential that ESS have on firming wind capacity, e.g. [2, 10, 16, 50, 51]. In [10, 50] the authors not only access the contribution of ESS in balancing wind generation but include transmission system constraints which undermine the economics of wind generation. The analysis show that ESS can effectively support the economics of wind plants by firming wind capacity and correcting imbalances, but [10] goes further in the analysis and compares independent and coordinated operation of ESS with wind plants and shows that being constrained to wind balancing services and constrained transmission capacity the ESS is reported to lose revenue when compared to an independent operation in the energy market and located closer to load centres.

A key aspect of wind generation is its unpredictability and in this context [51] proposes a stochastic model to provide wind balancing services by an ESS and improve the economics of the set (ESS and wind farm) in the day ahead spot market. The study includes uncertainty in energy prices and wind generation in a two stage stochastic problem, with first stage decisions being the scheduled operation in the day ahead market and second stage decisions being the real time (ESS) operation for balancing wind forecast errors and minimise imbalance costs. In a similar approach to [10], the authors benchmark the joint operation of ESS and wind farm with uncoordinated operation, and although an increase in joint revenues is reported this is only of 2.5%.

The study presented here focus on the contribution of a distributed ESS providing wind balancing as a long term service and contracted ahead of real time. The analysis will be comprised within the long term commercial strategies framework and therefore provided as an additional service among the portfolio of multiple services hold by the ESS.

3.7.1 Modelling Considerations and Input Data

The mathematical formulation presented in section 3.5.3 associated with the multiple service business model framework was adapted to take into consideration scenarios of wind imbalances and respective constraints that characterize the wind balancing service. For the sake of clarity the full set of constraints will not be replicated here since little or no changes will be required, nevertheless those who suffer significant alterations – mainly ESS power and energy constraints – will be reproduced next. Moreover, further constraints added to the modelling to define the additional service being provided by the ESS will also be presented next.

A key aspect of wind generation is its unpredictability which raises major challenges with wind power forecasts. In this context, the wind balancing service has been formulated as a stochastic problem with multiple scenarios of wind forecasts which thus create scenarios of wind imbalances, assumed equiprobable. The model objective function – namely the sub-problems objective function, i.e. Eq. (3.23) – was then updated in order to account for the multiple scenarios of wind imbalances and their respective probability as shown in Eq. (3.53).

$$Q_{k,\omega} = Max \left\{ \sum_{i \in I} p_i \cdot \sum_{t \in T} \left(P_{\omega,i,t}^S \cdot \pi_{\omega,t}^E \right) \cdot d \right\} \quad \forall \, \omega \in \Omega, i \in I$$
(3.53)

ESS scheduled operation will have to accommodate scenarios of wind power deviations (imbalances) and therefore ESS charge and discharge outputs need to be limited by ESS maximum power capacities. For this study, Eqs. (3.54) and (3.55) need to be included in the modelling, which ensure that charge and discharge outputs do not violate ESS maximum power capacities.

$$D_{\omega,i,t}^{s} + D_{\omega,i,t}^{W} \le \overline{D}^{s} \quad \forall t \in T, \omega \in \Omega, i \in I$$

$$(3.54)$$

$$C_{\omega,i,t}^{s} + C_{\omega,i,t}^{W} \le \overline{C}^{s} \quad \forall t \in T, \omega \in \Omega, i \in I$$
(3.55)

Regarding Eq. (3.24) which combines the ESS charge and discharge outputs in a single variable, it should be updated with Eq. (3.56) to account for outputs associated with wind balancing service.

$$P_{\omega,i,t}^{S} = D_{\omega,i,t}^{S} - C_{\omega,i,t}^{S} + D_{\omega,t}^{W} - C_{\omega,i,t}^{W} \quad \forall t \in T, \omega \in \Omega, i \in I$$

$$(3.56)$$

ESS energy balance was also restructured for this study, i.e. charge outputs associated with wind power excess should be absorbed by the ESS and discharge outputs associated with wind power shortage should be secured by the ESS, and therefore in both circumstances ESS energy levels should be updated - Eq. (3.57) should replace Eq. (3.27) and model ESS energy levels.

$$E_{\omega,i,t} = E_{\omega,i,t-1} - \left(D_{\omega,i,t}^{S} + D_{\omega,i,t}^{W} - (C_{\omega,i,t}^{S} + C_{\omega,i,t}^{W}) \cdot \eta \right) \cdot d \quad \forall t \in T, \omega \in \Omega, i \in I$$

$$(3.57)$$

Wind balancing service, similar to the DNO service, is not included in the objective function and therefore will be modelled through a constraint that ensures the service is provided on every period. Hence, if the service is contracted as part of ESS commercial strategies for the whole 3 months operation, any imbalances due to forecast errors have to be secured by the ESS, i.e. discharge for negative imbalances (wind power shortages) and charge for positive imbalances (wind power excess). Eq. (3.58) models provision of wind balancing service as part of ESS business model.

$$W_{\omega,i,t} + D_{\omega,i,t}^{W} - C_{\omega,i,t}^{W} = 0 \quad \forall t \in T, \omega \in \Omega, i \in I$$
(3.58)

Note that wind imbalances, $W_{\omega,i,t}$, are positive if wind power out-turn is higher than wind power forecasted – expressing a wind power excess - or negative if wind power out-turn is lower than wind power forecasted – expressing a wind power shortage -, as presented in Figure 3.13.

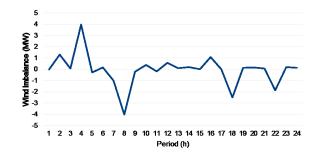


Figure 3.13: Wind imbalance for a single day with positive imbalances representing power excess and negative imbalances representing power shortage.

In addition to the aforementioned constraints and modifications to variables, it should be noted that variables $Rese_{\omega,i,t}^{Up}$, $Rese_{\omega,i,t}^{Dw}$, $Resp_{\omega,i,t}^{Up}$, $\hat{X}_{\omega,i,t}^{Up,Rese}$, $\hat{X}_{\omega,i,t}^{Up,Rese}$, $\hat{X}_{\omega,i,t}^{Up,Resp}$, $\hat{X}_{\omega,i,t}^{Dw,Resp}$, $\hat{X}_{\omega,i,t}^{Up,Resp}$

Wind imbalances were determined based on the studies carried out by [52, 53] which analysed wind forecast errors based on 1 hour persistence models from single wind farms for over a year of operation. Both authors show similar observed probability distributions for 1 hour persistence wind forecast errors (imbalances) although, interestingly the adopted distribution functions to fit the observed data are different; [52] uses a normal distribution function to fit the observed data whereas [53] tests both normal and Cauchy distribution functions and reports better fits with a Cauchy distribution function. Figure 3.14 shows the observed and tested distribution functions for (a) studies carried in [52] and (b) studies carried in [53].

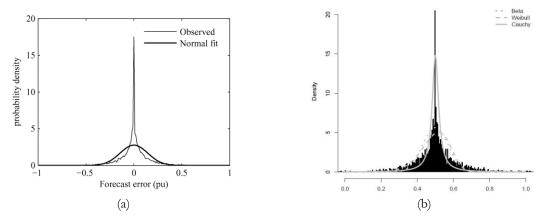


Figure 3.14: Observed and fitted distribution functions of wind imbalance data from (a) [52] and (b) [53].

The wind imbalance forecast errors used as input data in this particular case study were modelled using a Cauchy distribution function with parameters $x_0 = 0.5$ and $\gamma = 0.0215$. The adopted distribution is a continuous distribution function supported in all the real line (set R), i.e. any given real number in the interval [- ∞ , ∞] has a given probability of occurring which could result in wind imbalances greater than the wind farm installed capacity (e.g. imbalance of 1000 MW in a 10 MW installed capacity wind farm). To overcome this, the adopted distribution function was truncated to the interval of [-0.4, 0.4] – following the data presented in Figure 3.14 - and therefore wind imbalances will at mostly represent a 40% change from the forecasted wind power. The following studies were performed taking into account a 10 MW installed capacity wind farm with the 10 MWh, 6MW ESS medium.

3.7.2 Value of ESS in Support of Wind Imbalances

Low capacity value plants and associated operational forecast errors – in the particular case of wind generation – are a major challenge for power system stability and may undermine the plant's economics. Contracts with third parties to manage wind volatility and generation imbalances are the current practice among wind producers to hedge against the alternative of recurring to imbalance markets, which could result in significant balancing costs. However, as the proposed model suggests, ESS are also capable of providing wind balancing services given appropriate sizing characteristics that could accommodate all excess and shortage of energy due to wind forecast errors. Figure 3.15 shows a comparison of the expected cost for wind balancing services among three different strategies: using an ESS, a PPA contract or recurring to the imbalance market.

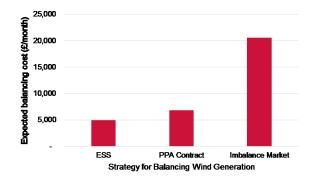


Figure 3.15: Cost for wind balancing service with three different strategies.

The results show that using an ESS for providing wind balancing services is overall more beneficial, i.e. with reduced costs for the wind plant, comparatively to the alternatives of PPA contracts or being compelled to buy energy at the imbalance market to cover for energy shortages. Note that costs with a PPA contract are directly associated with a contracted fee, which in this study was assumed as 5% of the strike price for onshore wind power plants (in 2015 set as 95 f_c/MWh) [54].

From the ESS owner perspective, providing wind balancing services for the 3 month period defers power and energy capacity that could be allocated to other services and therefore leads to a reduction on the total revenue. Determined as an opportunity cost, the value for providing the service may reach up to circa 5,000 f/month, as shown in Figure 3.16.

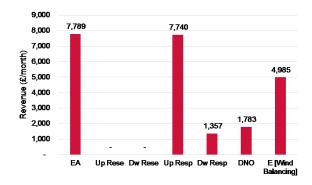
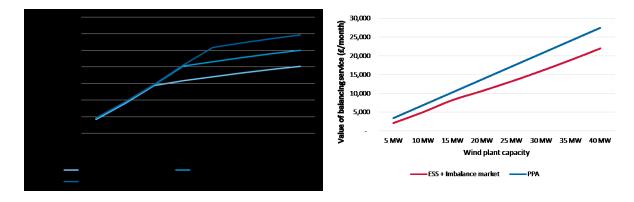


Figure 3.16: ESS monthly average revenues for individual services when including provision of wind balancing services.

Note that using an ESS for provision of wind balancing services allows a wind plant to save up to 1,885 £/month against the alternative of using a PPA contract (shown in Figure 3.15). How the overall benefit of contracting an ESS to provide the wind balancing service (with a cost of 4,985 £/month) rather than a PPA contract (with a cost of 6,870 £/month) should be allocated between the two parties is out of the scope of this research and could be the subject for further work to investigate how the benefit should be efficiently allocated for maximum social welfare.

3.7.3 Impact of ESS Sizing Characteristics on its Economics

The adequate sizing of an ESS with respect to wind farm installed capacity is crucial for an effective and economically efficient provision of wind balancing services, i.e. if ESS is incapable of managing wind imbalances due shortage of energy or power resources the wind producer will be required to access the imbalance market to correct additional imbalances not covered by the ESS and this may undermine the business case in support for wind balancing service by the ESS. In this context, the provision of wind balancing services for different sized wind farms was investigated against three ESS capacities - 6 MW/10 MWh, 7.8 MW/13 MWh and 9.6 MW/16 MWh, respectively base case (100%), medium (130%) and high capacity (160%) - shown in Figure 3.17 (a). Moreover, this section also analyses the service value when ESS cannot manage wind imbalances in full due to high volumes of power or energy deviations, and compares it against the alternative of a PPA contract, presented in Figure 3.17 (b).



(a)

(b)

Figure 3.17: (a) Opportunity cost of wind service for ESS with different power and energy capacities and (b) service value when provided by a PPA contract or an ESS & Imbalance market for various sized wind plants.

Figure 3.17 (a) shows that when wind plant capacity is approximately 50% higher than ESS power capacity, the latter is overloaded with power deviations from wind imbalances and is fundamentally operating exclusively to provide the wind balancing service. This changes the rate at which the service is valued by the ESS and ultimately represents the cost of using an ESS to exclusively provide wind balancing services.

Likewise, in Figure 3.17 (b) provision of wind balancing service to a 15 MW wind plant with a 6 MW/ 10 MWh ESS shows a similar effect on the service value curve, however wind imbalances that are not covered by ESS operation are still considered and their cost determined by accessing the imbalance market. In addition, Figure 3.17 (b) also shows that joint provision of wind balancing services by ESS and imbalance market is overall more beneficial than a PPA contract.

In addition to wind plant's capacity, ESS revenue is also affected differently with regards to increase in ESS capacities, as shown in Figure 3.18; increase in ESS power capacity produces higher revenues than an increase in ESS energy capacity.

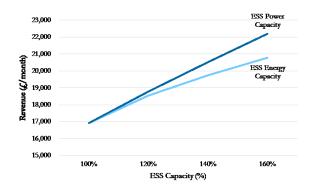


Figure 3.18: ESS revenue with various power and energy capacities.

The most striking result from Figure 3.18 is the fact that higher ESS power capacity allows higher revenues from a multiple service business model framework when compared to increased ESS energy capacity, i.e. a unit increase in power capacity (+1 MW) has a higher value than a unit increase in energy capacity (+1 MWh). An increase in power allows higher volumes of frequency response services to be provided, which being the most valuable service among the whole portfolio results in higher revenue increase. In contrast, higher energy capacity allows an increase in provision of energy services – such as energy arbitrage or reserve services – which in comparison to frequency response services have a lower value and therefore result in lower ESS revenues.

3.8 Conclusion

Chapter 3 introduced and demonstrated a novel heuristic based on a Benders decomposition which enables ESS commercial strategies on long time scales to be determined considering uncertainty on energy prices. The two stage model determines optimum volumes of balancing services to contract ahead of real time and scheduled operation to seize arbitrage opportunities in the energy market with no knowledge on energy prices. In addition, the set of studies investigated in this chapter allowed to: determine the impact of markets and system conditions on ESS commercial strategies, identify hedging strategies against volatility on energy prices, determine the value of reactive power and its relevance to provide DNO service, investigate ESS revenues sensitivity to roundtrip efficiency and its impact on commercial strategies, determine the impact of utilisation of balancing services on ESS revenues, determine the cost for the ESS of each MWh of exercised balancing service, study economics of ESS in future flexible power systems and the business case in support of ESS to provide wind balancing services.

A key contribution of this chapter is the Benders decomposition based heuristic which extends on the model of Chapter 2 by considering a longer time scale (3 months) for ESS commercial strategies and considers uncertainty on energy prices. The results have shown that the Benders decomposition and linearization of sub-problems are both effective and efficient at achieving an optimum solution for ESS commercial strategies; on average, the heuristic achieves similar solutions (with differences as low as 0.07% from optimum solution) but convergence times up to 240 times faster than original non-decomposed formulation.

The analysis on ESS commercial strategies has shown that specific markets and system conditions in a year should be addressed with specific portfolios of services for maximum ESS revenue. In particular, the studies have shown that in summer, due to expected low revenue from energy prices, ESS commercial strategies should consider provision of higher volumes of reserve services and allocate a higher share of ESS energy and power resources for DNO service. Energy market prices and local demand driven by seasonal conditions, affect ESS revenues up to 10%, with the lowest revenue occurring in summer and highest in autumn. In addition, the findings have shown that provision of reserve services can be used to hedge against uncertainty on energy arbitrage revenue - due to volatility on energy prices - in particular and as shown with commercial strategies for summer months, i.e. provision of down reserve services achieves both the highest expected revenue and lowest risk.

Reactive power is crucial to support delivery of DNO service and support provision of energy arbitrage and balancing services. The value of actively coordinating operation of active and reactive power exceeds 2,000 \pounds /month, which represents a value 30 times higher than current remunerative schemes for reactive power services in GB. Ensuring that ESS is remunerated accordingly to the benefits delivered is priority for its efficient deployment, however, the study of remunerative schemes for reactive power services provided by ESS is considered as potential future work to this research.

A high efficient ESS ensures higher remunerability in contrast to operating at inferior roundtrip efficiencies, albeit investment decisions between different roundtrip efficiencies should be made based on the revenue surplus achieved with a higher efficiency. Therefore, the option for a 10% higher ESS efficiency should be taken if the annuitized investment is lower than: 4,000 f_{c} /month when expecting the topmost revenues and thus with associated higher level of risk, or lower than 2,000 f_{c} /month with associated low risk levels on ESS revenues.

Real time exercise of balancing services which were contracted ahead of real time is associated with a change on ESS scheduled output and therefore different energy arbitrage revenue; the change on revenue is thus associated with the frequency that balancing services are exercised. The studies have shown that both increase and decrease in energy arbitrage revenue is possible, depending when and which type of service is exercised. ESS revenues may incur in a loss of up to 6 f_c /MWh exercised which in turn may be used to value utilisation of balancing services delivered by an ESS.

When comparing ESS commercial strategies in future power systems associated with different levels of flexibility, the studies indicate that provision of frequency response services is a key service to be provided. On the other hand, reserve services with their associated severe energy requirements are not economically efficient in a high flexible power system market, and therefore not included in ESS commercial strategies

Chapter 4

Value of Network Support with Distributed Energy Storage Systems

ESS can provide services to several sectors in electricity industry, including generation, transmission and distribution, where conflicts and synergies may arise when the ESS is used to manage distribution network congestion and provide services in energy and balancing markets – demonstrated in Chapter 2. In this context, this chapter investigates an alternative method based on corrective control actions to manage distribution network congestion by an ESS within a multi service business model framework. The proposed method uses a corrective control approach to deliver network services (e.g. congestion management and security of supply) and to resolve conflicts between this and other ESS applications.

The results have shown that adopting corrective security⁴ to provide network services and deal with network congestion in a post-fault fashion, is overall more beneficial despite the levels of energy needed during pre-fault conditions for post-contingency actions right after a network fault occurs. Furthermore, adopting corrective security can benefit both (i) ESS owners through increased revenues in energy and balancing services markets and (ii) DNOs through reduction in payments to ESS owners and increased utilisation of network infrastructure.

⁴ Corrective security is the mode of operation for providing peak demand shaving actions and ensuring security of supply by means of corrective control.

4.1 Nomenclature

Sets

T Set of operating periods

Parameters (in normal font)

d	Duration of standardised period (e.g. 1h or 0.5h)	[h]
Ē	ESS maximum energy capacity	[MWh]
$\mathrm{E}_{\mathrm{t}}^{\mathrm{E}}$	Energy excess for security of supply at period t	[MWh]
М	Auxiliary large number used for endogenous constraints relaxation	
S ^N	Installed apparent power capacity of primary substation	[MVA]
\overline{S}^{N}	Secured apparent power capacity of primary substation (N-1 limit)	[MVA]
α, α'	Binary parameters to increase robustness of corrective security mode	
π^E_t	Energy price at period t	[£/MWh]
$\pi_t^{\text{Dw.Rese}}$	Availability price for downwards reserve at period t	[f/MW/h]
$\pi_t^{\text{Dw.Resp}}$	Availability price for downwards frequency response at period t	[f/MW/h]
$\pi_t^{\text{Up.Rese}}$	Availability price for upwards reserve at period t	[f/MW/h]
$\pi_t^{\text{Up.Resp}}$	Availability price for upwards frequency response at period t	[f/MW/h]
τ^{Rese}	Maximum utilisation time for reserve services	[h]
τ^{Resp}	Maximum utilisation time for frequency response services	[h]

Variables (in italic font)

E_t	ESS energy level at period t	[MWh]
P_t^N	Active power through primary substation at period t	[MW]
P_t^S	ESS scheduled active power output at period t	[MW]
Q_t^N	Reactive power through primary substation at period t	[MVAr]
$Rese_t^{Dw}$	Downwards reserve power committed at period t	[MW]
$Rese_t^{Up}$	Upwards reserve power committed at period t	[MW]
$Resp_t^{Dw}$	Downwards frequency response power committed at period t	[MW]
$Resp_t^{Up}$	Upwards frequency response power committed at period t	[MW]
$X_t^{Dw.Rese}$	Downwards reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Dw.Resp}$	Downwards frequency response commitment status at period t: 1 if committed, $\boldsymbol{0}$ otherwise	
$X_t^{Dw.R\&R}$	Simultaneous downwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Up.Rese}$	Upwards reserve commitment status at period t: 1 if committed, 0 otherwise	

$X_t^{Up.Resp}$	Upwards frequency response commitment status at period t: 1 if committed, 0 otherwise
$X_t^{Up.R\&R}$	Simultaneous upwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise

4.2 Introduction

In Chapter 2, operation of ESS has been proven to be capable of efficient delivery of network services to DNO's (e.g. congestion management and security of supply) while delivering other ESS applications to various markets (e.g. energy arbitrage and balancing services). However, the results have also shown that provision of network services (i.e. DNO service) may conflict with other applications and undermine ESS economics (e.g. revenue on energy arbitrage and provision of balancing services). In this context, this chapter investigates the operation and economics of ESS within a multiple service business model framework which adopts a corrective security method to provide the DNO service and resolve the conflicts between this and other ESS applications.

The proposed model determines scheduled operation of ESS connected to a distribution network by co-optimising multiple services delivered to various stakeholders. Multi service coordination aims at maximising ESS's revenues and is sensitive to market and system conditions such as prices of energy and balancing services, and demand levels at the primary substation. The unique feature of the model is its ability to provide DNO service in a corrective control mode, allowing substation net demand to exceed N-1 security limit as long as ESS maintains sufficient margin to respond in real time against a fault in a substation's transformer or line. Figure 4.1 shows a schematic of the modelled ESS.

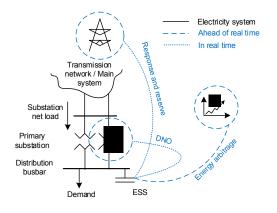


Figure 4.1 Schematic of electricity system and services provided by the ESS.

Similarly to Chapter 2 and Chapter 3, the analysis comprises the following services: energy arbitrage, system balancing services - in particular upwards and downwards reserve and frequency

response and DNO service through corrective security, i.e. ESS can provide peak demand shaving through active and reactive power in post-fault conditions right after a distribution network fault occurs (rather than pre-fault like in preventive mode presented in Chapter 2) in order to avoid network overloads.

In contrast to the preventive control framework for provision of DNO service - presented in Chapter 2 - that secures substation operation by limiting its net demand to the N-1 capacity limit, the model proposed here allows substation net demand to exceed the N-1 capacity limit. When doing so, the model ensures that sufficient ESS power capacity and energy is maintained in the reservoir in case a transformer or line outage occurs. Hence, corrective control mode can ensure same levels of security of supply as preventive control mode does. Furthermore, the model fundamentally allows ESS to determine an optimum balance between preventive (e.g. alleviating substation net demand) and corrective control actions (e.g. maintaining sufficient energy in the ESS reservoir in case an outage occurs when substation net demand is beyond the N-1 limit), taking advantage of flexibility of ESS operation to rapidly change real time outputs and hence enhancing the value of ESS.

The rest of this chapter is organised as follows: section 4.3 introduces a set of studies related with the research presented here; section 4.4 presents and discusses the mathematical formulation, in particular a summary of the novelty of the proposed model. Section 4.5 describes the input data used for the case studies presented in 4.6 where the new 'storage centric' approach for profit-maximisation operation of ESS through corrective security is investigated and section 4.7 presents and discusses the main results for a real ESS operating in the UK. Finally, Section 4.8 concludes.

4.3 Related Work

A number of optimisation models for ESS applications have been reported in the literature [3, 7, 8, 10, 12, 13, 16-18, 22, 24, 25, 32, 55-61]. Models developed in references [7, 8, 17, 24, 25, 55-57] identified and valued the benefits of ESS for network support, and in particular [17, 55-57] recognised its importance in providing peak shaving services and deferring network reinforcements. Optimisation models for further applications of ESS have also been reported: references [12, 13, 32, 58] analysed the value and ability of ESS to provide price arbitrage services in the energy market; [16, 59, 60] optimised operation to facilitate integration of renewable generation; and [3, 10, 61] presented models to support system operation by managing imbalances and providing frequency control services.

Further studies have identified the potential of ESS to provide simultaneous services to several electricity sectors, such as energy and balancing services markets [10, 18]. Recently, reference [22] proposes a Mixed Integer Linear Programing (MILP) model to schedule operation of distributed ESS by coordinating provision of a range of system services rewarded at different market prices. The model maximises distributed ESS revenue while providing distribution network congestion management, energy price arbitrage and various reserve and frequency regulation services through both active and reactive power control.

In this context, this chapter expands on the MILP model for optimising multi-service portfolios of distributed ESS presented in [22] and introduces a corrective control mode of operation for provision of distribution network congestion management or peak demand shaving/reduction service to DNOs.

As explained in [43, 44, 62-64], corrective control can be used to provide network services through post-contingency remedial actions and thus reduce power transfers right after a fault occurs (rather than reducing power transfers in a preventive mode as done in [22]). Hence it is demonstrated that adopting corrective security to provide network services and deal with network congestion in a post-fault fashion, is overall more beneficial despite the levels of energy needed to be maintained in ESS reservoir during pre-fault conditions for applying post-contingency actions right after a network fault occurs.

4.4 Mathematical Formulation

Power systems, in particular network infrastructure, are usually built and operated with redundancy standards to prevent supply outages due to planned (e.g. maintenance) and unplanned (e.g. failures) outages. In the particular case of distribution networks, this means that infrastructure is operated at approximately half of its rated capacity, i.e. operation is managed in order to maintain high capacity margins available for unplanned events. As consequence, even during congested periods the distribution network infrastructure still has a high capacity margin which could be used to effectively operate the system (although at a high risk of load curtailment).

The model proposed here is designed to take advantage of this additional capacity margin and use ESS scheduled output to efficiently maximise its revenues in the energy and balancing markets – and therefore be able to charge and discharge freely even during network congested periods – but maintain power and energy margins to rapidly change its output in real time if a network fault occurs and network capacity limit is suddenly reduced.

4.4.1 Objective Function

The model's objective function maximises ESS revenues associated with energy arbitrage and balancing services such as provision of frequency response and reserve services. Balancing services' revenues are determined based on ESS scheduled output rather than real time output, and hence revenue of a system balancing service (upwards and downwards frequency response and reserve) in a given period is equal to the product of the committed capacity margin, the associated price, and the period duration. Similarly, energy arbitrage revenue in a given period is equal to the product of bought or sold energy (power times duration) and the associated energy price of that period, according to scheduled output. All revenues are summed across various periods (through a month or season) and this is shown in Eq. (4.1).

$$\operatorname{Max}\left\{\sum_{t\in T} \begin{bmatrix} P_t^S \cdot \pi_t^E + \\ Rese_t^{Up} \cdot \pi_t^{Up.Rese} + Rese_t^{Dw} \cdot \pi_t^{Dw.Rese} + \\ Resp_t^{Up} \cdot \pi_t^{Up.Resp} + Resp_t^{Dw} \cdot \pi_t^{Dw.Resp} \end{bmatrix} \cdot d\right\}$$
(4.1)

DNO service's revenue is not considered in Eq. (4.1) and this is determined through sensitivity analysis on distribution network capacity which is explained in Section 4.7.2.

4.4.2 DNO Service Constraints with Corrective Security

With corrective security, substation capacity S^N used to limit power transfers in Eq. (4.2) corresponds to transformers' nameplate ratings rather than the N-1 secured capacity used under preventive security mode (Eq. (3.45) in Chapter 3). Note that local demand P_t^p is unlikely to exceed total substation installed capacity S^N and therefore ESS output is unlikely to reduce DNO peak demands during pre-fault conditions (due to substation overloads), which is fundamentally different to ESS operation with preventive security.

$$(P_t^N)^2 + (Q_t^N)^2 \le (S^N)^2 \quad \forall t \in T$$
(4.2)

If a fault occurs, however, ESS output will be rapidly increased to reduce peak demand down to substation's N-1 security limit. To do so, ESS should maintain sufficient energy stored so as to, if a fault occurs, supply the energy associated with upcoming peak demands and this is ensured by Eq. (4.3).

$$E_{t-1} \ge E_t^E \quad \forall \ t \in \mathcal{T} \tag{4.3}$$

 E_t^E , namely energy excess or surplus, is the energy associated with peak demands above the N-1 security limit from period t onwards and therefore that needs to be supplied by ESS if a substation

fault occurs. Calculation of E_t^E (which is a parameter) also considers that there may be multiple peak demands within a day and so that ESS can charge while demand is below the substation secured capacity and this is illustrated in Figure 4.2.

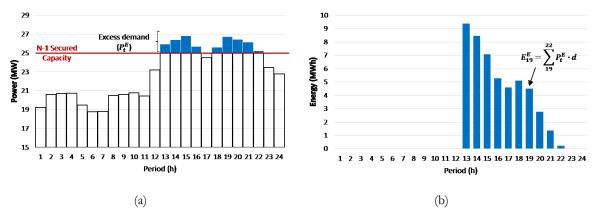


Figure 4.2: (a) Local demand and demand excess or surplus in a day (in white and blue, respectively), and (b) energy required (at every period t) to exercise DNO service in post-fault conditions.

Note that none of the two operating modes (preventive or corrective security) will be able to provide DNO service if local demand exceeds substation N-1 security limit by more than the ESS maximum discharge capacity (in terms of both power and energy).

4.4.3 System Balancing Services Constraints

In a multi service framework, it is critical to ensure that ESS scheduled outputs are robust and can be adapted in real time to deliver the services contracted in advance. In this context, Eqs. (4.4) to (4.6) ensure real time deliverability of downwards balancing services even if substation capacity is reduced due to a fault ($\alpha = 1$). Alternatively, it can be assumed that most of the time, real time substation net demand could be allowed to go beyond its N-1 security limit when ESS provides a downwards balancing service, provided that its output will be increased if a fault occurs ($\alpha = 0$).

$$(P_t^N + Rese_t^{Dw})^2 + (Q_t^N)^2 \le (\alpha \cdot \overline{S}^N + (1 - \alpha) \cdot S^N)^2 + M \cdot (1 - X_t^{Dw.Rese}) \quad \forall \ t \in T$$

$$(4.4)$$

$$(P_t^N + \operatorname{Resp}_t^{Dw})^2 + (Q_t^N)^2 \le (\alpha \cdot \overline{S}^N + (1 - \alpha) \cdot S^N)^2 + M \cdot (1 - X_t^{Dw, \operatorname{Resp}}) \quad \forall \ t \in \mathcal{T}$$

$$(4.5)$$

$$(P_t^N + Rese_t^{Dw} + Resp_t^{Dw})^2 + (Q_t^N)^2 \le (\alpha \cdot \overline{S}^N + (1 - \alpha) \cdot S^N)^2 + M \cdot (1 - X_t^{Dw.R\&R}) \quad \forall \ t \in T \quad (4.6)$$

Note that if a balancing service is not contracted or committed, upper bound of the associated constraint (in Eqs. (4.4) to (4.6) will become a very large number (M), relaxing the optimisation problem.

Likewise, Eqs. (4.7) to (4.9) ensure robustness of scheduled outputs against multiple potential real time operating conditions by maintaining sufficient margins of energy stored if simultaneous

services are exercised at the maximum contracted volumes (i.e. worst-case scenario optimisation). More robust solutions can be obtained when assuming that ESS has to maintain sufficient energy to deliver all balancing and DNO services simultaneously and through independent post-contingency actions ($\alpha' = 1$). Alternatively, it can be assumed that a single post-contingency action could deliver DNO and balancing services ($\alpha' = 0$) and thus Eqs. (4.3), Eqs. (4.7) - (4.9) will ensure that energy stored is sufficient to deliver the service with the most demanding energy requirements. For the sake of simplicity, the equivalent of Eqs. (4.7) to (4.9) for downwards balancing services are not presented here albeit they were included in the modelling.

$$-\mathbf{M} \cdot \left(1 - X_{t}^{Up.Rese}\right) \leq E_{t-1} - \left(P_{t}^{S} + Rese_{t}^{Up}\right) \cdot \tau^{\text{Rese}} - \alpha' \cdot \mathbf{E}_{t}^{\mathbf{E}} \leq \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_{t}^{Up.Rese}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(4.7)$$

$$-\mathsf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \le E_{t-1} - \left(P_t^S + Resp_t^{Up}\right) \cdot \tau^{\operatorname{Resp}} - \alpha' \cdot \mathsf{E}_t^{\mathsf{E}} \le \overline{\mathsf{E}} + \mathsf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \quad \forall \ \mathsf{t} \in \mathsf{T}$$

(4.8)

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \le E_{t-1} - \left(P_t^S + Rese_t^{Up}\right) \cdot \tau^{\text{Rese}} - Resp_t^{Up} \cdot \tau^{\text{Resp}} - \alpha' \cdot \mathbf{E}_t^{\mathbf{E}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(4.9)$$

Further constraints of the corrective security model were omitted here for the sake of clarity and briefness since they have already been reproduced in Chapter 2, in particular constraints that refer to ESS energy balance, power and energy limits – respectively Eqs. (2.2) to (2.6) - and ensure real time deliverability of committed balancing services – Eqs. (2.7) to (2.26).

In the above formulation $Rese_t^{Up}$, $Rese_t^{Dw}$, $Resp_t^{Up}$, $Resp_t^{Dw}$ and E_t are positive decision variables, i.e. greater or equal to zero, and $X_t^{Up.Rese}$, $X_t^{Dw.Rese}$, $X_t^{Up.Resp}$, $X_t^{Dw.Resp}$, $X_t^{Up.Resp}$, $X_t^{Up.Resp}$, $X_t^{Dw.Resp}$, $X_t^{Dw.Resp}$, and $X_t^{Dw.Resp}$ are binary variables.

4.4.4 Further Modelling Constraints

Prescribed windows for the provision of balancing services

Committed volumes of balancing services are assumed to be constant within a prescribed time window. For example, if a prescribed time window is defined between 16:00 h and 21:00 h for a given balancing service, its committed volume (e.g. 3 MW) must remain constant during the whole window. Thus additional constraints were added to the above model in order to ensure that balancing services can only be provided in certain hours of the day (within the prescribed windows) and its provision must remain constant throughout the window.

Linearization

The proposed model optimises active and reactive power and hence is clearly nonlinear (see Eqs. (4.2), Eqs. (4.4) - (4.6); therefore the same technique illustrated in [22] was used which fundamentally determines a set of tangent planes over a bounded convex region (i.e. described by $P^2 + Q^2 \le S^2$) to linearize the problem.

4.5 Input Data

Energy prices and distributed local demand at the level of primary substation from real GB time series with hourly resolution are used in the case studies to optimise ESS operation. Monthly profiles for energy prices and demand were considered in order to account for credible operating and market conditions in the GB market. Figure 4.3 shows energy prices and demand profiles for a typical week in winter and summer.

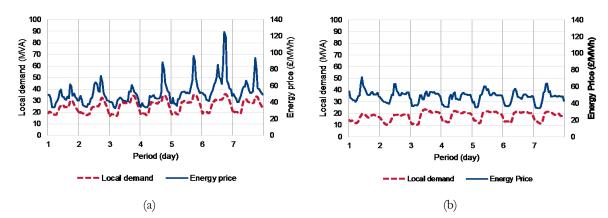


Figure 4.3: Energy price and local demand profiles during a typical week in (a) winter and (b) summer.

Figure 4.4 (a) and (b) shows histogram of energy prices and load duration curve of local demand, respectively, for a month in winter and summer.

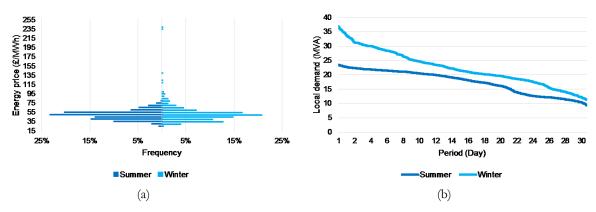


Figure 4.4: (a) Histogram of energy prices in a month during summer and winter and (b) load duration curve in a month for summer and winter.

The model assumes a maximum duration to exercise upwards and downwards reserve and frequency response services up to 2h and 30min, respectively (i.e. $\tau^{\text{Rese}} = 2h$ and $\tau^{\text{Resp}} = 0.5h$). Following actual practices observed for the provision of balancing services in GB, it was defined a prescribed window for frequency response in the morning between 4:00 h and 8:00 h. For reserve services, a prescribed window was defined in the evening from 19:00 h to 22:00 h during April-August, and from 16:00 h to 21:00 h during September-March. Availability prices to remunerate provision of balancing services are assumed as follows:

- Up and down reserve: 5 f/MW/h
- Up and down response: 7 f/MW/h

ESS power and energy capacities, roundtrip efficiency and substation capacity ratings are assumed as follows:

- ESS power and energy capacities: 6 MW, 7.5 MVA and 10 MWh;
- ESS roundtrip efficiency: 85%;
- Primary substation nameplate ratings: 2 x 31.9 MVA (which is derated in summer up to 70% according to Figure 2.4).

4.6 ESS Operation with Corrective Network Security in a Day

This section presents a set of results, all for the day shown in Figure 4.5 (observed in a real GB distribution network substation), which will be used to compare ESS operation under preventive and corrective security modes. This section also validates the model and show its main features.

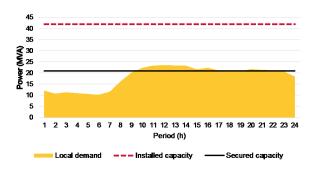


Figure 4.5: Local demand, substation installed and N-1 secured capacity.

4.6.1 Optimised ESS Scheduled Output with Corrective Network Security

Figure 4.6 shows the ESS scheduled operation when providing multiple services and its effect on substation net demand under (a) preventive and (b) corrective network security mode.

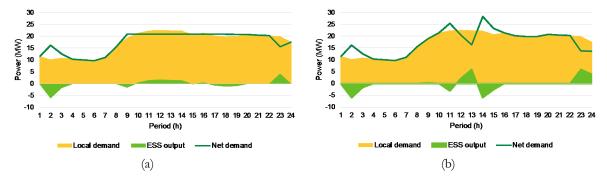


Figure 4.6: ESS scheduled operation, local and net demand with (a) preventive and (b) corrective network security.

Figure 4.6 (a) clearly shows that ESS operation is constrained to discharge and provide peak demand shaving services to the DNO (from period 10:00 h to 16:00 h) in a preventive fashion to maintain substation net demand below its secured capacity limit. Figure 4.6 (b), in contrast, shows that ESS scheduled output is not constrained to maintain substation net demand below its N-1 security limit. Moreover, note that in Figure 4.6 (b) ESS even charges at maximum output during peak demand. Next, deliverability of DNO service in real time will be analysed along with economic efficiency of ESS scheduled outputs in energy and balancing services markets.

4.6.2 Deliverability of DNO Service and Security of Supply

Although Figure 4.6 (b) shows that substation net demand can be above its N-1 security limit since ESS is not constrained to discharge during peak demand, it is demonstrated that network operation is still N-1 secured. Indeed, Figure 4.7 shows that energy stored in the ESS is above the levels needed to supply peak demand surplus (i.e. the proportion of demand beyond N-1 security limit) at all times. This means that sufficient energy is stored to adapt ESS output in real-time if a network outage occurs and so discharge during peak demand in order to decrease substation demand down to the capacity of the remaining infrastructure.

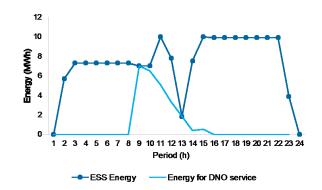


Figure 4.7: ESS energy levels and levels of energy required to deliver DNO service in post-contingency conditions.

Furthermore, Figure 4.8 illustrates scheduled and real-time ESS output (a and c) and the energy level (b and d) under two possible network contingencies. Figure 4.8 (a) and (b) show scheduled and real-time operation when a network contingency occurs at 10:00 h (and lasts until 16:00 h which will require large amounts of energy stored to discharge and supply demand peak surplus beyond the N-1 security limit); Figure 4.8 (c) and (d) show scheduled and real time operation when a contingency occurs at 14:00 h (when substation net demand is maximum). Hence, Figure 4.8 clearly illustrates that the model determines robust scheduled outputs that can deliver DNO service through efficient corrective control actions, while maximising revenues without being constrained to de-rate substation net demand.

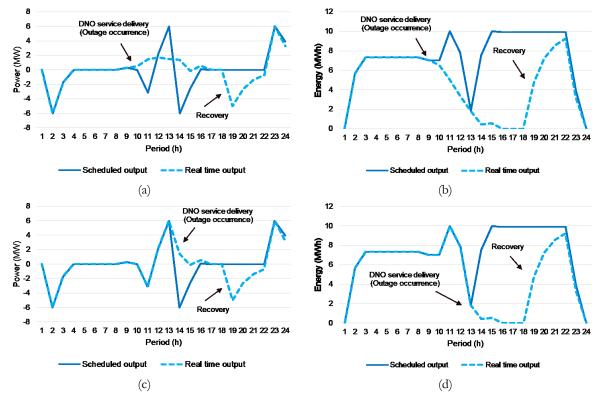


Figure 4.8: ESS scheduled and real-time (a) power output and (b) energy level for a contingency at 10:00 h, and (c) power output and (d) energy level for a contingency at 14:00 h.

4.6.3 Increased Energy Arbitrage Revenue through Corrective Security

Corrective network security allows ESS to charge and discharge more freely without compromising the levels of security of supply and increase revenue in energy market. In this context, Figure 4.9 (a) shows ESS operation under preventive and corrective security mode and Figure 4.9 (b) presents the associated revenues due to energy arbitrage actions. Interestingly, under corrective security mode, arbitrage opportunities emerge where ESS needs to charge and discharge while local demand is high. These opportunities cannot be taken under a preventive security mode since charging ESS at high demand periods is clearly problematic.

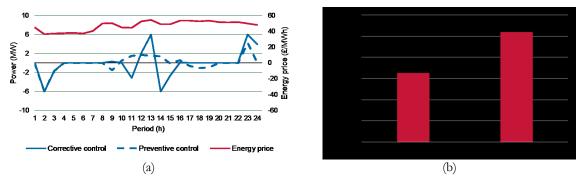
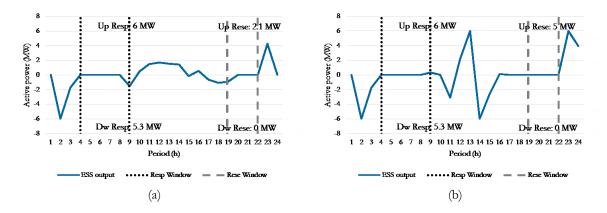


Figure 4.9: (a) ESS output with preventive and corrective security and energy prices, and (b) revenue associated with energy arbitrage actions under preventive and corrective security mode.

4.6.4 Increased Balancing Services Revenues through Corrective Security

As shown in Figure 4.10, ESS under corrective security mode may also provide higher volumes of balancing services to system operator and thus collect higher revenues. Figure 4.10 (a), for example, shows that ESS can provide limited upwards reserve service since its energy stored has been importantly reduced earlier after providing (pre-fault) DNO peak demand shaving services. On the other hand, Figure 4.10 (b) shows higher provision of upwards reserve service (increase from 2.1 MW to 5.0 MW) since there is no need to discharge ESS during peak demands (if a network outage does not occur) which results in higher levels of energy stored for the subsequent reserve period.



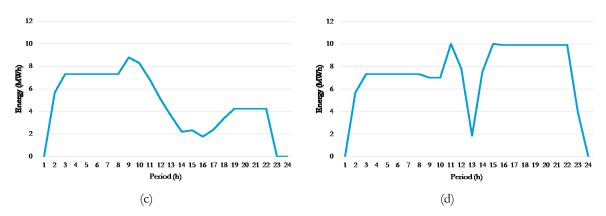


Figure 4.10: ESS power output and balancing services provided under (a) preventive and (b) corrective security modes.

4.7 Business Case in Support of Corrective Security: Yearly Impact Assessment

4.7.1 Yearly Revenues in Energy and Balancing Services Markets

Figure 4.11 shows the ESS revenues in a year under preventive and corrective security modes when assuming different levels of robustness in the application of corrective security (through adjustment of binary parameters α and α). In particular, Figure 4.11 (a) shows that, although all revenue components are increased under corrective control operation, reserve revenue significantly escalates, demonstrating that conflicts between DNO and reserve services can be more efficiently managed through corrective security.

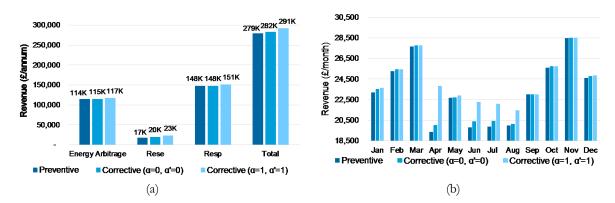


Figure 4.11: Revenues under preventive and corrective control strategies by (a) services and (b) month.

Interestingly, the increase in ESS revenue is higher during April, June, July and August (i.e. spring and summer) rather than during period between November and March (i.e. winter) and this is so due to the higher number of congested hours during summer (decrease in substation's thermal rating during summer is disproportionally larger than the decrease in demand). Clearly, the value of corrective security (i.e. revenue difference between preventive and corrective security) is higher when more severe substation congestions occur. Also, Figure 4.11 shows that corrective security can improve yearly revenue in energy and balancing services markets by circa 5% (in this particular GB case).

4.7.2 Yearly Revenues of DNO Rervice

According to [22], revenue associated with DNO service is equal to the opportunity cost of providing such service and it refers to the revenue increase in energy and balancing services markets when no ESS capacity is allocated to provide DNO service (i.e. $\overline{S}^{N} = \infty$ and $S^{N} = \infty$). In this context, Figure 4.12 shows the opportunity cost of providing DNO service under preventive and corrective security mode.

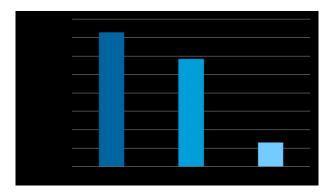


Figure 4.12: Opportunity cost of providing DNO service under different security modes.

Figure 4.12 shows that the opportunity cost of providing DNO service decreases when corrective security is applied since conflicts between provision of DNO service and further applications can be managed more efficiently. Moreover, the reduction in opportunity cost of providing DNO service (e.g. \pounds 14 592 – \pounds 2 597 = \pounds 11 995 in Figure 4.12) is equal to the value of corrective control (e.g. \pounds 291 333 – \pounds 279 338 = \pounds 11 995 in Figure 4.11). It is therefore worth discussing whether the actual revenue of DNO service should be proportionally reduced according to its opportunity cost under corrective control (benefiting DNO) or whether part of the savings in opportunity cost should be kept by ESS owner in order to incentivise deployment of advanced corrective control technology.

4.8 Conclusion

ESS can bring benefits to several sectors in electricity industry, including generation, transmission and distribution, while providing services to support balancing of demand and supply, network congestion management and reduce the need for investment in system reinforcement.

In this context, a novel 'storage centric' framework has been proposed for coordinating multiservice portfolios of distributed ESS that supports distribution network operation through application of corrective security (i.e. post-fault rather than pre-fault peak demand shaving/reduction service). Through a MILP model that schedules ESS outputs (in terms of active and reactive power) by coordinating various services to multiple stakeholders, it was demonstrated that adopting corrective security to provide network services and deal with network congestion in a post-fault fashion, is overall more beneficial despite the levels of energy needed to be maintained in ESS reservoir during pre-fault conditions for applying post-contingency actions right after a network fault occurs. Furthermore, the analysis shows that application of corrective security can benefit both (i) ESS owners through increased revenues in energy and balancing services markets and (ii) DNOs through reduction in payments to ESS owners and increased utilisation of network infrastructure.

The model and developed framework can promote efficient integration of new distributed ESS projects and new smart grid technology that can enable application of corrective network security. The developed framework can also provide insights associated with the development of appropriate market mechanisms to ensure that investors in ESS and those interested in providing services through advanced corrective control technology, are adequately rewarded for the delivery of value to multiple electricity sectors.

Energy Storage Systems Business Models with Oversell Operating Policies

ESS can deliver benefits to system operators in the form of balancing services contracted ahead of real time which are later exercised to balance system demand and supply in real time. Instructions by the system operator to deliver balancing services are associated with a probability of exercise and a probability of delivering the service for a given duration – e.g. reserve services may be exercised with 10% probability and exercise may last up to 1 hour with a 20% probability.

A new operating policy for ESS within the multiple service business model framework is proposed here which considers the probability of exercising services in real time and minimises ESS yield losses by allocating ESS energy and power capacity to the most valuable service. The studies presented in this chapter address the possibility of overselling ESS energy and power capacity to the DNO and balancing services and investigate the impact that such operational policy might have on system conditions and ESS economics.

The results have shown that overselling ESS resources allocated to the DNO service allow higher volumes of balancing services to be contracted and enhance the ESS economics. In addition, the studies have shown that overselling ESS resources in small amounts is an economically efficient operating policy.

5.1 Nomenclature

Sets

Т	Set of operating periods
R	Set of scenarios for reserve services utilisation time

Parameters (in normal font)

d	Duration of standardised period (e.g. 1h or 0.5h)	[h]
Ē	ESS maximum energy capacity	[MWh]
М	Auxiliary large number used for endogenous constraints relaxation	
p^{Res}	Probability of a delivery instruction for reserve services	[%]
p^{Resp}	Probability of a delivery instruction for frequency response services	[%]
$p_r^{U.Res}$	Probability of utilisation time for reserve services	[%]
$\overline{S}{}^{N}$	Secured apparent power capacity of primary substation (N-1 limit)	[MVA]
Ur	Utilisation time for reserve services	[h]
π^{E}_{t}	Energy price at period t	[£/MWh]
π^{DNO}	Penalty fee for non-delivery of DNO service during utilisation of balancing services	[f/MW/h]
$\pi_t^{Dw.Rese}$	Availability price for downwards reserve at period t	[f/MW/h]
$\pi^{\text{Dw.Rese.0}}$	Penalty fee for non-delivery of downwards reserve services	[£/MWh]
$\pi_t^{Dw.Resp}$	Availability price for downwards frequency response at period t	[f/MW/h]
$\pi^{Dw.Resp.O}$	Penalty fee for non-delivery of downwards frequency response services	[£/MW/h]
$\pi_t^{Up.Rese}$	Availability price for upwards reserve at period t	[f/MW/h]
$\pi^{Up.Rese.O}$	Penalty fee for non-delivery of upwards reserve services	[f/MWh]
$\pi_t^{\text{Up.Resp}}$	Availability price for upwards frequency response at period t	[f/MW/h]
$\pi^{Up.Resp.O}$	Penalty fee for non-delivery of upwards frequency response services	[£/MW/h]
τ^{Rese}	Maximum utilisation time for reserve services	[h]
τ^{Resp}	Maximum utilisation time for frequency response services	[h]

Variables (in italic font)

E_t	ESS energy level at period t	[MWh]
P_t^N	Active power through primary substation at period t	[MW]
P_t^S	ESS scheduled active power output at period t	[MW]
$O_t^{Dw.Rese}$	Oversold downwards reserve energy at period t	[MWh]
$O_t^{Up.Rese}$	Oversold upwards reserve energy at period t	[MWh]
Q_t^N	Reactive power through primary substation at period t	[MVAr]

$Rese_t^{DNO}$	Downwards reserve power associated with oversold DNO service at period t	[MW]
$Resp_t^{DNO}$	Downwards frequency response power with oversold DNO service at period t	[MW]
$Rese_t^{Dw}$	Downwards reserve power committed at period t	[MW]
$Rese_t^{Dw.O}$	Oversold downwards reserve power at period t	[MW]
$Rese_t^{Up}$	Upwards reserve power committed at period t	[MW]
$Rese_t^{Up.O}$	Oversold upwards reserve power at period t	[MW]
$Resp_t^{Dw}$	Downwards frequency response power committed at period t	[MW]
$Resp_t^{Dw.O}$	Oversold downwards frequency response power at period t	[MW]
$Resp_t^{Up}$	Upwards frequency response power committed at period t	[MW]
$Resp_t^{Up.O}$	Oversold upwards frequency response power at period t	[MW]
$X_t^{Dw.Rese}$	Downwards reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Dw.Resp}$	Downwards frequency response commitment status at period t: 1 if committed, $\boldsymbol{0}$ otherwise	
$X_t^{Dw.R\&R}$	Simultaneous downwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Up.Rese}$	Upwards reserve commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Up.Resp}$	Upwards frequency response commitment status at period t: 1 if committed, 0 otherwise	
$X_t^{Up.R\&R}$	Simultaneous upwards frequency response and reserve commitment status at period t: 1 if committed, 0 otherwise	

5.2 Introduction

The concept of overselling a particular service has been current practice among other industries such as the airline or hospitality industry, where for example flight tickets are frequently oversold (i.e. number of tickets sold is higher than the actual airplane capacity) in order to maximize revenue for every flight. The operating policy relies on passengers with valid tickets which frequently cancel or fail to materialize which then results in empty seats on popular flights, i.e. available resources (empty seats) which could therefore be utilised and efficiently managed for maximum revenue. However, occasionally, passengers will actually materialize and show up at the boarding gate, this then results in overbooked seats and leads to some of the passengers to be prompted to defer their ticket for a later flight and given some type of compensation. In this context, the policy for overselling flight tickets in the airline industry should balance the historic probability of cancelations/no-shows and associated penalty/compensation for overbooked passengers with revenue from oversold tickets.

An analogy between the airline business model and ESS business model can be made to reflect the fundamental philosophy behind overselling ESS capacity, either energy or power capacity, to various services. The airline and ESS business model have several common features such as constrained capacity and probabilities of services materialization (i.e. exercise); in the particular case of the ESS multiple services business model framework, balancing services committed ahead of real time follow a probability of being exercised. This allows the ESS owner to consider oversell operating policies and allocate ESS resources that have been previously allocated to other services, and therefore risking of being required to provide both services and be forced to pay a penalisation for non-delivery.

The proposed model takes into consideration the probability of exercising balancing services – reserve and frequency response services – which are committed 3 months ahead of real time and the probability of reserve services to be exercised for shorter periods than the 2 hours maximum utilisation time. Since reserve services are fundamentally an energy service with an exercise duration of up to 2 hours, the model describes oversold resources for reserve services as oversold energy capacity. In contrast, for frequency response services, which are fundamentally power services, the oversold resources are associated with oversold active power capacity. In addition, the model also considers the possibility to oversell DNO service by means of active power, i.e. allow ESS to operate beyond the substation secured capacity limit (N-1).

ESS revenue is therefore maximised by considering long term provision of multiple services (as demonstrated in Chapter 3) and allowing ESS power and energy capacities to be oversold to various services while considering the penalisations for non-delivery.

Ultimately, overselling ESS capacity will improve utilization of ESS finite resources by allocating those to services with potential low probability of being utilised while taking advantage of optimum conditions in other markets, and thus enhance ESS economics. In addition, this allows ESS owners to efficiently manage their business model by reducing yield losses, i.e. allocating ESS resources to the most valuable services.

5.3 Related work

In various business sectors such as airline and hospitality industries with finite resources (e.g. airplane seats or hotel rooms) and associated uncertainty on materialization of purchased service (e.g. cancelled flight reservations or delayed passengers), faced with strategies to manage yield losses, managers often engage in oversell/overbooking policies [65, 66].

Fundamentally, oversell policies are considered when passengers with paid tickets do not materialize and result in flights with empty seats. In this context, yield management strategies consider the probability of passengers to materialize and determines in a cost efficient way the number of tickets to be sold beyond the airplane capacity, taken into account that possible compensations need to be paid to passengers who are denied boarding due to unavailable airplane capacity (i.e. number of seats). These operating policies have been widely reported in the literature and is still an on-going topic of research [67, 68].

Although airline and electricity industry are different in many aspects, both rely on finite resources and services that though contracted ahead of real time may not materialize in real time operations. As the authors of [69] suggest in their study, an analogy can be made between the airline and electricity industry, and in the context of this research between the airline and ESS business model. In the ESS business model framework proposed in Chapter 3, balancing services and DNO service are contracted ahead of real time (analogously to flight tickets sold weeks before the flight day) and the materialization of those in real time will depend on system conditions, e.g. instructions from system operator to deliver frequency response or reserve services (i.e. in analogy to passengers showing up for boarding on flight day). Moreover, a similar study considering the historic energy utilization levels for reserve services is proposed in [14]. The authors use a distributed ESS to provide services to system operator and take into account the service's low utilization factors to enhance ESS energy levels and improve its economics, albeit ESS operation is not sensitive to penalisations for service non-delivery and potentially fail to determine cost efficient ESS operation.

Hence, in contrast to a robust operating policy where services' delivery is ensured at all times and for all possible realisations, the proposed framework determines cost efficient operating policies that consider the possibility to oversell ESS capacity to reduce yield losses. The model takes into consideration historic probabilities of services delivery in real time and balances the volumes of ESS energy and power capacity to be oversold for maximum revenue. In addition, penalisations for non-delivery of contracted services are also considered in the modelling framework and can potentially be hedged through demand response contracts, as investigated in [69].

5.4 Mathematical Formulation

The proposed model uses the long term business model framework for commercial strategies presented in Chapter 3 to determine ESS scheduled operation which includes overselling operating policies for maximum utilisation of ESS finite resources in real time. This chapter's main

contribution is the adaptation of oversell/overbook policies, which are current and common practice in other industries, into the ESS business model framework. This allows overselling of ESS energy and power resources for maximum revenue in a cost efficient way by considering: probability of services exercise, added revenue for overselling capacity and possible penalisations for non-delivery of oversold services.

5.4.1 Objective Function

The model objective function maximises ESS revenue on arbitrage actions and provision of reserve and frequency response services, additionally manages in a cost efficient way the volumes of oversold energy and power capacity respectively to reserve services and, frequency response and DNO service, shown in Eq. (5.1).

$$\operatorname{Max}\left\{\sum_{t\in T} \begin{bmatrix} P_t^S \cdot \pi_t^E + \\ Rese_t^{Up} \cdot \pi_t^{Up.Rese} + Rese_t^{Dw} \cdot \pi_t^{Dw.Rese} + \\ Resp_t^{Up} \cdot \pi_t^{Up.Resp} + Resp_t^{Dw} \cdot \pi_t^{Dw.Resp} - \\ O_t^{Up.Rese} \cdot \pi^{Up.Rese.O} - O_t^{Dw.Rese.O} - \\ O_t^{Dw.Rese.O} - O_t^{Dw.Rese.O} - \\ Resp_t^{Up.O} \cdot p^{Resp} \cdot \pi^{Up.Resp.O} - Resp_t^{Dw.O} \cdot p^{Resp} \cdot \pi^{Dw.Resp.O} - \\ (Rese_t^{DNO} \cdot p^{Res} + Resp_t^{DNO} \cdot p^{Resp}) \cdot \pi^{DNO} \end{bmatrix} \cdot d\right\}$$
(5.1)

The penalisations for non-delivery of committed balancing services are determined individually for reserve and frequency response services; for the former by considering the volume of short ESS energy capacity at period t (i.e. $O_t^{Up.Rese}$ or $O_t^{pw.Rese}$) multiplied by a penalty fee associated with non-delivery of reserve services and for the latter by considering the oversold ESS power capacity for frequency response services at period t (i.e. $Resp_t^{Up.0}$ or $Resp_t^{Dw.0}$) multiplied by the probability of service exercise and the associated penalty fee. Likewise, the penalisation for overselling DNO service is determined by the oversold active power capacity that is respectively allocated to provide higher volumes of reserve or frequency response services and multiplied by the probability of exercising each of these balancing services in real time, and the associated penalty fee. Note that in this context the probability of exercising balancing services is also equivalent to the probability of exceeding substation secured capacity in real time.

The volumes of energy shortage for delivery of reserve services are determined through Eqs. (5.2) and (5.3), respectively for up and down reserve.

$$O_t^{Up.Rese} \ge \sum_{\mathbf{r}\in\mathbf{R}} \left(Rese_t^{Up} \cdot \mathbf{U}_{\mathbf{r}} - \left(Rese_t^{Up} - Rese_t^{Up.0} \right) \cdot \tau^{\text{Rese}} \right) \cdot \mathbf{p}^{\text{Res}} \cdot \mathbf{p}_{\mathbf{r}}^{\text{U.Res}} \quad \forall \ \mathbf{t}\in\mathbf{T}$$
(5.2)

$$O_t^{Dw.Rese} \ge \sum_{r \in \mathbb{R}} (Rese_t^{Dw} \cdot U_r - (Rese_t^{Dw} - Rese_t^{Dw.O}) \cdot \tau^{Rese}) \cdot p^{Res} \cdot p_r^{U.Res} \quad \forall \ t \in T$$
(5.3)

Oversold ESS energy capacity for reserve is determined by the difference between energy required for exercising committed volumes of reserve (i.e. possible durations of service exercise, U_r , multiplied by the committed volume for reserve, $Rese_t^{Up}$ or $Rese_t^{Dw}$) and the actual energy that was allocated in the scheduling phase (i.e. $(Rese_t^{Dw} - Rese_t^{Dw.0}) \cdot \tau^{Rese}$). Note that oversold volumes of energy capacity may not be sufficient for service delivery for 2 hours, but ESS may still be able to ensure service delivery for 30 minutes or 1 hour.

5.4.2 DNO Capacity Constraints with Overselling Policies

In Chapter 2 and Chapter 3, ESS scheduled operation including commitment of balancing services was determined by considering substation secured capacity (N-1 limit) and therefore ensuring robust delivery of all services both for scheduled and real time operation (i.e. robust optimization). In contrast, Eq. (5.4) allows ESS to operate beyond the substation secured capacity at specific periods in time by overselling active power previously allocated for peak shaving service (DNO service) and associated with higher volumes of reserve and frequency response services, $Rese_t^{DNO}$ or $Resp_t^{DNO}$.

$$(P_t^N - (Rese_t^{DNO} + Resp_t^{DNO}) + Rese_t^{Dw} + Resp_t^{Dw})^2 + (Q_t^N)^2 \le \overline{S}^N \quad \forall \ t \in T$$
(5.4)

Peak demand periods - although rare and of short duration - may undermine ESS commercial strategies by preventing provision of downwards balancing services for a whole season due to constrained substation capacity. In this context, overselling DNO service is likely to reduce the conflicts between DNO and balancing services (studied in section 2.6) and allow higher volumes of balancing services to be committed. Note that if DNO service is oversold, non-delivery will occur at maximum for 2 hours (i.e. in the worst case scenario for the whole duration of reserve services exercise up to 2 hours) and with a frequency of occurrence as low as the probability of exercising balancing services precisely at the same time a transformer fault occurs.

5.4.3 Balancing Services Constraints with Overselling Policies

Oversold volumes of reserve and frequency response services are limited by committed volumes of each service through Eqs. (5.5) to (5.8), which means that oversold capacity is not allowed if service was not committed (i.e. 0 MW).

$$Rese_t^{Dw.0} \le Rese_t^{Dw} \tag{5.5}$$

$$Rese_t^{Up.0} \le Rese_t^{Up} \tag{5.6}$$

$$Resp_t^{Dw.O} \le Resp_t^{Dw} \tag{5.7}$$

$$Resp_t^{Up.O} \le Resp_t^{Up} \tag{5.8}$$

Likewise, oversold DNO capacity is also limited by the volume of committed balancing services, i.e. by reserve or frequency response services as shown in Eqs. (5.9) and (5.10).

$$Rese_t^{DNO} \le Rese_t^{Dw} \tag{5.9}$$

$$Resp_t^{DNO} \le Resp_t^{Dw} \tag{5.10}$$

Note that overselling DNO service is limited to periods of reserve or frequency response exercise, i.e. ESS is limited to oversell DNO service for exclusive delivery in real time of reserve or frequency response services.

ESS energy levels for delivery of balancing services should also consider the volumes of oversold capacity as shown in Eqs. (5.11) to (5.18). This way the allocated ESS energy resources (to deliver balancing services) are reduced by the amount of oversold energy to each service.

Note that exercise of reserve services are associated with larger amounts of energy levels compared to frequency response and although oversold resources for reserve are associated with active power, penalisations for non-delivery are associated with energy capacity.

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \le E_{t-1} - \left(P_t^S + Rese_t^{Up} - Rese_t^{Up.O}\right) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(5.11)

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \le E_t - \left(P_t^S + Rese_t^{Up} - Rese_t^{Up.0}\right) \cdot \tau^{\operatorname{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Rese}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(5.12)

$$-\mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \le E_{t-1} - (P_t^S - Rese_t^{Dw} + Rese_t^{Dw.0}) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(5.13)

$$-\mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \le E_t - (P_t^S - Rese_t^{Dw} + Rese_t^{Dw.O}) \cdot \tau^{\text{Rese}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot (1 - X_t^{Dw.Rese}) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(5.14)

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \le E_{t-1} - \left(P_t^S + Resp_t^{Up} - Resp_t^{Up.O}\right) \cdot \tau^{Resp} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(5.15)

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \le E_t - \left(P_t^S + Resp_t^{Up} - Resp_t^{Up.0}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.Resp}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(5.16)

$$-\mathbf{M} \cdot \left(1 - X_t^{Dw.Resp}\right) \le E_{t-1} - \left(P_t^S - Resp_t^{Dw} + Resp_t^{Dw.O}\right) \cdot \tau^{\operatorname{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Dw.Resp}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$
(5.17)

$$-\mathsf{M}\cdot\left(1-X_{t}^{Dw,Resp}\right) \leq E_{t}-\left(P_{t}^{S}-Resp_{t}^{Dw}+Resp_{t}^{Dw,O}\right)\cdot\tau^{\operatorname{Resp}} \leq \overline{\mathsf{E}}+\mathsf{M}\cdot\left(1-X_{t}^{Dw,Resp}\right) \quad \forall \ \mathsf{t}\in\mathsf{T}$$

$$(5.18)$$

Simultaneous provision of reserve and frequency response services should also take into consideration oversold volumes of ESS capacity, as shown in Eqs. (5.19) to (5.22).

$$-\mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \le E_{t-1} - \left(P_t^S + Rese_t^{Up} - Rese_t^{Up.0}\right) \cdot \tau^{\text{Rese}} - \left(Resp_t^{Up} - Resp_t^{Up.0}\right) \cdot \tau^{\text{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$-\mathsf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \leq E_t - \left(P_t^S + Rese_t^{Up} - Rese_t^{Up.O}\right) \cdot \tau^{\text{Rese}} - \left(Resp_t^{Up} - Resp_t^{Up.O}\right) \cdot \tau^{\text{Resp}} \leq \overline{\mathsf{E}} + \mathsf{M} \cdot \left(1 - X_t^{Up.R\&R}\right) \quad \forall \ \mathsf{t} \in \mathsf{T}$$

(5.19)

$$-\mathbf{M} \cdot (1 - X_t^{Dw.R\&R}) \leq E_{t-1} - (P_t^S - Rese_t^{Dw} + Rese_t^{Dw.O}) \cdot \tau^{\operatorname{Rese}} + (Resp_t^{Dw} - Resp_t^{Dw.O}) \cdot \tau^{\operatorname{Resp}} \leq \overline{\mathbf{E}} + \mathbf{M} \cdot (1 - X_t^{Dw.R\&R}) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$-\mathbf{M} \cdot (1 - X_t^{Dw.R\&R}) \le E_t - (P_t^S - Rese_t^{Dw} + Rese_t^{Dw.O}) \cdot \tau^{\text{Rese}} + (Resp_t^{Dw} - Resp_t^{Dw.O}) \cdot \tau^{\text{Resp}} \le \overline{\mathbf{E}} + \mathbf{M} \cdot (1 - X_t^{Dw.R\&R}) \quad \forall \ \mathbf{t} \in \mathbf{T}$$

$$(5.22)$$

5.5 Input Data and Modelling Considerations for GB Studies

Energy prices and local demand of primary substation from real GB time series with hourly resolution – used in Chapters 2, 3 and 4 - were used in the case studies presented next. Figure 4.3 (in Chapter 4) illustrates one typical week (in summer and in winter) for energy prices and local demand, in addition Figure 5.1 shows an aggregated demand curve for the whole 10 years data used in these case studies and illustrates peak demand that occurs during the prescribed reserve window – which represents approximately 95% of all peak demand periods.

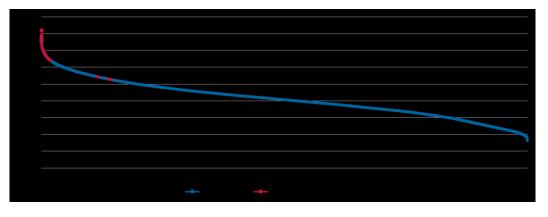


Figure 5.1. Aggregated local demand and peak demand occurring during reserve window.

Likewise, ESS characteristics such as maximum capacities and efficiency were the same as used in Chapters 2, 3 and 4 and are given in Table 2.1.

Probabilities for exercise of balancing services were assumed constant for all days and determined based on the contracted volumes of short term operating reserve (daily average of 2376 MW) and the utilisation levels (216 GWh) for the year of 2014 obtained from [26]. The assumed probabilities for exercise of reserve and frequency response services are detailed in Table 5.1.

Table 5.1. Probabilities of exercise of reserve and frequency response services used in the modelling.

Probability of exercise of reserve services (p ^{Res})	10 [%]
Probability of exercise of frequency response services (p ^{Resp})	20 [%]

Note that probability of exercise of frequency response services are twice than for reserve services since frequency response services are the first line response to correct system imbalances and therefore likely to be exercised by system operators more often than reserve services.

In addition to the probability of services exercise, reserve services are also associated with different durations of exercise and associated probabilities. Figure 5.2 (a) shows historic probabilities of various durations of exercise of short term operating reserve according to [26]. Note that the proposed model only considers a maximum duration for exercising reserve services of 2 hours (τ^{Rese}) and thus durations longer than 2 hours (120 min in Figure 5.2 (a)) were not considered. Figure 5.2 (b) shows a discretised probability distribution function with the probabilities and associated exercise durations for reserve services considered in the case studies.

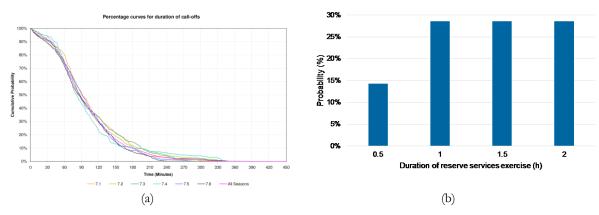


Figure 5.2. Duration of exercise of reserve services and associated probabilities in (a) real GB data for 2014 and (b) input data for the proposed model.

Overselling ESS energy and power capacity to balancing services or DNO service maximises utilisation of ESS resources and thus its revenue, albeit non-delivery of services committed ahead of real time is also penalised based on power or energy shortage. These should reflect the cost of delivering the service with more expensive alternatives (e.g. bilateral contracts between ESS and demand response service providers) and ultimately the cost of non-delivery (e.g. the value of lost load). The penalty fee for reserve services was assumed as 200 f/MWh and for frequency response and DNO service assumed as 300 f/MW/h.

5.6 Oversell Opportunities in a Day

Commitment of balancing services ahead of real time requires allocation of ESS energy and power resources that limit energy arbitrage actions, especially in the particular case of reserve services which require large volumes of energy levels. Therefore, oversell operating policies can be used to maximise ESS utilisation and improve revenues by seizing unique arbitrage opportunities that occur with extreme energy prices. Figure 5.3 shows for a single day two ESS outputs, considering robust and oversell operating policies, with an extreme case of energy prices.

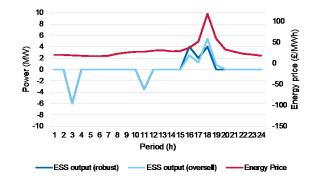


Figure 5.3. ESS operation and energy prices considering robust and oversell operating policies.

The results show that considering oversell operating policies allows the ESS to take advantage of peak energy prices during the window for reserve services (between 16:00 h to 21:00 h for this day in November) and thus maximise revenue by risking against the probability of exercising reserve.

Overselling ESS energy capacity which has been previously allocated for reserve services allows it to seize more arbitrage opportunities by compromising the robust delivery of reserve services. Figure 5.4 shows, for the same day of Figure 5.3, ESS energy levels and energy (headroom) required for robust delivery of down reserve with (a) robust operating policies and (b) considering oversell operating policies.

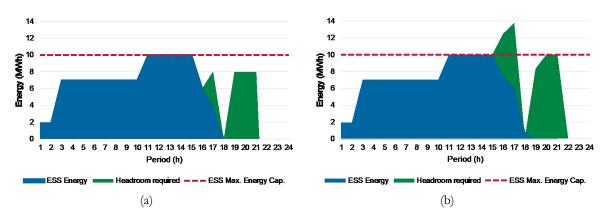


Figure 5.4. ESS energy levels and headroom required for delivery of down reserve considering (a) robust and (b) oversell operating policies.

Note that overselling energy capacity to take advantage of extreme cases of energy prices is affecting the robust delivery of down reserve for the first 2 hours of reserve window as shown in Figure 5.4 (b). However, ESS energy levels ensure robust delivery of down reserve (i.e. exercise duration of up to 2 hours) if a delivery instruction occurs between 18:00 h and 21:00 h; moreover, note that at periods 16:00 h and 17:00 h ESS energy levels can still ensure delivery of down reserve services if these are exercised up to 1 hour.

Peak local demand during balancing services window (as shown in Figure 5.1) may limit commitment of reserve or frequency response services for a whole season (i.e. 3 months) and undermine ESS economics due to a single occurrence of peak demand. In this context, overselling DNO capacity allows ESS to exercise balancing services and operate (if needed) beyond the substation secured capacity, as shown in Figure 5.5 (b).

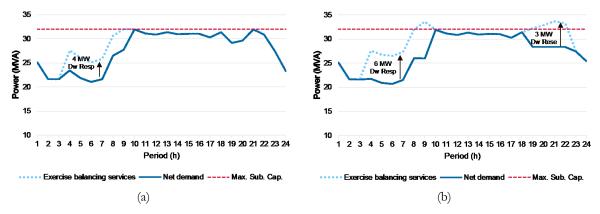


Figure 5.5. Scheduled and real time net demand considering (a) robust and (b) oversell operating policies.

The results in Figure 5.5 (a) show that net demand with scheduled or real time ESS operation for frequency response respects substation secured capacity. Note that reserve services are not committed due to congested network capacity. Figure 5.5 (b) shows that scheduled net demand also respects substation secured capacity but in contrast, ESS real time operation for frequency response or reserve services may exceed the N-1 secured capacity limit up to two hours.

Note that overselling DNO capacity for real time delivery of balancing services is associated with the probability of exercise and may occur up to a maximum of 2 hours (i.e. maximum duration of reserve services exercise), in contrast this enables higher volumes of balancing services to be committed every day for the whole contract duration (i.e. 3 months).

5.7 Business Case in Support of Oversell Operating Policies

The proposed model manages ESS oversell operating policies in a cost efficient way by balancing the volumes of oversold capacity to various services and the expected penalisations for nondelivery of contracted services. Figure 5.6 shows two cases of ESS oversell operating policies and the associated revenues increase; (a) and (b) shows a case of ESS overselling energy capacity allocated to reserve services for maximum revenue in energy arbitrage and down reserve and, (c) and (d) show a case of ESS overselling DNO service for maximum revenue in balancing services.

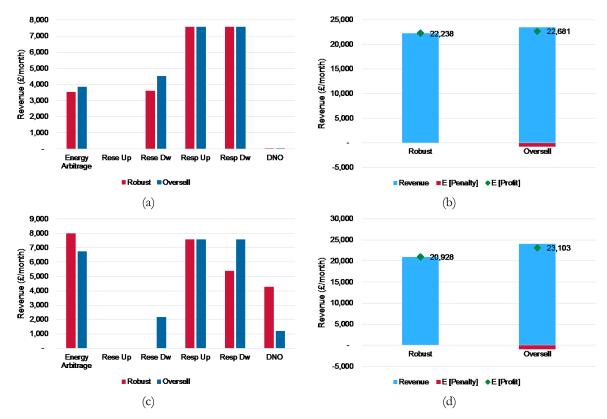


Figure 5.6. ESS revenue on single services for (a) oversold capacity to reserve services and (c) oversold capacity for DNO, including associated revenue, and expected penalties and profit (b) and (d) respectively.

Figure 5.6 (a) shows ESS revenue in individual services and (b) total revenue, expected penalty and profit when overselling ESS energy resources previously allocated for robust provision of down reserves services. Note that overselling operating policies allow higher volumes of down reserve to be committed resulting in an increase in revenue from reserve services; additionally enhanced energy arbitrage actions also allow an increase in revenue.

Figure 5.6 (c) shows ESS revenue in individual services and (b) total revenue, and expected penalty and profit when overselling ESS resources previously allocated to ensure robust deliverability of DNO service when balancing services are exercised in real time. Note that in contrast to overselling balancing services such as reserve or frequency response which allows higher volumes to be committed, overselling DNO capacity has the opposite effect; since less ESS capacity is allocated for the service a decrease in revenue should be expected (as shown in Figure 5.6 (c)). Moreover, in this particular case, ESS allocates resources for down reserve services that were previously used for arbitrage actions which explain the decrease in energy arbitrage revenues.

ESS improves utilisation of its resources by efficiently managing the risk of services non-delivery (and associated penalisations) with increased revenues as shown in Figure 5.6 (b) and (d). However, note that expected profit from oversell operating policies may increase if services are not exercised in real time, i.e. if delivery of services is not affected by oversold ESS resources or system operator does not exercise committed services, and thus penalisations associated with overselling operating policies are not enforced.

Figure 5.7 (a) shows ESS revenue increase by adopting overselling operating policies over a whole year of operation and analysed in yearly seasons and Figure 5.7 (b) shows frequency of occurrence of oversell operating policies for the considered services and divided in yearly seasons.

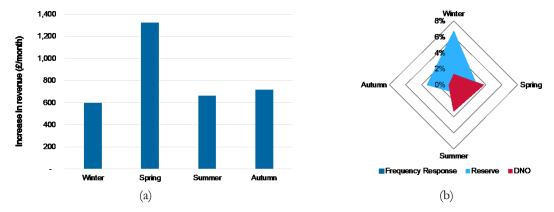


Figure 5.7. (a) Average increase in ESS revenue due to oversell operating policies differentiated by yearly seasons and (b) frequency of occurrence differentiated by oversold service.

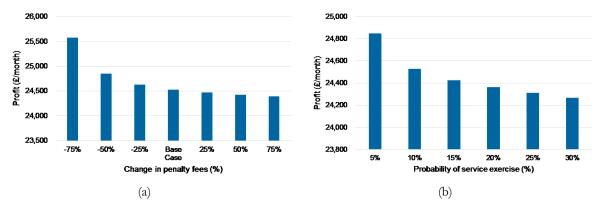
The results show that oversell operating policies are more beneficial in spring than in other seasons and this is because of the higher value associated with overselling DNO capacity as shown in Figure 5.6 (d), i.e. the higher revenue increase in spring is associated with overselling DNO capacity which allows higher volumes of balancing services to be committed. This result is consistent with those presented in section 3.6.2, in particular in Figure 3.4 that show DNO service being more valuable in spring since distribution network is more congested in those months.

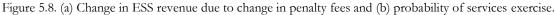
Reserve services are more frequently oversold in winter months in order to take advantage of peak energy prices and be able to seize more arbitrage opportunities, and in contrast it is less frequent in summer months as these are typically characterised by lower arbitrage opportunities (due to lower price differentials) as shown in Figure 5.7 (b). In addition, DNO service is more often oversold in summer and spring months as these are typical months where distribution network is more congested as mentioned in section 3.6.2, in particular in Figure 3.4. Oversell operating policies for frequency response services rarely occur due to the high value of penalisations and higher probability of services exercise but also because frequency response window is defined during hours of typical low energy prices (i.e. between hours 4:00 h and 8:00 h)

5.8 Impact of System Conditions on Oversell Operating Policies

The studies presented in section 5.7 have shown that energy market conditions are the main reason for reserve oversell operating policies and that these occur with higher frequency in winter months – driven by peak energy prices. Moreover, peak demand periods and de-rated substation secured capacity in spring and summer lead to higher frequency of oversell operating policies for DNO service to allow higher volumes of balancing services to be committed. In this context, the impact that penalty fees and probability of services exercise have on ESS oversell operating policies is investigated in this section.

Figure 5.8 (a) and (b) show how ESS profit (i.e. revenue minus penalisations) changes respectively with different levels of penalty fees and probabilities of services exercise.





The results show that ESS profit decreases exponentially with increasing penalty fees – associated with oversold balancing services and DNO service – and this is because, although the risk of services exercise remains constant, the penalisation for non-delivery is too high compared to the value of overselling ESS resources and therefore not cost efficient. Likewise, ESS profit decreases exponentially with linear increase of probability of services exercise.

5.9 Conclusion

A novel business model framework was proposed for ESS operating policies which maximises utilization of its resources – energy and power capacities – and allocates these to the most valuable service in order to minimise yield losses. In this context the novelty in the research conducted in this chapter is associated with the possibility of overselling ESS energy or power capacity to various services and take advantage of low frequencies of instructions to exercise services.

The results have shown that, if allowed, ESS will oversell resources that were previously allocated for robust delivery of DNO service in order to provide higher volumes of balancing services. ESS power capacity is oversold in order to allow higher volumes of reserve or frequency response services to be committed usually in spring and summer months as substation secured capacity is often congested during windows of reserve services. This result is consistent with the conflicts identified between the DNO and balancing services (addressed in section 2.6). In this context overselling DNO service for reserve and frequency response results in the highest profits among oversell policies.

On the other hand, reserve services are often oversold to take advantage of extreme events of peak energy prices, which typically occur in winter months, and also to increase committed volumes of reserve. Therefore, reserve services are oversold mostly during winter months when peak energy prices are more frequent, which is consistent with the results of Figure 3.4 that show higher value for energy arbitrage in winter. In contrast, frequency response services are very rarely oversold due to hours when frequency response window is defined (i.e. during typical low energy prices, between 4:00 h and 8:00 h) and the higher penalisations associated with high probability of service delivery.

Oversold resources for reserve services and DNO service occur respectively in less than 8% and 2% of the total number of hours that oversell policies were made available; over the total number of hours in the 3 months operation these represent less than 2% and 1% respectively. In addition, note that due to various aspects - such as exact time that services are instructed for delivery, duration of service exercise and system conditions – probability of non-delivering a particular service might be even lower than those aforementioned.

ESS operation considering oversell policies might be seen as a perverse mode of operation for maximum revenue which may ultimately compromise power systems stability and services value. In this context, in order to mitigate and dissuade ESS from overselling its resources and operate under robust policies, severe penalisations should be put in place to reduce volumes of ESS oversold capacities as the results have shown

Chapter 6

Concluding Remarks and Further Work

This chapter highlights the contributions and findings from the research conducted on Chapters 2 to 5, and whose conclusions were detailed accordingly, and outlines possible directions for further studies on ESS. A summary of research achievements is presented herein and how they contributed to successfully address the research objectives outlined in Chapter 1.

To conclude, a brief discussion regarding the implications that the research findings have on the current understandings of ESS and how it can be used to develop appropriate market mechanisms to support the efficient deployment of ESS technologies in the electricity sector is also addressed in this chapter.

6.1 Research Achievements and Contributions

This research work and associated case studies were conducted with two main objectives in focus: (I) determine ESS operations that being sensitive to markets and system conditions would deliver maximum benefits to the electricity industry in the form of a single or multiple services and (II) develop novel operational policies for ESS commercial strategies that maximise utilisation of its resources and would enhance its economics. The former was addressed in Chapter 2 and Chapter 3 and the later addressed in Chapter 4 and Chapter 5.

In Chapter 2, a novel modelling framework for distributed ESS was developed, which considers provision of multiple services - aggregated in a single business model - to various stakeholders and designed to maximise ESS economics while being sensitive to services value and system operating conditions. Likewise, Chapter 3 expanded the mathematical model in order to determine ESS long term commercial strategies - within the multiple services business model framework - and select portfolio of services that maximise ESS revenues in typical markets and system conditions. A computationally efficient model was developed to cope with the problem size and be able to achieve optimum (or near optimum) solutions within appropriate operational time frames. Among the various studies and associated results that addressed the proposed objective, the contributions that emerged from the research conducted in those chapters were as follows:

- Validated the efficient coordination of multiple services being delivered, simultaneously, to various stakeholders by determining optimum ESS active and reactive power outputs.

This will allow ESS owners to contract multiple services and thereby enhance the investment economics opportunities by collecting multiple revenue streams with a single ESS device improving not only the revenue obtained but also enabling hedging strategies to be put in place against services volatility, i.e. by providing more than one service. ESS owners can hedge against volatility or expected low revenue on a particular service.

 Determined ESS operations that deliver maximum benefits to the various stakeholders while being sensitive to market and system operating conditions and different sets of services should be provided, particularly in summer and winter months

A key contribution from the research conducted is the insight that ESS business models should not be implemented based on a fit and forget approach for the entire life span of the ESS. The business model should be dynamic and sensitive to market and system operating conditions in order to achieve maximum benefits for the stakeholders. So as shown in Chapter 3, different seasons in the year are associated with different sets of services and different volumes. - Coordinated ESS operation of active and reactive power is fundamental to efficiently provide DNO service and supports provision of active power services only (such as energy arbitrage and balancing services).

It has been shown that coordination of active and reactive power can be exploited to support revenue with active power services only and therefore should be considered in ESS sitting and sizing decisions. Recent studies typically address investment decisions in ESS devices by determining energy and active power capacities (i.e. MWh and MW capacities), although the research conducted has shown that reactive power is essential to provide DNO service and support revenue in energy arbitrage and balancing services. In this context, future sizing decisions for ESS should consider reactive power capacity and thus determining apparent power capacity for ESS (i.e. MVA capacity rather than just MW capacity) is fundamental to ensuring efficient investment decisions.

The research in Chapter 4 and Chapter 5 was conducted to address ESS operating policies and increase utilization of ESS resources for further improvement of its economics. Chapter 4 focused on operating policies which are current practice among network system operators - either for voltage control or post-fault contingency actions - and develop a similar operating framework for ESS to provide DNO service. Similarly, Chapter 5 focused on adapting current practices in other industries (such as airline and hospitality industries) to ESS business model in order to improve utilization of its resources and ensure that these are allocated to the most valuable service. The contributions to emerge from this research were:

- Developed ESS corrective control operating strategies that achieve same levels of security of supply when providing DNO service.

Corrective control strategies have been shown to ensure the same levels of security of supply while providing other benefits to the DNO and ESS stakeholders. During post-fault conditions ESS robust energy levels have been shown to ensure security of supply as with preventive control.

- Enhanced ESS economics with novel operating policies and the benefits for DNOs with reduced cost for DNO service.

Adopting corrective control strategies not only enhances distribution network utilization levels but also resolves the ESS conflicts between DNO and other services, thereby enhancing ESS economics. In this context, with corrective control strategies, the cost for providing DNO service with an ESS is reduced and thus bringing benefits to DNOs and ESS stakeholders. This also supports the development of new market mechanisms to efficiently reward ESS for peak shaving services. Demonstrated that oversell operating policies are cost efficient and can potentially enhance
 ESS economics in the long term.

In Chapter 5 it was demonstrated that oversell operating policies are economically viable and potentially cost efficient for ESS investments, although the risks of such operating policies may undermine the stability of the electricity system and potentially result in severe damages to the electricity system which are not easily quantifiable. In this context, the results can inform regulators and policy makers and support the development of regulatory framework in order to dissuade such practices. Note that if ESS owners are purely driven by economic reasons, even with high penalties, overselling ESS resources would result in higher revenues and therefore improved return of investment, which incites ESS owners to adopt such policies.

6.2 Suggestions of Future Work

6.2.1 Implications of Energy Storage Systems Operating Strategies on Services Value

The research scope was set in determining ESS operations that maximise the benefits delivered to multiple markets considering a price taker approach, i.e. services values were assumed to be independent of ESS operation. Although this is fundamentally valid with small scale ESS, the same assumption might not hold if large scale ESS are considered or when considering various small scale ESS operating in a coordinated fashion. Further studies regarding the impact that ESS commercial strategies have on services value – such as energy prices – and develop an operating framework that could potentially take that into account and maximise ESS revenue would be worthwhile.

6.2.2 Market Mechanisms for Energy Storage Systems Efficient Remunerability

One of the key contributions of this research was to demonstrate that coordinated operation of active and reactive power is crucial to an efficient delivery of DNO service and can further support services like energy arbitrage and balancing services. The studies have shown that the value for coordinating ESS active and reactive power outputs was considerably higher than current remunerative schemes in GB markets. In addition, the DNO service besides supporting operation of distribution network during peak demand periods, also defers investment costs associated with upgrading distribution network infrastructure. The challenge of developing appropriate market mechanisms that efficiently reward ESS for the value delivered either to DNOs or other stakeholders in general - either by deferring investment on network capacity or by coordinating operation of active and reactive power - could be explored in further research.

6.2.3 Energy Storage Systems Operating Strategies Considering Market Power

Chapter 5 proposed a new operating policy for ESS that considers the possibility to oversell energy and/or power capacity to DNO or balancing services. Future research could also be conducted to investigate potential ESS operating policies that "undersell" ESS resources for maximum revenue, i.e. considering the impacts that ESS operation can have on services value (e.g. energy prices) by holding ESS capacity and thus delivering suboptimum benefits to the market, ESS can potentially enhance their revenue. Such study could potentially determine and evaluate ESS market power and the impact of such operating policies on social welfare.

6.3 Concluding Remarks

A novel business model with multiple services, implemented through a MILP formulation, has been developed to coordinate provision of various services by distributed ESS while being sensitive to markets and system conditions for maximum revenue. Moreover, a computationally efficient modelling formulation has been developed to determine ESS commercial strategies over long time scales and achieve optimum solutions within operational time frames. In this context, the research conducted and contributions have successfully addressed objective 1 defined in section 1.2 by demonstrating that ESS can efficiently provide simultaneous services to various actors in the electricity industry - both energy and power related services – while capturing the value delivered. Moreover, it has been shown that the different services should be provided according to different markets and systems conditions to maximise ESS value delivered to the electricity industry. The scope of this research was set to investigate the various operational aspects of ESS and has done so by determining robust solutions for schedule and real time operations, albeit the modelling framework is limited to the economic aspects of scheduled operations.

A practical implication of these findings is the fact that ESS business models should be dynamic over a year of operation for enhanced ESS economics and delivery of maximum benefits to the various electricity sectors, in contrast to a fit and forget approach.

The second main objective (i.e. objective 2 in section 1.2) was addressed by developing novel ESS operating policies that maximise utilization of its resources and thus enhance the value of ESS. In particular, an operating policy considering corrective control security actions has been proposed and demonstrated that could enhance ESS value for DNO service while ensuring the same levels of security as preventive actions. Such information can be used to develop new market mechanisms to ensure that ESS are efficiently rewarded for the services provided to DNOs and support deployment of ESS.

In addition, further research was carried out to develop a cost efficient framework that considers the possibility of overselling ESS power and energy resources to various stakeholders to further enhance its value. The results have a number of practical implications to develop appropriate market mechanisms to facilitate the efficient integration of ESS in power systems and ensure effective delivery of benefits. An aspect that was not addressed in this research, and in the particular case of oversell operating policies, was to fully incorporate the implications and risk associated with overselling ESS resources. Although penalisations for service non-delivery were taken into account, the implications of overselling balancing services are potentially high risk and not cost effective for system operation.

Overall the conducted research has demonstrated that ESS can efficiently support integration and operation of future power systems by providing benefits to multiple sectors of the electricity industry while maximising ESS economics. Moreover, ESS benefits have been demonstrated with several operating policies which not only validate its flexibility but enhances the understanding of business models for ESS. Together, this research work contributes to develop appropriate market mechanisms and operational frameworks for ESS that efficiently support their deployment in the electricity industry and ensure they are adequately rewarded for the benefits delivered.

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Appendix A: Performance of Benders Decomposition

Chapter 3 proposes a stochastic decomposition approach for the multiple services business model framework using a Benders decomposition with an additional heuristic technique to eliminate the need of integer variables in the sub-problems formulation. Using a constraint relaxation and problem simplification, the new mathematical formulation is an approximation of the original problem described in Chapter 2 and therefore solutions obtained with the original and decomposed formulation are likely to differ from each other. To adequately represent input data - explicitly, sufficient number of scenarios for energy prices – and achieve reduced optimisation times, such differences are often overlooked given their reasonable insignificance within the overall value of objective function – differences of up to 5% are often accepted as a pragmatic rule.

The validity of the decomposed formulation was evaluated by comparing the solutions (value of objective functions) between the decomposed and original formulation with different numbers of scenarios, shown in Figure A.1.

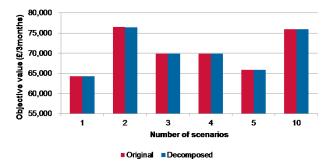


Figure A.1: Comparison of value of objective functions between original and decomposed problems for different number of scenarios of energy prices.

As the results show the decomposed approach achieves satisfactory solutions with minor differences comparatively to the original formulation. The highest difference encountered between the two approaches was obtained with 2 randomly selected scenarios where difference between objective values is only of 50 $\pounds/3$ months (76 473 $\pounds/3$ months in the original approach and 76 423 $\pounds/3$ months in the decomposed approach) which represents less than 0.07% of total solution. Although with an exceptionally small and insignificant inaccuracy when compared to the magnitude of solutions, the decomposed approach main objective was to reduce optimisation times to adequate operational time scales. Figure A.2 shows a comparison between the two approaches regarding optimisation times.

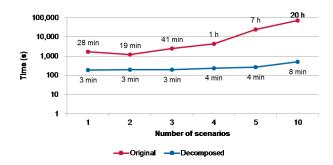


Figure A.2: Comparison of optimisation time between original and decomposed problems with different number of scenarios of energy prices.

Note that even for a small number of scenarios (10 randomly selected) the improvement in optimisation time is massive with a reduction of more than 240 times; with original formulation it would take 20 hours (1200 minutes) to find an optimal solution whereas with the decomposed formulation it only needs 8 minutes to find a solution which differs from the optimal solution only by 0.01%.

In order to confirm that the new decomposed approach is overall beneficial comparatively to the original formulation and not only due to unique particular characteristics of the randomly selected scenarios a new case study was performed in order to access the consistency of the method. In this context Figure A.3 presents 4 independent simulations with different sets of 5 scenarios of energy prices along with the solution and optimisation time for each scenario set.

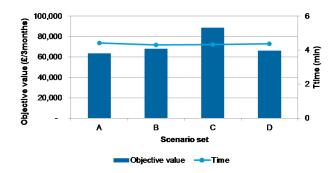


Figure A.3: Comparison of optimisation times and objective function values with different sets of scenarios using a decomposed formulation.

The results shown that the method remains consistent even with different input data (explicitly scenarios of energy prices) by achieving fairly regular optimisation times to find an optimal solution.

Appendix B: Value of Uncertainty

Chapter 3 expands on the MILP model proposed in Chapter 2 by considering a longer time scale for ESS operation (i.e. 3 months) and incorporating uncertainty of energy prices in the modelling formulation. Besides increasing the size of the optimization problem with larger number of variables, adding stochastic (uncertain) energy prices also adds further to the complexity of the problem. In this context, the studies presented here address the value of considering uncertain energy prices in the modelling and discuss the significance of adding further complexity to the modelling formulation.

To determine the value of uncertainty, ESS operation considering the full set of energy prices scenarios - and therefore accounting for uncertainty on energy prices – was compared to the ESS operation determined for a single scenario and then assessed under different scenarios of energy prices. The fundamental difference between the two approaches is that using uncertainty (Stochastic approach) ESS operation is determined considering multiple possible outcomes of energy prices while in contrast the Determinist approach determines the ESS operation for a single scenario of energy price and then applied to whichever outcome of energy price. Figure B.1 (a) shows the average ESS revenue in considering the two approaches in different yearly seasons and (b) shows the difference in ESS revenue between the two approaches.

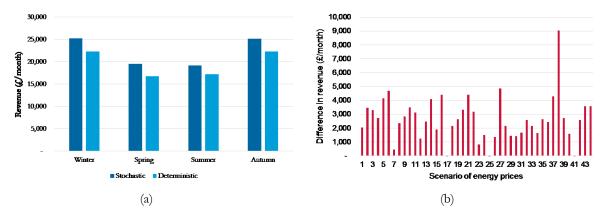


Figure B.1. (a) Average monthly ESS revenue considering uncertainty (Stochastic) or deterministic energy prices (Deterministic) and (b) different in revenue across different scenarios when uncertainty is not considered.

Note that in Figure B.1 (b) in some scenarios the difference in revenue is insignificant comparatively to other scenarios and this is because, eventually the outcome of energy prices will be the exact same scenario that ESS operation was determined for. However, note that differences in revenue can add up to 9,000 f/month.

Figure B.2 shows the value of considering uncertainty in energy price in multiple seasons of the year.

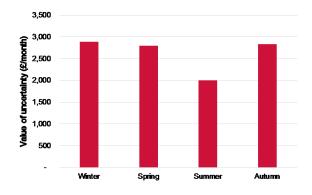


Figure B.2. Value of uncertainty across different seasons.

The reason behind the lower value of uncertainty in summer is due to the fact that energy prices in summer (shown in Figure 2.3 (b) and a histogram in Figure 3.3 (a)) are less volatile and similar profiles for different days. Therefore, determining ESS operation in summer (considering a single scenario only) affects its revenue on a lower scale since energy prices are often similar in summer.

The results of Figure B.2 show that without considering uncertainty in energy prices and therefore simplifying the modelling formulation to a deterministic approach is not economically efficient and would decrease ESS value.

Appendix C: Definitions of ESS Services

Arbitrage actions – are pursued by scheduling ESS charge and discharge outputs to make a revenue from buying (charging) energy at low energy prices (in the energy market) and selling (discharging) this energy at later periods and at higher energy prices (in the energy market). In principle, arbitrage actions are associated with temporal price differences that allow ESS to make a revenue.

Black-start – is a term used to restore a generation plant or part of the electric grid to normal operation after a complete black-out and without relying on an external transmission network, i.e. generators and electric grids when disconnected from the transmission network require an external source of energy (e.g. a battery) to restart and be able to reconnect to the transmission network.

Frequency response – the system operator procures frequency response services in order to ensure that system frequency (i.e. variable associated with the balance between demand and generation) is controlled within system technical limits. These services are associated with additional ESS active power charging or discharging outputs (respectively to respond to sudden increases in generation or demand) for very short periods (i.e. typically a few seconds up to a few minutes).

Manage congestions – due to network infrastructure thermal limits, peaks of demand need to be effectively accounted for in order to maintain network within its thermal operational limits. If network capacity is not capable of withstanding demand growth or sudden increases in demand then network operators need to invest in network capacity upgrades or procure congestion management services (such as demand response, peak demand shaving by ESS, among others).

Power quality – services may be described through a set of parameters measurements, such as continuity of service, voltage variation, transient voltages and current, harmonic content and frequency variation. These are typically controlled by voltage frequency and phase that allows electric devices to function within their technical limits and minimise loss of performance/life.

Reliability – services are associated with the idea that an item or component (in this case network infrastructure) is fit to perform or sustain a specific process (e.g. electricity distribution) given its technical constraints. In power systems, reliability measures are used to ensure that network faults and end-consumers supply interruptions are minimised in a cost efficient way. Typical measurements are associated duration and frequency of interruptions in a given year of operation.

Reserve services - are used by the system operator to deal with unforeseen sudden increases/decreases of demand or generation (particularly with renewable generation). These are typically procured up to 3 months ahead of service delivery in the form of auctions and are associated with increase of ESS charging or discharging output (i.e. respectively low or high frequency events) for extended time periods (i.e. typically longer than 30 minutes).

Support intermittent generation – renewable generation sources such as wind and solar power plants are associated with high levels of volatility and uncertainty and therefore power outputs are extremely difficult to schedule and predict. ESS can support intermittent generation by acting as a buffer and correct any imbalances between forecasted and real power outputs.

Voltage support – services include voltage magnitude correction either by means of active or reactive power outputs and phase corrections. These are associated with power supply quality and intended to maintain electric grids within their technical limits and minimise equipment loss of performance/life.