Ollscoil na hÉireann, Corcaigh

National University of Ireland, Cork

Integrating project planning objectives as part of sizing battery energy storage systems

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for the degree of

Doctor of Philosophy

University College Cork

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2022

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"This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism and intellectual property."

JOSEPH KELLY

For my mother Frankie Kelly…

a wonderful woman who gave me the best start in life.

ACKNOWLEDGEMENTS

This research would not have been possible without the support and guidance of my supervisor Dr Paul Leahy. I want to thank Paul for his dedication and backing throughout this dissertation. I owe a great deal to him ever since I set foot through his door to start his Masters of Science in Marine Renewable Energy. Undertaking that Masters was the best career decision I ever made, which has led me to where I am now. I also want to thank Dr Alan Morrison for his help and prudent advice which has undoubtably made my dissertation a better body of work. A sincere thank you also to Dr Eamon McKeogh for the discussions and instruction at the beginning of my dissertation.

I want to give a wholehearted thank you to everyone at DP Energy, past and present. I couldn't have asked for a nicer or more supportive group of people to share the last number of years with. A specific mention to Marie Nagle for all the help whenever I needed it. I particularly want to express my warmest gratitude to Maureen and Simon De Pietro for supporting this research financially, allowing me the time to purse this research and your patience in getting to this stage. To Niamh Kenny, for showing the level of interest in my career which I will never forget.

Sincerest appreciation to everyone at UCC who helped me in my research endeavours. To Science Foundation Ireland (SFI) and Marine and Renewable Energy Ireland (MaREI) Centre for funding this research. A special mention to Angela Pope and Dr Gillian Bruton, who provided me with the necessary support as and when I needed. I can't thank you enough. To Sean O'Mahony in the IT department of UCC who helped me with virtual machine setup. This was vital in completing my dissertation. Also, thank you to the Single Electricity Market Operator for supplying the necessary data.

A special thank you to all the Healys in West Cork. I want to give particular thanks to Niall and Mary Healy for their kind and generous words over the past number of years.

To my family, I want to thank my sisters Maria and Deirdre Kelly who are always there for a chat, whether it's needed or not. To my father Padraic Kelly, and Mary Ferguson, thank you for all the welcomed distractions you provided during the PhD years. Believe me when I say it was needed. To my late grandfather, Paddy Kelly, who got to see me start my PhD but not finish it. He would have had a special appreciation for seeing this dissertation completed. Also, thank you to my extended family and friends in Kilcummin Co. Mayo and elsewhere.

Last but not least, to my wife Mary Kelly, I reserve for you the greatest admiration a husband can have. Thank you for all the encouragement, understanding and support you gave me throughout this long process. It goes without saying that this PhD would have been much harder without you by my side.

ABSTRACT

Development of Battery Energy Storage System projects and their subsequent installation and connection to electrical grids throughout the world is expected to increase over the coming years. Two key concerns are at the forefront of entities undertaking these installations. The first is determining the optimal BESS size for a given application. The second is whether this optimal BESS size reflects the goals (referred to as planning objectives in this dissertation) set out in the BESS project planning phase. Recognising these two concerns, it is determined that BESS sizing approaches must be fit for purpose, can be used adequality as a planning tool and capable of modelling important planning objectives.

The Front-End Planning framework was utilised in this dissertation as a means to assess if existing BESS sizing approaches are suitable for modelling planning objectives as part of BESS project planning. In total, 32 of the most-cited articles from the BESS sizing literature were reviewed for their inclusiveness of scoping elements set out by the Front-End Planning framework. The results of this review showed that existing BESS sizing approaches are lacking in three key planning objectives called *Investment Scale*, *Investment Timing* and *Dispatch Adaptability*. This research sought to answer the following questions: 1) Is it possible to form the planning objectives Investment Scale, Investment Timing and Dispatch Adaptability as part of optimising energy capacity size for new BESS installations seeking maximum profit? 2) Are there any circumstances where the inclusion of the three planning objectives as part of BESS sizing helps overcome shortcomings of existing sizing approaches?

To incorporate the planning objective Investment Scale as part of BESS sizing, maximisation of opposing financial objective functions using two different multi-objective optimisation methods called Rating Method and Paired Comparison was used. These approaches were tested on a simple microgrid under various electricity price scenarios. The results show that the Rating Method performed best when selecting BESS size in significant knee regions near maximum daily worth. The

Rating Method can also select optimal BESS size at maximum daily worth when less-significant knee regions are present. This approach gives an appropriate balance between forming the planning objective Investment Scale and maximising profit.

To incorporate the planning objective Investment Timing as part of BESS sizing, two different models were used, referred to as the operational model (controlling operational decisions i.e. BESS dispatch) and the planning model (controlling BESS size at different yearly intervals). Reinforcement learning was used as the operational model solution method, while global optimisation was used as the solution method for planning model. This approach was tested on data from the Integrated Single Electricity Market Day-Ahead Market. It was found that splitting BESS operational decisions and BESS planning decisions into two different models is an effective technique.

To incorporate the planning objective Dispatch Adaptability as part of BESS sizing, model-based and model-free stochastic optimisation methods are used. This was done for model-free optimisation by utilising deep reinforcement learning methods, while stochastic programming was used as the solution method for model-based approach. Both approaches were tested on historical Day-Ahead and Intraday Markets electricity clearing prices from the Integrated Single Electricity Market. It was found that the model-based approach outperformed the model-free approach. However, it is not clear that such a broad statement can be made about model-free and model-based approaches in general based on the results gained through this thesis.

The significance of this study's results is that BESS sizing is now more functional and adaptable for project planning purposes. It is now possible to size BESS without suffering scale issues resulting from ever-diminishing returns of larger BESS sizes, where the timing of the investment can be chosen optimally rather than assuming "here and now" investment, and where the operational strategy employed to simulate BESS dispatch is more reflective of actual BESS use and adaptability.

PUBLICATIONS DURING THIS DISSERTATION

Published

J. J. Kelly and P. G. Leahy, "Sizing Battery Energy Storage Systems: Using Multi-Objective Optimisation to Overcome the Investment Scale Problem of Annual Worth," *IEEE Transactions on Sustainable Energy*, pp. 2305 - 2314, 2019.

J. J. Kelly and P. G. Leahy, "Optimal investment timing and sizing for battery energy storage systems," *Journal of Energy Storage*, vol. 28, p. 101272, 2020.

Under Review

J. J. Kelly and P. G. Leahy, " Incorporating cross-market dispatch adaptability when sizing battery energy storage systems via model-based and model-free methods," 2022.

Authorship Contribution

The following contribution was made by each author for the above publications:

Joseph Kelly - Development of conceptual ideas and methodologies. All modelling work, testing and validation of hypothesis. Writing of complete original draft and subsequent drafts, completion of all visualisation material.

Dr Paul Leahy- Providing resources, reviewing draft outlines and providing feedback, supervision and project administration outside that with journals.

CHAPTER ONE

1 INTRODUCTION

The advancement of battery energy storage systems (BESS) over the past decades has led to an increase in their deployment throughout electrical grids worldwide. As an example, Li-ion technology has seen a greater than two-fold increase in energy density compared with early Li-ion concepts, Zinc-Air technology has seen advances in terms of rechargeability and active research is underway to reduce the operating temperatures of Na-S BESS technology [1]. From 2015 to

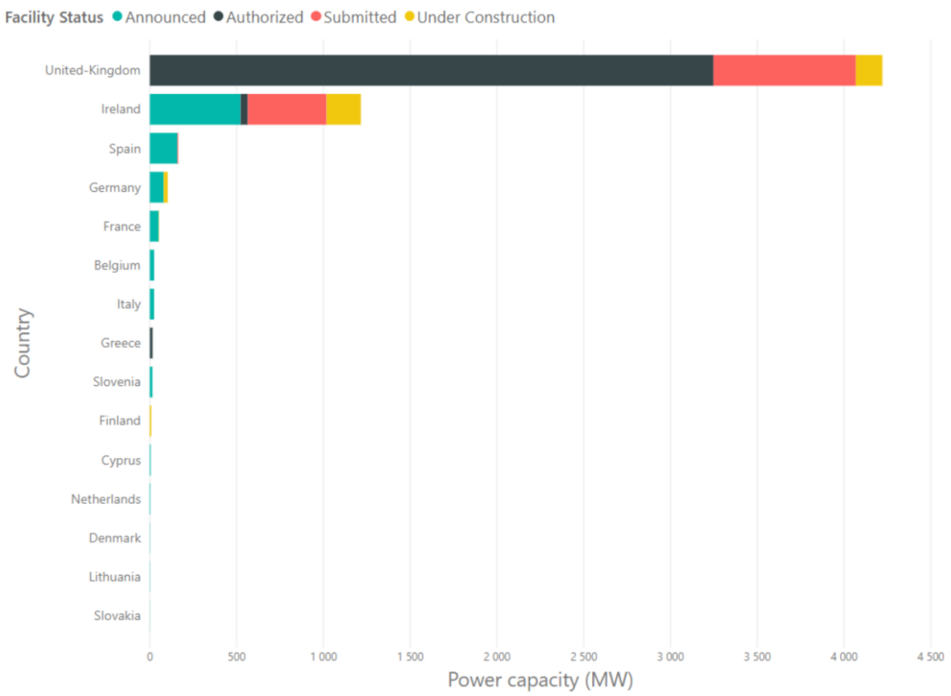

Fig.1.1 – Electrochemical storage planned capacity by country within the EU-28 as of March 2020

2018, utility scale battery storage costs declined by 70% as reported by the U.S. Energy Information Administration [2]. Research and innovation of BESS technology will continue into the future, as more and more electrical systems around the world seek to install renewable generation as a means to decarbonise. Fig.1.1 (extracted from [3]) outlines the planned EU-28 electrochemical storage power capacity as of

March 2020, with Ireland and United Kingdom showing aggressive expansion of BESS installations compared with the rest of Europe. Of noteworthiness is the number of proposed BESS installations on the island of Ireland given the relative size of its electrical grid. This is in part due to the enduring predicted increase in System Non-Synchronous Penetration (SNSP[1]) limit to 75% in 2022 [4], its minimal interconnectivity compared with other European member states, and the recently launched systems services market [5]. In addition, the European Commission envisages that the market size for energy storage by 2030 within the EU-28 could be as high as 108 GW [3].

1.1 BACKGROUND

The pursuant development of a new BESS installation follows a logical question: what size BESS should be installed? The answer to this question is not always obvious. This question stems from the reality that unlike traditional sources of electricity (e.g. coal, nuclear, gas, wind, solar, etc.), BESS are not a generation source. Rather, BESS can occupy both demand and generation, but more importantly are limited in duration for both. This limitation is the BESS size, also known as the energy storage capacity and typically measured in megawatt-hours (MWh). This is what sets BESS apart from other non-energy storage technologies connected to electrical grids. Therefore, the capacity size question is unique to energy storage systems. Currently, there is a plethora of BESS sizing approaches in use as shown in review articles [6-8]. The predominant approach taken in the literature is to develop objective functions as part of a mathematical optimisation problem, with the optimised solution resulting in two important outcomes, the first being a solution to the BESS size variable and the second being an objective function scalar value. The objective function can take various forms, such as financial or technical objectives. The principle of the objective function is to size a BESS for a specific purpose called a goal, and it is accordingly modelled in such a way as to capture this goal. Sizing a BESS to increase renewable energy penetration is one such example. Depending on the goal, objective functions have wide-ranging modelling flexibility, with the challenge being the solution method. Ideally, a sizing

[1] SNSP = (all non synchronous generation + HVDC imports) / (demand + HVDC export).

objective function for a potential BESS installation should reflect or incorporate as many important project goals as possible. This can be magnified through a thought-provoking question: how can one take confidence in sizing a BESS correctly unless the objective function contains all project goals either directly/indirectly? This is very important question when BESS sizing approaches are required to be used as a project planning tool. Including as many project goals as part of sizing optimisation ensures that the built BESS project is the right BESS project, and aligns the BESS project with any goals set out before execution. BESS project planners require that sizing approaches are capable of modelling prescribed goals set out at the initial planning phase. These project planners are the very entities undertaking such BESS projects as those outlined in Fig.1.1.

The ability of existing BESS sizing approaches to model important project planning goals must first be determined. To achieve this, an already established program for project planning is required. The Front-End Planning (FEP) framework is the project planning program used in this dissertation to provide a comprehensive list of possible goals used by project planners for a range of different project types. FEP, which is described further in Section 2.2, is a process in which important project scoping elements are defined for a potential project and assessed for their completeness before embarking. The level of completeness of each scoping element informs if the project is worthwhile to continue (i.e. acceptance criteria resulting in either pass or fail). Such a framework provides a selection of BESS project goals to choose from. These goals are referred to as planning objectives herein.

1.2 PROBLEM STATEMENT

Within the scope of this dissertation, a review of the literature shows that BESS sizing approaches are lacking in three key planning objectives called *Investment Scale*, *Investment Timing* and *Dispatch Adaptability*. Arriving at this conclusion was done by reviewing existing BESS sizing approaches' inclusiveness of select FEP scoping elements (see Chapter 2). These three planning objectives are identified as the problems requiring resolution through this research. These are significant problems when BESS sizing approaches are used as planning tools. Not only does this study seek to rectify these problems but also highlights and brings awareness as they are not widely explored within the BESS sizing community. The reflection of this can be seen in the literature review of this study which is designated largely for confirmation of this problem statement. Through review of literature, two other planning objectives are also identified as lacking within BESS sizing approaches, called *Location* and *Capacity (Power)*[2]. However, resolution of these planning objectives requires grid system modelling and electricity competitive market modelling which is outside the scope of this research. Nevertheless, they are included within the literature review as a point of reference for future work.

1.3 PLANNING OBJECTIVE DESCRIPTION

Expanding further from the problem statement, the following outlines a description of the planning objectives.

1.3.1 INVESTMENT SCALE

An important planning objective for a BESS project is whether or not the capital outlay (also called scale of investment) to achieve the project is wisely considered. Typically, selecting a BESS size is based on maximising a financial objective function such as the difference between potential benefit and cost (i.e. maximum profit), or minimising cost of operation. By maximising these types of objective functions an optimal BESS size is based on argmax or argmin. However, this may not always be desirable. If one was to look at all BESS sizes from 0 MWh up to the optimal BESS size, it is possible that the objective function would show diminishing returns for ever larger BESS sizes. In such a scenario, selection of optimal BESS size can become unclear for a project under design. Ultimately, the best BESS size choice is one which balances maximum/minimum objective function value and scale of investment. Therefore, implementing the Investment Scale planning objective requires selecting BESS sizes away from optimal argmax or argmin. These BESS sizes represent a sounder investment choice.

[2] Capacity of a BESS can mean both the energy capacity and/or power capacity. This dissertation's primary aim is sizing the optimal energy capacity of a BESS. However, the FEP framework refers to all capacity decisions. Therefore, to distinguish power capacity from energy capacity, the term Capacity (Power) is used.

1.3.2 INVESTMENT TIMING

The Investment Timing planning objective is complementary to BESS sizing. Traditionally, existing BESS sizing objective functions have used financial objectives such as NPV or annualised cost. These types of objective functions size a BESS for only the initial year of BESS project operation. However, BESS sizing can also have a timing dimension. This situation appears after the initial capacity installation with subsequent capacity installed at intervening years. Including this timing dimension as part of BESS sizing fundamentally changes the structure of BESS sizing objective function compared to NPV, as an example. Firstly, the number of BESS sizing decision variables increases from one to twenty (if it is assumed that BESS capacity can be added each year of a 20-year project lifecycle), Secondly, the consideration of future expansion relies on simulation of future events such as electricity market clearing prices which are stochastic. Furthermore, introducing this timing dimension as part of BESS sizing means that other specific factors need to be considered which could influence the sizing and timing decisions. Two such factors considered as part of this study are future BESS capital costs and BESS degradation. The structure of an objective function which captures all these requirements for Investment Timing can be referred to as Real Options, which is capable of modelling dynamic and stochastic decisions.

1.3.3 DISPATCH ADAPTABILITY

Simulation of BESS operational decisions are required as part of an objective function so that BESS benefits can form part of the optimisation. Most BESS sizing approaches up until now have simulated stationary BESS operational decisions. These daily dispatch decisions are modelled as once-a-day decisions, and not modified at available permitted intervals. This represents potential loss of predicted revenue by not optimally adapting daily dispatch decisions through cross-market arbitrage. The Dispatch Adaptability planning objective refers to the simulation of BESS operational decisions ability to change at different epochs. This adaptability can be viewed in a positive sense, as optional adaptable operational decisions are only pursued under the premise of achieving greater project benefit. As BESS benefit is modelled as part sizing objective functions, this adaptability will directly influence BESS size and/or improve financial performance.

1.4 RESEARCH QUESTION

To assess the validity of including the aforementioned planning objectives as part of BESS sizing, the following research questions have been developed. This research seeks to answer the following questions:

1. Is it possible to form the planning objectives Investment Scale, Investment Timing and Dispatch Adaptability as part of optimising energy capacity size for new BESS installation seeking maximum profit?
2. Are there any circumstances where the inclusion of planning objectives Investment Scale, Investment Timing and Dispatch Adaptability as part of BESS sizing helps overcome shortcomings of existing sizing approaches?

It is prudent at this juncture to ask the question: why should the reader care about whether or not BESS sizing approaches include project planning objectives? In answer to this question, if the inclusion of planning objectives as part of BESS sizing approaches has a positive effect on BESS optimal size and/or financial performance then this could hasten the development of BESS projects. However, the opposite is also true, and if the effect is negative it could paint a bleaker picture which could have harmful connotations. Irrespective of positive or negative results that will be presented throughout this study, the knowledge must be obtained regardless. In view of this fact, planning objectives are focused and deliberate ways of ensuring that the correct projects are built. Therefore, the motivation of this dissertation is to develop BESS sizing optimisation approaches that include the project planning objectives of Investment Scale, Investment Timing, and Dispatch Adaptability.

1.5 AIMS AND OBJECTIVES

The first aim of this dissertation is to study the effects of employing opposing financial objective functions maximised using multi-objective optimisation (MOO) as an approach to form the planning objective Investment Scale as part of BESS sizing.

RO1.1[3] Objectively, this will be achieved by utilising and comparing two different MOO models called Paired Comparison and Rating Method.

RO1.2 The next objective applies both models to BESS sizing for a simple microgrid under various electricity price scenarios with the optimal BESS size and financial performance noted.

The second aim of this dissertation is to analyse the effects of separating BESS sizing optimisation into hourly (operational decisions i.e. BESS dispatch) and yearly decisions (BESS size at different yearly intervals) as an approach to form the planning objective Investment Timing as part of BESS sizing, resulting in two different models, called the operational model and the planning model.

RO2.1 Objectively, this will be achieved by employing reinforcement learning as the operational model solution method and global optimisation as solution method for the planning model.

RO2.2 Use data from the Integrated Single Electricity Market (I-SEM) Day-Ahead Market as the test bed for the operational model, while the planning model utilises various future BESS CAPEX and degradation scenarios.

RO2.3 NPV will also be solved for comparison purposes through modified constraints.

The third aim of this dissertation is to examine the effects of utilising model-based and model-free stochastic optimisation methods as a means to form the planning objective Dispatch Adaptability as part of BESS sizing.

RO3.1 Objectively, this will be achieved for model-free optimisation by suitably utilising deep reinforcement learning methods as an approach to allow for Day-Ahead and Intraday Market BESS dispatch. Similarly, stochastic programming will be utilised as the solution method for model-based approach.

[3] Research Objective (RO)

RO3.2 The next objective will test both approaches on historical Day-Ahead and Intraday Markets electricity clearing prices from the Integrated Single Electricity Market (I-SEM).

RO3.3 Removing of Intraday dispatch capability will also be achieved so that comparison with and without planning objective Dispatch Adaptability is possible.

Fig.1.2 is an illustrative relationship of this dissertation's research question, aims and research objectives. The research question is the overarching question that this dissertation seeks to answer (i.e. high level research idea), which in this case is made up of three different distinctive strands, called Investment Scale, Investment Timing and Dispatch Adaptability. Within this dissertation each of these strands are examined in isolation of one another, with each strand having its own dedicated research chapter. This is done so as to allow examination of effects of each strand individually on BESS sizing rather than collectively. One analogy which is helpful is partial differentiation. Each strand has its own singular aim, which outlines what each chapter seeks to achieve, which will ultimately inform on research question answers. Furthermore, each aim has Research Objectives (RO), which outline the steps taken to achieve each aim.

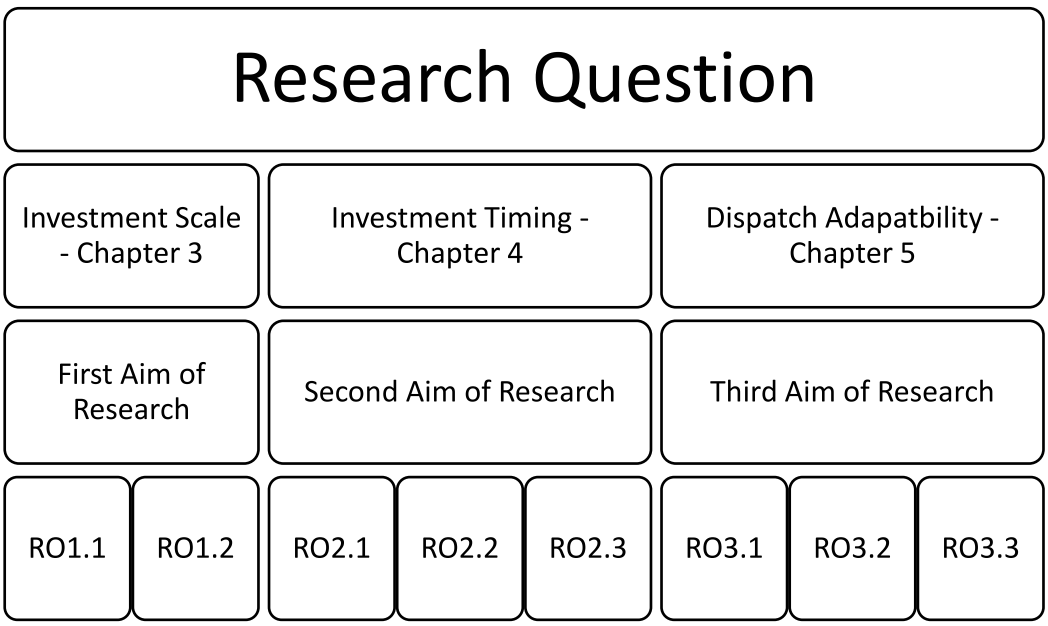

Fig.1.2 – Interaction between Research Question, Aims and Research Objectives throughout this dissertation.

1.6 DOCUMENT STRUCTURE AND LAYOUT

The emphasis of the literature review in Chapter 2 is to confirm the problem statement existence from Section 1.2 through appraising existing BESS sizing approaches inclusiveness of planning objectives. There are also shorter and more focused literature reviews within each research chapter (Section 3.3, 4.3 and 5.3). These shorter reviews are concentrated on any literature that has similar tendency for modelling planning objectives but not too far removed from BESS sizing topic area. Casting a wider net allows for a review of useful solution methods or modelling techniques used in similar topics or areas that may not have found their way into BESS sizing research field.

The aims/objectives, methods, results and discussions in relation to planning objectives Investment Scale, Investment Timing, and Dispatch Adaptability are set out in Chapters 3, 4 and 5 respectively. Inherently, each planning objective has its own dedicated research chapter.

1.7 PROPOSED OUTCOMES

The following outlines possible outcomes of forming the aforementioned planning objectives as part of BESS sizing approaches. A brief description of the approach taken within this dissertation to incorporate the planning objective as part of BESS sizing, the hypothesis and implications of this hypothesis are provided.

To incorporate the planning objective Investment Scale as part of BESS sizing, two competing financial objectives are maximised for optimal BESS size via Multi-Objective Optimisation. It is hypothesised that such an approach will prevent nonsensible BESS sizes from being suggested as possible solutions. This is achieved through opposing objective functions with dissimilar rates of change. For example, if one objective function’s rate of change diminishes significantly at a certain BESS size and the other objective function’s rate of change remains constant, then a distinctive knee region will form as part of Pareto front. If this region is convex under maximisation, then BESS sizes outside this region may represent less gains for greater outlay (i.e. diminishing returns), and therefore may not represent a satisfactory BESS size choice. Depending on the application, using the above approach will result in a smaller BESS size with less profit. However, the financial performance will improve compared with the investment undertaken. Confirmation of this hypothesis through this research implies that sizing a BESS with maximum profit is not always the best approach.

Forming the planning objective Investment Timing as part of BESS sizing is done through utilising two different models called operational model (hourly decisions) and planning model (yearly decisions) which are maximised for profit. It is hypothesised that the inclusion of Investment Timing as part of BESS sizing will defer BESS investment from Year 1 to a later year. This deferral is driven by the fact that BESS costs are due to decline in coming years and are modelled as such in this dissertation. Therefore, future BESS sizing decisions can avail of less expensive capacity expansion. Another possible outcome is that BESS size at year 1 will remain the same with Investment Timing modelled as compared with the same scenario modelled without Investment Timing. Although, it is expected that capacity expansion may happen at a later year. Another aspect that can influence the timing and size of BESS investment is degradation, although at this point the outcome is unclear. It is possible that BESS capacity will not be replaced closer to end of project life as there will be less time to recoup investment. It is also possible that the inclusion of Investment Timing will reduce financial performance of a BESS project. This is due to the degradation effect, along with the cost of replacing degraded capacity. If the above hypotheses hold true, the consequences for BESS sizing as a whole is that without the inclusion of future decisions the true value of the project cannot be known. This could lead to false beliefs about profit maximisation value of BESS sizes unless Investment Timing is incorporated.

To model the planning objective Dispatch Adaptability as part of BESS sizing, two different approaches known as Deep Reinforcement Learning and Stochastic Programming are utilised and compared. The proposed result of these approaches has two mutually exclusive outcomes that may occur. The first possible outcome is that modelling Dispatch Adaptability as part of BESS sizing optimisation will result in smaller optimal BESS sizes when compared to sizing approach without Dispatch Adaptability. This is due to the fact that cross-market dispatch adaptability does not require extra BESS capacity, but rather is based on modifying already established dispatch decisions. Therefore, the same level of revenue can be achieved utilising a smaller BESS with Dispatch Adaptability compared with a larger BESS without Dispatch Adaptability. This only leaves the cost component of the objective function which is less for a smaller BESS, and therefore through maximisation, the optimal BESS size will be smaller. The second possible outcome is that optimal BESS size will remain the same but profitability will increase, when sized with Dispatch Adaptability compared without. The primary reason is that inclusion of Dispatch Adaptability will result in all BESS sizes increasing revenue. If the scale of this increase is similar for all BESS sizes, then a change in optimal BESS size is unlikely as BESS cost has not changed through the inclusion of the planning objective Dispatch Adaptability. If the proposed outcome of increased profitability comes to fruition through this research, then there is potential to utilise Dispatch Adaptability for converting unprofitable BESS projects into profitable ones.

CHAPTER TWO

2 LITERATURE REVIEW

The purpose of this literature review is to confirm the problem statement set out earlier in Section 1.2. The problem statement, set out that existing BESS sizing approaches are lacking in three key planning objectives called *Investment Scale*, *Investment Timing* and *Dispatch Adaptability*. Arriving at this conclusion was done through a two-step process which is set out in this chapter. The requirement for this two-step process is described herein.

2.1 OVERVIEW

At the beginning of this research, the extent of knowledge was that a BESS sizing objective function should include as many planning objectives as possible if utilised as a planning tool (refer to Section 1.1). Introduced later within Section 2.2 of this chapter, the Front-End Planning (FEP) framework provides an evidence based rigorous approach to scoping necessary planning objectives for certain project types for which BESS can be considered. The FEP framework was chosen for this study due to the usability of toolkits provided (described later in Section 2.2) as part of FEP. Furthermore, these toolkits were derived from extensive survey efforts of project development professionals undertaken by Construction Industry Institute (CII) which demonstrates the ability of FEP application to a wide variety of project types. Including all planning objectives derived from FEP as part of BESS sizing would present too large a task for this study. Therefore, to fit within the confines of this dissertation, the number of planning objectives investigated was reduced to three: Investment Scale, Investment Timing and Dispatch Adaptability. The remainder of this chapter is dedicated to outlining this two-step reduction process. The first step seeks to reduce the number of FEP planning objectives to a subset via suggested significance to BESS sizing. The second step reviews existing BESS sizing literature against this subset of planning objectives to establish the “research gap”, and through deduction confirm the Problem Statement.

For now, the discussion will revert from planning objectives to scoping elements. “Scoping element” is a FEP term. As part of this dissertation, multiple scoping elements can form a planning objective. Reverting back to planning objectives occurs at the end of this chapter through consolidation and renaming of scoping elements into planning objectives. As will be shown, the FEP framework provides a list of scoping elements that are required for wide range of different project types.

Step one involves a description of the relationship between the FEP framework and its toolkits (Section 2.2.1 and 2.2.2). The toolkits provide a list of scoping elements to select from. Some scoping elements within toolkits are applicable, while others are unrelated to BESS projects. Of those being applicable, it is also the case that some of these scoping elements may present as difficult to incorporate within an objective function. Regardless, the number of scoping elements is reduced to a workable subset for this dissertation. Rather than selecting scoping elements arbitrarily, some thought is given to the selection process. The approach taken to developing a subset of scoping elements is to suggest likely significant relationships between these scoping elements and BESS sizing at the outset. In other words, a significant relationship is one where optimising any objective function modelled with a scoping element would likely result in very a dissimilar optimal BESS size compared with the same optimised objective function without the scoping element. Likewise, a less significant relationship is one where the change in optimal BESS size is minimal with or without a scoping element as part of objective function. This is not to suggest that scoping elements deemed less significant would not alter BESS size. Scoping elements deemed less significant at this stage could form future research to either confirm or deny this attribution.

Step two, completed within Sections 2.3 through to 2.8 of this chapter, reviews existing BESS sizing approaches from literature against the previously suggested subset of scoping elements. In total, 32 suitable BESS sizing journal articles have been identified [9-40]. This was achieved by compiling a database of 200 most cited research articles over the past decade using the search term “energy storage sizing”. This list was reduced by removing non-BESS sizing articles, review articles, microgrid/grid sizing articles and non-electrical grid applications. Each remaining article is reviewed against its inclusiveness of each scoping element from subset. The results of this gives a status quo, which confirms the premise within the Problem Statement.

Lastly, within Section 2.9, consolidation and renaming of scoping elements into planning objectives which can be studied as part of this dissertation is provided.

2.2 SELECTING SCOPING ELEMENTS FOR STUDY

Formalisation of the FEP process was undertaken by the Construction Industry Institute (CII) in the mid-nineties [41]. Officially, FEP can be defined as “*The essential process of developing sufficient strategic information with which owners can address risk and make decisions to commit resources in order to maximize the potential for a successful project*” [42]. Other terms which are synonymous with FEP and may be familiar to the reader are front-end engineering design (FEED), front end loading (FEL), pre-project planning (PPP), feasibility analysis, programming and conceptual planning [42]. See Fig.2.1 for an illustration of FEP dominion within project development, extracted from [43].

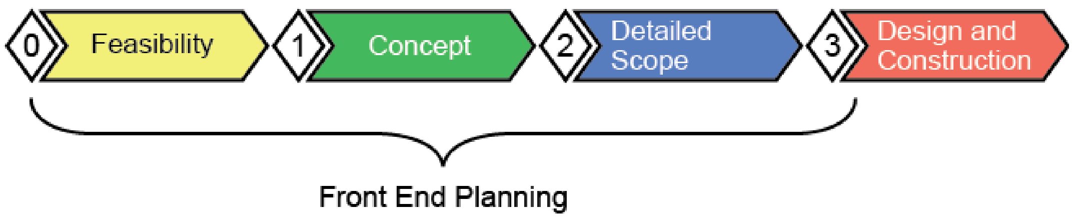

Fig.2.1 – Occurrence of Front-End Planning within project development

The CII sought FEP improvement via the development of scoping tools [44]. Three overarching Project Definition Rating Index (PDRI) toolkits were developed as methods to scope building projects [45], industrial projects [46] and infrastructure projects [47]. These toolkits were developed through collaboration with project development professionals. Each toolkit contains necessary scoping elements (i.e.

"*strategic information"* from the FEP definition). The scoping elements within each toolkit are deliberately maintained as generic to cover a wide variety of project types e.g. waste processing, chemical plants, dams, air terminals, etc. Of the three PDRI toolkits available, only the infrastructure toolkit (see Table 2.1 extracted from [47]) and the industrial toolkit (see Table 2.2 extracted from [46]) are applicable to BESS installations, given that each toolkit can be applied to "power generation facilities" which is the closest facility type to a BESS installation. The infrastructure toolkit and the industrial toolkit follow the same section classification approach. They also share similar categories and elements but on the whole are devised in such a way as to capture unique characterises of infrastructure projects and industrial projects. New BESS installations can fall between these two classifications which is why both toolkits are utilised. A review of both toolkits and the likely significant impact of scoping elements on BESS sizing is dialogued subsequent to this section.

2.2.1 REVIEWING FEP INFRASTRUCTURE TOOLKIT

The scoping elements within Table 2.1 under Section III – Execution Approach for the infrastructure toolkit are most concerned with project execution plan subsequent to the scoping stage and therefore are deemed to have minimal impact on BESS size. For example, J. – Land Acquisition Strategy and K. – Procurement Strategy would likely not alter optimal BESS size if modelled as part of an objective function. Important scoping elements for any facility type are M.1 – Safety Procedures and L.4 – Project Schedule Control, but these remain unlikely to meaningfully alter BESS size if modelled.

Within Section II – Basis of Design from Table 2.1, there are numerous important elements for consideration. Any environmental elements should be given the utmost importance when designing a BESS facility. Environmental elements in this context refers to the impact of BESS installations and not BESS manufacturing. However, it is currently difficult to see any extensive change in BESS size with the inclusion of environmental aspects as part of an objective function. An interesting scoping element is presented with F.4 – Permitting Requirements. It is probable that greater BESS sizes give way to exponentially harder permit authorisation from governing authorises for BESS installations. However, this does have a degree of subjectivity attached to it from governing authorises and therefore would prove impractical to model as part of an optimisation problem. Another significant scoping element exists in I.1 – Capacity. More specifically, a Capacity scoping element refers to any sizing decision for a project. Designing a BESS project can involve at a minimum two sizing decisions, the energy capacity and power capacity. Sizing BESS energy capacity is already the sole focus of this dissertation. The subsequent literature review examines the inclusiveness of each proposed scoping element within existing BESS energy capacity sizing approaches. Therefore, energy capacity does not warrant its own dedicated scoping element section within the literature review, as it is the overarching concept of this dissertation through which all scoping elements are reviewed. Sizing BESS power capacity will not be undertaken as part of this dissertation. That being said, sizing BESS power capacity

Table 2.1 – Scoping Elements of PDRI for Infrastructure Projects

SECTION I. BASIS OF PROJECT DECISION
A. Project Strategy
- A.1 Need & Purpose Documentation
- A.2 Investment Studies & Alternatives Assessments
- A.3 Key Team Member Coordination
- A.4 Public Involvement

B. Owner/Operator Philosophies
- B.1 Design Philosophy
- B.2 Operating Philosophy
- B.3 Maintenance Philosophy
- B.4 Future Expansion & Alteration Considerations

C. Project Funding and Timing
- C.1 Funding & Programming
- C.2 Preliminary Project Schedule
- C.3 Contingencies

D. Project Requirements
- D.1 Project Objectives Statement
- D.2 Functional Classification & Use
- D.3 Evaluation of Compliance Req.
- D.4 Existing Environmental Conditions
- D.5 Site Characteristics Available vs. Req.
- D.6 Dismantling & Demolition Req.
- D.7 Determination of Utility Impacts
- D.8 Lead/Discipline Scope of Work

E. Value Analysis
- E.1 Value Engineering Procedures
- E.2 Design Simplification
- E.3 Material Alternatives Considered
- E.4 Constructability Procedures

SECTION II. BASIS OF DESIGN
F. Site Information
- F.1 Geotechnical Characteristics
- F.2 Hydrological Characteristics
- F.3 Surveys & Mapping
- F.4 Permitting Requirements
- F.5 Environmental Documentation
- F.6 Environmental Commitments & Mitigation
- F.7 Property Descriptions
- F.8 Right-of-Way Mapping & Site Issues

G. Location and Geometry
- G.1 Schematic Layouts
- G.2 Horizontal & Vertical Alignment
- G.3 Cross-Sectional Elements
- G.4 Control of Access

H. Associated Structures and Equipment
- H.1 Support Structures
- H.2 Hydraulic Structures
- H.3 Miscellaneous Elements
- H.4 Equipment List
- H.5 Equipment Utility Requirements

I. Project Design Parameters
- I.1 Capacity
- I.2 Safety & Hazards
- I.3 Civil/Structural
- I.4 Mechanical/Equipment
- I.5 Electrical/Controls
- I.6 Operations/Maintenance

SECTION III. EXECUTION APPROACH
J. Land Acquisition Strategy
- J.1 Local Public Agencies Contracts & Agreements
- J.2 Long-Lead Parcel & Utility Adjustment Identification
- J.3 Utility Agreement & Joint Use Contract
- J.4 Land Appraisal Requirements
- J.5 Advance Land Acquisition Req.

K. Procurement Strategy
- K.1 Project Delivery Method & Contracting Strategies
- K.2 Long-Lead/Critical Equipment & Materials Identification
- K.3 Procurement Procedures & Plans
- K.4 Procurement Responsibility Matrix

L. Project Control
- L.1 Right-of-Way & Utilities Cost Estimate
- L.2 Design & Construction Cost Estimate
- L.3 Project Cost Control
- L.4 Project Schedule Control
- L.5 Project Quality Assurance & Control

M. Project Execution Plan
- M.1 Safety Procedures
- M.2 Owner Approval Requirements
- M.3 Documentation/Deliverables
- M.4 Computing & CADD/Model Req.
- M.5 Design/Construction Plan & Approach
- M.6 Intercompany & Interagency Coordination & agreements
- M.7 Work Zone and Transportation Plan
- M.8 Project Completion Requirements

as part of sizing BESS energy capacity will be reviewed as part of this literature review (see Section 2.8), which will outline a justification for excluding BESS power capacity sizing from this dissertation and also inform on possible future work for its inclusion. As a clarification step, the “Capacity” scoping element will be reverted to “Capacity (Power)” for this dissertation to distinguish between power capacity and energy capacity. For the remaining elements within G. – Location and Geometry and H. – Associated Structures/Equipment it is proposed that their significance to altering BESS sizes is minimal if included as part of optimisation.

Also contained in Table 2.1 is Section I – Basis of Project Decision which has three elements with probable significant impact on BESS sizing. The first element is A.2 – Investment Studies and Alternatives Assessments, which seeks to understand if the investment into a BESS project is sensibly considered. Depending on the level of investment, significantly varying BESS sizes can be expected as the final optimal result. The second element is B.2 – Operating Philosophy. Here, modelling BESS operation is required to size a BESS through an optimisation problem. It is hypothesised that operating strategy choice could have a wide-ranging effect on overall BESS performance and in turn affect optimal BESS size. The second element is B.4 – Future Expansion & Alteration Considerations. This accounts for factors which could affect the future state of BESS energy storage capacity. One such factor is degradation which reduces the available energy storage capacity over time and through repeated use. Depending on the rate of degradation, it is theorised that replacement of this lost capacity could make financial sense. Another factor is the decline in future BESS cost which could present a situation where it makes sense to hold off BESS installation until a later date. Outside of this, all other scoping elements as part of Section I – Basis of Project Decision remain important but less significant, and will therefore not be considered candidates for inclusion as part of this dissertation.

2.2.2 REVIEWING FEP INDUSTRIAL TOOLKIT

To begin with, the industrial toolkit shown in Table 2.2 has various similar scoping elements to that of the infrastructure toolkit. Moreover, the industrial toolkit also contains scoping elements which are already identified as having a proposed significant impact on BESS sizing. These include B6. – Future Expansion Considerations, A.3 – Operating Philosophy, as well as I.1 – Capacity (Power). Similar also to the infrastructure toolkit, the industrial toolkit contains important scoping elements for project design but less significant for altering BESS size such as F3. – Environmental Assessment and P. – Project Execution Plan. An additional scoping element which gets little attention is D4. – Dismantling & Demolition Requirements. However, it is not included as part of the FEP framework moving forward as the requirements are expected to increase linearly with increasing BESS size.

Table 2.2 – Scoping Elements of PDRI for Industrial Projects

SECTION I. BASIS OF PROJECT DECISION

A. Manufacturing Objectives
- A1. Reliability Philosophy
- A2. Maintenance Philosophy
- A3. Operating Philosophy

B. Business Objectives
- B1. Products
- B2. Market Strategy
- B3. Project Strategy
- B4. Affordability/Feasibility
- B5. Capacities
- B6. Future Expansion Considerations
- B7. Expected Project Life Cycle
- B8. Social Issues

C. Basic Data Research & Development
- C1. Technology
- C2. Processes

D. Project Scope
- D1. Project Objectives Statement
- D2. Project Design Criteria
- D3. Site Characteristics Available vs. Req'd
- D4. Dismantling & Demolition Requirements
- D5. Lead/Discipline Scope of Work
- D6. Project Schedule

E. Value Engineering
- E1. Process Simplification
- E2. Design & Material Alternatives
- E3. Design for Constructability Analysis

SECTION II. FRONT END DEFINITION

F. Site Information
- F1. Site Location
- F2. Surveys & Soil Tests
- F3. Environmental Assessment
- F4. Permit Requirements
- F5. Utility Sources with Supply Conditions
- F6. Fire Protection & Safety Considerations

G. Process/Mechanical
- G1. Process Flow Sheets
- G2. Heat & Material Balances
- G3. Piping & Instrumentation Diags. (P&ID's)
- G4. Process Safety Management (PSM)
- G5. Utility Flow Diagrams
- G6. Specifications
- G7. Piping System Requirements
- G8. Plot Plan
- G9. Mechanical Equipment List
- G10. Line List
- G11. Tie-in List
- G12. Piping Specialty Items List
- G13. Instrument Index

H. Equipment Scope
- H1. Equipment Status
- H2. Equipment Location Drawings
- H3. Equipment Utility Requirements

I. Civil, Structural, & Architectural
- I1. Civil I Structural Requirements
- I2. Architectural Requirements

J. Infrastructure
- J1. Water Treatment Requirements
- J2. Loading/Unloading/Storage Facilities Req'mts.
- J3. Transportation Requirements

K. Instrument & Electrical
- K1. Control Philosophy
- K2. Logic Diagrams
- K3. Electrical Area Classifications
- K4. Substation Req'mts./Power Sources Identified
- K5. Electrical Single line Diagrams
- K6. Instrument & Electrical Specs.

SECTION III. EXECUTION APPROACH

L. Procurement Strategy
- L1. Long Lead/Critical Equipment & Materials
- L2. Procurement Procedures and Plans
- L3. Procurement Responsibility Matrix

M. Deliverables
- M1. CADDI Model Requirements
- M2. Deliverables Defined
- M3. Distribution Matrix

N. Project Control
- N1. Project Control Requirements
- N2. Project Accounting Requirements
- N3. Risk Analysis

P. Project Execution Plan
- P1. Owner Approval Requirements
- P2. Engr./Constr. Plan & Approach
- P3. Shut Down/Turn-Around Req'mts.
- P4. Pre-Commissioning Turnover Sequence Req'mts.
- P5. Startup Requirements
- P6. Training Requirements

A notable scoping element from Table 2.2 within Section II. – Front End Definition which is likely to have a significant impact on BESS sizing is F1. – Site Location. Potential connection points of a BESS installation to an electrical grid cannot all be treated equally. Some connection points may require substantial grid upgrades for larger BESS sizes resulting in higher costs, while other connection points may have local marginal pricing which can affect revenue. It is connection point differences similar to the aforementioned which could have significant influence on optimal BESS size. Finally, the scoping element C1. – Technology can significantly alter optimal BESS size as different BESS technologies have varying functionalities. This functionality, when incorporated into an optimisation problem, has the potential to alter BESS size significantly and therefore also needs to be investigated.

2.2.3 SUMMARY

In summary, and after reviewing each toolkit, the following is a list of scoping elements which are proposed as having the most significant impact on BESS sizing presently: Investment Studies and Alternatives Assessments, Future Expansion, Operation Philosophy, Technology, Location, and Capacity (Power). Each of these elements will form the basis on which to assess existing BESS sizing methodologies. In doing this, a status quo is established between existing BESS sizing methodologies and their applicability as planning tools. The subsequent questions outlined in bullet point form are framed in such a way as to provide a method of investigating existing BESS approaches' applicability as a planning tool for each proposed scoping element respectively. The results are presented in Sections (2.3 to 2.8) and will lay the foundations on which the aims and objectives of this work can be pursued.

- Investment Studies and Alternative Assessments
    - *What are the financial objective functions used within existing BESS sizing methodologies, and do they account for scale of investment?*
    - *Are there any restrictions on capital spend as part of existing BESS sizing approaches?*
- Future Expansion
    - *Do existing BESS sizing methodologies have full view of future capacity expansion potential?*

- *What parameters are maintained as uncertain for future decisions concerning BESS sizing?*
- Operation Philosophy
  - *What are the key criteria for simulating the operation of BESS within sizing methodologies?*
  - *Are existing BESS approaches towards Operation Philosophy geared towards wider grid benefit or sole BESS benefit?*
- Technology
  - *How do current BESS sizing methodologies account for different BESS technology types?*
  - *Are there different BESS technology traits that need to be modelled which could have significant impact on optimal BESS size or can methodologies be maintained generic?*
- Location
  - *Do existing BESS sizing methodologies also account for optimal location placement within electrical grid?*
  - *Are these approaches applicable in deregulated electricity markets?*
- Capacity (Power)
  - *How is the power capacity design variable accounted for within BESS sizing methodologies?*
  - *Are these approaches applicable in deregulated electricity markets?*

2.3 REVIEWING INVESTMENT STUDIES AND ALTERNATIVE ASSESSMENTS SCOPING ELEMENT WITHIN BESS SIZING

By its very nature, optimising a BESS sizing objective function is synonymous with selecting an optimal BESS over alternative BESS sizes i.e. Alternative Assessment. This can be done either one of two ways: 1) through Analytical means [10, 13, 14, 16, 20, 21, 23, 24, 26, 27, 31, 39], where BESS dispatch variables are optimised for maximum or minimum objective function value at different constant BESS sizes and 2) Direct-Searched Based Methods [11, 12, 17-19, 22, 25, 29, 30, 32, 34-36, 38, 40], which optimises over a BESS size variable and BESS dispatch variables simultaneously. However, none of these approaches informs on diminishing returns for ever larger BESS sizes. A simplified illustrative version of this issue can be seen graphically in Fig.2.2, where depending on objective function formulation (f_1, f_2, f_3), the path from zero to optimal maximum value can vary. Assuming the scale of $f(x,y)$ and x are similar, it makes little sense selecting a BESS size which gives maximum optimal objective function value if the rate of change nearing maximum optimal $f(x,y)$ value is lessened significantly. One has to remember that the variable x represents BESS project capital cost, and x should be expended as sparingly as possible. This may give rise to a situation whereby selecting BESS size coinciding with the optimal value of $f(x,y)$ it is not always the best decision. The issue can be seen more distinctly in $f_3(x,y)$ which shows a much lesser rate of change compared with $f_2(x,y)$. In this instance, it is more considered to select a BESS size smaller (i.e. less expensive) than optimal point BESS size for

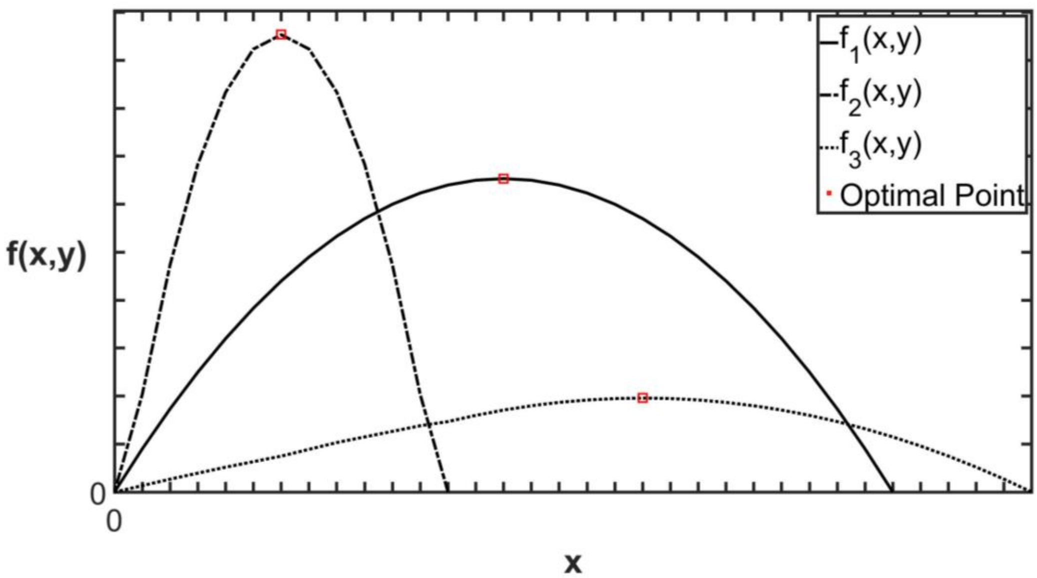

Fig.2.2 – Demonstration of different rate of change for diverse objective function formulations.

x in this instance represents capital expenditure of BESS project which starts at zero in the bottom left corner with cost increasing from left to right in equal units. Typically, the greater BESS project size equates to greater cost. Therefore, the increase in cost from left to right can also be seen as an increase in BESS size. $f(x,y)$ represents the objective function used to select BESS size. Typically, this objective function is Net Present Value, profit or return of the BESS project which, along with capital expenditure x, includes a benefit variable denoted here as y. The optimal value of the objective function will have accompanying cost and benefit value based on one distinct BESS size.

$f_3(x, y)$, as the return of $f_3(x, y)$ stays near constant approaching optimal point all the while x increases at the same rate. Whereas, it can be argued that optimal point BESS size is a better choice for $f_2(x, y)$ as the rate of change for $f_2(x, y)$ nearing optimal point is more comparable with x. It is likely that such phenomena explained thus far are application specific, similar to the illustration provided in Fig.2.2. Nevertheless, it cannot be determined if the issue occurs, let alone can be fixed, using existing BESS size approaches from the literature. Therefore, a new BESS sizing approach is required which can achieve two outcomes. The first is to select a smaller BESS size compared with optimal BESS size when situations arise similar to those in $f_3(x, y)$. The second is to select optimal BESS size when rates of change do not diminish significantly as optimal objective function value is approached, such as those in $f_2(x, y)$.

The BESS sizing problem as discussed thus far can be considered one of scale. In other words, the objective functions typically used in literature (i.e. Net Present Value, Annualised Cost, etc.) do not account for the scale of investment to reach maximum or minimum value, and as a result do not discourage ever larger BESS sizes with diminishing returns. One approach taken within the literature to reduce the impact of this scaling issue is to apply a budget/investment constraint [16, 22]. Here, the authors define a level of investment that is not to be exceeded, which also enforces that BESS sizes remain smaller, but only if cost of optimal BESS size is greater than investment constraint. This approach, although useful, does not achieve the aforementioned two desired outcomes for a BESS sizing approach when the capital expenditure for the optimal BESS size is much less than the budget constraint value. Therefore, a new approach is required.

2.4 REVIEWING FUTURE EXPANSION SCOPING ELEMENT WITHIN BESS SIZING

Expansion in this instance is used to describe potential opportunities during the lifecycle of a BESS project to increase the overall MWh rating of the project. There are two points to note when introducing future expansion as part of BESS sizing. The first point is that with any potential BESS installation project requiring capital, the BESS size decision is based on existing belief of future outcomes. For example, before investment it is required to estimate future electricity market price assumptions so that the likely benefit can be approximated, which in turn will inform the optimal BESS size. As with any assumption of future events it may not be realised when the time arrives. Therefore, accounting for this uncertainty is paramount and to size BESS accordingly. This uncertainty typically takes the form of objective function parameters and/or constraint parameters. The second point to note in addition to uncertainty is that dynamic decisions also form part of investment. This situation arrives after the initial decision (i.e. BESS size) to invest where new decisions are presented at multiple future intervals. If these future decisions are omitted within the optimisation problem, the initial decision can be suboptimal. Future expansion is one such dynamic decision. Outlined herein is a review of uncertainty and dynamic decisions application within existing BESS sizing literature.

Of the 32 BESS sizing literature sources identified at the beginning of this chapter, only 12 have considered uncertainty parameters as part of an objective function. The most common uncertainty parameters are load [11, 13, 17, 22, 23, 32, 33, 38] and renewable generation [11, 17, 22, 23, 32, 33, 38]. The addition of load and renewable generation parameters within objective functions by these authors is part of a grid expansion problem, where addition of a BESS to an electrical grid is sought. A less common uncertainty parameter is electricity clearing price [11, 22, 32, 33]. Others have not modelled the electricity clearing price parameter [17], or assume a deterministic value [13, 16, 23, 38]. Outside of case studies meeting grid load, renewable generation is the most commonly-occurring uncertainty parameter in the literature, with electricity clearing price not forming part of the optimisation problem [18, 19]. Of the discussed literature so far, no studies have extended the problem setting to include dynamic decisions (i.e. future expansion) over a planning horizon of one year. Only one previous study has applied future expansion as part of a BESS methodology while also including load and renewable generation uncertainties [26]. Here, the authors took a 10-year planning horizon and sought the addition of increased BESS capacity for each year. The inclusion of future BESS expansion over ten years was shown to reduce operation cost by 9.4% when compared with BESS sizing installation restricted to year one. Furthermore, the size of year one BESS capacity reduced by 91.3% when future expansion was permissible. To compensate for this reduction in capacity, year two sees a large increase in BESS size. Also, each of the 10 years saw an expansion of BESS capacity for three different battery technologies.

The applicability of the previously-discussed BESS sizing literature to this dissertation project will be further discussed now. Firstly, the inclusion of load as an uncertainty parameter should not be considered as this responsibility is with grid operators. A BESS enters competition with other entities to meet grid load, which can be successful or unsuccessful. Therefore, load is not a constraint and will not be included as an uncertain parameter for Future Expansion. Next, the inclusion of renewable generation remains important for BESS coupled to wind or solar. However, this work only considers standalone BESS and therefore has no requirement to include renewable generation uncertainty. Another uncertain parameter discussed thus far was the inclusion of electricity market clearing prices. Given that the expected benefit for a BESS project is determined via the revenue collected from participation within electricity markets, electricity clearing price will be included as an uncertain parameter in this study. The merits of future expansion have been shown by [26], and will also be modelled as part of this work. An important component of future expansion is the future BESS cost. This was not included in [26] but will be utilised in this work. Lastly, none of the previous studies allowed for delay of the initial BESS size decision until a later date. The previous approach was to expand capacity on the initial size decision of Year 1 at different subsequent yearly epochs [26]. This dissertation will seek to allow delay of initial size decision.

2.5 REVIEWING OPERATIONAL PHILOSOPHY SCOPING ELEMENT WITHIN BESS SIZING

Typically, when sizing a BESS through objective function optimisation, there are two types of variables solved for: the energy capacity variable which is the primary interest of this dissertation, and operational variables whose purpose is to simulate BESS operation so that benefit of BESS inclusion can be determined. What is clear from the majority of previous BESS sizing attempts cited in this chapter is that the operational strategies are purposefully utilized for the socialised benefit of a wider grid or microgrid. In such a scenario, the addition of a BESS is sought for the overall benefit of a grid system, be it large or small. As a result, little attention has been given to BESS sizing where the sole economic beneficiary is the independent owner of a BESS. For example, much focus has been on the addition of a BESS to reduce the operational cost of microgrid [11, 13, 15, 17, 20, 26, 31, 38], all the while ensuring microgrid load is matched with generation. Others have included different grid system services as part of this optimisation either through maintaining reliability constraints for a grid [16, 29, 33], spinning reserve [21, 24, 27, 35], grid voltage support [14, 25, 32, 37, 39], reduced grid congestion [34] or frequency response [9, 28]. The operational strategies used in these studies has been designed in such a way to allow the grid owner/operator take the benefit of BESS inclusion. Transferring these approaches for BESS as part of larger grids is problematic, as outlined in European Directive 2019/944, "*System operators should not own, develop, manage or operate energy storage facilities*" [48]. This means that independent project developers must undertake the task of supplying BESS projects. Therefore, it can be argued that operational strategies used to size a BESS for transmission or distribution networks do not require any elements outside the BESS developer's control, such as meeting load, reducing grid operating costs, maintaining grid reliability, providing adequate spinning reserve, etc. Rather, BESS sizing operational strategies should be more concerned with the benefit of being successful in competitive auctions created by grid and market operators, and the intricacies of such auctions modelled accurately as part of the operational strategy.

The importance of developing sizing approaches for BESS projects as the sole beneficiary can be seen in Fig.1.1, where proposed BESS capacity numbers are based on connection to geographical transmission and distribution systems for the EU-28. Given that much of these countries operate a deregulated competitive electricity markets, a BESS operating in such a market can only be concerned with its own benefit. As shown thus far, BESS sizing approaches to operational philosophy within literature are not readily transferrable when BESS sizing is concerned with its own benefit. To correct this, new BESS sizing approaches are required which will model operational philosophies that are focused on owners of BESS being the sole beneficiary. This has been previously attempted, although in a somewhat limited manner. For example, the authors in [18, 19] sized BESS to reduce forecast uncertainty associated with a windfarm. However, their approaches did not account for the benefit of doing so and therefore sizing was not done on a purely economic basis. Another example, albeit still reducing microgrid operating cost, uses a minimum acceptable profit constraint for a BESS installation [22, 23]. This type of approach does alleviate some concerns for BESS project developers but does not seek to extract the maximum amount of benefit from a project. Another approach taken in [10] could readily be applied to size a BESS as part of reducing curtailment levels of an individual windfarm (both co-owned), although some work needs to be done to extend the economic benefits of doing so. A different approach which fully focuses on the sole benefit of energy storage within Alberta electricity market is given by [30].

To further develop sole beneficiary BESS sizing as part of this dissertation, a number of different singular operational strategies or combinations of operational strategies could be explored. For example, singular trading in day-ahead markets, participation in reserve auctions both short and long term, partaking in capacity markets towards scarcity, etc. However, it is the author’s opinion that the most significant BESS sizing operational strategy worthy of investigation within this dissertation is cross-market arbitrage. Such an approach would allow operational decision modification at different trading epochs, where changes in electricity wholesale prices at these epochs could present opportunities for greater benefit. As of yet, and to the best of the author’s knowledge, this approach has not been applied to BESS sizing. In doing so through this study, will plug a gap in knowledge and further align BESS sizing with a more suitable operational philosophy, all the while increasing the likely benefit of BESS projects.

2.6 REVIEWING TECHNOLOGY SCOPING ELEMENT WITHIN BESS SIZING

Currently, there is a variety of different BESS technologies available to select from. Each technology has characteristics that differentiate one from another. A review of BESS technologies' dominant characteristics has been identified [49]. Although somewhat dated, the said review shows the key technological features that can influence a potential BESS installation. For discussion within this literature review, efficiency, degradation (called reduced storage capacity in [49]) and self-discharge are selected as the key BESS features for connecting to an electrical grid. These key BESS features are always present as they are a consequence of BESS technologies, however the values associated with these BESS features continue to improve year on year. Other features from [49] which are not discussed within this literature review are specific energy (energy capacity per mass) and energy density (energy capacity per volume). Although useful metrics for BESS comparisons, specific energy and energy density do not play a critical role in grid storage applications compared with automotive applications as an example. Also, two other features outlined in [49] are the number of useable cycles and autonomy (i.e. C-Rate). However, these two features can be considered functional inputs rather than characteristics to include in BESS sizing objective functions or constraints. In other words, efficiency, degradation and self-discharge are functions of cycle numbers and C-Rate. Therefore, the inclusion of efficiency, degradation and self-discharge within BESS sizing models will implicitly also include the effects of cycle numbers and C-Rate.

The efficiency, degradation and self-discharge features can each play an important role throughout the lifecycle of a BESS installation, and can directly influence the potential benefit/value of a project. Through BESS use (cycle numbers) and how it's used (C-Rate) triggers the internal impedance of BESS to increase thereby reducing efficiency, causing degradation and increasing self-discharge. This is outlined for lithium-ion batteries where an increase in internal impedance was seen to cause reduced efficiency in a study by Waag et al., 2013 [50]. Similarly, the internal resistance of sodium-sulphur batteries has also been shown to increase with use [51]. Likewise, efficiency is dependent on the instantaneous state of charge of BESS [52, 53]. This makes efficiency a dynamic parameter as part of a BESS sizing objective function. For degradation, Fig.2.3 (extracted from [54]) outlines the phenomenon that is present within lithium-ion batteries, showing effect of cycle number and C-rate. This reduction in energy

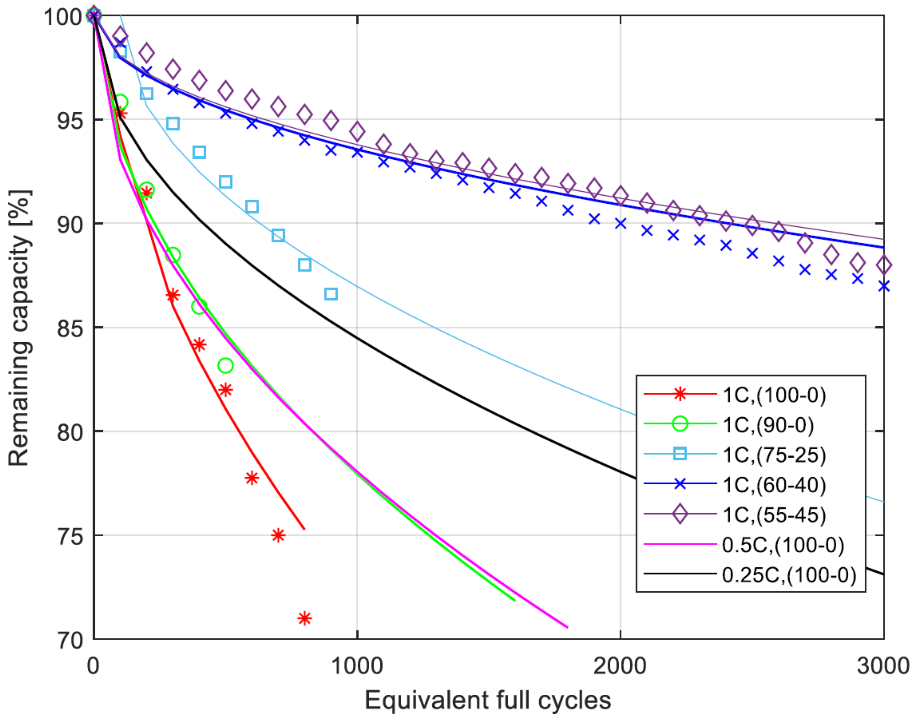

Fig.2.3 – Empirical (marks) and fitted (lines) model of lithium-ion energy capacity reduction via degradation.

capacity over time can have a significant impact on BESS project viability. A similar outcome is caused through the use of lead-acid batteries [55]. In another review, the authors outlined that room temperature sodium-sulphur battery degradation is also a function of cycle number and C-rate [56]. An example of a BESS technology which exhibits very little degradation is redox flow batteries such as vanadium which can achieve 200,000 cycles without significant degradation [57], while different chemistries of Aqueous Organic Redox Flow Batteries have shown on average less than 0.1% energy capacity degradation over 1000 cycles [58]. The impedance rise in lithium-ion batteries through use has also been noted to modify the rate of self-discharge (i.e. increase) [59]. Self-discharge can also take other forms. In molten sodium-sulphur batteries self-discharge is primarily due to thermal energy losses, where self-discharge rate can increase due to the corrosion of the insulator [60]. In short, efficiency, degradation and self-discharge are dynamic parameters rather than static parameters. If modelled as part of a BESS sizing objective function, the simulated operation of BESS dispatch actions will cause technology efficiency, degradation and self-discharge to worsen.

The existing BESS sizing methodology literature is assessed against its effort to incorporate the above BESS features (efficiency, degradation, self-discharge), and against how inclusive these features are (i.e. static or dynamic). Firstly, only one member of previously identified literature has incorporated dynamic efficiency within BESS constraints of a Vanadium Redox flow battery [31]. Their approach applied the charge and discharge efficiencies curves shown in Fig.2.4 (extracted from [31]), which vary based on the dispatch decisions shown along the x-axis and efficiency shown on the y-axis. All other literature applied either a static efficiency approach [10-13, 15, 17, 19-24, 26-29, 34-36, 38-40] (i.e. constant efficiency value regardless of BESS operation) or no efficiency parameters [9, 14, 16, 18, 25, 33]. In terms of modelling degradation, two different approaches have been observed.

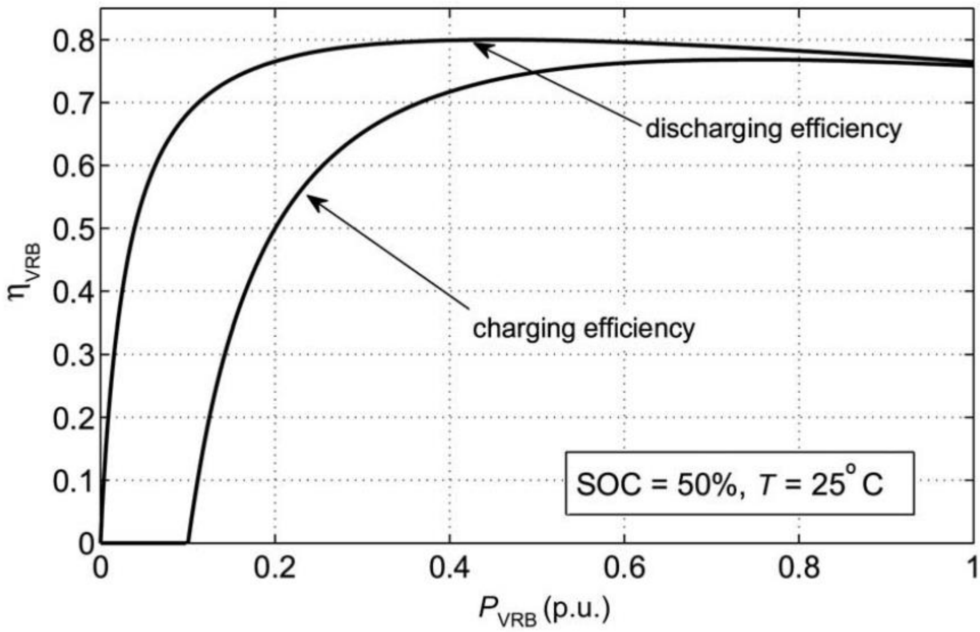

Fig.2.4 – Dynamic charging and discharging efficiency values for Vanadium Redox flow battery.

One approach applies a lifecycle constraint [11, 26, 36, 39], whereby the point of BESS failure (i.e. state of battery health below some minimum threshold) is incorporated within BESS sizing model. This ensures the throughput does not exceed required limits. The second approach taken applies a somewhat subjective residual value to remaining good health energy capacity at year's end [40]. If this is included within an objective function, the optimiser attempts to maintain a high-level residual capacity. Both these approaches to degradation provide no modelling link between degraded energy capacity and dispatch variables, and therefore are limited in their ability to incorporate the effects of degradation. Other literature did not consider degradation [9, 10, 12-25, 27-29, 31, 33-35, 38]. Alternatively, self-discharge was included within a BESS sizing model [40], albeit maintained as static and not adaptive to BESS health over time. Also, the authors in [29] sized a sodium-sulphur BESS on the basis that this technology doesn't exhibit self-discharge. This approach is consistent with no electrochemical self-discharge but doesn't account for the thermal losses of molten sodium-sulphur BESS. While slightly outside the scope of this work, an energy storage sizing model that included a flywheel did not account for self-discharge [38], even though flywheel technology has high rates of self-discharge. Lastly, BESS sizing approaches have remained mostly technology agnostic [14, 16, 18, 19, 22, 23, 25, 28, 33, 34]. Others have sized individual BESS such as Lithium-Ion [10, 15, 17, 21, 27, 35, 38, 39], Lead-Acid [24, 36], Vanadium Redox [31] and Sodium-Sulphur [29]. A comparison analysis of different technologies has been achieved, whereby BESS sizing model is solved separately for varying technology types [12, 13, 26, 40]. A slight variation on this incorporates technology selection as part of the objective function and therefore technology choice is directly optimised [11, 38]. In light of the similar characteristics of each BESS technologies, the value of a generic approach is clear.

Based on the review of literature presented, constant efficiency (i.e. static) values rather than dynamic values are used throughout this work. Also, self-discharge will not be included within any BESS sizing methodologies. These two decisions are taken to reduce the computational complexities that dynamic efficiency and self-discharge would introduce. For example, inserting dynamic efficiency values within a BESS sizing methodology has the potential convert a linear formulation into a nonlinear formulation, given that the product of efficiency and dispatch decisions must be included in either the objective function or constraints. The same can also be said of self-discharge as this would form a product with the same or possibly other variables (e.g. sum of dispatch decisions). Furthermore, all dispatch decisions as part of BESS sizing methodologies used throughout this work are based on a 24-hour time horizon. This short time horizon means the implications of self-discharge are reduced. From 2015, self-discharge losses are estimated for lithium-ion batteries at 0.5% per week [61], lead-acid batteries at 1-5% per month [62] and redox flow batteries at less than 5% per month [63] . The self-discharge values are low for these popular BESS technologies and therefore are unlikely to greatly affect the profitability of a BESS installation. Therefore, the modelling advantages of self-dispatch omission outweigh its admission. One BESS technology which has a higher self-discharge rate than others is molten sodium-based BESS such as sodium-sulphur. This is due to thermal losses through molten based electrolytes, with self-discharge rates up to 5% per day [64]. However, molten based sodium-sulphur batteries have seen significant safety concerns over recent years. Research now is focused on developing room temperature sodium-sulphur battery chemistries without thermal losses [65].

While the addition of degradation will also induce computational complexities, the negative difficulties of modelling degradation as part of BESS sizing optimisation are outweighed by the positives of degradation inclusion. This is largely due to aggressive rate of BESS degradation and loss of capacity, as seen in Fig.2.3. Additionally, previous attempts by literature are limited in their application of degradation to BESS sizing. Therefore, degradation will be discussed further and modelled as part of BESS sizing methodology used in dissertation. Lastly, application of all BESS sizing approaches within this work will be confined to lithium-ion BESS. As has already been established, all BESS technologies discussed experience the same traits of efficiency, degradation and self-discharge, with only the values of each varying. The purpose of this work is to test the validity of proposed BESS sizing methodologies and not to inform technology selection. Therefore, as part of this work, there is a requirement to develop generic sizing methodologies which can maintain transferability to different BESS technologies.

2.7 REVIEWING LOCATION SCOPING ELEMENT WITHIN BESS SIZING

When connecting BESS to an electrical grid, there is only a finite number of locations available for a possible connection. The connection process is usually handled by either the Transmission System Operator (TSO) or Distribution System Operator (DSO). Using Ireland as an example, this will typically be ≥110kV (TSO) for any generation projects greater than 50MW and ≤38kV (DSO) for generation projects less than 40MW [66], although each project is assessed on a case-by-case basis. Before a discussion on existing BESS sizing methodologies approach to grid location can take place, a summary of the influence of the grid connection process on BESS investment projects is provided herein.

In deregulated electricity market jurisdictions, new entrants can apply to connect to the electrical grid. For grid location to have a bearing on potential BESS investment, different grid locations must influence either the cost and/or benefit (i.e. revenue) of project. Taking cost as an example firstly, each potential grid location in a deregulated market can have varying connection costs. This is in part due to upgrade (if any) that is required to the electrical grid to accommodate the extra generation added through a new grid connection, such as BESS. There is also the electricity import aspect that BESS requires which needs to be taken into consideration. Secondly, the revenue of a project can be affected by constraining actions taken by System Operators (SO) to ensure system stability. This situation presents itself when SO has the authority to “dispatch down” electricity market participants from their established market positions. The market participant can be remunerated for this SO action if all electrical grid upgrades associated with a generator are completed. If the opposite is true, it can also not receive remuneration (known as non-firm access [67]). Therefore, grid location has the potential to affect both the cost and short-term benefit of BESS installation. However, these grid location effects are driven by the power rating of a grid connection and not energy capacity. Therefore, any literature discussed within this section must incorporate power system modelling to determine the necessary upgrades to the electrical grid. This constitutes the deregulated electricity market perspective for connecting BESS.

A significant proportion of the literature does not consider the nuances of grid location within the BESS sizing problem. Others have placed BESS sizing decisions and grid location decisions within the same objective function as solvable variables, known as the allocation problem [10, 11, 14, 22, 23, 32-34, 38]. Not only do these approaches solve for the optimal BESS size but they also introduce the selection of optimal grid locations for BESS. Continuing on, each source that searches for optimal grid locations is assessed in terms of its grid location cost parameters and benefit. The presence of these parameters within an objective function is necessary to model varying connection costs and benefits. Assessing cost first, none of the existing BESS sizing methodologies and optimal grid location research have varying connection cost parameters attributed to power capacity of a new BESS installation [10-14, 22, 23, 25, 32-34, 37, 38, 40]. One approach did incorporate the cost of upgrading the electrical grid within an NPV objective function, however this was in the context of competing with BESS to meet future load requirements of a microgrid, which similar to other studies, does not account for varying connection costs [20]. Another cost component that has been modelled is power losses, which the authors reduced through placing BESS at different locations throughout a distribution system [12]. However, the reduction of systemwide power losses cannot be considered a singular objective of a BESS project developer. Power loss charges are a function of all generation and demand within an electrical grid, and are calculated as such. Therefore, due to the fact that a BESS project will not have control over how electrical grids change over time, there is little point in reducing grid power losses. Rather than reducing power losses, location-specific parameter should be included in the objective function to capture power losses. These are known as Transmission Use of System (TUoS) charges and Distribution Use of System (DUoS) charges [68], though these were not included in the literature surveyed.

In terms of benefit, the approaches taken in literature are not applicable to BESS project developers within deregulated electricity markets. Four separate pieces of work sized the addition of a BESS at optimal grid locations for the purpose of reducing voltage fluctuations caused by renewable generation [14, 25, 32, 37]. While each of these works contributes value to the literature, none incorporate any renumeration for providing these services, thereby reducing the usefulness of the methodologies. For example, providing voltage support can be remunerated through different products within system services market such as Delivering a Secure, Sustainable Electricity System (DS3) [69], which can have varying remuneration values depending on grid location. One approach did apply a tariff as part of offering system balancing services and provision of reactive power to the TSO, but did not contain any specific grid location information for this tariff [20]. A final point to note is that nodal pricing is used within some jurisdictions, which reflects scarcity of energy within the electricity market. Nodal prices can directly affect the benefit received by BESS. One such work applied nodal pricing (also called Locational Marginal Pricing) to optimal BESS sizing and location [22]. It should be noted that this work is within the European context which uses zonal pricing compared with nodal pricing used within the United States.

Of all the literature mentioned so far, none has captured the BESS project developer's perspective regarding either cost and/or benefit of sizing BESS at different grid locations. As stated previously, only an objective function with parameters for both grid location cost and grid location benefit can achieve this outcome. This literature review has demonstrated that there is a substantial amount of work that needs to be completed to include grid location as part of BESS sizing. However, grid location will not be modelled as part of this work. The use of power system modelling to determine estimated grid upgrade costs (for a large grid) is outside the scope of this work. System service markets can have enhanced benefits for project owners to locate a BESS project at certain grid locations. Inclusion of any enhanced locational benefits as part of an optimisation model would incentivise locating BESS projects in certain areas of the grid. However, the system services market is outside the scope of this work and therefore varying benefits from different grid locations is unattainable. Likewise, zonal pricing is used rather than nodal pricing.

2.8 REVIEWING CAPACITY (POWER) SCOPING ELEMENT WITHIN BESS SIZING

The design variable that will be pursued throughout this dissertation is BESS size, which is another name for the energy capacity of a BESS. However, another capacity design decision available is BESS power. This design component, Capacity (Power), controls the ability to change BESS stored energy per unit time. A higher power capacity allows greater changes to BESS stored energy for the same length of time. This is an important design component as BESS operation within deregulated electricity markets is constrained by the duration of trading periods. The addition of power capacity as a decision variable within BESS sizing methodologies has been done by numerous authors [10-13, 16, 17, 19, 20, 22-24, 29, 32-34, 38]. Their approach was the inclusion of a BESS to reduce the operational cost of a grid. In doing this, the objective function they used was minimised thereby putting "downward pressure" on costs and BESS energy and power size. This concept can be seen graphically in Fig.2.5 (extracted from [16]). Through the use of

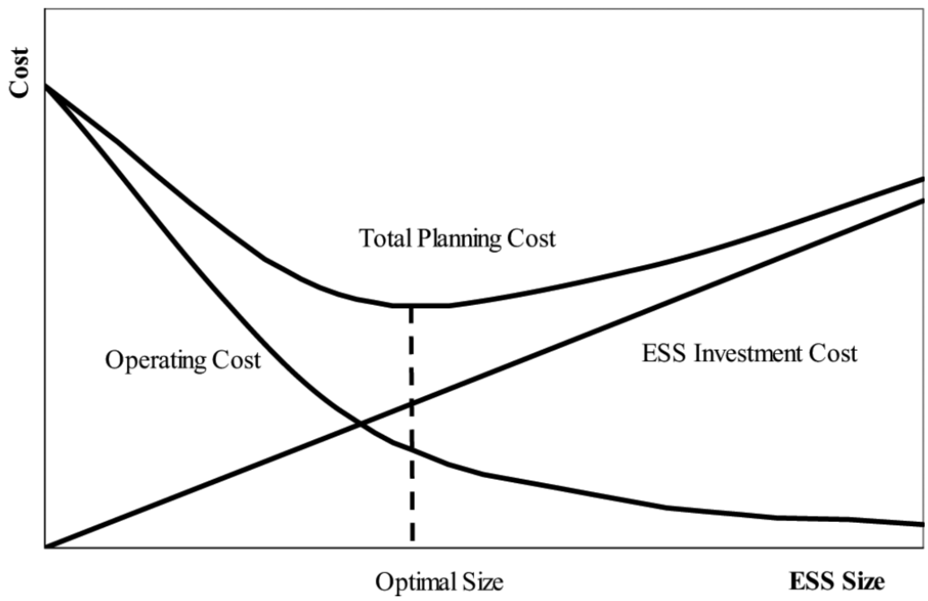

Fig.2.5 – Objective function minimisation which uses "downward pressure" preventing diverging BESS power and energy capacity variables.

minimisation, the optimal power capacity component will not diverge. The use of minimisation is not always ideal as this can leave profit for BESS too low (or negative). To overcome this in minimisation applications, profit constraints are used to ensure that BESS operators can attain enough revenue to be profitable [22].

However, an issue arises when maximisation (difference between costs and benefits) applications are introduced, which is the typical scenario for sole beneficiary BESS. If an objective function contains an optimisable power capacity variable and is also maximised, there is a possibility that the power capacity variable could diverge i.e. become unbounded. To overcome this, one option is to place a constraint on the maximum allowable power capacity variable size [31], but then selecting this size upper bound becomes subjective. Other options is to remove the power capacity variable from the objective function altogether which has been considered by many [14, 15, 21, 27, 35, 40], or assume a constant size for the power capacity variable but leave the cost component within the objective function so that the overall result is more reflective [39]. These methods for maximisation can best be considered as mere stopgaps. Ideally, the approach taken should be one of actual consequences encountered, that being the competitive nature of deregulated electricity markets. Here, if market bidding is done with large bids compared to grid size, this could have too much influence on the market clearing prices which could then lead to BESS beginning to cannibalising itself and becoming unprofitable. Large bids coincide with large available power capacity from BESS. Elaborating on this further, if a large enough BESS was to bid generation into an electricity market auction at a really low price, it would force more expensive generation to be unsuccessful in electricity market auctions. This in turn would reduce the price for this auction as electricity markets are usually paid-as-clear and not paid-as-bid. One approach to overcome this is to bid BESS generation at a higher price but this then runs the risk of not getting dispatched in a competitive auction. If this type of penalty approach was modelled as part of the overall optimisation process, it would prevent BESS power capacity variables from diverging (i.e. becoming unbounded). The penalties within the market would put “downward pressure” on the power capacity variable. One method reported in the literature applied the above penalty approach for pumped hydro station within the grid of Alberta which is transferable to BESS [30].

Ultimately, the inclusion of the power capacity variable will not form part of this work. This is mainly due to the fact that assumed values for BESS power capacity where used, are small values compared to grid size. Where applicable, the power capacity variable cost will be included within objective functions, similar to the approach used throughout literature. Also, it is important to note that BESS energy size variable won't diverge (i.e. become unbounded) under maximisation. Once power capacity is maintained constant, BESS only has a certain amount of time to either charge or discharge (i.e. it is not infinite). Therefore, when maximising, an ever-bigger BESS size increases costs but does not increase revenue which in so doing reduces overall profit.

2.9 CONSOLIDATION AND RENAMING

So far, existing BESS sizing approaches have been reviewed through the lens of six FEP scoping elements. It has been determined that conventional BESS sizing approaches are lacking in all six. Two such scoping elements, Location and Capacity (Power), remain outside the domain of this dissertation. Investment Studies and Alternative Assessments, Future Expansion, Operational Philosophy and Technology are the remaining scoping elements which require consolidation and renaming for applicability to BESS projects. Having reviewed all proposed FEP scoping elements within BESS sizing, it is now possible to consolidate the proposed scoping elements into planning objectives. The term planning objective is the original term set out at the beginning of this dissertation and has greater natural connotations within the BESS sizing community, given that sizing is typically executed via optimising an objective function which is modelled to capture the goals of a BESS project.

As already mentioned in relation to scoping element Investment Studies and Alternative Assessments, the issue for BESS sizing is one of scale i.e. existing objective functions do not discourage ever-larger BESS sizes. Therefore, it is fitting and straightforward to denote Investment Scale as the BESS sizing planning objective which encompasses this issue. Research involving planning objective

Investment Scale is associated with the first aim of this dissertation and is undertaken in Chapter 3.

Based on the BESS sizing review concerning scoping elements Future Expansion and Technology, there is important crossover between both. Firstly, while BESS capacity expansion can be one aspect of BESS sizing, a more accurate connotation is timing of multiple BESS size decisions. The addition of a timing component allows for the initial sizing decision at year 1 to be delayed or reduced, if economically advantageous to do so. The introduction of long-term BESS timing and size decisions opens up to amalgamation of different BESS technological characteristics. Such characteristics have already been deliberated as part of Section 2.6, with degradation being the one chosen as part of this study. This is of particular importance, as future timing decisions coupled with degradation can give rise to previously unknown outcomes. Recognising the discussion outlined so far, both scoping elements Future Expansion and Technology are consolidated into one focused planning objective called Investment Timing. The research associated with this planning objective is captured in the second aim of this dissertation and is set out in Chapter 4.

Lastly, on review of existing BESS sizing approaches in relation to the scoping element Operational Philosophy, a lack of modelling effort is observed which focuses on BESS owner as sole beneficiary. To combat this, cross-market arbitrage is suggested as the initial area of focus which this dissertation should partake. Therefore, the term Dispatch Adaptability is used to signify the planning objective which seeks to include cross-market arbitrage as part of BESS sizing. Use of the phrase “dispatch” is in reference to the operational decisions available to BESS throughout its lifecycle. This planning objective is encapsulated in the third aim of this dissertation and is set out in Chapter 5.

CHAPTER 3

3 OVERCOMING THE INVESTMENT SCALE PROBLEM OF ANNUAL WORTH WHEN SIZING BATTERY ENERGY STORAGE SYSTEMS

Incorporating planning objectives as part of BESS sizing is the sole purpose of this entire dissertation. In total, three planning objectives have been identified as requiring attention in this thesis, and are denoted as Investment Scale, Investment Timing and Dispatch Adaptability (see Section 2.9 for how planning objectives were determined and consolidated). The specific research within this chapter incorporates exclusively the planning objective Investment Scale as part of BESS sizing. This chapter was first published in IEEE Transactions on Sustainable Energy [70], and remains unchanged.

3.1 ABSTRACT

The financial objective, when sizing a Battery Energy Storage System (BESS) for installation in a microgrid, is to maximise the difference between discounted BESS benefits and discounted BESS costs. This may be described as maximising Annual Worth (AW). However, one drawback of sizing microgrid BESS using AW is that the scale of investment is not taken into consideration. This can lead to unrealistic BESS sizes. This chapter presents two multi-objective optimisation (MOO) models to account for the scale of investment required in sizing BESS. The first model, Paired Comparison, utilises two objective functions: Daily Worth (DW), which maximises daily benefit cost differences a BESS installation provides a microgrid; and Daily Cost (DC), which minimises the daily cost of a BESS installation. The second model, called Rating Method, uses the objective functions DW and Daily Benefit-Cost Ratio (DBCR), the latter of which maximises the relative measure of

BESS benefit and BESS cost. Both models are solved for a test microgrid system under three different scenarios using Compromise Programming (CP). For system designers who rank objective functions by importance, the Rating Method is the appropriate approach, whereas system designers who rank objective functions by absolute values should use Paired Comparison.

3.2 INTRODUCTION

Each year more and more renewable generation is connected to electrical grids around the world. The European Union alone has seen a net increase of 158.3GW of installed wind and 107.3GW of installed solar PV from 2000-2017 [71]. The added value of renewable generation is that it reduces CO_2 per MWh of energy produced when compared with traditional thermal generation. However, this added benefit comes with the disadvantage of intermittency, which can lead to scheduling, frequency and voltage difficulties for the grid. To overcome this intermittency, Battery Energy Storage Systems (BESS) are one possible solution. For a BESS to be connected to a grid (microgrid, distribution grid, etc.) it must be sized appropriately. Sizing of BESS entails determining the optimum power rating (e.g. MW) and/or energy capacity rating (e.g. MWh). “Optimum” in this case means, that for all feasible BESS sizes available for a given grid connection, only one power rating and/or one energy capacity rating represents the best-case scenario.

BESS can have financial objectives or technical objectives as in [72], or a hybrid of the two [8]. Outlining BESS objectives before sizing allows optimisation models to maximise or minimise power and/or energy ratings, which results in the optimum BESS size. This chapter is solely concerned with the treatment of financial objectives. The most common financial objective in BESS sizing is reducing the operational cost of a either a microgrid [16, 21, 24, 31] or distribution grid [12, 73]. Here the addition of BESS to a grid allows the transfer of energy over time, with charging and discharging periods optimised to reduce the overall grid operation cost. The reduction in grid operation cost can be interpreted as an added benefit of installing a BESS within the grid. Optimum BESS size is established when the benefit value is furthest from the BESS cost. Other financial objectives include installing a BESS to maximise the profit of a renewable energy installation, with a wind farm example given by [74]. While this approach is different to [12, 16, 21, 24, 31, 73], the same concept applies, that is, maximising difference between added benefits and costs of BESS. The discounted cash flows methods used by [12, 16, 21, 24, 31, 73] are known as Equivalent Annual Cost (EAC) or Annual Worth (AW) [75]. A positive AW value indicates that benefits are greater than costs. AW is analogous to Net Present Value (NPV) [76], with AW widely used in the engineering community and the accounting community preferring NPV. For simplicity, this chapter uses the term AW when referring to the absolute difference between annual discounted benefits and costs.

Selecting an investment project size by maximising the difference between discounted benefits and costs has significant disadvantages. The issue that AW demonstrates is one of scale. AW is an absolute measure and therefore does not take into account the effort required to achieve the objective. Table (3.1) illustrates the scale problem of AW, modified from [77]. Project S is given as the best option with an AW twice that of project T. However, the capital expenditure of Project S is 2000 times that of Project T. As access to capital is limited in real-world cases, clearly Project T is the preferred option. As highlighted by [77], for AW to be an appropriate metric for comparing and ranking mutually exclusive projects, the budget must be fixed and each project must have the same investment, which is impracticable for BESS sizing. Importantly, this investment scale problem is applicable to BESS sizing methodologies that employ a direct search approach, such as those in [40, 74]. This approach uses an algorithmic strategy that does not evaluate incremental BESS sizes but rather directly searches for the optimum solution. Maximisation of the objective function is carried out using optimisation software packages which directly search for values of the decision variables that

Table 3.1 – Illustration of AW criterion masking scale of effort required

Project	Annual Benefit ($)	Annual Cost ($)	AW ($)	AW as % of cost
S	2,002,000	2,000,000	2000	0.1
T	2000	1000	1000	100

give the maximum value of the objective function. This direct search approach results in a single optimal BESS size that satisfies the maximum AW. All other BESS sizes are deemed suboptimal, however there could exist BESS sizes unconsidered which retain a significant portion of AW but with much less cost. Since only a single optimal BESS size is outputted using direct approaches, this results in BESS sizing by direct search suffering the same investment scale issue as those outlined in Table 3.1.

To overcome the scale problem, other financial objectives must be considered, while still attempting to maximise AW. These financial objectives must address the core issue, i.e. consideration of the scale of investment required. One approach is to make investment an objective function itself. Maximising AW while minimising investment are conflicting objectives as increasing AW will require a larger BESS with higher cost. The other approach is to utilise relative rather than absolute measures as an objective function. One such measure is Benefit-Cost Ratio (BCR). Maximising BCR and maximising AW are conflicting as BCR is a relative measure of the same variables used by AW. It is possible to have both AW and BCR increasing over certain BESS size ranges, but ultimately as maximum AW is being reached, the rate of change of AW will decrease and therefore BCR will also decrease. The investment scale problem is inescapable in any setting which maximises AW, regardless of consideration of technical objectives or location. Therefore, since technical objectives or location do not negate the issue of investment scale they are omitted from this chapter for clarity purposes.

The aim of this chapter is to investigate if sizing a BESS via multiple financial objectives is an effective technique for overcoming the scale problem of AW. The multi-objective combinations considered are 1) AW and BESS Cost, and 2) AW and BCR. Objectively, this is achieved by developing a microgrid optimisation model where the addition of BESS is sought. The multi-objective combinations 1) and 2) are optimised for sizing BESS being added to a microgrid. To determine the effectiveness of each approach, different scenarios are analysed, and results compared.

3.3 LITERATURE REVIEW

While optimising a sole objective function has been extensively studied for sizing BESS [12, 16, 21, 24, 31, 73, 74], optimising multiple conflicting objectives has been given less attention. One approach taken by [78] optimised simultaneously three financial objective functions, 1) maximise operating profit of a BESS installation in a distribution grid, 2) minimise BESS energy capital cost and 3) minimise BESS power capital cost. This approach did not size a BESS but rather the authors determined which BESS capital cost combination would give a positive AW and by extension what AW can be expected for a given capital cost combination. A constant BESS was chosen, and capital costs varied. As part of future work the authors suggest that other financial indicators should be considered such as Internal Rate of Return (IRR) and Return of Capital Employed (ROCE). Both these indicators offer different investment performance evaluation than AW which makes them of interest for this chapter. Calculating IRR is finding the discount rate which gives a value of zero AW. IRR can be interpreted as a rate of investment measure. Maximising IRR can give conflicting investment decisions compared with maximising AW when different project initial investment levels are compared [79, 80]. IRR has been used by [81] to evaluate the financial performance of BESS. However, IRR can be a complex calculation for direct search optimisation procedures by either trial and error approach or extracting the discount rate which is raised to different power values for every time period. ROCE is a relative measure and is very similar calculation to BCR. BCR has been used by [82] for energy storage planning in distribution networks. The authors maximised the AW of energy storage but did not co-optimise two other objectives – Discounted Payback Period (DPP) and BCR. Rather, DPP and BCR were evaluated at maximum AW. This approach does not allow for co-optimisation and therefore the energy storage size is selected post optimisation. Others have used BCR to evaluate the performance of optimal power flow model for sizing and allocating BESS in a microgrid [83].

Optimising multiple objective functions has also been applied to objectives other than financial indicators. The authors in [84] used multi-objective Mixed Integer Linear Programming (MILP) to minimise CO_2 emissions and minimise operating cost for a community energy storage system. A single BESS size is considered for multiple battery technologies and the levelized cost of electricity and payback period are evaluated. Another study which sized a BESS for a PV-based microgrid maximised both the annual net profit and PV consumptive rate [85]. The problem was solved using non-dominated sorting genetic algorithm II (NSGA-II). Interestingly, [78, 85] did not make any reference to weighting of their respective objective functions, whereas [84] indicates that each objective function is equally weighted. This implies that the authors were more interested in a set of solutions rather than a single output from their models.

Other works closely related to this study use Bilevel Optimisation (BO) with two financial objective functions. BO captures hierarchical processes, where optimisation of a lower level objective function acts as a constraint in an upper level objective function. If a hierarchical process exists in a problem, then BO is considered a suitable method [86]. BO was used by [87] to size and site a BESS within a transmission grid. Here the authors considered two financial objectives. The upper level objective seeks to minimise the grid operation cost and BESS cost with profit constraints, while the lower level objective seeks to minimise grid operating cost. Similar to [87], the authors in [88] also used BO for different perspectives within the grid. Their model seeks to solve an upper level objective by maximising the profit of merchant Energy Storage (ES), while at the same time minimising grid operating cost in the lower level objective. While BO is a suitable method for hierarchical processes, and a suitable technique for capturing different perspectives within the electrical grid, the problem being considered in this chapter is a perspective-neutral approach, and therefore does not lend itself to using BO. The financial objectives as part of this chapter are competing objectives and not hierarchical. Furthermore, both [87] and [88] used profit and investment constraints for BESS installation. These constraints can provide some success in avoiding the pitfalls of maximum AW, as highlighted in the previous section. Placing these constraints into a BESS sizing optimisation model allows minimum rates of return to be enforced. However, these constraints have significant disadvantages which are discussed from this point onwards. Placing a rate of return within the profit constraint allows the ES owner to apply a relative measure to BESS investments, similarly a maximum investment constraint can have the same outcome. Although this method can be effective, using the same rate of return value while varying model input parameters may lessen its effectiveness for overcoming the AW scale problem. Having knowledge about the final solution beforehand may allow rate of return adjustment, however this knowledge may not be readily available. Another point to note is that rate of return values greater than one are difficult to interpret. It is given that investment projects with rate of return greater than or equal to one are accepted and those values of less than one are rejected [89]. However, deciding on a particular rate of return value from those that are greater than one may be difficult, as theoretically all investment projects are deemed acceptable. While the authors of both [87] and [88] used profit and investment constraints, these were not discussed in the context of overcoming the pitfalls of maximising AW.

3.4 PROBLEM FORMULATION

Multi-objective optimisation (MOO) allows for tradeoff analysis of two or more objective functions. The problem structure is outlined by (3.1) and (3.2) and is formulated as two separate MOO problems capturing two different approaches.

$$F_1(x) = [f_{AW}(x),\ f_{Cost}(x)]^T \tag{3.1}$$

$$F_2(x) = [f_{AW}(x),\ f_{BCR}(x)]^T \tag{3.2}$$

where $f_{AW}(x)$ is the AW objective function (3.28), $f_{Cost}(x)$ is the cost objective function (3.29) and $f_{BCR}(x)$ is the BCR objective function (3.30). There is a significant difference between $F_1(x)$ and $F_2(x)$. This difference is due to the individual ability of $f_{Cost}(x)$ or $f_{BCR}(x)$ to size BESS separately of $f_{AW}(x)$. For approach (3.2) both objective functions are capable of sizing BESS autonomously. Each contains both benefits and costs within its objective function. For approach (3.1) $f_{AW}(x)$ has this ability, whereas $f_{Cost}(x)$ only considers BESS cost and therefore is incapable of sizing a BESS independently. Rather, $f_{Cost}(x)$ is used as a measure of amount spent. This difference leads to different interpretations of the tradeoff within each approach. In approach (3.1) the question for tradeoff is, how much change is allowed in $f_{AW}(x)$ with respect to change in $f_{Cost}(x)$. In approach

(3.2), the question for tradeoff is deciding which objective function is more important.

This difference between $F_1(x)$ and $F_2(x)$ requires different solution techniques for MOO methods involving weighted objective functions. Weights are assigned to each objective function for a priori articulation of preferences in certain MOO methods [90]. The authors of [91] identify two broad classes of approach, Paired Comparison and Rating Method. In Paired Comparison the objective functions remain in their original state so that tradeoff analysis between absolute values of each objective function is permitted. This approach lends itself to $F_1(x)$ where the change in AW with respect to change in cost is sought. In the Rating Method approach the objective functions are normalised. This provides a unitless comparison of the objective functions while also reducing any magnitude dominance of either objective function. This allows objective functions to be ranked in terms of importance where system designers select a ranking out of 10 for each objective function [92]. The Rating Method described is equivalent to the problem described by $F_2(x)$. Given that $F_1(x)$ is Paired Comparison and $F_2(x)$ is Rating Method, the appropriate techniques are applied to each. Fig.3.1 gives an overview of the problem formulation.

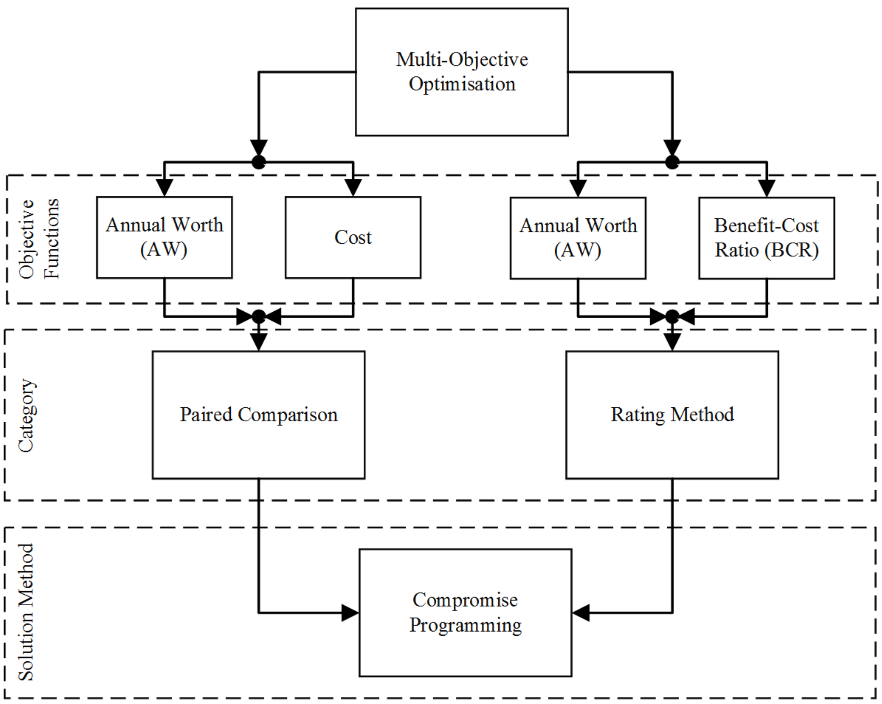

Fig.3.1 – Structure of MOO problem formulation used in this chapter.

3.5 SYSTEM MODELLING

A microgrid without a BESS is used as the reference case. The reference microgrid consists of two microturbines, wind turbine, solar PV, connection to large external grid and load. The owner of the BESS is the owner of the microgrid, who also owns the generation and demand. The first microturbine is must run while the second has a minimum generation limit with startup cost. No microgrid reserve requirement and no power losses is assumed. The addition of a BESS is sought to improve the financial performance of the microgrid i.e. to operate the microgrid at lower cost.

3.5.1 MODEL

3.5.1.1 BESS MODEL

The BESS energy capacity rating is given by (3.3), where S_i is a set of parameters signifying BESS size and XB_i is a set of binary decision variables.

$$E_{BESS} = \sum_{i=1}^{b} S_i XB_i \quad \forall i, \tag{3.3}$$

There are two reasons for implementing E_{BESS} as a summation of binary variables. The first is that BESS are manufactured based on incremental sizes rather than a continuous range of sizes. The second reason allows for the linearization of the BCR objective function, which is described in more detail in 3.5.2 of this section. S is given by (3.4).

$$S_{i+1} = 2 \times S_i \quad \forall i, \tag{3.4}$$

The initial value of S_i is the size increment available for BESS. The value given to b needs to be large enough to capture all available BESS sizes but not so large as to increase computation time significantly.

C-rate is a design constraint that limits the number of power and energy rating combinations for BESS and is given by (3.5) and (3.6).

$$XP_t^- \geq C_{rate} E_{BESS} \; \forall t \tag{3.5}$$

$$XP_t^+ \leq C_{rate} E_{BESS} \; \forall t \tag{3.6}$$

Where t is time period, XP_t^- and XP_t^+ are the charging and discharging power variables respectively, located at the BESS and microgrid connection point and are bounded by (3.7) and (3.8).

$$-WP_t - SP_t \leq XP_t^- \leq 0, \forall t \tag{3.7}$$

$$0 \leq XP_t^+, \forall t \tag{3.8}$$

where WP_t and SP_t are the amount of power at time t interval from wind and solar respectively. This constraint enforces BESS charging from renewable energy. Allowing $XP_t^+$to have no upper bound, the C-rate constraint in (3.6) ensures that the BESS discharge power variable is within acceptable limits.

The equations to govern the amount of energy in the BESS during each time interval is given by (3.9) and (3.10).

$$\Delta t XP_t^- \eta_c + \Delta t XP_t^+ / \eta_d + \sum_{i=1}^{t-1} \Delta t SP_i^- \eta_c + \Delta t SP_i^+ / \eta_d \leq 0, \forall t \tag{3.9}$$

$$\begin{aligned} &\Delta t XP_t^- \eta_c + \Delta t XP_t^+ / \eta_d + \sum_{i=1}^{t-1} \Delta t SP_i^- \eta_c + \Delta t SP_i^+ / \eta_d \\ &\geq -E_{BESS}, \forall t \end{aligned} \tag{3.10}$$

Where η_c and η_d are the charge and discharge efficiencies respectfully, Δt is the time interval, SP_i^- and SP_i^+ are BESS power variables and are given by (3.11) and (3.12).

$$XP_t^- = SP_i^-, t = i \tag{3.11}$$

$$XP_t^+ = SP_i^+, t = i \tag{3.12}$$

BESS manufacturers place limits on the allowable energy throughput over a period of time, such as a year. In exchange for these limits, customers receive a warranty for their BESS. It is assumed that the warranty period is sectionalized into yearly limits. This is a further BESS model constraint as is given by (3.13) where T is the number of time intervals in one year, E_{thru} is the energy throughput allowed by the BESS manufacturer under warranty.

$$\sum_{t=1}^{T} \Delta t XP_t^+ / \eta_d \leq \frac{E_{thru}}{365} \tag{3.13}$$

3.5.1.2 MICROGRID MODEL

The variable L_t represents the microgrid load at time interval t. This load must equal generation at all times t and is specified by (3.14)

$$XM_{1,t} + (M_2^-)XM_{2,t}^b + XM_{2,t} + WP_t + SP_t + XP_t^- + XP_t^+ + XG_t^- + XG_t^+ = L_t \;\forall t \tag{3.14}$$

where $XM_{1,t}$ is the first microturbine (must run) with a minimum value as shown in (3.15), the second microturbine has the binary variable $XM_{2,t}^b$ for minimum generation at start-up (M_2^-) and $XM_{2,t}$ for dispatchable power, XG_t^- and XG_t^+ are power exported and imported from the external grid respectively. No curtailment of renewable energy is assumed so that all power from renewable sources must be accepted. The variables in (3.14) are bounded by (3.15), (3.16), (3.17) and (3.18).

$$M_1^- \leq XM_{1,t} \leq M_1^+ \;\;\forall t \tag{3.15}$$

$$0 \leq XM_{2,t} \leq M_2^+ - M_2^- \;\;\forall t \tag{3.16}$$

$$-G^- \leq XG_t^- \leq 0 \quad \forall t \tag{3.17}$$

$$0 \leq XG_t^+ \leq G^+ \quad \forall t \tag{3.18}$$

Given that the second microturbine requires a minimum generation of M_2^-, a further constraint (3.19) is applied to the model. This ensures that if $XM_{2,t}$ is selected to run then the minimum generation requirement is imposed. The variable XU_t (3.20) is introduced to capture the start-up cost of the second microturbine.

$$(M_2^+ - M_2^-)XM_{2,t}^b \geq \;XM_{2,t} \quad \forall t \tag{3.19}$$

$$XU_t \;\geq XM_{2,t+1}^b - XM_{2,t}^b \;\forall t \tag{3.20}$$

3.5.1.3 TIME HORIZON

Typically, AW and BCR are maximised over one year if the same cash flows are assumed for each year. The purpose of this chapter is to demonstrate the effectiveness of the methodology for a simple microgrid test case. Therefore, to save computation time, BESS sizing is done over one day, with 24-hour periods. The BESS benefit per day is given by the added benefit over 24 hours, whereas the coefficient for BESS cost per day is given by (3.21). This approach has been used by [21, 31].

$$E_{Cost} = \left(\left(\left(\frac{r(1+r)^l}{(1+r)^l - 1} \right) E_{CC} \right) + E_{MC} \right) \frac{1}{365} \tag{3.21}$$

where r is the financing interest rate, l is length of the project, E_{CC} (\$/kWh) is the capital expense of the BESS along with auxiliary equipment and civil works, E_{MC} is the annual maintenance cost in \$/kWh per year.

3.5.2 OBJECTIVE FUNCTIONS

The objective functions used for Paired Comparison are $f_{AW}(x)$ (3.28) consisting of benefits and cost, and $f_{Cost}(x)$ (3.29) with only cost. Rather than analysing the total benefit and cost of the microgrid for a given day, the added benefit of the BESS is considered. This requires optimisation of the microgrid without a BESS to find reference case for comparison. The operational cost of the microgrid without a BESS is given by (3.22).

$$C_{Grid}^{BESS^-} = \sum_t \left(XM_{1,t}C_{M1} + XM_{2,t}^{SU}C_{M2}^{SU} + (M_2^-)XM_{2,t}^{b}C_{M2} + XM_{2,t}C_{M2} \right) \tag{3.22}$$

where $C_{Grid}^{BESS^-}$ is the cost to run the microgrid with no BESS, $XM_{2,t}^{SU}$ is a binary variable for startup cost, C_{M1} is the dispatch cost of microturbine 1, C_{M2}^{SU} and C_{M2} are the startup and dispatch costs of microturbine 2 respectively. It is assumed that wind, solar, external grid and BESS have no dispatch costs. The total benefits of the microgrid without BESS are given by (3.23).

$$B_{Grid}^{BESS^-} = \Delta t \sum_t XM_{1,t}Q_t + (M_2^-)XM_{2,t}^{b}Q_t + XM_{2,t}Q_t + WP_tQ_t + SP_tQ_t + XG_t^+(-Q_t) \tag{3.23}$$

Where Q_t is the price of electricity for time interval t. For XG_t^+ the price of electricity is negative as this is buying electricity from the external grid. The maximum difference between microgrid benefit and cost without a BESS is given by (24). This value remains constant and only requires solving once.

$$OC = max\left(B_{Grid}^{BESS^-} - C_{Grid}^{BESS^-}\right) \tag{3.24}$$

As the BESS considered here has no dispatch cost, then $C_{Grid}^{BESS^-} = C_{Grid}^{BESS^+}$, where $C_{Grid}^{BESS^+}$ is the cost of operating the microgrid when a BESS is installed. The benefit of BESS connected to a microgrid is given by (3.25).

$$B_{Grid}^{BESS^+} = \Delta t \sum_t XM_{1,t}Q_t + (M_2^-)XM_{2,t}^bQ_t + XM_{2,t}Q_t + WP_tQ_t + SP_tQ_t + XP_t^-Q_t + XP_t^+Q_t + XG_t^+(-Q_t) \tag{3.25}$$

Therefore, the added benefit of installing a BESS to a microgrid is shown in (3.26) and the cost of BESS is shown in (3.27).

$$B_{BESS} = \left(B_{Grid}^{BESS^+} - C_{Grid}^{BESS^+}\right) - OC \tag{3.26}$$

$$C_{BESS} = E_{Cost}E_{BESS} \tag{3.27}$$

Taking (3.26) and (3.27) as the benefit and cost respectively, the objective functions for Paired Comparison are formulated in (3.28) and (3.29). As this analysis is for one day, the AW term is restated as Daily Worth $f_{DW}(x)$ and the term $f_{Cost}(x)$ is changed to $f_{DC}(x)$. For the decision variable $x = \{XM_{1,t}, XM_{2,t}^{SU}, XM_{2,t}^b, XM_{2,t}, XP_t^-, XP_t^+, XG_t^-, XG_t^+, XB_i\}$

$$\frac{f_{AW}(x)}{365} = f_{DW}(x) = B_{BESS} - C_{BESS} \tag{3.28}$$

$$\frac{f_{Cost}(x)}{365} = f_{DC}(x) = C_{BESS} \tag{3.29}$$

$$\frac{f_{BCR}(x)}{365} = f_{DBCR}(x) = \frac{B_{BESS}}{C_{BESS}} \tag{3.30}$$

$$f_{DBCR}(x) = \gamma \tag{3.31}$$

$$z_i \leq \gamma^+ XB_i \tag{3.32}$$

$$z_i \leq \gamma \tag{3.33}$$

$$z_i \geq \gamma - \gamma^+(1 - XB_i) \tag{3.34}$$

$$\sum_{i=1}^{a} XB_i \geq 1 \tag{3.35}$$

For the Rating Method, objective functions $f_{DW}(x)$ and $f_{DBCR}(x)$ are optimised. The change of annual BCR to Daily Benefit Cost Ratio (DBCR) is shown as $f_{BCR}(x)$ to $f_{DBCR}(x)$, where $f_{DBCR}(x)$ is given by (3.30).

To ensure that the problem remains linear, the constraints (3.31), (3.32), (3.33), (3.34) and (3.35) are applied to convert the nonlinear equation (3.30) to linear form, where γ^+ is some value larger than the maximum of γ, z_i is the variable assigned to the product of γ and XB.

3.5.3 MULTI OBJECTIVE – PAIRED COMPARISON, RATING METHOD AND COMPROMISE PROGRAMMING

Compromise Programming (CP) is a MOO method which can find non-convex solutions within a Pareto set. Non-convex solutions are of importance to the sizing problems being considered as large benefit gains are expected from the reduction in startup cost of microgrid generators. The CP formulation, developed by [93, 94], is shown in (3.36) for Paired Comparison and in (3.37) for the Rating Method, whose form is applicable to the MOO problem in this chapter.

$$min\left\{\left[w_1\left(f_{DW}^+ - \boldsymbol{P}_{a,1}\right)\right]^p + \left[w_2\left(f_{DC}^+ - \boldsymbol{P}_{a,2}\right)\right]^p\right\}^{\frac{1}{p}} \tag{3.36}$$

$$min\left\{\left[\lambda_1\left(\frac{f_{DW}^+ - \boldsymbol{P}_{a,1}}{f_{DW}^+ - f_{DW}^-}\right)\right]^p + \left[\lambda_2\left(\frac{f_{DBCR}^+ - \boldsymbol{P}_{a,2}}{f_{DBCR}^+ - f_{DBCR}^-}\right)\right]^p\right\}^{\frac{1}{p}} \tag{3.37}$$

where w is the corresponding weight for each objective function. The interpretation of the weights is given by $dF_{DC}/dF_{DW} = w_1/w_2$. $\lambda \in \mathbb{Z}^+$ and is the importance of each objective function, p is a metric parameter, f_{DW}^+, f_{DBCR}^+ and f_{DC}^+ are utopia points, f_{DW}^- and f_{DBCR}^- are nadir points. $\boldsymbol{P}$ is a matrix of Pareto solutions for DW and DBCR objective functions. $\boldsymbol{P}$ is evaluated using the solution algorithm in the next section. As a MOO method, CP attempts to find a set (or point) on the Pareto front that is closest to the infeasible utopia point. The Euclidean distance from the Pareto front to the utopia point is minimised. Typically, the utopia point is the maximum or minimum (depending on problem) of each objective function. When p is equal to one, this minimises the distance of minimum regret of not achieving the utopia point, and when equal to ∞, minimises the distance of maximum regret of not achieving the utopia point [93, 94]. Varying p from 1 to ∞ can also give a set of points on the Pareto front, called the compromise set.

3.6 SOLUTION ALGORITHM

The software used for this analysis was MATLAB 9.3 with the intlinprog function for optimisation. To utilise CP from the previous section, within MATLAB's functionality, the Pareto Front is evaluated beforehand. The Pareto front is developed by employing the Normal Boundary Intersection (NBI) method. NBI is a MOO method, and was developed by [95] to overcome disadvantages of the Weighted Sum Method, namely, generating points in non-convex regions and even spacing of Pareto points. The NBI formulation is shown in (3.38) and is applied to the MOO problem in this chapter by (3.39), (3.40) and (3.41), where e is a column vector of ones, j is DW, k is DC when optimising Paired Comparison or DBCR when optimising the Rating Method.

$$\max_{x,D} D \; s.t., \Phi\beta + D\hat{n} = F(x) \tag{3.38}$$

$$\Phi\beta = \begin{bmatrix} \left(\dfrac{f_j(x) - f_j(x_j)}{f_j(x_k) - f_j(x_j)}\right) & \left(\dfrac{f_j(x) - f_j(x_j)}{f_j(x_k) - f_j(x_j)}\right) \\ \left(\dfrac{f_k(x) - f_k(x_k)}{f_k(x_j) - f_k(x_k)}\right) & \left(\dfrac{f_k(x) - f_k(x_k)}{f_k(x_j) - f_k(x_k)}\right) \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \tag{3.39}$$

$$D\hat{n} = D(-\Phi e) \tag{3.40}$$

$$F(x) = \begin{bmatrix} \left(\dfrac{f_j(x) - f_j(x_j)}{f_j(x_k) - f_j(x_j)}\right) \\ \left(\dfrac{f_k(x) - f_k(x_k)}{f_k(x_j) - f_k(x_k)}\right) \end{bmatrix} \tag{3.41}$$

The matrix Φ is also called the pay-off matrix and when combined with β gives the Convex Hull of Individual Minima (CHIM). In two-dimensional space, CHIM can be thought of as a line connecting the maximum of two conflicting objective functions. The values in Φ are as follows: $f_j(x_j)$ which is the value of f_j when j is maximised, $f_j(x_k)$ which is the value of f_j when k is maximised, $f_k(x_j)$ which is the value of f_k when j is maximised and $f_k(x_k)$ which is the value of f_k when k is maximised. Also shown in Φ is the normalisation of the values. $\hat{n}$ is the unit normal to the CHIM. Therefore, by maximising D, the resulting expression $\Phi\beta + D\hat{n}$ gives access to all points along the normal and varying β allows for selecting different points along CHIM. The equality in (3.38) ensures that the maximum value of D is constrained by the boundary of the Pareto Front at $F(x)$, while maximising x gives the largest value for F. The outline for the solution algorithm is shown in Fig.3.2. The change in β is determined by the number of points that are needed in the Pareto front. For every iteration of maximising D, the value of each objective function is recorded in matrix $\boldsymbol{P}$. Equation (3.36) and (3.37) is evaluated for every row of matrix $\boldsymbol{P}$, with the minimum value being the optimum point for CP. The algorithm was run on a Dell Latitude E5470 laptop with Intel Core i7-6600 CPU @2.60GHz and 16GB of RAM. For scenario 1, with the algorithm running 24 electricity trading periods of analysis, the time to completion is 22 seconds, for comparison with 96 trading periods taking 183 seconds. The number of variables to solve for in the 24 electricity periods is 273 with 993 variables to solve for in the 96 trading periods.

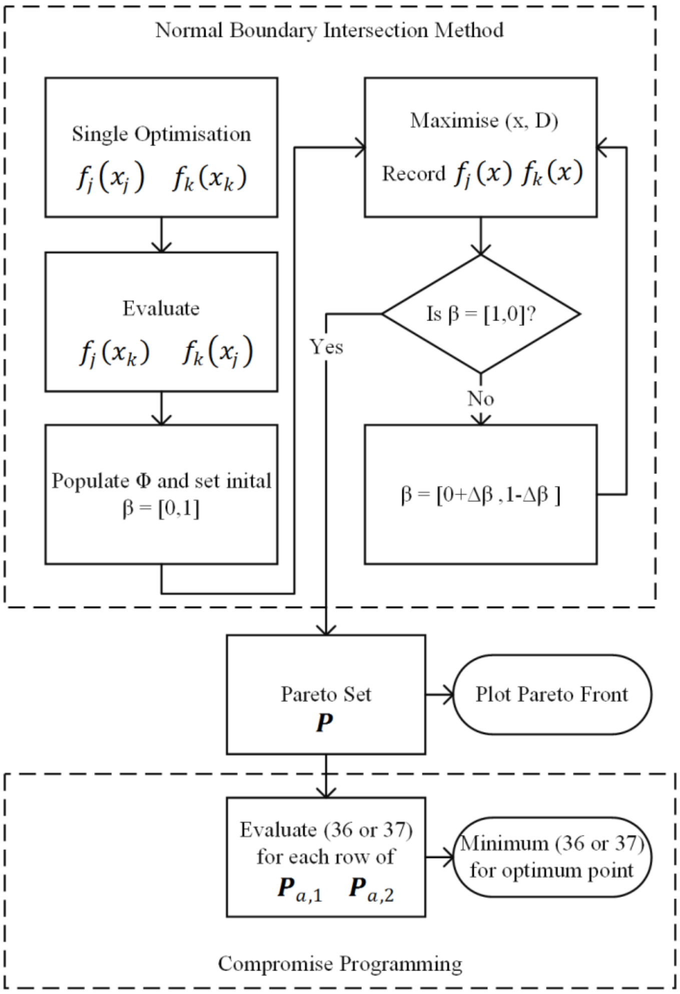

Fig.3.2 – Flow diagram of solution algorithm. The NBI method develops the Pareto Front first and CP uses the developed Pareto set to find the BESS solution

3.7 SCENARIOS AND DATA

Three different illustrative scenarios of electricity market price are utilised, shown in Fig.3.3, so that different Pareto Front shapes can be analysed. This is a methodology chapter where the focus is not to generate a specific system design but to show the workings of the proposed methodology. Therefore, the scenarios are for illustrative purposes. Electricity market price has a significant role in determining which generators are dispatched, which in turn influences Pareto Front shape. Scenario 1 is a 75% increase in electricity market price for each trading period from the scenario based on the widely used paper [21]. Scenarios 2 and 3 are a 50% and 25% decrease in electricity market price respectively for each trading period from the same scenario used in [21]. The price increase of scenario 1 promotes the dispatch of expensive generation whereas scenario 2 and 3 import more electricity from the external grid. Scenario 1 has capital costs (E_{CC}) of 593 \$/kWh, operation and maintenance cost (E_{MC}) of 0.04 \$/kWh per year and efficiency values η_c and η_d both 86% respectively. All values are taken from [96] based on Lithium BESS. Scenarios 2 and 3 have capital costs of 342 \$/kWh.

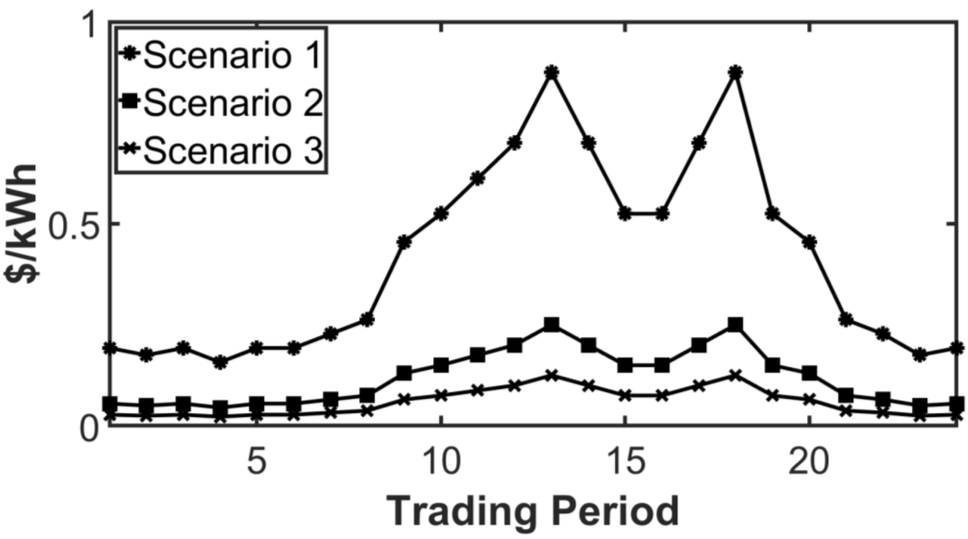

Fig.3.3 – Market Price scenarios utilised in this study. Variation of market prices over one day for three scenarios used in this study. Prices shown in decreasing order from scenario 1 with the highest price to scenario 3 with the lowest price.

The following assumptions are used for each scenario: C_{rate} is 0.5, b is 14, initial S_i is 1, Δt is 1, E_{thru} is 1kWh throughput per 1kWh of installed BESS capacity, Interest rate of finance r is 8%, project length is 10 years and γ^+ is 10. The load of the microgrid (L_t) is shown in Fig.3.5 (b) and (c) along with wind ($WP_t -$ highlighted blue) and solar ($SP_t -$ highlighted orange) power profile respectively. Given that wind and solar must be dispatched, their values do not change for each scenario. The data in Table 3.2 is taken from [21] and is the same for each scenario.

Table 3.2 – Microgrid Data for Cost and Generation

Gen	($/kW) variable	($/start) variable	(Min P kW) variable	(Max P kW) variable
MT1	(0.13) C_{M1}	N/A	(1000) ${M_1}^-$	(2000) ${M_1}^+$
MT2	(0.35) C_{M2}	(30) C_{M2}^{SU}	(100) ${M_2}^-$	(1000) ${M_2}^+$
External Grid	N/A	N/A	(-1000) G^-	1000 G^+

3.8 ANALYSIS

The effectiveness of each approach, Paired Comparison and Rating Method, is assessed for their ability to size projects within the "knee" region of the Pareto Front. The knee region is a set of points on the Pareto Front where a small change in either objective function corresponds to a large change in another objective function. The significance of this is that reducing or increasing objective functions within the knee region has damaging effect on the optimum solution. Therefore, choosing a point within the knee region represents a better decision. This concept has been used to find knee regions at any location along a Pareto Front [97, 98]. However, the main concern for this chapter is knee regions presented near maximum DW which allows focus of this analysis on weighting allocation of each objective function.

Taking Scenario 1 for each approach, Paired Comparison and Rating Method are shown in Fig.3.4 (a) and (b) respectively. For Paired Comparison, objective functions DW and Cost are optimised. Point A in Fig.3.4 (a) has a weighting w_1 of 2 and w_2 of 1, with a p value of 2 to realise any non-convex Pareto points. By applying these values, the system designer is inferring that they are willing to accept a DW change of \$1 for a change of \$2 in increased cost. Using these weightings, the BESS size at Point A is 1964 kWh. However, Point A is not in the knee region. Assigning weights in an absolute tradeoff situation, such as in Paired Comparison, only allows

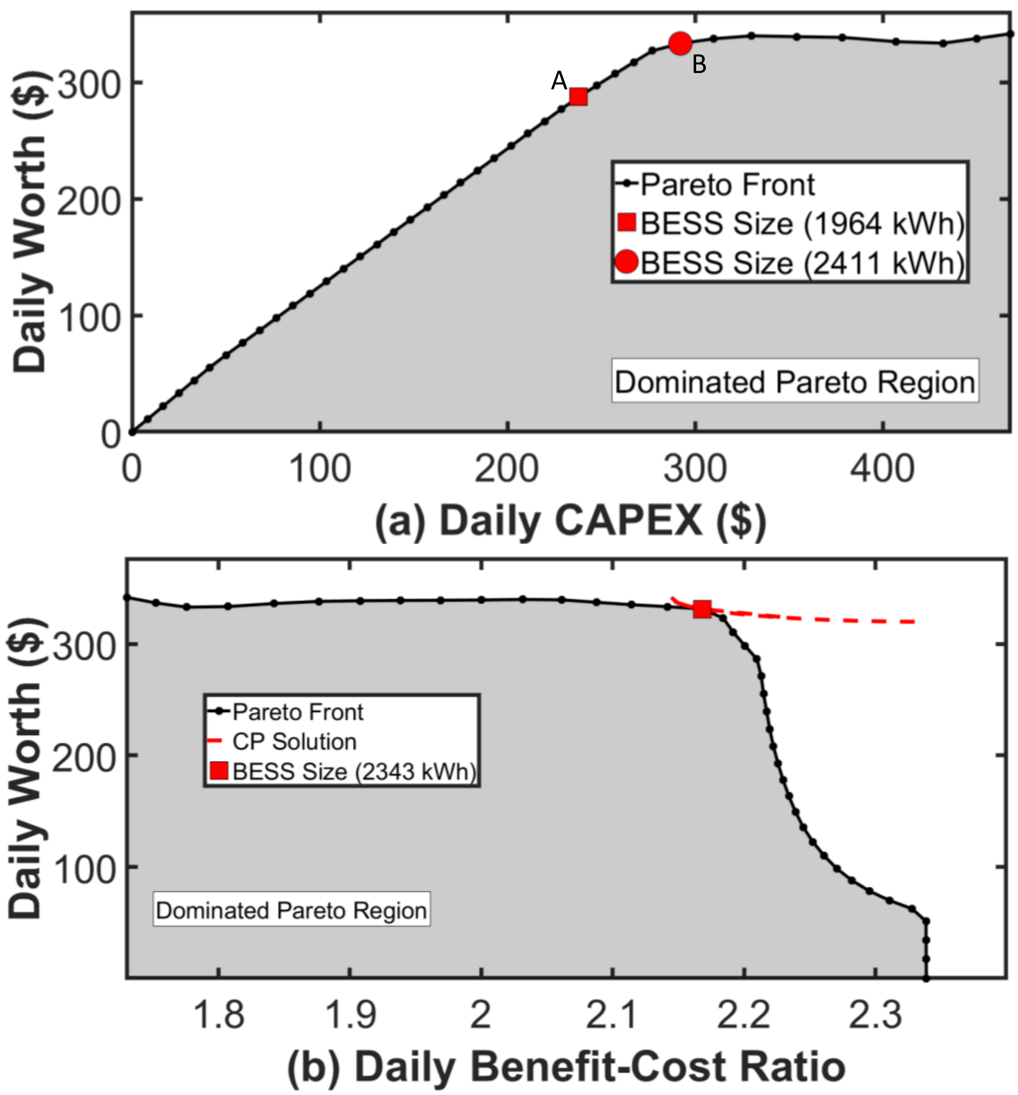

Fig.3.4 – (a) Paired Comparison of DW and Cost objective functions with tradeoff of two different weight values for scenario 1 and (b) Rating Method of DW and DBCR objective functions for scenario 1.

system designers to allocate preference to objective functions by the absolute difference between them. This approach does not allow system designers to find knee regions. Knee regions can form in any location on the Pareto Front under any circumstances. For example, if DW values where changed but the shape of the Pareto remained the same, then the weighting values w_1 of 2 and w_2 of 1 could give solutions within the knee region but only under these changed DW values. This highlights that two Pareto fronts with the same shape, but different absolute values, will give different optimal solutions for the knee region when the same weightings are used. Therefore, in Paired Comparison, knowledge about the final solution is required to ensure certainty of obtaining values within the knee region. One possible workaround is to normalise both DW and Cost objective functions, however as stated earlier, the cost objective function is incapable for sizing a BESS in isolation and therefore normalising would be meaningless. Point B in Fig.3.4 (a) has a weighting w_1 of 8 and w_2 of 1. Point B is located in the knee region. However, as stated earlier, these weightings may not work for different Pareto sets. While the Paired Comparison approach is not suitable for sizing within knee regions, it does have merit. If the system designer understands the tradeoff they are seeking, meaning they are unconcerned with finding knee regions, then this method does allow for obtaining a meaningful solution.

Unlike the Paired Comparison approach which infers weightings as absolute tradeoff values, the Rating Method determines solutions by importance of each objective function. The Rating Method ask system designers to rank each objective out of 10. For BESS sizing this presents system designers with an easier question to answer than the tradeoff question for Paired Comparison. The Rating Method captures the importance of objective functions through normalising. This also allows the same weighting allocation across different Pareto Fronts, which is not suitable in Paired Comparison. Fig.3.4 (b) outlines the optimum BESS size with weightings λ_1 and λ_2 as 10 and 2 respectively. This can be interrupted as DW with a rating of 10 out of 10 and DBCR with a rating of 2 out of 10. These weighting values reflect the interest in knees regions close to maximum DW. Selecting a higher value for λ_2 would move the focus closer to maximum DBCR.

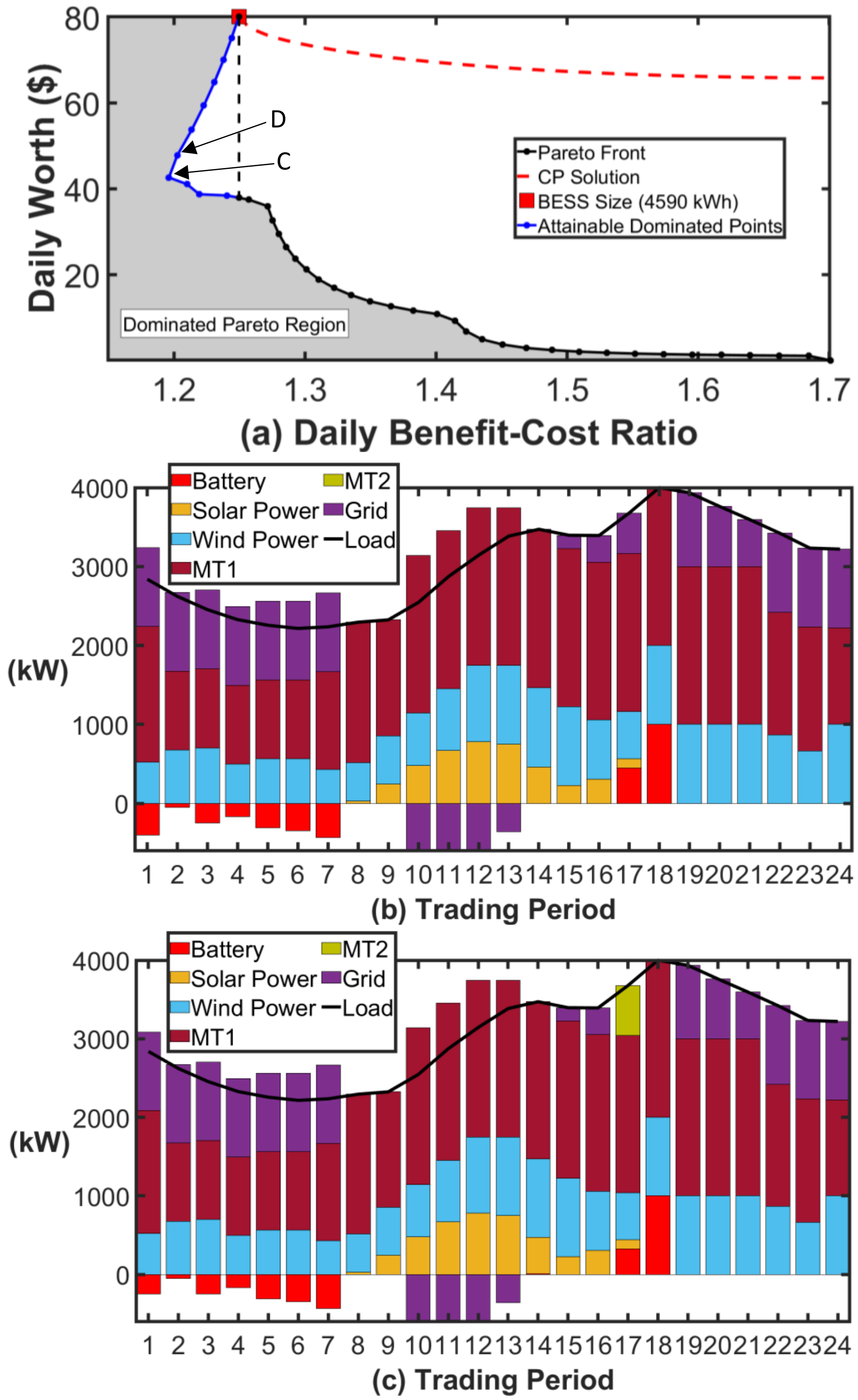

Fig.3.5 – (a) DW and DBCR showing effect of microgrid dispatch on Pareto Front (b) Dispatch Profile at point D with DW of $47.9 and (c) Dispatch Profile at point C with DW of $42.7. All for scenario 2.

The p value is maintained at 2. What is clear from Fig.3.4 (b) is that there is a predominat knee region. A significant point to note is the large BESS size difference between maximum DW and the optimised BESS size in Fig.3.4 (b). The BESS size at maximum DW ($342) is 3862 kWh whereas the Rating Method solution BESS size is 2343 kWh with a DW of $331. The Rating Method solution BESS size has 97% of the total DW available but achieves this with a BESS size that is 60.7% of the maximum BESS size. Therefore, allowing a drop of 3% in (DW) profit will give a reduction of 39.3% in BESS size and capital spending. This solution represents a more realistic sizing approach and helps overcome the AW scaling problem.

Pareto Front shape and the formation of knees is influenced be several factors. For scenario 2, the Pareto front, CP solution, attainable dominated points and microgrid dispatch profiles are shown in Fig.3.5. Solution points to the left of the vertical dashed line in Fig.3.5 (a) are attainable dominated points and are therefore not part of Pareto front. The attainable dominated points undergo a significant change between DW $40 and $50, where both functions begin to increase. This change is caused by the shutdown of generator two when the BESS reached critical size. Fig.3.5 (b) is the dispatch profile at point D where DW is $47.90 and BESS size is 3379 kWh. Fig.3.5 (c) is the dispatch profile at point C with DW equal to $42.7 and BESS size of 3119 kWh. These two points represent a significant shift. The main difference occurs at trading period 17, with a smaller difference at trading period 14. Point D represents the next BESS size after point C where the DW value is greater than $42.7. When the BESS reaches point D, the BESS is large enough to shut down microturbine 2 generator for trading period 17. This shutdown gives a large sudden increase in benefit value to the microgrid as the startup costs are replaced with cheaper electricity stored in a BESS. This reduced cost in the form of extra benefit causes a significant rise in DW value along with a rise in DBCR. This particular situation occurs when large sudden benefits are realised and can have significant effect on the shape of the Pareto. Points C and D are attainable dominated points and cannot been recommended as potential BESS sizes for this application as better solutions exist on Pareto front.

The percentage differences shown for scenario 1 may not exist in every BESS sizing problem. The following example show this and why the methods used in this chapter hold regardless. Fig.3.6 illustrates the Pareto Front of DW and DBCR for scenario 3. The weighting values used for λ_1 and λ_2 are 10 and 2 respectively. Fig.3.6 has no knee region within the vicinity of maximum DW, with only two slight knees in the middle and near maximum DBCR. The maximum BESS size 1944 kWh is selected for scenario 3. This point is selected as the change in DBCR objective function is relatively constant in the region of maximum DW. Therefore, DBCR has less influence on the final decision. This demonstrates the ability of the Rating method to also select maximum DW BESS sizes.

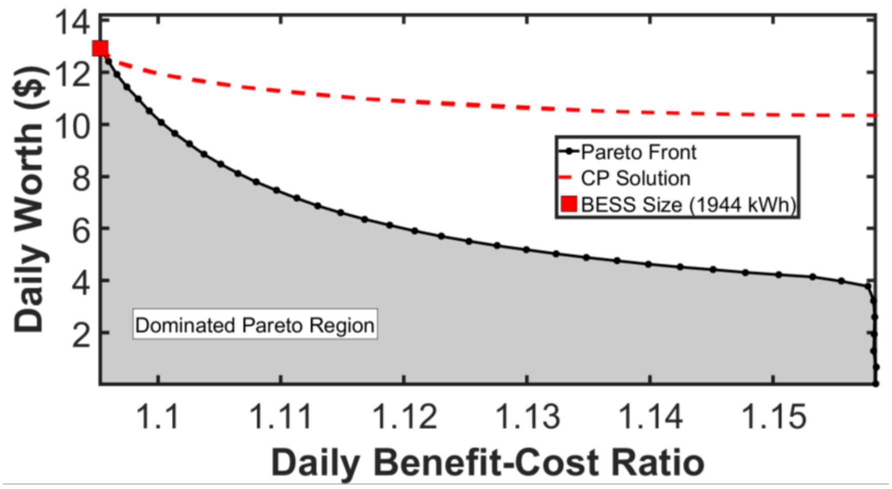

Fig.3.6 – DW and DBCR for scenario 3 showing insignificant knee regions

System designers need to know which values of w_1, w_2, λ_1 and λ_2 to use. As highlighted previously the main concern for sizing BESS is significant knee regions near maximum DW. These knee regions represent a large change in capital spend for a small gain in DW (depending on the severity of the knee region). It was shown that Paired Comparison is not effective for finding knee regions near maximum DW due to the inability of constant w_1 and w_2 values to produce consistent results for varying DW values but with similar Pareto Front shapes. Therefore, having a prescribed value for w_1 and w_2 is not possible. The only possibility for w_1 and w_2 is that the system designer knows the absolute trade-off they want beforehand, which may be the case. For the Rating Method, an acceptable value to use is 10 for

λ_1 and 2 for λ_2 which gives the system designer the flexibility to size BESS up to maximum DW when no knee regions are present. Also, this provides protection for sizing BESS when knee regions are more pronounced near maximum DW.

3.9 CONCLUSION

The problem of scaling associated with sizing BESS by maximising DW is addressed utilising the methods outlined in this chapter. This chapter presents a novel method for determining BESS size based on multi-objective optimisation of two financial objectives. Compromise Programming is utilised to apply weightings to objectives functions in both Paired Comparison and Rating Method. Three different price scenarios are modelled to show the effectiveness of each approach. Analysis of the methods show that:

- CP is an effective MOO technique for finding the optimal BESS size to overcome the investment scale problem. The advantage of using CP is that it provides a single solution from a Pareto Front when the weightings are applied to represent objective function importance. Also, CP is able to provide solutions in non-convex regions which is likely in microgrid settings due to the change in DW that occurs from the minimum power start-up requirements of dispatchable generators.
- Applying absolute tradeoff measures for determining knee regions is not an effective technique for finding optimum BESS sizes. Absolute value tradeoff is suitable for system designers who can clearly identify their absolute tradeoff values between objective functions and are not concerned with finding solutions in knee regions.
- The Rating Method is more applicable for BESS sizing. For scenario 1, the Rating Method provided a drop in DW of 3% with a capital expenditure drop of 39.3%, which represents a more realistic BESS sizing decision. Further to this, not all knee regions will give such percentage differences. The Rating Method presents an easier question for system designers to answer and is more suitable for finding knee regions than Paired Comparison. Also, the Rating Method can find maximum DW with no knee region in the Pareto Set.

- Finding solutions within the maximum DW regions requires a high weighting value for DW objective function and low value for DBCR objective function. The values used in this study, 10 for λ_1 and 2 for λ_2, represent acceptable weightings that can find optimal BESS sizes when the investment scale has and doesn't have a significant influence on the final BESS size.

It is acknowledged that other objectives rather than just purely financial objectives should be considered as part of any future work. For example, system operational requirements such as reserve provision or voltage/frequency regulation could be incorporated in the approach, or microgrid operational constraints associated with dispatch of the MT units and renewable generators.

CHAPTER FOUR

4 OPTIMAL INVESTMENT TIMING AND SIZING FOR BATTERY ENERGY STORAGE SYSTEMS

Incorporating planning objectives as part of BESS sizing is the sole purpose of this entire dissertation. In total, three planning objectives have been identified as requiring attention in this thesis, and are denoted as Investment Scale, Investment Timing and Dispatch Adaptability (see Section 2.9 for how planning objectives were determined and consolidated). The specific research within this chapter incorporates exclusively the planning objective Investment Timing as part of BESS sizing. This chapter was first published in Journal of Energy Storage [99], and remains unchanged.

4.1 ABSTRACT

Due to electricity market deregulation over the past two decades, the responsibility for new generation is with private investors who seek profit maximisation. Battery Energy Storage Systems (BESS), which are one solution to combat the intermittent nature of renewable energy sources, also require private investment for widespread deployment. This chapter develops a methodology for applying Real Options Analysis to a BESS project from the perspective of private investors to determine the optimal investment time and BESS capacity size (MWh). Two models with different timescales are utilized: the operational model which is hourly, and the planning model which is yearly. The operational model is solved using a reinforcement learning algorithm called Deterministic Policy Gradient, while the planning model is solved using a MATLAB inbuilt nonlinear global optimiser called patternsearch. The methodology is demonstrated for a 100 MW BESS connected to the Irish grid and trading exclusively in the day-ahead market. Three different BESS CAPEX future realisations are analysed along with three different

BESS manufacturers' degradation warranties for C-Rates under 0.37C. The results show that BESS CAPEX has minimal influence on investment timing but has a significant effect on BESS size. Furthermore, extrapolating degradation warranty for C-Rates greater than 0.37C does not influence optimal investment timing or sizing, while a change in BESS energy retention limit at year 10 can have a significant influence on the viability of a BESS project.

4.2 INTRODUCTION

Due to the deregulation of electricity markets over the past two decades, more responsibility has been placed on private investors (e.g. generation companies, renewable energy developers) to meet requirements of the electrical grid e.g. replacing existing end-of-life generators, meeting increasing demand, increasing the amount of renewable generation. System Operators and Regulators must put in place the necessary investment signals to ensure system security. In the future, a similar investor approach will be required for widespread Battery Energy Storage System (BESS) installations. BESS are already being installed throughout the world, with 272 electrochemical BESS above 1 MW operational as of 2019, and a further 46 either under construction or announced [100]. BESS allow for the decoupling of generation and demand which is necessary given the intermittent nature of renewable generation. For investors to consider developing BESS projects, the investment must ultimately make financial sense. The most holistic approach to assessing the financial viability of a BESS investment is Real Option Analysis (ROA) [101].

ROA is a capital budgeting method which accounts for the dynamic and stochastic elements of any investment. "Dynamic" in this case denotes any flexibility offered to investors to modify/change their investment throughout its lifetime, and "stochastic" implies accounting for any uncertainty which could affect the profitability of a project in the future. This ROA approach is different from that of traditional capital budgeting methods such as Net Present Value (NPV) which is static and deterministic. Currently, within power system engineering literature, it is common to use the term NPV when accounting for multi-stage (i.e. dynamic) decisions with uncertainty, even though the term NPV is solely reserved for single-stage (i.e. static) deterministic decisions within the financial community [75, 89]. Likewise, the financial community have chosen the ROA term to account for dynamic stochastic decisions. Given that NPV and ROA are financial terms, and in the pursuit of correctness, the author of this chapter has chosen to retain the financial terminology NPV for static deterministic problems and ROA for multi-stage decisions with uncertainty. Hence, ROA has the advantage of being able to consider dynamic stochastic decisions over NPV, which is required for BESS installations which have flexible options such as added capacity or delaying installation. See Fig.4.1 for a graphical representation of the difference between ROA and NPV (extracted from [102]). Flexibility within a project can have a variety of different

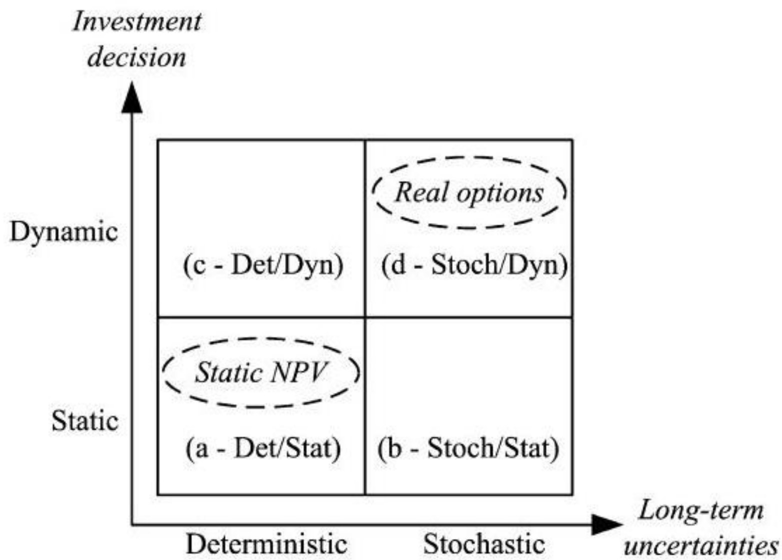

Fig.4.1 – Illustration of difference between Real Options Analysis and more traditional method Net Present Value. This study utilises Real Options which is both dynamic and stochastic.

options which are all inherent characteristics of an individual project – examples include the option to expand/contract the project in the future, the option to stage investment, the option to abandon the project, the option to change operational strategy, etc. The authors in [103] reviewed the application of ROA to renewable energy projects by type of uncertainty considered, flexibility sought and solution methods utilised. The authors found that of the 101 papers reviewed, 41% considered the uncertainty of electricity price which was the most frequent uncertainty variable. Other uncertainties considered were technology price and production levels from renewable generators to name a few. In terms of flexibility, the most common theme is investment timing, represented in 60% of papers reviewed, with 20% considering investment timing alone. Investment timing is significant as it allows the investor to decide to wait for more information to become available before investing. To solve ROA, a number of different mathematical formulations can be used, such as partial differential equations, dynamic programming or Monte Carlo simulation. For investment timing decisions, the most common solution method is dynamic programming which is an optimisation technique. Given that uncertainty is considered for ROA, a more applicable approach would be to utilise stochastic optimisation methods.

Stochastic optimisation encompasses a vast variety of methodologies and notation. In fact, such is the size and diversity of different stochastic optimisation techniques, it has been classed as the "jungle of stochastic optimisation" [104]. As one example, the operations research community use x_t for decision variable at time t, while the control and reinforcement learning community use u_t and a_t respectively. Further complicating this is the control community using x_t to represent the state variable. Motivated by this, while identifying the need for a stochastic optimisation canonical model (as is already the case with deterministic optimisation), the author in [105] developed a unified framework for modeling stochastic optimisation. The modeling framework proposed by the author consists of five different dimensions – state variables, decision variables, exogenous information, transition function and objective function. Given these elements, any stochastic problem can be modeled. A larger discussion on these elements and their notation is given in Section 4.4.

For investors wanting to undertake a BESS project, there are a number of different uncertainties and flexible options to consider. The three uncertainties as part of this work are electricity price, which is a highly stochastic process, BESS Capital Expenditure (CAPEX) which is envisaged to decline over the coming years and BESS degradation which is not fully deterministic due to environmental and operational conditions throughout project lifetime. BESS investments also have flexible options such as investment timing, increasing BESS energy capacity (MWh) and replacing degraded BESS capacity. Examples of options that are unlikely as part of a BESS project, and are not considered in this chapter, are contraction of project size and abandoning. Both these options require a strong after sale market which is currently non-existent. The literature review within this chapter will show that no existing study simultaneously determines the optimal size and investment time for a BESS project; which considers future BESS CAPEX decline and degradation; from the perspective of an individual investor. This chapter incorporates all these aspects. Studies to date focus on the optimal size and investment time from the perspective of the grid, which results in a BESS operational strategy that is not maximising the benefit of the investor. Given that investors are the most likely avenue for new BESS installations in deregulated electricity markets, their perspective must be understood. No study from either grid or investor perspective has considered the effect future BESS CAPEX decline will have on optimal size and investment timing which must also be understood.

Therefore, the aim of this research is to develop a methodology for applying ROA to BESS projects where flexible options of investment timing and sizing are both considered. This is different to other BESS ROA applications which consider either timing or sizing but not both. Objectively, a standalone BESS project with a notional 100 MW inverter is used as the test case. The developed methodology is applied to the day-ahead market within the Integrated Single Electricity Market (I-SEM) on the island of Ireland. Two different optimisation models are required, 1) called the operational model for determining BESS dispatch strategy (also called policy) and expected daily revenue from BESS, and 2) the planning model which optimises the BESS investment timing and sizing decisions. The operational model is solved using a Reinforcement Learning Algorithm called Deterministic Policy Gradient (DPG). The planning model is solved as a direct-search based approach using a nonlinear optimiser in MATLAB called *patternsearch*. Various future scenarios of BESS CAPEX and BESS degradation are modeled to determine the effect of each on timing and sizing decisions.

4.3 LITERATURE REVIEW

Literature related to sizing and investment timing of BESS installations has two different perspectives. One perspective is the grid (e.g. transmission, distribution, micro) as a whole, where objectives include but are not limited to: minimising operating cost, maintaining frequency balance and matching load growth. The other perspective is that of an individual investor who responds to market forces with a goal of maximising the difference between benefit and costs.

On the perspective related to the grid, numerous studies have analysed the impact of BESS sizes and investment timing, as shown in the comprehensive review of distribution networks by [106]. The authors identified each study as either single-stage planning (only BESS sizing) or multi-stage planning (both sizing and investment timing). Multi-stage planning allows for dynamic decisions to be made over a given planning horizon. Of the multi-stage planning studies identified [26, 107-111] , each considered planning objectives which incorporated BESS installation flexibility over multiple stages. In a different approach shown by [112], the authors sized wind and diesel units by trialling four different BESS separately, which is analogous to an Analytical Method (discussed later within this section). From these studies, the BESS operational strategy is to minimise the installation and operating cost of the grid. Only the authors in [112] seek to maximise the arbitrage benefit of a BESS. However, this is still in respect to minimising the overall gird planning cost i.e. it is assumed that the distribution generation units are owned and operated by the grid distribution company. None of the aforementioned studies considered future BESS declining capital costs or BESS degradation. In [109], the authors did conduct a sensitivity analysis of BESS capital cost but only on the initial stage cost which was maintained constant throughout all subsequent stages. Also, the authors in [112] did account for replacement costs of BESS due to degradation, however their approach specifies that if BESS capacity is installed it must be replaced which is not a fully flexible model.

Studies which focus on the perspective of the investor are more relevant to this chapter. Only one approach reported so far in the literature has applied ROA to appraise a BESS project from the perspective of an individual investor [113]. The authors determined a single optimal investment time for two Lithium-Ion BESS projects participating in Germany and United Kingdom day-ahead and reserve markets respectively. A single BESS size of 10 MWh was considered along with future BESS CAPEX decline. Their approach is limited in the number of flexible options available to BESS projects, such as option to expand BESS energy capacity. Furthermore, it was not determined if 10 MWh was the optimum BESS size, and therefore a higher RO could be available, which then would have the potential to alter the aforementioned optimum investment time. Of particular notice is the lack of attention given to degradation. Given the significant role of degradation in energy capacity availability as time passes, it is clear that flexible options related to degradation should be considered. Others have applied ROA to energy storage technologies other than BESS. Implementing the same flexible option as [113], but only modelling the day-ahead market, the author in [114] presented a methodology for finding the optimal investment time for a technology neutral energy storage system. The approach tells investors the optimal profit threshold they need to attain for each time step (i.e. yearly). The optimal time to invest is based on whatever time step the profit is greater than threshold value. This method still leaves the investor with a separate optimisation step to solve for the chosen technology to ascertain the attainable profit, along with implementing any constraints that are necessary, be they technology or application specific. Another ROA undertaken on energy storage is the addition of a hydrogen energy storage project to a wind farm [115]. Here, the authors considered the optimal investment time option along with different operational strategies. A single hydrogen storage capacity was modelled. This is less significant for hydrogen energy storage compared with BESS, as the hydrogen storage device is the least expensive component of the system when compared to fuel cells. While no future CAPEX was modelled (necessary given that grid-connected hydrogen is a less mature technology than BESS), the authors did consider future improvement in energy conversion efficiency. The efficiency analysis was presented as sensitivity and showed that with increasing efficiency the value of waiting decreases.

One important aspect from studies [113-115] is that energy storage size is not optimised. For energy storage systems, the MWh energy capacity (i.e. size) is a unique aspect, as this is what drives the economic return. For BESS, considerable effort has been applied to finding optimum sizes, highlighted by a review of BESS sizing methodologies [8]. Of the methodologies reviewed by the authors, static NPV approaches (Section (a) of Fig.4.1) are most popular BESS sizing method when optimising financial objectives across multiple applications such as microgrids, standalone hybrid renewable energy systems and renewable power plants. In terms of finding the optimal size, two important solution methods were identified, Analytical Method and Directed Search-Based Methods. The distinction between both has influenced the methodology of this chapter. Using Analytical Methods, optimising some decision variables is achieved by manually varying the variables across a range of possible values, after which the maximum or minimum of the objective function from this range of possible values is given as the optimal solution. This approach may seem intuitive to use for ROA. However, in Direct Search-Based Methods no variables are manually altered, with the optimising algorithm solving for all variables. This removes the burden of variable granularity choice as is the case with Analytical Methods. This chapter will solve ROA using a Direct Search-Based approach.

Previous literature which combines ROA and sizing is naturally closely related to this study. In [116], the authors applied ROA and capacity choice to a pumped hydropower storage project. The option in question was whether project construction should wait or start immediately. It was found that an optimal wait time of 8 years was appropriate when an annual increase of 8% in electricity volatility is modeled. Capacity choice was based on determining the RO for a set of five different MW options (analogous to the Analytical Method mentioned previously). The optimal capacity was 2,400 MW which is the maximum capacity modeled. This approach did not optimise pumped hydropower storage energy size (assumed to be 75,000MWh). Rather than predicting future technology costs, a sensitivity analysis was done to understand the effect of increased/decreased CAPEX on RO, with a 25% reduction in CAPEX modifying the optimal from year 8 to year 5. A similar approach is used in this chapter for future BESS CAPEX and also used by [115] for changes in future hydrogen storage conversion efficiencies. A different approach to energy storage sizing with ROA was taken by [117]. Here the authors “pre-sized” a Pumped Hydro Storage project and Compressed Air Energy Storage project before undergoing ROA for three different flexibility options. The Analytical Method was used to determine the optimal size with traditional NPV used as the objective function. It is unclear if this approach would give a different optimal BESS size to that when determining the optimal BESS size within ROA. This point will be addressed within this chapter.

As part of this research, three uncertainties are accounted for (electricity market clearing price within the day-head market, future BESS CAPEX, BESS degradation). Importantly, the treatment of uncertainty in ROA is not a “one size fits all” approach. Two different important categories of uncertainty within ROA are identified by [118]: parametric uncertainty and structured uncertainty. Therefore, it is important to understand which uncertainty category electricity market clearing price, BESS CAPEX and degradation fall into, and what is the consequence of this. Parametric uncertainty (electricity markets fall under this category) is when the underlying uncertainty is knowledge of parameters, is classed as quantitative and generally a probability distribution is known. Structural uncertainty (which applies to BESS CAPEX and degradation) is when less information about the underlying system is available, is classed as qualitative and generally a probability distribution is not known. The authors in [118] highlight that ROA can be applied to parametric uncertainty but the effectiveness on structural uncertainty is debatable, and some methods can only give ‘rough’ answers. Therefore, rather than simulating future BESS CAPEX and degradation, a sensitivity analysis is done on different future realizations of each. The chapter presented herein throughout can be viewed as ROA of the parametric uncertainty (electricity price) with sensitivity analysis of the structural uncertainty (BESS CAPEX and degradation).

Lastly, determining the optimal dispatch strategy for a BESS via stochastic optimisation is given by [119, 120], and is closely related to this chapter. Optimal BESS dispatch is required so that BESS revenue can be modelled. While their study covers the area of modelling and different classes of policy in stochastic optimisation, the BESS is used as a test case for their modelling and policy classes with little given in terms of the algorithmic structure used. The same modelling notation is used in this chapter.

4.4 MODELING

Optimal decisions over two different timescales are required as part of the methodology used in this chapter – the optimal dispatch of BESS which is hourly and BESS investment timing and sizing decisions which are yearly. While yearly decisions are the main topic of this chapter, optimal hourly dispatch decisions are also required for calculating BESS revenue. To account for this timescale difference, an operational model and planning model are developed for hourly and yearly decisions respectively. Similar terminology has been used by [121], referring to the planning model as the strategic model. The operational model is solved first and determines how the asset (i.e. BESS) will operate, whereas the planning model is solved afterwards and uses the expected daily revenue output of the operational model.

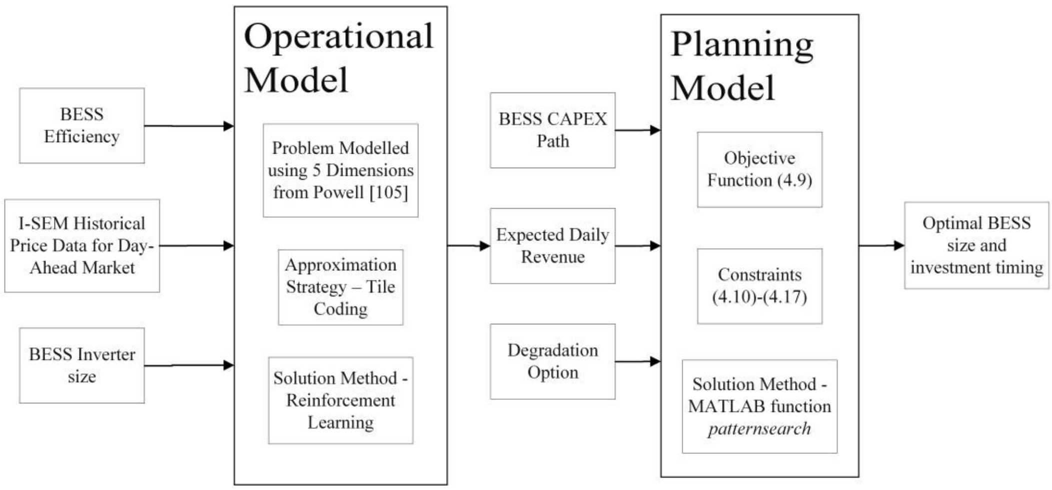

Fig.4.2 – Outline of operational model and planning model, their interactions and inputs.

4.4.1 OPERATIONAL MODEL

Revenue from a BESS project operating in the day-ahead market is based on optimal dispatch for arbitrage opportunities (i.e. charging BESS when electricity market price is low and discharging when high). Electricity is traded for one trading day broken into hourly segments. Given that electricity market price is uncertain, stochastic optimisation is used to solve for the operational model. As mentioned previously, a stochastic optimisation problem can be modelled using five dimensions as shown here. For a more detailed discussion interested readers are referred to [105]. To keep computation requirements low, the time horizon of the operational model is maintained at 24 hours. The stored energy within the BESS will always be in a state of empty at the beginning and end of trading day.

4.4.1.1 STATE VARIABLE

The state variable encompasses all the information required to compute the cost function, decision function and transition function from time t_o onwards. The state variable for the operational model (4.1) is composed of three different components

$$S_{t_o} = (E_{t_o}, P_{e,t_o}, B) \tag{4.1}$$

E_{t_o} which is the amount of energy stored (MWh) in the BESS at time t_o, P_{e,t_o} is the electricity market clearing price (€/MWh) for the day-ahead market at time t_o and B is the BESS size (MWh) which is constant across each iteration (κ). The E_{t_o} value changes for each timestep depending if the BESS was charged or discharged. P_{e,t_o} is sampled from previous electricity market data for the day-ahead market.

4.4.1.2 DECISION VARIABLE

The decision variable for the operational model, x_{t_o}, is how much energy (MWh) should be charged or discharged to/from the BESS at each t_o. x_{t_o} is bounded by the following constraints shown in (4.2) and (4.3).

$$\eta \times (\max(-\mathrm{Y} \times t_d, 0 - E_{t_o-1})) \leq x_{t_o} \tag{4.2}$$

$$x_{t_o} \leq \frac{\min(\mathrm{Y} \times t_d, B - E_{t_o-1})}{\eta} \tag{4.3}$$

These constraints ensure that x_{t_o} does not overcharge or over discharge the BESS, where S_{t_o-1} is the state variable at the previous time step, t_d is the duration of time for the trading period set to 1 hour for this study, η is the conversion efficiency of the BESS set at 0.87 [122], and Y is the inverter size which is assumed to be 100 MW for this study. x_{t_o} is positive for charging and negative for discharging.

4.4.1.3 EXOGENOUS INFORMATION

Exogenous information is the information that is revealed at time t_o and is available when decision x_{t_o} is made. For the methodology used in this chapter, the decision maker has access to the electricity market clearing price for each trading period when making decision x_{t_o} for that trading period. The exogenous electricity trading price is given by $\hat{P}_{e,t_o}$.

4.4.1.4 TRANSITION FUNCTION

Linking the state variable and decision variable is the transition function. This models how the state of the BESS changes with time depending on what decisions are made. Equations (4.4), (4.5) and (4.6) outline the transition of the energy stored variable E_{t_o} and P_{e,t_o}.

$$E_{t_o+1} = \begin{cases} E_{t_o} + (\eta \times x_{t_o}), & x_{t_o} < 0 \\ E_{t_o} + \dfrac{x_{t_o}}{\eta}, & x_{t_o} > 0 \end{cases} \tag{4.4}$$

$$P_{e,t_o+1} = \hat{P}_{e,t_o+1} \tag{4.5}$$

$$S_{t_o+1} = (E_{t_o+1}, P_{e,t_o+1}, B) \tag{4.6}$$

Given that the electricity market clearing price is known when the decision is made at t_o, there is no transition relationship modeled for P_e between t_o and $t_o + 1$. B remains constant throughout state transitions for the trading day, and S_{t_o+1} represents the state variable at $t_o + 1$.

4.4.1.5 OBJECTIVE FUNCTION – (OPERATIONAL MODEL)

The canonical form for the objective function in stochastic optimisation is given by (4.7).

$$\max_{\pi \in \Pi} \mathbb{E}^{\pi} \sum_{t_o=1}^{T_o} C\left(S_{t_o}, X_{t_o}^{\pi}(S_{t_o})\right) \tag{4.7}$$

$$C(S_{t_o}, x_{t_o}) = P_{e,t_o} x_{t_o} \tag{4.8}$$

For the operational model, equation (4.8) quantifies how much energy is bought and sold at price P_{e,t_o} for each trading period within the trading day. T_o is the time horizon for the trading day which is 24 trading periods. Rather than specifying the decision variable x_{t_o} in (4.7) for time t_o, stochastic optimisation maps the function from state to policy, which determines the best decision to take given the current state. This is known as a policy and is signified by $X^{\pi}_{t_o}(S_{t_o})$, where π is a policy and is an element of all possible policies Π. For definition of $X^{\pi}_{t_o}(S_{t_o})$ see Section 4.5.1. The goal of stochastic optimisation is to find the best policy, the result being a function which maps states to decisions.

4.4.2 PLANNING MODEL

The planning model time scale is yearly, through which decisions are based on how much BESS capacity should be invested in at every year of the project, considering the decline of BESS CAPEX and BESS degradation over time.

4.4.2.1 OBJECTIVE FUNCTION – (PLANNING MODEL)

The planning model objective function is shown in (4.9). The goal is to maximise the value of a BESS project. The baseline function V (equation (4.20)) from the operational model gives the daily expected revenue for a BESS when t_o is 1. This baseline function is inputted into planning model objective function to give yearly revenue. Equation (4.9) is solved using MATLAB global optimisation function patternsearch which can be applied to nonlinear objectives functions and constraints.

$$\max_{B_{t_p}} \sum_{t_p=1}^{T_p} \gamma_{p,t_p} \left(\sum_{j=1}^{J} \left(\frac{V^{v_1}\left(B_{t_p,j} - \frac{D_{t_p+1}}{J}\right) \times 365}{J} \right) - P_B(t_p)\left(\frac{B_{t_p} - H_{t_p}}{U_L}\right) - P_I Y_{t_p} \right) \tag{4.9}$$

where B_{t_p} (MWh) is the usable BESS size investment decision variable at time t_p which is yearly, Y_{t_p} signifies the inverter's first year of operation (enforced by constraint (4.17)) , T_p is the lifetime of the project at 20 years, where γ_{p,t_p} is the time value of money given by $\frac{1}{(1+r)^{t_p}}$ with the discount rate r at 0.08. To improve accuracy, degradation is accounted for within yearly revenue in objective function (4.9) by assigning a value to J. A higher value of J will improve accuracy but increase computation time. The maximum value of J is 365. J is set to 4 for this study (i.e. setting J to 4 ensures that degradation is accounted for quarterly). D_{t_p+1} is the degradation after year t_p but before the year beginning t_{p+1}. $B_{t_p,j}$ is the BESS capacity left after degradation every quarter when J is 4. $P_B(t_p)$ is BESS capacity CAPEX at time t_p (see Section 4.6.2), P_I is the BESS inverter CAPEX, $H_{t_p}$is the amount of usable BESS capacity already installed at time t_p and U_L is the usable energy limit of the BESS capacity set arbitrarily at 95% for this study. The use of this usable limit implies that more capacity must be purchased above what is available for use by the operational model. For Section 4.4.2.2 and 4.6.3, it is assumed that all constraints and degradation modeling are referring to the usable energy amount.

4.4.2.2 CONSTRAINTS

Given that degradation is dependent on the size of the BESS installed, the constraints are nonlinear. Equations (4.10), (4.11), (4.12), (4.13), (4.14), (4.15), (4.16) and (4.17) outline the constraints applied to the planning model. Equation (4.13) ensures that no added BESS capacity ever falls below 30% (when Q is equal to 0.3) of initial value throughout the lifetime of the project. This helps alleviate the issue of BESS capacity becoming redundant. Constraint (4.16) allows the planning model to select battery sizes between 20 and 500 MWh. These values have been chosen arbitrarily to reflect a C-rate of 5 and 0.2 respectively, which ensures a wide enough range of possible BESS sizes. $L_{t_p}$is the amount of BESS capacity that has been installed cumulatively at time t_p, D_C is the energy retention limit (see Section 4.6.3).

In this chapter, a ROA model of a BESS project is optimised using only the upper term in equation (4.14). However, an NPV model of the same BESS project (see scenario 1 in Section 4.7) was also optimised. This was done as a reference point, as NPV is more common than ROA. To change the model from ROA to NPV, only the lower term in equation (4.14) is used. The lower term in equation (4.14) constraints the model to only one decision at the initial decision stage.

$$H_{t_p+1} = B_{t_p} - D_{t_p+1} \tag{4.10}$$

$$L_{t_p+1} = B_{t_p} - H_{t_p} + L_{t_p} \tag{4.11}$$

$$D_{t_p+1} = \min\left(\frac{L_{t_p+1} \times D_C(L_{t_p+1})}{10}, B_{t_p}\right) \tag{4.12}$$

$$\left(B_{t_p} - H_{t_p}\right) - \left(min\left(\frac{\left(B_{t_p} - H_{t_p}\right) \times D_C(L_{t_p+1})}{10}, B_{t_p} - H_{t_p}\right) \times \left(T_p - t_p\right)\right) \geq \left(B_{t_p} - H_{t_p}\right) Q \tag{4.13}$$

$$\begin{cases} B_{t_p} - B_{t_p+1} \leq D_{t_p+1}, & when\ ROA \\ B_{t_p} - B_{t_p+1} = D_{t_p+1}, & when\ Static\ NPV \end{cases} \tag{4.14}$$

$$H_1 = 0, D_1 = 0, L_1 = 0 \tag{4.15}$$

$$20 \leq B_{t_p} \leq 500 \tag{4.16}$$

$$Y_{t_p} = \begin{cases} Y, & H_{t_p} = 0\ and\ B_{t_p} > 0 \\ 0, & otherwise \end{cases} \tag{4.17}$$

4.5 REINFORCEMENT LEARNING ALGORITHM

The optimal BESS dispatch policy for the operational model is determined using a reinforcement learning algorithm called Deterministic Policy Gradient (DPG) [123] subject to equations (4.1)-(4.8). Reinforcement learning was used as the stochastic optimisation method in this study as a means to learn an optimal function approximator of the operational model. The reinforcement learning choice was fundamental in allowing the splitting of operational and planning decisions into two different models. Reinforcement learning is predominantly a computer science discipline. The problem faced by this community is sequential decision making under uncertainty, which is the same problem faced when dispatching a BESS within day-ahead electricity market. References such as [124, 125] give an introduction into this vast subject. More recently, more advanced reinforcement learning algorithms have gained distinction for their ability to master the game of Go [126] and greater than human level performance in a selection of Atari games [127]. Reinforcement learning can optimise within two different spaces, the value function space or the policy space, with a large number of algorithms to choose from such as Monte Carlo, SARSA, Q-Learning, REINFORCE, etc. The algorithm used in this study (DPG) is a hybrid of policy and value functions known as actor-critic. Unlike other policy gradient reinforcement learning algorithms, DPG output is a deterministic policy rather than stochastic. This is beneficial for dispatching a BESS system, as BESS operators' decisions are not probabilistic.

Expanding reinforcement learning to large scale problems requires approximating the function space. For continuous state space and decision space, the number of possible realisations is infinite. To overcome this, a function approximator is utilised. This study applies tile coding to the state space. Tile coding discretizes the state space with overlapping tilings divided into equally sized squares called tiles. The benefit of tile coding is that this overlapping allows for generalisation from one state to another, thereby removing the need to account for every state. For a more detailed description of tile coding, see [125] pp. 217. The number of tilings used in this study is 16 which follows the rule $N_{tilings} = 2^z \geq 4q$ given by [125] pp. 220, where q is the dimension of the state variable and z must be a positive integer. The width of the tiles is given an arbitrary value of 95 which ensures a balance between generalisation of the state space and computation time. The number of tiles per tiling is 1728. Each tile represents one feature of the feature vector $\phi(S_t)$, which has a length equal to the total number of features. Activation of features occurs when S_t is inside the boundary of a particular tile/feature which is then assigned a value of 1. All other features are set to zero.

4.5.1 DETERMINISTIC POLICY GRADIENT ALGORITHM

Of particular interest for this study is the ability of DPG to handle continuous decision space (i.e. dispatching a BESS in day-ahead market allows any value of charge/discharge between equation (4.2) and (4.3)). Furthermore, even though DPG is a bootstrapping algorithm, no bias is introduced into the solution through the use of a compatible function approximator. Another common issue in reinforcement learning is the topic of exploration of the state space. To ensure adequate exploration, the deterministic policy $X_{t_o}^{\pi}(S_{t_o})$ is learnt from trajectories of a stochastic policy $X_{t_o}^{\beta}(S_{t_o})$, which is categorized as off-policy learning. The DPG algorithm uses gradient Q-learning in the critic to prevent divergence.

DPG Algorithm applied to BESS problem

1. $\rightarrow$ Initialize: $\boldsymbol{\theta}_{t_o}, \boldsymbol{w}_{t_o}, \boldsymbol{v}_{t_o}, \boldsymbol{u}_{t_o}$ to 0, $\forall\, t_o \in T_o$,
2. $\rightarrow$ Set hyperparameters: $\alpha_{\theta,t_0}, \alpha_{w,t_0}, \alpha_{v,t_0}, \alpha_{u,t_0}, \forall\, t_o \in T_o$,
   - 2.1. $\rightarrow$ Loop for predefined number of iterations (κ)
   - 2.2. $\rightarrow$ Initialize: S_1
     - 2.2.1. $\rightarrow$ Loop for each time step t_o until S_{T_o}
     - 2.2.2. $\rightarrow$ $X_{t_o}^{\pi}(S_{t_o}) = \boldsymbol{\theta}_{t_o}{}^{\mathrm{T}}\phi(S_{t_0})$ – deterministic policy π
     - 2.2.3. $\rightarrow$ $X_{t_o}^{\beta}(S_{t_o}) \sim \mathcal{N}(X_{t_o}^{\pi}(S_{t_o}), \sigma_{\beta}^2)$ – stochastic policy β
     - 2.2.4. $\rightarrow$ From $X_{t_o}^{\beta}(S_{t_o})$, observe S_{t_o+1} and R_{t_o}. (if $S_{t_o+1} = S_{T_o}$, then $V(S_{t_o+1}, \cdot) = 0, A(S_{t_o+1}, \cdot) = 0$)
     - 2.2.5. $\rightarrow$ $X_{t_o+1}^{\pi}(S_{t_o+1}) = \boldsymbol{\theta}_{t_o+1}{}^{\mathrm{T}}\phi(S_{t_0+1})$ – deterministic policy π for next state
     - 2.2.6. $\rightarrow$ $\delta_{t_o} = R_{t_o} + \gamma_o Q^{w_{t_o+1}}\left(S_{t_o+1}, X_{t_o+1}^{\pi}(S_{t_o+1})\right) - Q^{w_{t_o}}\left(S_{t_o}, X_{t_o}^{\beta}(S_{t_o})\right)$
     - 2.2.7. $\rightarrow$ $\zeta = \begin{cases} \frac{Eq.(3) - X_{t_o}^{\pi}(S_{t_o})}{Eq.(3) - Eq(2)}, & \left(\nabla_{\theta_{t_o}} X_{t_o}^{\pi}(S_{t_o})^{\mathrm{T}} w_{t_o}\right) > 0 \\ \frac{X_{t_o}^{\pi}(S_{t_o}) - Eq(2)}{Eq(3) - Eq(2)}, & \left(\nabla_{\theta_{t_o}} X_{t_o}^{\pi}(S_{t_o})^{\mathrm{T}} w_{t_o}\right) < 0 \end{cases}$
     - 2.2.8. $\rightarrow$ $\boldsymbol{\theta}_{t_o} = \boldsymbol{\theta}_{t_o} + \alpha_{\theta,t_0}\left(\nabla_{\theta_{t_o}} X_{t_o}^{\pi}(S_{t_o})\right)\left(\nabla_{\theta_{t_o}} X_{t_o}^{\pi}(S_{t_o})^{\mathrm{T}} w_{t_o}\right) \times \zeta$
     - 2.2.9. $\rightarrow$ $\boldsymbol{w}_{t_o} = \boldsymbol{w}_{t_o} + \alpha_{w,t_0}\delta_{t_o}\phi\left(S_{t_o}, X_{t_o}^{\beta}(S_{t_o})\right)$
     - 2.2.10. $\rightarrow$ $\boldsymbol{w}_{t_o+1} = \boldsymbol{w}_{t_o+1} - \alpha_{w,t_0}\gamma\phi\left(S_{t_o+1}, X_{t_o+1}^{\pi}(S_{t_o+1})\right)\left(\phi\left(S_{t_o}, X_{t_o}^{\beta}(S_{t_o})\right)^{\mathrm{T}} \boldsymbol{u}_{t_o}\right)$
     - 2.2.11. $\rightarrow$ $\boldsymbol{v}_{t_o} = \boldsymbol{v}_{t_o} + \alpha_{v,t_0}\delta_{t_o}\,\phi(S_{t_o})$
     - 2.2.12. $\rightarrow$ $\boldsymbol{v}_{t_o+1} = \boldsymbol{v}_{t_o+1} - \alpha_{v,t_0}\gamma\phi(S_{t_o+1})\left(\phi\left(S_{t_o}, X_{t_o}^{\beta}(S_{t_o})\right)^{\mathrm{T}} \boldsymbol{u}_{t_o}\right)$
     - 2.2.13. $\rightarrow$ $\boldsymbol{u}_{t_o} = \boldsymbol{u}_{t_o} + \alpha_{u,t_0}\left(\delta_{t_o} - \phi\left(S_{t_o}, X_{t_o}^{\beta}(S_{t_o})\right)^{\mathrm{T}} \boldsymbol{u}_{t_o}\right)\phi\left(S_{t_o}, X_{t_o}^{\beta}(S_{t_o})\right)$
     - 2.2.14. $\rightarrow$ $S_{t_0} = S_{t_0+1}$

Fig.4.3 – Deterministic Policy Gradient Algorithm applied to BESS dispatch problem. The introduction of decision clipping ensures that decisions stay bounded.

Fig.4.3 outlines the DPG algorithm. This form of the algorithm is modified to fit the BESS dispatch problem. For the generic form of this algorithm, readers are referred to [123]. The focus of the DPG algorithm is to learn the parameter values $\boldsymbol{\theta}_{t_o}, \boldsymbol{w}_{t_o}, \boldsymbol{v}_{t_o}, \boldsymbol{u}_{t_o}$. The parameter $\boldsymbol{\theta}_{t_o}$ is the actor parameter which, when coupled with the feature vector $\phi(S_{t_0})$, learns the deterministic policy $X_{t_o}^{\pi}(S_{t_o}) = \boldsymbol{\theta}_{t_o}{}^{\mathrm{T}}\phi(S_{t_0})$. The parameters $\boldsymbol{w}_{t_o}$ and $\boldsymbol{v}_{t_o}$ are critic parameters and learn the value of being in state S_{t_o} and taking a decision from the stochastic policy $X_{t_o}^{\beta}(S_{t_o})$. The critic value function is shown in equation (4.18) and is made up of an advantage function (4.19) and a baseline function (4.20).

$$Q^{w_{t_o}}\left(S_{t_o}, X_{t_o}^{\beta}\left(S_{t_o}\right)\right) = A^{w_{t_o}}\left(S_{t_o}, X_{t_o}^{\beta}\left(S_{t_o}\right)\right) + V^{v_{t_o}}\left(S_{t_o}\right) \tag{4.18}$$

$$A^{w_{t_o}}\left(S_{t_o}, X_{t_o}^{\pi}\left(S_{t_o}\right) + \lambda\right) = \lambda^{\mathrm{T}} \nabla_{\theta_{t_o}} X_{t_o}^{\pi}\left(S_{t_o}\right)^{\mathrm{T}} \boldsymbol{w_{t_o}} \tag{4.19}$$

$$V^{v_{t_o}}\left(S_{t_o}\right) = \boldsymbol{v_{t_o}}^{\mathrm{T}} \phi(S_t) \tag{4.20}$$

where $\nabla_{\theta_{t_o}} X_{t_o}^{\pi}\left(S_{t_o}\right) = \phi(S_t)$ and λ is a small deviation from the deterministic policy and is set to $\lambda = \frac{X_{t_o}^{\beta}(S_{t_o}) - X_{t_o}^{\pi}(S_{t_o})}{Y}$. The parameter $\boldsymbol{u_{t_o}}$ is learned to negate the potential divergence of the parameters under off-policy learning through stochastic policy β.

The hyperparameters $\alpha_{\theta,t_0}, \alpha_{w,t_0}, \alpha_{v,t_0}, \alpha_{u,t_0}$ follow conditions similar to those outlined by [128], shown in (4.21) and (4.22).

$$\alpha_{\theta,t_0} = \frac{0.001}{t_o \times N_{tilings}} \tag{4.21}$$

$$\alpha_{w,t_0}, \alpha_{v,t_0}, \alpha_{u,t_0} = \frac{0.1}{t_o^{\frac{2}{3}} \times N_{tilings}} \tag{4.22}$$

This ensures that the critic learns at a faster rate than the actor. The number of iterations (κ) is set large enough to guarantee algorithm convergence (1 million iterations were used in this chapter). For line 2.1 of Fig.4.3, the amount of energy stored in the BESS (E_1) at the beginning of a trading day is initialized to zero, initialization of BESS size (B) is taken from a uniform random distribution of available BESS sizes (20 MWh – 500 MWh). $P_{e,1}$ is initialized using historical data from day-ahead electricity market clearing prices in I-SEM (see Section 4.6.1). Once the algorithm runs through all available trading day data, it restarts at the initial data point. This process is repeated until the DPG algorithm converges. For line 2.2.3 in Fig.4.3 the value of σ_{β}^{2} set to 80 MWh to enforce adequate exploration. In line 2.2.6, the value of R_{t_o} is calculated at every time step using (4.23) and the value of gamma (γ_o) is set to 1.

$$R_{t_o} = P_{e,t_o} X_{t_o}^{\beta}(S_{t_o}) \tag{4.23}$$

In line 2.2.7, the parameter $\boldsymbol{\theta}_{t_o}$ is clipped using the approach given by [129]. This ensures that any decisions learnt must be within boundary limits otherwise the problem would keep learning to infinity. Lastly, the critic features $\phi\left(S_{t_o}, X_{t_o}^{\beta}(S_{t_o})\right)$ are given by $\phi(S_t) \times \frac{X_{t_o}^{\beta}(S_{t_o})}{\Upsilon}$.

4.6 DATA AND MODEL INPUTS

4.6.1 DAY-AHEAD ELECTRICITY PRICE

The electricity market in Ireland covers the whole of the island. Until October 2018, Ireland's electricity market was a gross mandatory pool market with single-sided participation of generators. Since October 2018, Ireland has been operating a new market called Integrated Single Electricity Market (I-SEM) which is more closely aligned with other power markets in the EU. Any generator greater than or equal to 10 MW must participate in the market. The data shown in Fig.4.4 is taken from I-SEM power exchange [130]. This data is assigned the variable P_{e,t_o}, where t_o is a trading period from 1 to 24, with trading period 1 starting at 23:00 hours. P_{e,t_o} is used in the operational model objective function (4.8) to determine the optimal trading strategy and expected daily revenue of BESS. It is assumed that any scheduled dispatch established by the BESS in the day-market is adhered to in

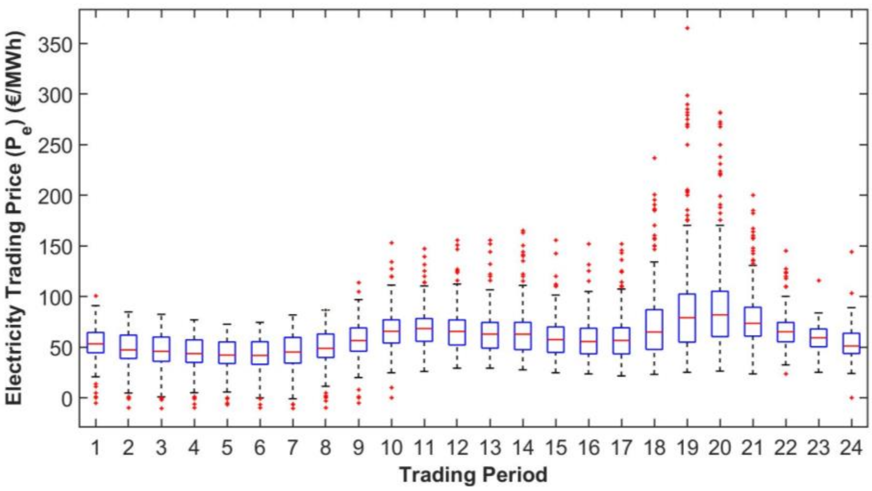

Fig.4.4 – Boxplot showing the variation of electricity market clearing prices within the I-SEM day-ahead market from October 2018 until July 2019.

real time, therefore no penalties for deviations from this scheduled dispatch is considered.

4.6.2 BESS CAPEX

Currently, Lithium-ion BESS CAPEX is predicted to decline over the coming years. The Lazard's Energy Storage document published in November 2018 outlines a Compounded Annual Growth Rate (CAGR) of 8% decrease over the next 5 years [122]. CAGR was averaged by Lazards over all possible BESS sizes. For this study, the decline predicted by [122] is modeled along with two alternatives, referenced as CAPEX Path 2 and CAPEX Path 3, whose purpose are for sensitivity analysis. Equation (4.24), which is CAGR formula rearranged algebraically, models BESS CAPEX before year 5. After 5 years, an exponential decaying function is used, given by equation (4.25).

$$P_B(t_p) = \begin{cases} P_S \times (d_{CAGR} + 1)^{t_p}, & t_p \leq 5 \quad (4.24) \\ P_L + (P_B(5) - P_L)e^{(-k\times(t_p-1))}, & t_p > 5 \quad (4.25) \end{cases}$$

where $P_B(t_p)$ is predicted future CAPEX of BESS at year t_p, P_S is the current CAPEX of BESS at $t_p = 1$, $d_{CAGR} = -\frac{CAGR}{5} \times (t_p - 1)$ and t_p is planning model discrete

Table 4.1 – BESS CAPEX Data

	CAPEX Path 1	CAPEX Path 2	CAPEX Path 3	Unit
P_S	210	210	210	€k/MWh
$CAGR$	0.08	0.065	0.05	-
P_L	65	77	90	€k/MWh
k	0.45	0.29	0.2	-

time interval. P_L is the predicted BESS CAPEX at the end of project life and k is decay rate. The values for the above variables are outlined in Table 4.1 for three different paths. The P_S value is taken from [122], and is representative of large-scale energy storage systems and is applied across all paths. The range of P_S values given by [122] for large scale lithium-ion is 210–360 (€/kWh) when currency exchange from August 2019 (1€=1.11$) is used. For this study, the lower value of 210 (€/kWh) is applied. CAGR for CAPEX Path 1 is also taken from [122], while all other values are assumed. Fig.4.5 illustrates each CAPEX path. The value given by P_S also includes BESS Operating Expenditure (OPEX). Furthermore, CAPEX for the BESS inverter (AC part) P_I is also taken from [122] using the lower value similar to P_S. P_I has a value of 44.14 (€/kW) when using the same currency exchange as above.

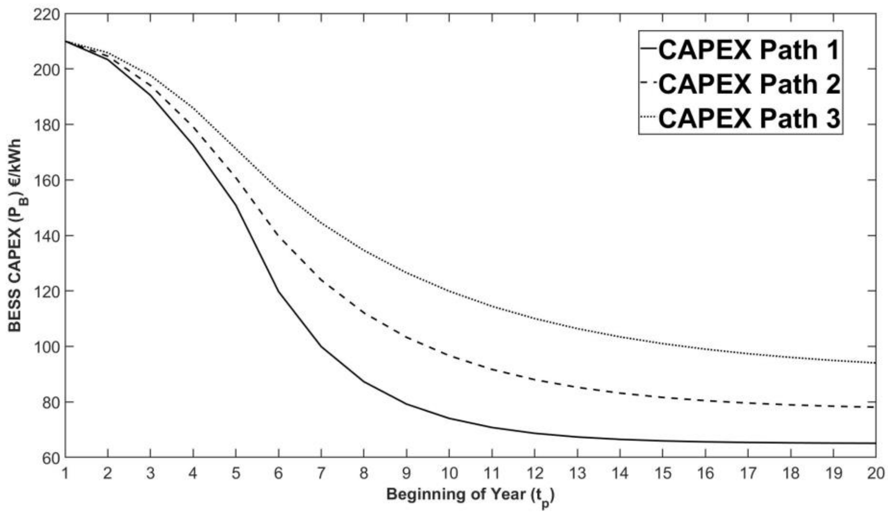

Fig.4.5 – Three BESS CAPEX paths used in the analysis of this study. CAPEX Path 1 is representative of predicted decline, while CAPEX Path 2 and 3 are for sensitivity analysis.

4.6.3 BESS DEGRADATION

Lithium-ion BESS undergo degradation via two mechanisms, cycling degradation which is degradation caused through charging/discharging BESS, and calendar degradation which is degradation caused by BESS age and environmental effects. Accurately modeling BESS degradation is highly complex and represents a risk for potential investors. To lessen this risk, BESS manufacturers provide investors with a warranty, which guarantees a certain level of BESS performance until a particular year of operation. The planning model in this chapter applies BESS manufacturers' warranty data for degradation. This negates the necessity to model actual degradation, thereby reducing complexity while also demonstrating the effect degradation has on potential investments. Typically, manufacturers outline their performance guarantee with an energy capacity retention limit at some time interval in the future. This limit will be used as worst-case performance for this study (i.e. the worst performance that can be expected at a certain year, as manufacturers will maintain this performance). Lithium-ion Nickel-Manganese-Cobalt BESS technology used by Tesla is the degradation model to test this chapter's methodology and has a value of 80% energy capacity retention at 10 years, which is used as the worst performance an investor can expect for a BESS C-rate of 0.37 [131, 132]. This also allows for a cycle limit of 37.8 MWh of aggregate throughput. However, for the purposes of this chapter it is assumed that the BESS has unlimited cycles available. This is in keeping with utility scale BESS warranties and also existing trends within the industry. Energy capacity retention limit changes are based on C-Rate, with a higher C-rate reducing the limit. Extrapolation of energy capacity limit to BESS sizes with a different C-Rate is done using the approach outlined in equation (4.26) and (4.27).

$$D_C(L_{t_p+1}) = m\frac{100}{(L_{t_p+1})} + c_d \tag{4.26}$$

$$c_d = (1 - R_E) - (mC_R) \tag{4.27}$$

c_d is determined from [132], where R_E is energy retention limit at 80% and C_R is the C-rate of that retention limit at 0.37C. m gives the rate of change of energy capacity limit to BESS size. Three different values of m are modeled in this study to determine the sensitivity of degradation to investment timing and sizing decisions, shown in Fig.4.6. The degradation options in Fig.4.6 are for an energy capacity retention limit at year 10. To extrapolate this over the full-time range of the planning model (i.e. year 1 to 20), a linear assumption was used (i.e. a constant annual energy capacity reduction is applied, equal to 1/10 of the reported energy capacity reduction over 10 years). This is due to the lack of available warranty data for years outside of year 10. Another point to note from Fig.4.6 is that if more capacity is added to a BESS project throughout its lifecycle then the increased BESS size will cause D_C degradation to decline. Therefore, the degradation amount is not based on the added capacity but rather on the existing capacity plus the added capacity.

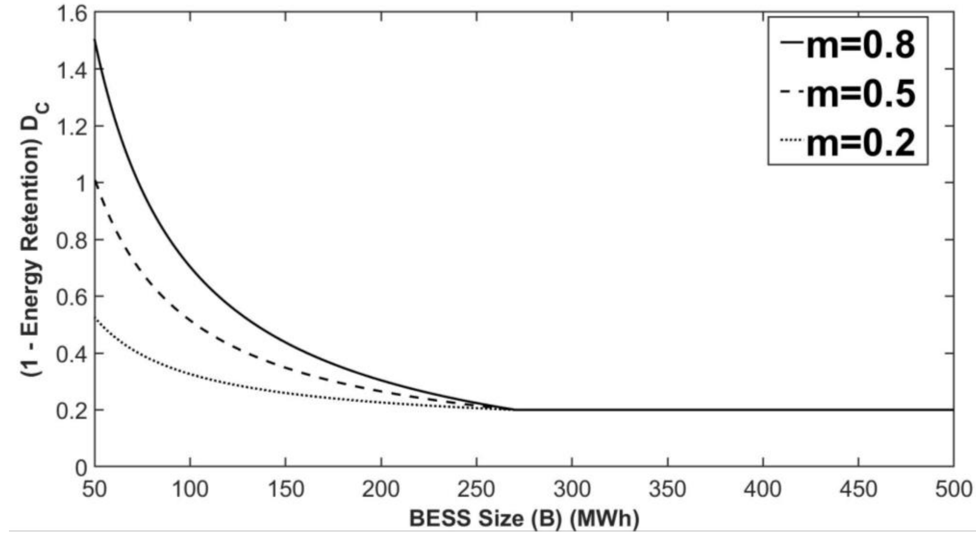

Fig.4.6 – Three different inferred degradation options for year 10 of BESS life. A common point for each inferred degradation is a C-rate of 0.37, which occurs at 270MWh for this 100MW study.

4.7 ANALYSIS

The operational model was solved using the reinforcement learning algorithm DPG. The expected daily revenue of the operational model is shown Fig.4.7. This is based on the learned deterministic policy, π, for optimal BESS dispatch strategy. $P_{e,1}$ is the electricity market clearing price state variable for the decision epoch at

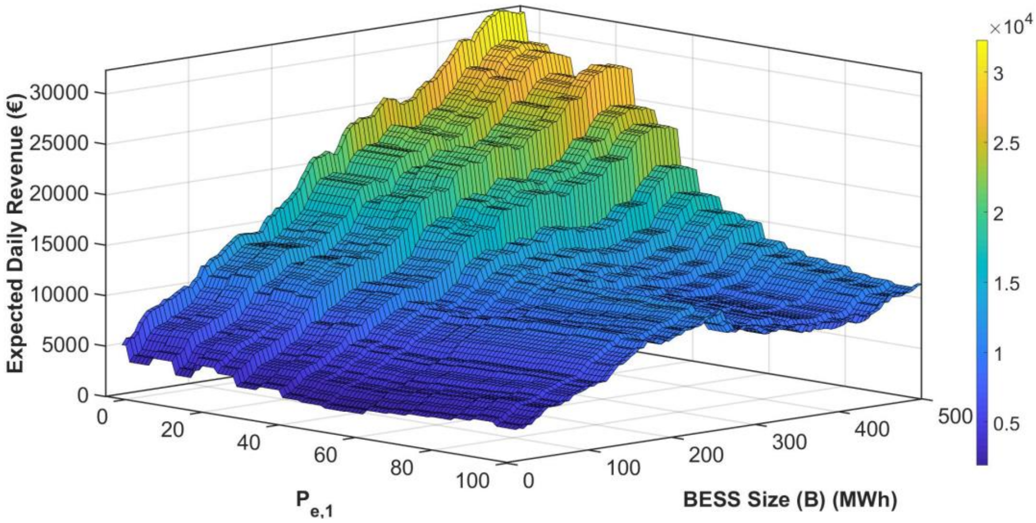

Fig.4.7 – Expected Daily Revenue given BESS size and $P_{e,1}$. $P_{e,1}$ state variable gives the expected daily revenue as it is the first stage of trading day.

first stage, with BESS size B the other state variable. The active energy stored state variable E_{t_o} is not shown here as it is assumed to be zero for the first stage (t_o=1). A certain tendency observed from Fig.4.7 is the rate of change between expected daily revenue and BESS size remains approximately constant from 20 MWh to 500MWh for $P_{e,1}$ less than approximately 36 €/MWh. This trend is based on a higher likelihood of more revenue when the initial electricity market price is low. When the electricity market clearing price is lower for the initial stage, the probability of subsequent stages $(t_o > 1)$ having a higher clearing price is increased. This gives the BESS more opportunity to obtain arbitrage benefits and therefore extra revenue. As a result, the BESS charges more often during low $P_{e,1}$. This learnt strategy is illustrated further in Fig.4.8, which shows the learnt deterministic policy. One noticeable difference in Fig.4.8 is that for values of $P_{e,1}$ under 10 €/MWh, the policy indicates significant charging instructions for all BESS sizes. For values of $P_{e,1}$ between 10 and 50 €/MWh, even though the expected daily revenue rate of change is increasing, the policy for BESS sizes under approximately 300 MWh tend to instruct no charging, whereas BESS sizes above tend to charge. This learnt strategy is based on $P_{e,1}$ having a higher value on average than trading periods up to and including trading period 8, as shown in Fig.4.4. This strategy shows that it is more beneficial for smaller BESS sizes to wait to charge as there is higher likelihood of lower prices at later trading periods. Larger BESS sizes are able

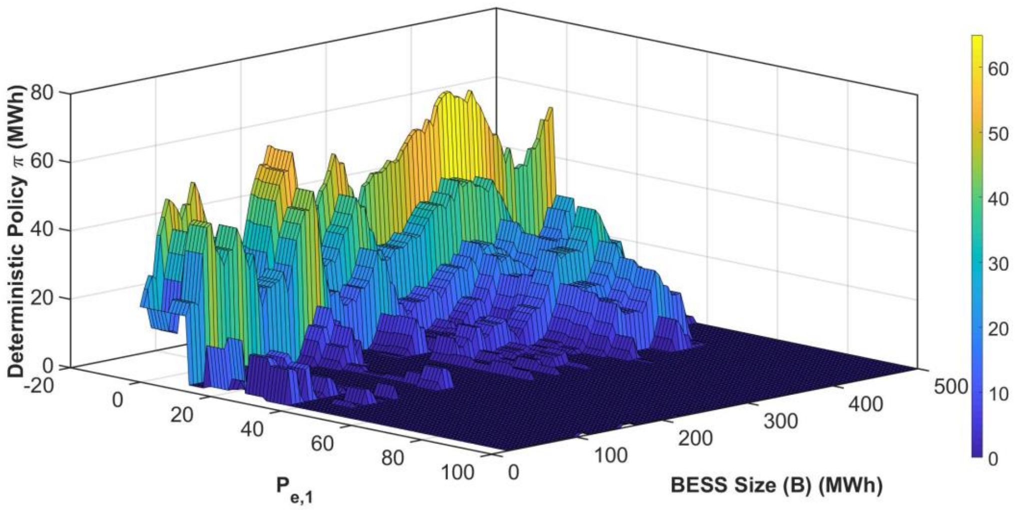

Fig.4.8 – Learnt deterministic policy for trading period 1 from solving operational model with Deterministic Policy Gradient Algorithm.

to capture both the low price of trading period 1 and other subsequent lower trading prices. One might expect to see more uniform, smooth results between adjacent states in Fig.4.8. However, it should be noted that the goal in stochastic optimisation is to obtain a good policy for a given state rather than optimal decision for every time step.

The planning model is solved using MATLAB version R2018b with a global optimisation function called patternsearch from the global optimisation toolbox version 4.0. The planning model requires three uncertainty inputs – 1) operational model value function $V^{v_1}(S_1)$, 2) a BESS CAPEX path and 3) a degradation option. These three inputs signify the uncertainty parameters for the planning model. To determine the effect of BESS CAPEX on investment decisions, the planning model was solved for the following scenarios:

- Scenario 1 – A traditional static NPV with operational model uncertainty is used as a base case scenario. The BESS CAPEX is maintained at P_S for $t_p = 1$ as there are no dynamic decisions allowed. Constraint (4.14) is set to static NPV. Degradation option is set to $m = 0.2$.
- Scenarios 2,3,4 – are real option analysis for CAPEX Path 1,2,3 respectively. Full dynamic decisions are allowed by setting constraint (4.14) to ROA. The degradation option is held at $m = 0.2$.

For scenario 1, the constraint (4.14) enforces that no decision is allowed after the first year. No BESS size available between 20 and 500MWh gave a positive value (which is needed for project to be accepted). The highest project value was zero with a BESS of 0 MWh, which is optimal. All other BESS sizes gave a negative project value. Therefore, using static NPV objective function, the project would not be built.

Fig.4.9 (a) outlines the optimal decision result for scenario 2, which is based on CAPEX Path 1 predicted by [122]. Scenario 2 allows for dynamic decisions at each decision epoch by setting constraint (4.14) to ROA. The optimal decision for scenario 2 is not to invest in BESS for the first 5 years. At year 6, investment in a 149 MWh BESS is deemed optimal. In year 7, a further 22 MWh is required which is based on further BESS CAPEX decline. All other years which add BESS capacity to the project do so in order to maintain overall capacity levels that would otherwise be lost to degradation. For the last 6 years of the project, no maintaining or expanding capacity is pursued as any further increase in CAPEX would not yield enough revenue to sustain the extra investment. Rather, the BESS capacity is

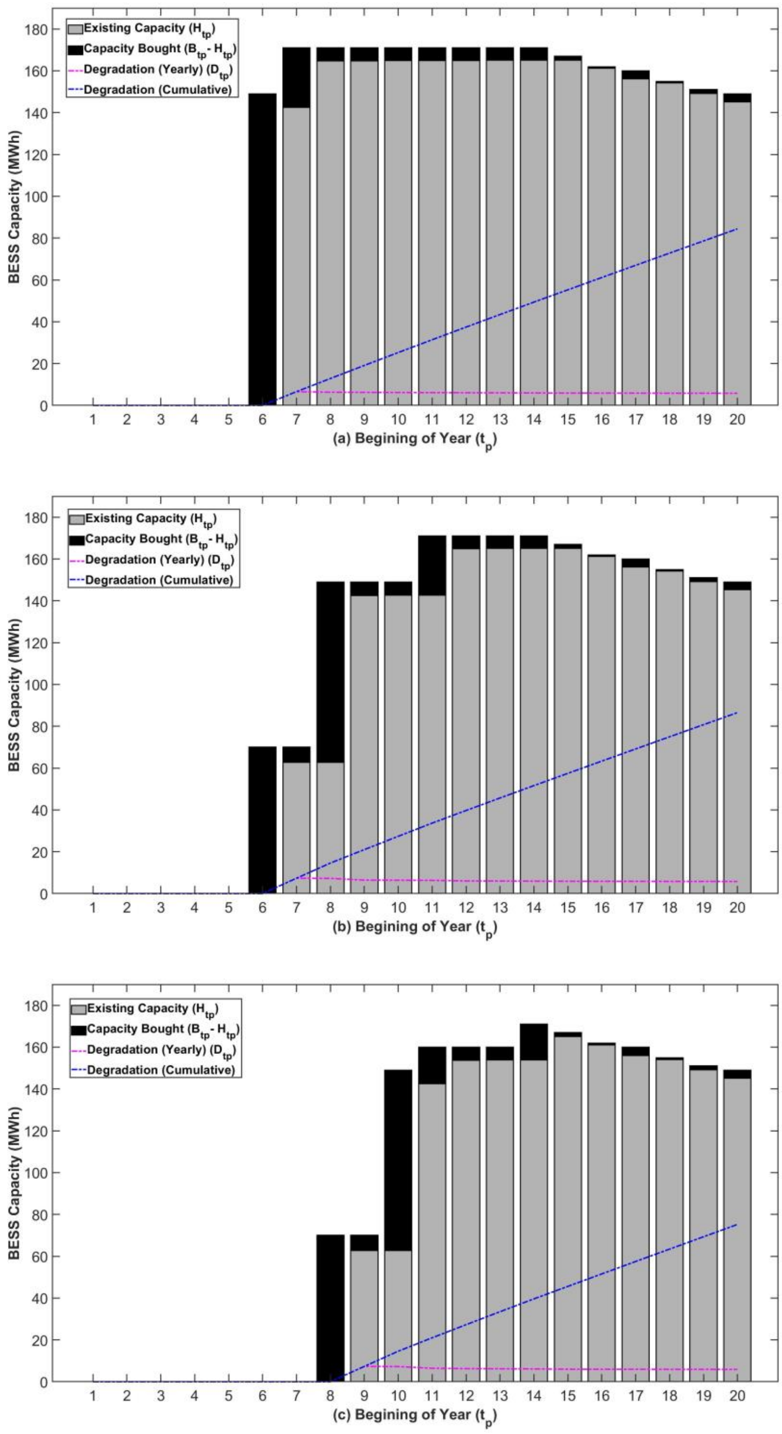

Fig.4.9 – The optimal investment timing and sizing for a 100MW BESS operating within the day-ahead market in I-SEM. (a) scenario 2 with CAPEX path 1 and degradation m =0.2 (b) scenario 3 with CAPEX path 2 and degradation m =0.2 (c) scenario 4 with CAPEX path 3 and degradation m =0.2.

allowed to reduce. The cumulative degradation at 20 years is 62.8 MWh with a project value of €5.85M. Based on this being the highest positive value obtainable, it is recommended to wait 5 years before starting this project for scenario 2.

In contrast to scenario 2, the optimal result of the third scenario has distinctive differences, shown in Fig.4.9 (b). Firstly, the proposed BESS size at year 6 is 70 MWh which is substantially smaller than scenario 2. Secondly, in year 8 a significant expansion is sought to bring BESS capacity up to 149 MWh. This capacity level is maintained against degradation effects until year 11 when BESS capacity is expanded once more to its maximum of 171MWh, which is the same maximum as scenario 2. Scenario 2 reaches its maximum size at year 7. This is attributed to more aggressive BESS CAPEX decline for scenario 2. Thirdly and similar to scenario 2, scenario 3 does not fully compensate for degraded BESS capacity after year 14 unlike the intervening years from 7 to 13. Scenario 3 has a cumulative degradation of 58.49 MWh at 20 years which is less than scenario 2 due to less BESS capacity installed. Scenario 3's project value is €3.21M which is therefore deemed investable.

For scenario 4, shown in Fig.4.9 (c), the initial investment time and size is different from that of scenario 2 and 3. In year 8, and initial BESS capacity of 70 MWh is deemed optimal. Three more expansions of capacity are sought in year 10, 11 and 14. This is attributed to scenario 4 having longer to wait for BESS CAPEX decline. The maximum value of BESS capacity at year 14 is 171 MWh. Scenario 4 has a project value of €0.93M. Similar to scenario 2 and 3, compensating for degraded BESS capacity is not fulfilled from year 15 to 20.

Two more scenarios are analysed to determine the effect degradation extrapolation to BESS sizes greater and less than 0.37C has on investment timing and sizing decisions. Scenario 5 and 6 are CAPEX path 1 with m equal to 0.5 and 0.8 respectively. When comparing scenario 2 to both scenario 5 and 6, neither scenario altered the initial investment timing or sizing capacity of scenario 2. Rather, B_{t_p} decisions were the same except for how much capacity had to be replaced after degradation. Therefore, the extrapolation of year 10 warranty energy retention limit for C-rate's other than 0.37C does not significantly affect the investment timing and sizing decisions. This is due the fact that the energy retention limit for BESS sizes changes only slightly near the optimal size for this study. The cumulative degradation for scenario 5 and 6 is 74.13 and 84.58 MWh respectively. Project values for scenario 5 and 6 are less than scenario 2 at €5.31M and €5.03M respectively. In addition to the above degradation sensitivity analysis, a further scenario 7 was analysed. Scenario 7 is hypothetical scenario representing increased degradation, where c_d is determined from R_E at 60%, C_R at 0.5C, CAPEX Path 2 and m equal to 0.2. Fig.4.10 outlines the results of scenario 7 with a project value of €1.03M, which is significantly less value than the corresponding CAPEX Path 2 for scenario 3 at €3.21M. The amount of degraded capacity is 123.9 MWh. The initial BESS capacity investment for scenario 7 is also much greater than scenario 3 due to the application of constraint (4.13) with the higher degradation of scenario 7. This could be relaxed if the value Q of constraint (4.13) was reduced from 30%. When compared to scenario 3, the optimal design now incorporates new BESS capacity for year 15, 16, 17 and 19, which is due to greater degradation of scenario 7. For the analysis of scenario 7, it is determined that the warranty available for a BESS has a consequential influence on the amount of degraded capacity that is accounted for with new capacity and also the project value.

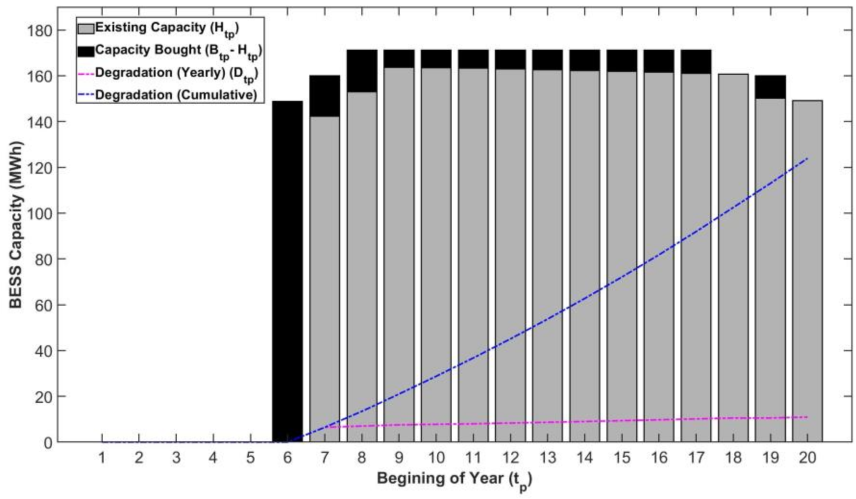

Fig.4.10 – The optimal investment timing and sizing for a 100MW BESS operating within the day-ahead market in I-SEM. Scenario 7 with an energy retention limit at 60%, a C-Rate of 0.5C, with CAPEX Path 2 and m equal to 0.2.

In general, regardless of BESS CAPEX realisation over the coming years, it is advisable to wait for 5 to 7 years before operating a BESS solely within the day-ahead market in I-SEM. While this shows somewhat low sensitivity of BESS CAPEX to investment timing, the optimal size of BESS over the first two to three years can be greatly affected by BESS CAPEX. Also, all scenarios maintained capacity levels that would otherwise be lost to degradation, up until the cost of doing so outweighs the benefits.

4.8 CONCLUSION AND FUTURE WORK

Given the success of reinforcement learning on gaming problems of late, it is applied here to determine the optimal dispatch of a BESS operating in the I-SEM day-ahead electricity market. The Deterministic Policy Gradient algorithm is used to solve a BESS operational model with the result being used in the planning model. The DPG is an effective method for finding optimal BESS dispatch strategy and calculating expected daily revenue. It should be noted that DPG goal is to find good policies and not the most optimal decision for every time step.

Using static NPV as a financial analysis method does not tell the entire picture. BESS investment projects have a variety of dynamic decisions available. ROA utilises dynamic decisions along with uncertainty. The application of ROA in this study is an effective technique for finding the optimal investment timing and BESS size.

Different future BESS CAPEX paths have minimal influence on the optimal investment time for a project. Rather, the optimal BESS size is heavily influenced by future CAPEX paths. This is a favorable outcome for investors. Given that the quantity of BESS capacity purchased is the most CAPEX intensive component of a project, investors do not need to upfront the investment at year 1, but can wait until year 7 or 8 to determine BESS CAPEX and then more accurately make a decision on how much capacity to purchase. Also, while benefits outweigh costs, the yearly degradation should be replenished with added capacity.

Accurately modeling degradation is a complex undertaking which is why manufacturers supply warranties to investors to reduce risk. Using a 10-year warranty retention limit as a worst-case scenario and considering different degradation options for values under a 0.37 C-Rate, degradation has little effect on the optimal investment timing and sizing. However, degradation does affect the value of a project.

For future work, more revenue streams need to be exploited to bring forward the optimal investment time and increase project value. Such revenue streams include, participation in the intra-day market and capacity market and co-location with a wind farm to reduce forecasting penalties. Furthermore, for this study the MW inverter parameter Y was held constant. To accurately reflect all decisions available to investors, this parameter can also be a decision variable which could impact investment timing.

CHAPTER FIVE

5 INCORPORATING CROSS-MARKET DISPATCH ADAPTABILITY WHEN SIZING BATTERY ENERGY STORAGE SYSTEMS

Incorporating planning objectives as part of BESS sizing is the sole purpose of this entire dissertation. In total, three planning objectives have been identified as requiring attention in this thesis, and are denoted as Investment Scale, Investment Timing and Dispatch Adaptability (see Section 2.9 for how planning objectives were determined and consolidated). The specific research within this chapter incorporates exclusively the planning objective Dispatch Adaptability as part of BESS sizing. This chapter has been submitted for review to a peer reviewed journal.

5.1 ABSTRACT

Existing operational strategies within literature are modelled as part of Battery Energy Storage Sizing (BESS) for the socialised benefit of a wider grid or microgrid. However, this does not comply with European Directive 2019/944 which states that "*System operators should not own, develop, manage or operate energy storage facilities*". This has created a disconnect between current BESS sizing approaches and the needs of future BESS sizing. In other words, BESS sizing needs to be capable of incorporating the requirements of BESS projects as sole beneficiaries rather than just wider grid benefits. The author of this chapter has put forward Dispatch Adaptability as one such requirement which has not been included in BESS sizing to date. Dispatch Adaptability is the term used to signify market participants' ability to change energy position in different markets. This ability allows for potential cross-market arbitrage, which if traded correctly, could increase the benefit received by market participants. The purpose of this chapter is to determine if it's possible to incorporate Dispatch Adaptability as part of

optimising energy capacity size for new BESS installation seeking maximum profit in a deregulated electricity market. Two models are formed, a model-based formulation which is solved via Stochastic Programming and a model-free formulation which is solved via the TD3 deep reinforcement learning algorithm. Both models are run using historical electricity market data without perfect foresight. Scenarios for model-based formulation are developed using the *k*-means algorithm. Artificial Neural Network inputs for the model-free formulation are taken directly from historical data (e.g. forecast data, previous market data). The results show that it is possible to incorporate Dispatch Adaptability as part of BESS sizing. The Stochastic Programming model-based approach outperformed the model-free approach when a simple artificial neural network was used. Furthermore, financially non-viable potential BESS installations can become financially viable projects with the inclusion of Dispatch Adaptability. Lastly, allowing BESS Dispatch Adaptability to avail of non-technically feasible trades in permitted markets can further improve Benefit-Cost Ratio (BCR).

5.2 INTRODUCTION

Dispatch adaptability is evident through different intraday market mechanisms, where jurisdictions have varying market designs [133, 134]. The example shown in Fig.5.1 (extracted from [135]) outlines dispatch adaptability available to market participants within the Integrated Single Electricity Market (I-

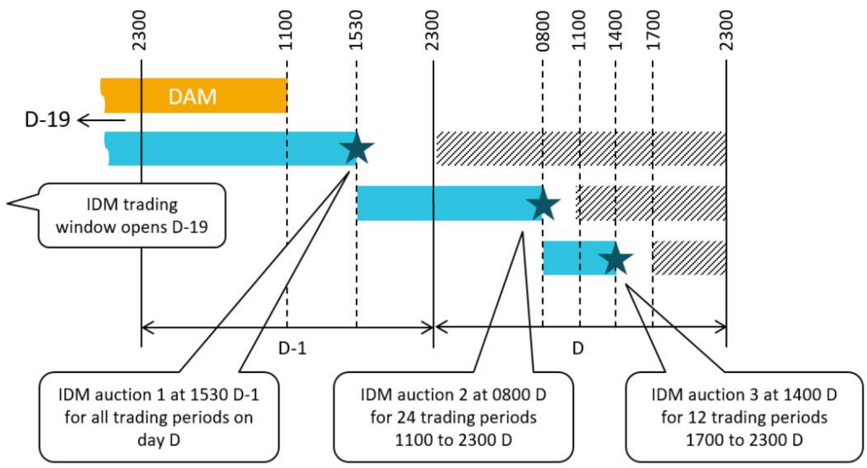

Fig.5.1 – Day-Ahead and Intraday Markets available within the Integrated Single Electricity Market.

SEM), which is the electricity market for the island of Ireland and is used as the test case in this chapter. There are four separate markets where a BESS can adapt its energy position: the Day-Ahead Market (DAM) and three Intraday Markets (IDM1-3). DAM opens 19 days before the trading day (D), has 24 hourly trading periods and closes at 11:00 D-1 where market participants must submit their bids/offers before this closure. IDM also open at D-19 with IDM1 closing 15:30 on D-1, IDM2 closing at 08:00 on D and IDM3 closing at 14:00 on D. All IDMs are based on half-hour trading periods, meaning IDM1 trades the entire 48 trading periods for D, while IDM2 trades the last 24 trading periods and IDM3 trades the last 12 trading periods. Along with IDM auctions, there is also a continuous trade matching service where bids and offers are matched as traded. Continuous trading is not considered as part of this research. These four markets offer participants the chance to alter their energy positions due to price differentials between each market (i.e. cross market arbitrage). For example, under certain circumstances it may be beneficial for a BESS to buy back energy sold in DAM for a certain trading period and sell at a higher price in IDM1 for a different trading period. Likewise, a BESS can avail of trades whereby energy is bought in IDM2 only to sell it again in IDM3 at a higher price. It is this dispatch adaptability through different markets which is of interest for this chapter, namely how to incorporate this adaptability into the optimisation of an objective function consisting of expected benefit and cost in order to size a BESS. For examples of trading options/strategies available to different market participants within I-SEM see "Industry Guide to I-SEM" published by Single Electricity Market Operator [136].

To model dispatch adaptability, an optimisation approach which can account for decision making under uncertainty at different epochs is required. One approach is to utilise a model-based formulation which is solved using deterministic linear equivalent Stochastic Programming (SP) via linear solvers. Another promising approach is solve a model-free formulation through Deep Reinforcement Learning (DRL) which has increased in popularity over recent years for use in power system applications [137, 138]. In essence, model-free DRL learns the transition function from past data samples. In this chapter, the DRL algorithm must accommodate multi-dimensional continuous action and state spaces. Two such Actor-Critic DRL algorithms that fit these requirements are Deep Deterministic Policy Gradient (DDPG) [139] and Twin Delayed Deep Deterministic Policy Gradient (TD3) [140]. Actor-Critic DRL algorithms maintain separate Artificial Neural Networks for the Actor (optimal decision) and Critic (value of optimal decision), where weight parameters for each network are learned through experience. This is described further in Section 5.4.2.1. The TD3 algorithm is an extension of DDPG where function approximation error is reduced through clipping exploration and delaying updates of target and policy networks. Both model-based and model-free approaches are used in this chapter.

The aim of this chapter is to determine if it is possible to incorporate Dispatch Adaptability as part of optimising energy capacity size for new BESS installation seeking maximum profit in a deregulated electricity market. Two sizing optimisation problems, model-based approach and model-free approach, are compared and contrasted. This is achieved through the following objectives: 1) utilise SP and TD3 to solve model-based and model-free respectively for the optimal BESS energy capacity size for a notional fixed 36MW import/export power capacity BESS coupled with historical I-SEM market price data with BCR as the objective function, 2) run multiple setups of different constraints to reflect bid/offer freedom within deregulated electricity markets.

5.3 LITERATURE REVIEW

Prior research on BESS sizing focussed on deterministic problems, as demonstrated by Yang et al., in [8]. Additionally, there is a lack of research which focuses on merchant electricity market participants' point of view. This literature review concentrates on BESS sizing for merchant entities, as this is the motivation for this chapter. To move BESS sizing from deterministic to the stochastic setting, a different approach is required, which can depend on the uncertainty type and the dynamic nature of decisions involved. A small number of different approaches have been considered by researchers to account for operational strategy decision-making under uncertainty for merchant BESS sizing. In [141] the authors used

Receding Horizon Control to maximise the profit of a wind farm by appropriately sizing a BESS for participation in the DAM and the balancing market. While their approach included wind, it did not allow for BESS scheduling within the DAM when the schedule deviation was set to zero within their model. This type of approach is too restrictive for BESS sizing within I-SEM, as BESS can set their position in the DAM. Another approach traded energy in IDM from a scheduled position in DAM to maximise NPV but did not allow for multiple stages of decision making [142]. The authors in [143] minimised the penalty costs of not meeting forecast generation but again available dispatch adaptability within deregulated electricity markets at different stages was not considered beyond altering the hourly BESS power output closer in time to the balancing market. There are two points to note from [141-143]. The first is that each used an objective function based on maximum difference between benefit and cost. However, the choice of objective function is not inconsequential, as maximising for net profit from discounted benefits and costs does not take account of the scale of effort required to achieve this net profit as has been previously shown by the author [70]. In fact, different objective functions have the potential to be inversely proportional to one another and therefore can recommend largely different optimal BESS sizes. Another option can be to select a relative measure (e.g. BCR) as the objective or to perform multi-objective optimisation of competing relative and absolute functions.

The second point to note is that no previous studies permitted the trading of the BESS within DAM, which will be addressed in this chapter. Furthermore, a consistent theme for the studies mentioned so far which considered stochastic optimisation, regardless of whether one or more different auctions were considered, is that each approached the optimisation problem using model-based forecasts (e.g. wind forecast, price forecast). The approach presented in this chapter not only uses a model-based formulation but also seeks to apply model-free stochastic optimisation through DRL. One other approach has used a model-free method for BESS sizing, however, it did not reflect any market rules and used a linear approximator without feature input [99].

Another area of research outside of merchant BESS sizing, but closely related, is the operational strategy used by merchant BESS. This serialises efforts for determining optimal dispatch decisions for a BESS operating in deregulated electricity markets under an assumed BESS size. Reviewing the literature associated with the operational strategy of merchant energy storage provides insight for solving the sizing problem, given that both include the same operational variables and parameters. Furthermore, literature which gives account of dynamic decisions across different electricity markets is sought, unlike the approach taken in [144, 145] which optimises merchant BESS participation in a single DAM and [146] which seeks the same but also considers market clearing as a bilevel optimisation problem. Two very similar dispatch modelling approaches to the one proposed in this chapter are presented in [147, 148]. For these, the authors modelled the participation of a BESS-coupled wind farm taking part in DAM, IDM and imbalance markets with stochastic programming used as the solution method. The approach taken in [149] accounts for dispatch decision by optimising over a longer time horizon. This is akin to modelling dispatch decision-making for two consecutive DAMs. This approach targets the question of whether energy should be stored for subsequent days for more profitable dispatch. This is outside the scope of this proposed research. Other research as shown by the authors in [150] for BESS and in [151] for Compressed Air Energy Storage (CAES), model dispatch decisions across different sequential markets. Their method called for solving two separate optimisation problems, for both the day-ahead and balancing market. This effectively means DAM decisions do not explicitly take account of balancing market decisions thereby negating the ability to trade across different markets. This is where the approach taken in this chapter differs. Others have focused on optimal dispatch concerning energy and reserve markets [88, 152]. This typically involves allocating a portion of BESS dispatch ability to either the energy market or the reserve market at any particular time period. However, neither of the studies incorporated the ability to modify dispatch decision in future markets so that a truer estimate of increased BESS value could be determined.

In addition to the above, studies have applied DRL and Reinforcement Learning (RL) to BESS dispatch adaptability in isolation from the BESS sizing question. These studies focused on the dispatch of a BESS where the size of the BESS is fixed. To compare previous DRL and RL studies with this research chapter, each is assessed using three of the five model dimensions proposed by [105], those being state variables, decision variables, and objective function. The choice of each can influence the selection of a suitable reinforcement learning algorithm. Another useful criterion by which to assess previous literature is the type of function approximation used and the reward function, which again influences the choice of reinforcement learning algorithm. In [153], the authors modelled arbitrage for a BESS using a discretised action space (i.e. a decision variable). This discretisation split the action space into five, thereby allowing five different values of the same decision variable available at each time step. Using this method permitted the authors to use Deep Q-Network (DQN) algorithms and further variations of DQN. Discretising the action space can lead to suboptimal dispatch strategies given that all the action space is not available to the DRL algorithm. These previous studies also included the degradation cost as part of the reward function, which is of noteworthy given that the reward function used in this chapter is BCR. Forecasted electricity price along with the BESS state of charge were used as the state variable. Similar to [153], the authors in [154] discretised the actions space. In [155], the authors also discretised the action space but used policy function approximation. They represented the state space for continuous trading within the German intraday market via offers available in the order book, capacity of the storage unit, previous market clearing prices, time to market closure, amount already traded, imbalance prevention and value of observable bids. The authors proved that these state variables are useful in the continuous trading problem setting. However, given that the approach used in this study is auction-based, all but one of these state variables are not relevant. The only similar state variable that is used in this study is the previous market clearing price.

Another important point to note from the DRL and RL papers reviewed thus far is that none modelled multi-dimensional decisions at decision epochs (i.e. more than one decision needed at each time step). Multi-dimensional decisions are more reflective of actual BESS market participation and are used in this study. For example, the DAM in I-SEM requires 24 decisions by market closure whereas the IDM1 market requires 48 decisions. The uniqueness of Actor-Critic DRL algorithms is that they can handle continuous multi-dimensional actions.

5.4 MODEL MATHEMATICAL FORMULATION

Benefit-cost ratio is chosen as the objective function. Two different variable types are involved when sizing a BESS, those being energy capacity decision and dispatch decisions. The BCR objective function contains both these variables, however solving for energy capacity decision and dispatch decision will be done separately. This can be understood as splitting out the BCR objective function into its constituent parts of expected benefit and cost, which presents distinct computational advantages. Firstly, it removes the need to solve for a non-linear objective function. Secondly, expected benefit is known once dispatch decision variables are solved for a particular BESS size, which leaves a simple evaluation of BCR using cost. This makes formulation of model-based and model-free approaches simpler. Therefore, dispatch decisions will be solved via Direct Search whereas energy capacity decision will be solved using Analytical Search. For a clearer illustration of the difference between Direct Search and Analytical Search see [8]. For the purpose of clarity, in this chapter energy capacity decision will also be referred to as B and BESS size. Dispatch decision may be referred to as bids/offers, charge/discharge, dispatch strategy, trading strategy, optimal policy, or trades. The choice of term used will depend on the context, as multiple names are used to accommodate the different perspectives of investors, market participants, system operators and optimisation communities.

5.4.1 BENEFIT-COST RATIO AND COST

Equation (5.1) outlines the BCR objective function for each BESS size, where Be and Co are the expected benefit and cost of a BESS respectively. Equation (5.1) is not solved via an optimisation algorithm but rather is evaluated once Be and Co are known for each possible BESS size. The maximum value for all evaluations of (5.1) gives the optimal BESS size. Equation (5.2) gives the maximum expected benefit available for each BESS size and is solved using either SP or TD3. The cost of a BESS

$$BCR(B) = \frac{Be}{Co} \tag{5.1}$$

$$Be = \begin{cases} \mathbb{E}Be_{SP}(B, Ps), & if\ solving\ using\ SP \\ \mathbb{E}Be_{TD3}(\pi, S), & if\ solving\ using\ TD3 \end{cases} \tag{5.2}$$

$$\begin{aligned} Co = B \times \left(\left(\left(\left(\frac{r(1+r)^l}{(1+r)^l - 1} \right) B_c(B) \right) + B_{mc} \right) \frac{1}{365} \right) \\ + \left(\left(\frac{r(1+r)^l}{(1+r)^l - 1} \right) P_c \times P_I \right) \frac{1}{365} \end{aligned} \tag{5.3}$$

$$B_c(B) = P_L + (P_U - P_L) e^{\left(-k \times \left(\frac{B}{10} - 1 \right) \right)} \tag{5.4}$$

installation Co is given by (5.3) which accounts for both the energy capacity cost and power cost, where r is the discount rate set at 8%, l is the length of time the BESS is installed, set at 20 years, B_{mc} is the BESS maintenance cost at the value of € 267.43/MWh [156], P_c is the power cost element at €52.4/MW and P_I is the size of the power element set arbitrarily at 36MW. Economies of scale are integrated via (5.4), where larger BESS cost less per MWh, P_L is the lower cost limit at €148.8k/MWh, P_U is the upper cost limit at €215.6k/MWh and k is a constant set at 0.2. The lower/upper limit and P_c are taken from [156] and converted to EUR using an exchange rate of USD 1 = EUR 0.8455. As can be seen in (5.3) both components of Co are multiplied by 1/365, which transforms the discounted yearly cost into a daily cost. This allows Be to be estimated on a daily basis. Therefore, any references to BCR, expected benefit or cost throughout this chapter are implicitly referring to the daily BCR, daily expected benefit and daily cost respectively.

5.4.2 EXPECTED BENEFIT OF BESS

Establishing expected benefit for a particular BESS size requires estimating dispatch decisions (DD) coupled with historical electricity market clearing price parameters. Determining DD using SP and TD3 is categorically different due the variances between each solution method. Regardless of method, both model-based and model-free approaches must account for dispatch adaptability available within the I-SEM market as shown in Fig.5.1. Section 5.4.2.1 outlines how dispatch adaptability decisions available within I-SEM (as shown in Fig.5.1) are formulated for both model-based and model-free approaches. Another point to note is that when operating within the I-SEM, market participants' successful bids/offers are pay-as-clear. For the purposes of this research, all price-quantity pairs (€/MWh, MWh) assume a price value of zero to guarantee dispatch which also assumes that BESS trading strategy does not significantly influence market clearing prices. Furthermore, the I-SEM balancing market is not modelled. The balancing market compels all participants less than the *de minimis* threshold to submit Physical Notifications (PN), Commercial Offer Data (COD) and Technical Offer Data (TOD) so that their energy positions can be adjusted closer to real time but after the closure of Intraday markets i.e. one before trading period. This allows the system operator to adjust participants' energy positions for system security reasons or where the result of the auction is either long or short. Not modelling the balancing market imposes no variation between submitted bids/offers and the level of dispatch. Another I-SEM market which is not modelled, as the solution methods used here are only suitable for discrete time steps, is the Continuous Intraday Market (CIDM). The CIDM matches bids and offers from participants on a continuous basis, after the closure of DAM but before the opening of the balancing market.

5.4.2.1 DISPATCH MODELS

The expected benefit for the model-based formulation is given by the objective function (5.5), where I-SEM dispatch adaptability from Section 5.2 is captured through four stages, where $\underline{a}$ represents the trading periods within stage 1 (Day-Ahead Market), $\underline{b}$ represents the trading periods within Stage 2 (Intraday Market 1), $\underline{c}$ represents the trading periods within Stage 3 (Intraday Market 2) and $\underline{d}$ represents the trading periods within Stage 4 (Intraday Market 3). This model-based formulation uses scenarios of electricity market clearing prices given by Ps for each stage and scenario n, with the probability of each scenario given by Y_n. See Section 5.5.1 outlining derivation of Ps and Y_n.

$$\mathbb{E}Be_{SP}(B,Ps) = \max_{x} \sum_{n=1}^{N} Y_n \cdot \left(\underbrace{{Ps_{n,1}}^{\top} x_{\underline{a},n}^{DAM}}_{Stage\ 1} + \underbrace{{Ps_{n,2}}^{\top}\left(x_{\underline{b},n}^{IDM1} - x_{\underline{b},n}^{DAM}\right)}_{Stage\ 2} \right.$$
$$\left. + \underbrace{{Ps_{n,3}}^{\top}\left(x_{\underline{c},n}^{IDM2} - x_{\underline{c},n}^{IDM1}\right)}_{Stage\ 3} + \underbrace{{Ps_{n,4}}^{\top}\left(x_{\underline{d},n}^{IDM3} - x_{\underline{d},n}^{IDM2}\right)}_{Stage\ 4} \right) \tag{5.5}$$

$$x^{DAM} = \begin{bmatrix} \frac{x_{\underline{a},n}^{c}}{\eta} + x_{\underline{a},n}^{d} . \eta \\ \vdots \\ \frac{x_{\underline{a},N}^{c}}{\eta} + x_{\underline{a},N}^{d} . \eta \end{bmatrix}, x^{IDM1} = \begin{bmatrix} \frac{x_{\underline{b},n}^{c}}{\eta} + x_{\underline{b},n}^{d} . \eta \\ \vdots \\ \frac{x_{\underline{b},N}^{c}}{\eta} + x_{\underline{b},N}^{d} . \eta \end{bmatrix},$$
$$x^{IDM2} = \begin{bmatrix} \frac{x_{\underline{c},n}^{c}}{\eta} + x_{\underline{c},n}^{d} . \eta \\ \vdots \\ \frac{x_{\underline{c},N}^{c}}{\eta} + x_{\underline{c},N}^{d} . \eta \end{bmatrix}, x^{IDM3} = \begin{bmatrix} \frac{x_{\underline{d},n}^{c}}{\eta} + x_{\underline{d},n}^{d} . \eta \\ \vdots \\ \frac{x_{\underline{d},N}^{c}}{\eta} + x_{\underline{d},N}^{d} . \eta \end{bmatrix} \tag{5.6}$$

$$\underline{a} = \{1, \dots ,24\}, \underline{b} = \{1, \dots ,24\}, \underline{c} = \{13, \dots ,24\}, \underline{d} = \{19, \dots ,24\} \tag{5.7}$$

The efficiency is given by η and is assumed to be the same for both charging and discharging at 0.95 [156]. The variables of $x^{DAM}, x^{IDM1}, x^{IDM2}$ and x^{IDM3} shown in (5.6) are the DD associated with stage 1, 2, 3 and 4 respectively for each scenario n. Solving for $x^{DAM}, x^{IDM1}, x^{IDM2}$ and x^{IDM3} is done via transforming (5.5) into a linear deterministic equivalent and solved using MATLAB solver (*linprog*).

Linear deterministic equivalent programming can be used to determine DD for the model-based formulation. For the model-free formulation, the DD (called an optimal policy within the DRL research community) is ascertained via learned and

$$\pi_{\phi_t}(S_t) \tag{5.8}$$

$$S_t = \begin{cases} \left(F_{t,e}, E_t, B\right), & t = 1 \\ \left(F_{t,e}, V_{t-1,e}, P_{t-1,e}, \pi_{\phi_{t-1}}(S_{t-1}), E_t, B\right), & t > 1 \\ \left(F_{t,e},, V_{t-1,e}, P_{t-1,e}, a_{t-1}, E_t, B\right), & t > 1\ explore\ using\ a_t \end{cases} \tag{5.9}$$

$$Q_{\theta_t}(S_t, a_t) = R_t(S_t, a_t) + Q_{\theta_{t+1}}\left(S_{t+1}, \pi_{\phi_{t+1}}(S_{t+1})\right) \tag{5.10}$$

$$R_t(S_t, a_t) = \begin{cases} (-a_t * \eta_t)^{\top} P_{t,e}), & t = 1 \\ ((-a_t - (-a_{t-1})) * \eta_t)^{\top} P_{t,e}), & t > 1 \end{cases} \tag{5.11}$$

updating weight parameters ϕ_t of an Artificial Neural Network (ANN) through experience. Optimal policy ANNs are given by (5.8) and referred to as an Actor. Four different Actors are used to model I-SEM dispatch adaptability as shown in Fig.5.1, where vector $t = \{1,2,3,4\}$ represents the four different stages (i.e. markets) of I-SEM. Using four different Actors is divergent from usual DRL approaches which only apply one Actor for each stage. However, the dispatch adaptability problem requires different Actor inputs/outputs at each stage thereby necessitating separate ANN arrangements. The Actor input is known as the state variable (5.9), where $F_{t,e}$ is the grid's demand forecast less the grid's wind forecast, $V_{t-1,e}$ is the previous market energy volumes traded, $P_{t-1,e}$ is the previous market clearing price, E_t is the stored energy within BESS before the market at stage t closes (calculated using (5.28)) and B is the BESS size. Model-free formulation is ensured as the variables within S_t are known before a decision is made by $\pi_{\phi_t}(S_t)$, further outlined in Section 5.5.2. As can be seen in (5.9) the Actor at stage 1 (Day-Ahead Market) does not include previous dispatch instructions or electricity market information as these are not available at stage 1. To learn the optimal policy, the gradient of the Q-function $\nabla_{\pi_{\phi_t}(S_t)} Q_{\theta_t}(S_t, \pi_{\phi_t}(S_t))$ with respect to the optimal policy (5.8) is used to iteratively update the weight parameters ϕ_t of the Actor, which is in accordance with the deterministic policy gradient theorem [123]. The Q-function $Q_{\theta_t}(S_t, a_t)$ is also an ANN with weight parameters θ_t which is estimated using the Bellman Equation (5.10) and updated iteratively via the Adam Optimiser. The Q-function (also called the Critic) can be thought of as the value of being in a certain state S_t and taking a certain action a_t. Actions a_t are the exploration of different dispatch instructions needed to find the optimal policy and are determined by adding noise to $\pi_{\phi_t}(S_t)$. The reward function (5.11) is modified for stage 1, where $P_{t,e}$ is historical I-SEM market clearing prices for market t and η_t is efficiency which is an equal sized vector to a_t taking an element value of 1/0.95 when the corresponding $(-a_t)$ element is negative and 0.95 when the corresponding $(-a_t)$ element is positive. Forecast of grid demand net wind, energy volumes traded and market clearing price form the tuple $\langle F_{t,e}, V_{t,e} P_{t,e} \rangle$ of previous experience i.e. historic I-SEM data. Demand net wind forecast [157], energy volume

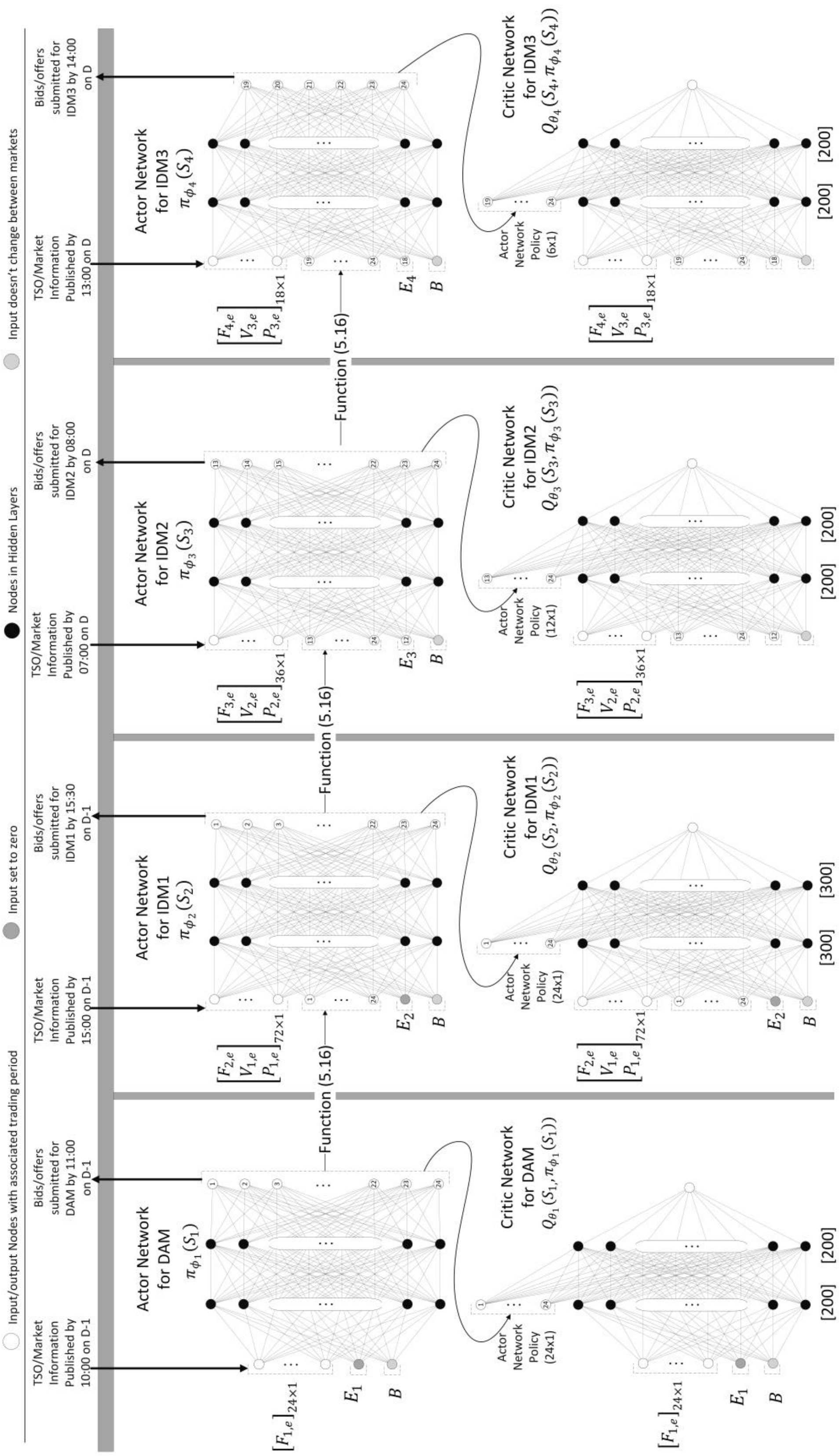

Fig.5.2 – Artificial Neural Networks used for both Actor and Critic for all electricity markets. Also, timing of TSO/market information and bid/offer submissions.

traded and market price pairs [158] are extracted from the I-SEM websites for dates between 1st Oct 2018 and 28th Feb 2020. After the removal of missing/errors in data, 463 tuple pairs are useable. During learning, the TD3 algorithm samples these tuples for the initial state S_1 by random uniform selection of an element from the set e where $\{e \in \mathbb{Z} | 1 \leq e \leq 463\}$. The Actor and Critic networks learn from experience generated through exploration by a_t. Once learning is completed, the optimal policy inputted into the Critic gives the maximum likely value. For further details on how the TD3 algorithm works see reference [140]. Fig.5.2 outlines the ANNs used, which are all Multi-Layered Perception (MLP) neural networks. Eight separate MLPs are formed, four Actors for each market and four Critics for each market. Separate Actor and Critic networks are a requirement for the TD3 algorithm. The number of nodes for each of the hidden layers is also shown within Fig.5.2 underneath each Critic network. The same number of nodes apply for the Actor. Normally, DAM has 24 trading periods of one hour each while IDMs utilise half-hour trading periods. To reduce computational effort, a one-hour rather than a 30-minute DAM trading period duration is used. This simplification is also used for the model-based formulation. A further reduction in the computation burden is provided by using the grid demand net of wind forecast variable $F_{t,e}$ as part of the state variable rather than separate grid demand and grid wind forecasts, thereby reducing the number of inputs by half. EirGrid, the transmission system operator (TSO) on the island of Ireland publishes the grid demand forecast every hour and grid wind forecast every six hours, each for the upcoming four days. The grid demand forecast is given in half hour intervals and grid wind forecast in 15-minute intervals. The model-free expected benefit of a BESS can be estimated by $\pi(S)$ via (5.12), where the benefit is summed over a dataset of size N_d and e can be any number between 1 and N_d.

$$\mathbb{E}Be_{TD3}(\pi, S) = \sum_{e} \frac{1}{N_d} . \begin{pmatrix} R_1\left(S_1, \pi_{\phi_1}(S_1)\right) + R_2\left(S_2, \pi_{\phi_2}(S_2)\right) \\ + R_3\left(S_3, \pi_{\phi_3}(S_3)\right) + R_4\left(S_4, \pi_{\phi_4}(S_4)\right) \end{pmatrix} \tag{5.12}$$

Where:

$$S_1 = \left(F_{1,e}, E_t, B\right)$$

$$S_2 = \left(F_{2,e}, V_{2-1,e}, P_{2-1,e}, \pi_{\phi_{2-1}}(S_{2-1}), E_2, B\right)$$
$$S_3 = \left(F_{3,e}, V_{3-1,e}, P_{3-1,e}, \pi_{\phi_{3-1}}(S_{3-1}), E_3, B\right)$$
$$S_4 = \left(F_{4,e}, V_{4-1,e}, P_{4-1,e}, \pi_{\phi_{4-1}}(S_{4-1}), E_4, B\right)$$

5.4.2.2 CONSTRAINTS AND BOUNDS

Trading across different markets allows market participants to adjust their energy positions closer to real time as previously outlined in Section 5.2 and Fig.5.1. It is this characteristic that gives market participants freedom to decide bids/offers which reflect their belief about the market rather than the technical capacities of their connection point, be it availability of BESS due to its stored energy level, or renewable availability such as wind or solar. Normally, any deviation in real-time from a participant's accepted bids/offers is charged or paid out at the balancing market price, depending on whether the participant is dispatched up or down by the system operator. However, as the balancing market is not modelled as part of this research and BESS are energy restricted devices, constraints are necessary to ensure that the final bid/offer for a trading day matches BESS technical ability. This is achieved through applying constraints (5.13) and (5.14), where tp is a trading period within D numbered 1 to 24.

$$\sum_{\underline{b} \leq \min(tp,12)} x^c_{\underline{b},n} + x^d_{\underline{b},n} + \sum_{\underline{c} \leq \min(tp,18)} x^c_{\underline{c},n} + x^d_{\underline{c},n} + \sum_{\underline{d} \leq tp} x^c_{\underline{d},n} + x^d_{\underline{d},n} \geq 0, \forall\, tp \text{ and } n \tag{5.13}$$

$$\sum_{\underline{b} \leq \min(tp,12)} x^c_{\underline{b},n} + x^d_{\underline{b},n} + \sum_{\underline{c} \leq \min(tp,18)} x^c_{\underline{c},n} + x^d_{\underline{c},n} + \sum_{\underline{d} \leq tp} x^c_{\underline{d},n} + x^d_{\underline{d},n} \leq B, \forall\, tp \text{ and } n \tag{5.14}$$

$$ac_{t,i} = a_{t,tp}, where\ i = tp \tag{5.15}$$

$$ac_{t,i} = \begin{cases} \max\left(-\left(E_t + \sum_{j=1}^{i} ac_{t,j-1}\right), -IN\right), & E_t + \sum_{j=1}^{i} ac_{t,j} < 0 \\ \min\left(B - E_t + \sum_{j=1}^{i} ac_{t,j-1}, IN\right), & E_t + \sum_{j=1}^{i} ac_{t,j} > B \end{cases}, \forall\, i \tag{5.16}$$

$$Py_t(a_t, ac_t, B) = abs(a_t - ac_t)^{\top}(-5) \tag{5.17}$$

For the model-free approach, rather than applying constraints through the final output layer of the Actor network, constraints are implemented through a penalty function given by (5.17). The penalty function is summed to the reward function (5.11) which gives the total reward for each set of actions, where ac_t are actions that do not violate the constraints. Initially ac_t is equal to a_t through (5.15), which is updated via (5.16). The penalty rate within (5.17) is set to negative €5/MWh which performed well under testing. The state variable E_t is determined using (5.28).

Applying said constraints to all trading periods in every market is not obligatory and can be overly restrictive, where IN is the power capacity of the BESS, set at 36MW. For example, it is possible to adjust all established positions from DAM in IDM1. This means that bids/offers to the DAM do not have to follow the technical capabilities of a BESS, which is energy-limited, and therefore a BESS can benefit from constraint-free bids/offers. This is also true for IDM2 and IDM3 albeit for an ever-smaller number of trading periods as Balancing Market commencement is approached. This can be understood further by setting parameters $Rule_L$ and/or $Rule_U$ within constraints (5.18), (5.19), (5.20) and (5.21) to varying values. Here, two different rulesets are used and results compared within Section 5.6. Rule 1 sets $Rule_L$ and $Rule_U$ to 0 and B respectively, while Rule 2 sets $Rule_L$ and $Rule_U$ to $-B$ and B respectively. Setting $Rule_L$ to $-B$ permits discharge variables x^d to discharge without the energy limiting constraint of a BESS but only for trading periods where x^d can be adjusted at a later stage (i.e. a later market). Rule 1 is applied to both the model-based and model-free formulations while Rule 2 is only applied to model-based.

$$\begin{gathered}\sum_{\underline{a} \leq tp} x^c_{\underline{a},n} + x^d_{\underline{a},n} \geq Rule_L, \forall\ tp\ and\ n \\ \sum_{\underline{a} \leq tp} x^c_{\underline{a},n} + x^d_{\underline{a},n} \leq Rule_U, \forall\ tp\ and\ n\end{gathered} \tag{5.18}$$

$$\begin{gathered}\sum_{\underline{b}\leq tp} x^{c}_{\underline{b},n} + x^{d}_{\underline{b},n} \geq Rule_{L}, \forall\ tp\ and\ n \\ \sum_{\underline{b}\leq tp} x^{c}_{\underline{b},n} + x^{d}_{\underline{b},n} \leq Rule_{U}, \forall\ tp\ and\ n\end{gathered} \tag{5.19}$$

$$\begin{gathered}\sum_{\underline{b}\leq 12} x^{c}_{\underline{b},n} + x^{d}_{\underline{b},n} + \sum_{\underline{c}\leq tp} x^{c}_{\underline{c},n} + x^{d}_{\underline{c},n} \geq Rule_{L}, \forall\ tp\ and\ n \\ \sum_{\underline{b}\leq 12} x^{c}_{\underline{b},n} + x^{d}_{\underline{b},n} + \sum_{\underline{c}\leq tp} x^{c}_{\underline{c},n} + x^{d}_{\underline{c},n} \leq Rule_{U}, \forall\ tp\ and\ n\end{gathered} \tag{5.20}$$

$$\begin{gathered}\sum_{\underline{b}\leq 12} x^{c}_{\underline{b},n} + x^{d}_{\underline{b},n} + \sum_{\underline{c}\leq 18} x^{c}_{\underline{c},n} + x^{d}_{\underline{c},n} + \sum_{\underline{d}\leq tp} x^{c}_{\underline{d},n} + x^{d}_{\underline{d},n} \geq Rule_{L}, \forall\ tp\ and\ n \\ \sum_{\underline{b}\leq 12} x^{c}_{\underline{b},n} + x^{d}_{\underline{b},n} + \sum_{\underline{c}\leq 18} x^{c}_{\underline{c},n} + x^{d}_{\underline{c},n} + \sum_{\underline{d}\leq tp} x^{c}_{\underline{d},n} + x^{d}_{\underline{d},n} \leq Rule_{U}, \forall\ tp\ and\ n\end{gathered} \tag{5.21}$$

Both model-based and model-free dispatch decision variables are arbitrarily bounded to values of 36MW for charging and -36MW for discharging. Implementing this within the TD3 algorithm is done through (5.22) which is a bounding method utilised by [129] for continuous action spaces. The gradient of the Critic Network with respect to the Actor policy, $\nabla_{\pi_{\phi_t}(S_t)} Q_{\theta_t}(S_t, \pi_{\phi_t}(S_t))$, is adjusted so that the suggested change in Actor policy is within the bounds of allowable values.

$$\nabla_{\pi_{\phi_t}(S_t)} Q_{\theta_t}(S_t, \pi_{\phi_t}(S_t)) = \begin{cases} \dfrac{IN - \pi_{\phi_t}(S_t)}{IN - (-IN)}, & \nabla_{\pi_{\phi_t}(S_t)} Q_{\theta_t}(S_t, \pi_{\phi_t}(S_t)) > 0 \\ \dfrac{\pi_{\phi_t}(S_t) - (-IN)}{IN - (-IN)}, & \nabla_{\pi_{\phi_t}(S_t)} Q_{\theta_t}(S_t, \pi_{\phi_t}(S_t)) \leq 0 \end{cases} \tag{5.22}$$

5.5 IMPLEMENTATION

As stated previously, expected benefit solutions for both model-based and model-free formulations are to be estimated using historical data i.e. past electricity market clearing prices for model-based along with past forecast data, energy volumes traded and electricity market clearing prices for model-free formulation. Given that the data used is historical, inputting them directly into model-based and model-free formulations as perfect foresight would lend itself to a unworthwhile analysis for future prediction of expected benefit. It is of more value to ensure that both model-based and model-free formulations use historical data in such a way that perfect foresight of electricity market clearing prices is not assumed. The following sections outline how historical data is incorporated along with the necessary implementation steps for each method.

5.5.1 MODEL-BASED STOCHASTIC PROGRAMMING

A linear deterministic equivalent SP is used to solve for DD in model-based formulations using (5.5) and (5.6). This requires N number of price path scenarios $Ps_{n,t}$ along with scenario probability Y_n. Of particular importance is the need to ensure that perfect foresight is not allowable when selecting scenarios. Therefore, rather than using known historical electricity market clearing prices with transition probabilities equal to 1, the k-means algorithm is used to generate price path clusters C from historical electricity market prices $P_{t,e}$. This concept is shown in Fig.5.3 which has five different price path clusters for each electricity market for illustrative purposes. The actual number of price paths clusters used in this analysis is 15 for each electricity market which keeps computation requirements low at $N = 15^4$. Also shown in Fig.5.3 are the price path cluster transition matrix probabilities for each stage given by $Y^{DAM\rightarrow IDM1}$, $Y^{IDM1\rightarrow IDM2}$ and $Y^{IDM2\rightarrow IDM3}$. The value of $y_{i,j}$ is determined via the number of $P_{t,e}$ observations belonging to price path cluster i,

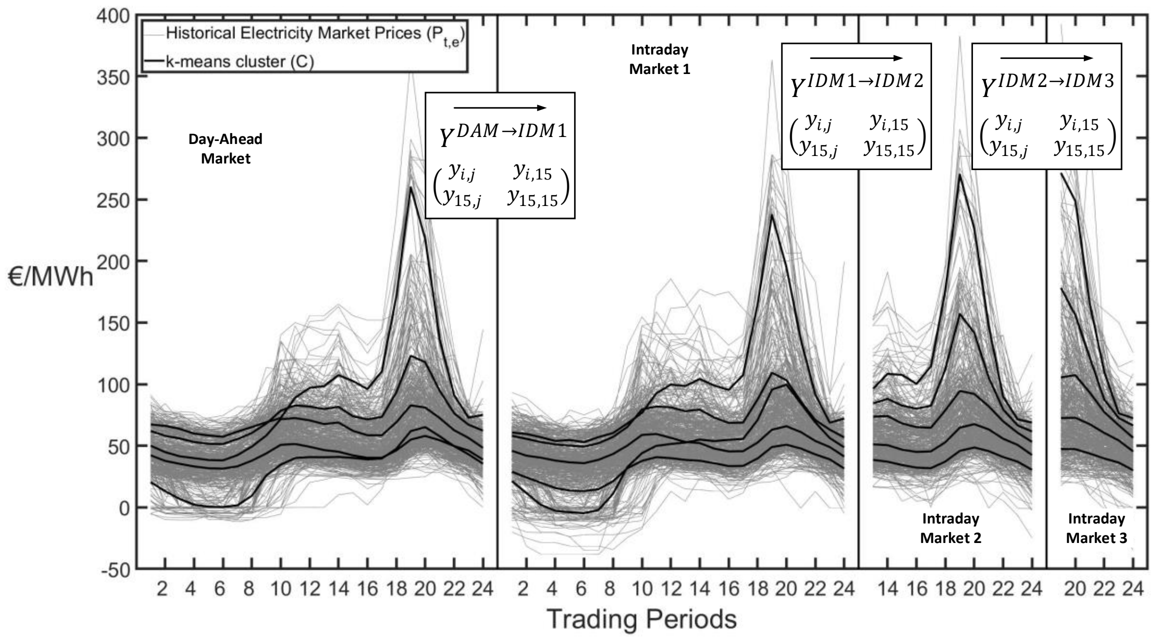

Fig.5.3 – Price path clusters developed from historical electricity market prices using k-means. Five clusters shown for illustrative purposes.

that transition into $P_{t+1,e}$ observations belonging to price path cluster j, divided by the total number of $P_{t,e}$ observations belonging to price path cluster i that transition into $P_{t+1,e}$ observations belonging to all price path clusters for stage $t+1$. The $P_{t,e}$ observations of historical electricity market clearing prices are the same electricity prices used within the tuples $\langle F_{t,e}, V_{t,e}, P_{t,e} \rangle$ from Section 5.4.2.1 .

To construct each price path probability scenario Y_n for a linear deterministic equivalent model (5.5), each value of n has a unique order pair of *4*-tuple from z, determined via Cartesian Product (5.24) of the sets $\underline{A}, \underline{B}, \underline{C}$ and $\underline{D}$ (5.23). Using this unique order

$$\underline{A} = \{1, \dots, 15\}, \qquad \underline{A} = \underline{B} = \underline{C} = \underline{D} \tag{5.23}$$

$$\begin{gathered} z = \underline{A} \times \underline{B} \times \underline{C} \times \underline{D} \\ v = \{(z_1, z_2), (z_2, z_3), (z_3, z_4)\} \end{gathered} \tag{5.24}$$

$$Ps_n = \left[C_{z_1}^{DAM}, \quad C_{z_2}^{IDM1}, \quad C_{z_3}^{IDM2}, \quad C_{z_4}^{IDM3} \right], \quad \forall\, N \tag{5.25}$$

$$Y_n = Y_{v_1}^{DAM \to IDM1} \cdot Y_{v_2}^{IDM1 \to IDM2} \cdot Y_{v_3}^{IDM2 \to IDM3}, \quad \forall\, N \tag{5.26}$$

pair gives all possible price path scenarios (5.25). Non-anticipative constraints are implemented for each price path cluster in each respective stage. The probability of each scenario is given by Y_n (5.26) which utilises the same order pair as (5.25) only indexed by v (5.24) rather than z to establish transitions.

Additionally, a single stage Day-Ahead Market is also modelled so that a meaningfully comparison with/without dispatch adaptability can be done. This involves modelling only stage 1 of (5.5), removing constraints (5.13) and (5.14), setting constraint (5.18) to Rule 1 and removal of constraints (5.19), (5.20) and (5.21).

5.5.2 MODEL-FREE TD3 ALGORITHM

Unlike the implementation of model-based formulation which assumes that no historical information is available during decision making, the model-free formulation has access to state variable $F_{t,e}$, previous market energy volumes traded $V_{t-1,e}$ and previous market electricity clearing prices $P_{t-1,e}$ before dispatch decisions are required. See Fig.5.2 for the timeline of decision making.

Consequently, using historical $F_{t,e}$, $V_{t-1,e}$, $P_{t-1,e}$ as part of the state variable rather than historical $P_{t,e}$ ensures that perfect foresight is not used and that the approach remains model-free.

For implementing the TD3 algorithm, updates of both Critic and Actor networks are done using the ADAM optimiser [159] along with backpropagation to determine the gradients of each network. The hyperparameters for ADAM are the same as outlined in [159], with the learning rate for the Critic and Actor networks set to 10^{-2} and 10^{-3} respectively. The initial weight parameters (ϕ_t and θ_t) of each network are determined via (5.27), where each weight used as an input for a specific node is calculated using the number of weights entering that node n_w and sampled from a normal distribution $\mathcal{N}$ with mean 0 and standard deviation of 1. The choice of activation function for the hidden network layers is leaky ReLu, with parameterisation set to 0.1 for negative inputs. A linear activation function is used for the output layer of both Critic and Actor, while the MLP inputs are normalised before being passed through. The number of nodes and layers are shown in Fig.5.2.

$$\mathcal{N}(0,1) \times \sqrt{\frac{2}{n_w}} \tag{5.27}$$

Other hyperparameters include, a batch size of 32, a replay buffer size of 240,000 tuple pairs of past experience, target networks updated every two iterations by 0.005 of learned network with Actor network also updated every two iterations, an exploration strategy using normal distribution with standard deviation of 7, with also target policy smoothing exploration using standard deviation of 0.5, and the reward function $R_t(S_t, a_t)$ scaled by 0.001. The model-free formulation is solved for BESS sizes B from a range of values between 10MWh and 200MWh in intervals of 20MWh to reduce computation effort. The BESS size corresponding to the maximum value of (5.12) is noted. Proceeding this, the TD3 algorithm is employed again on two more BESS sizes (+/- 10MWh of the BESS size from (5.12)) to increase the final accuracy level.

$$E_t = \begin{cases} 0, & t \le 2 \\ \sum_{i=1}^{12} ac_{t-1,i}\,, & t = 3 \\ E_{t-1} + \sum_{i=13}^{18} ac_{t-1,i}\,, & t = 4 \end{cases} \tag{5.28}$$

The energy state of the BESS (E_t) is required and known for the Critic and Actor networks in IDM2 and IDM3, seen in Fig.5.2 and outlined in (5.28). To model a single stage Day-Ahead Market for comparative purposes, the TD3 algorithm only learns the Actor and Critic Network for the first stage i.e. iterative learning starts and stops at $t = 1$.

5.6 RESULTS AND DISCUSSION

Model-based BCR results of (5.1) for single stage (i.e. Day-Ahead Market only) and multiple stages (Rule 1 and Rule 2) are shown in Fig.5.4. A BCR value greater than or equal to 1 is required for BESS installations to be permissible. From Fig.5.4 it is shown that when no dispatch adaptability is considered (i.e. single stage), none of the proposed BESS sizes have a BCR value greater than or equal to 1 and are therefore not permissible. The highest achievable BCR value for a single stage is 0.825 at 70 MWh. Only when dispatch adaptability is included (i.e. multiple stages) are BESS deemed allowable, with sizes from 40 MWh to 150 MWh permissible under Rule 1 and sizes 20 MWh to 180 MWh permissible when utilising Rule 2. Rule 1 allows for BESS technically feasible bids/offers in all markets while Rule 2 allows bids/offers which are less constrained by hourly BESS energy storage levels as outlined in Section 5.4.2.2. With greater bid/offer freedom in Rule 2, a superior BCR value is achievable as BESS can utilise dispatch adaptability to bid/offer energy quantities that are not technically feasible for the BESS, only to correct a technically feasible energy position in a later market. In doing this, and if market clearing prices are favourable, Rule 2 has more opportunity for expected revenue than Rule 1. It is noteworthy that the absolute difference between BCR Rule 1 and Rule 2 values reduces as BESS size increases, due to Rule 2's diminishing influence for larger BESS sizes. The only difference between both rules is that Rule 2 allows for cumulative bids/offers to reach $-B$ for any trading period as per constraints (5.18), (5.19), (5.20) and (5.21).

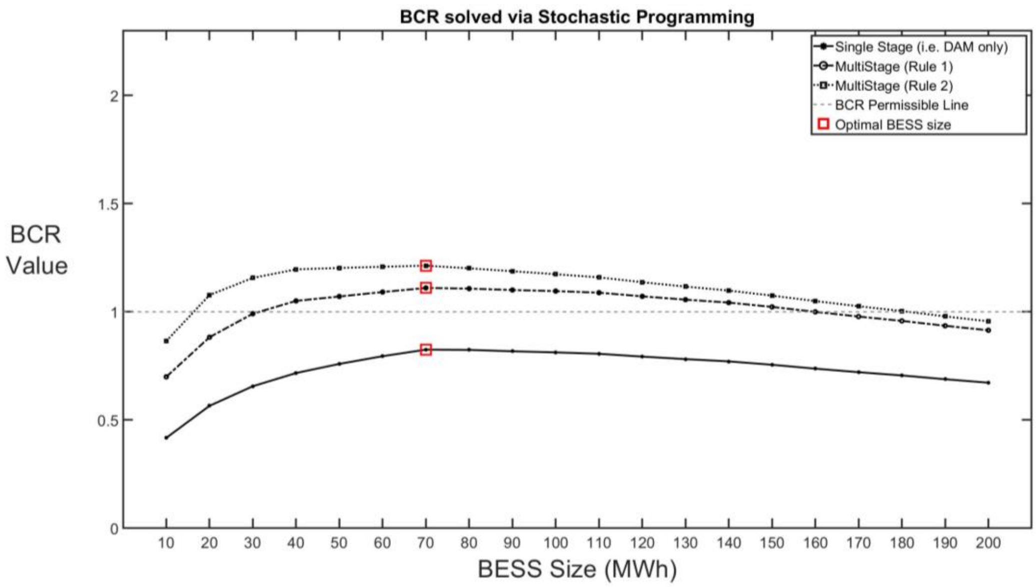

Fig.5.4 – BCR values for different BESS sizes of model-based formulation solved via Stochastic Programming for single stage and multistage. All BESS sizes on or above BESS permissible line are deemed acceptable.

Explaining this further using IDM2 as one possible example, it is highly probable that a BESS is significantly charged at trading period 18 in IDM2 given the need to be in position to avail of higher clearing prices in trading periods 19, 20, 21 and 22. In addition, the only way to reach $-B$ is to discharge more than charge. Therefore, the state of charge at trading period 18 in IDM2 heavily influences the likelihood of reaching $-B$ for trading periods 19 to 24 in IDM2 and IDM3. For a smaller BESS fully charged at IDM2 trading period 18, Rule 2 is required to achieve non-technically feasible favourable trades as a smaller BESS does not have sufficient capacity. However, due to their larger capacity, a fully charged larger BESS (compared to a smaller BESS) has greater opportunity to achieve favourable trades without requiring technically unfeasible trades and is therefore less reliant on Rule 2 to achieve favourable trades. Consequently, as BESS size increases, the BCR value for Rule 1 and Rule 2 begin to converge. Furthermore, the BESS size with the greatest BCR for both Rule 1 and Rule 2 is 70 MWh, with a BCR value for each at 1.11 and 1.213 respectively. Analysis of the above suggests that incorporating dispatch adaptability into BESS sizing model-based formulations solved using SP has the potential to make initially unviable proposed BESS projects viable. Also, while the inclusion of dispatch adaptability improves BESS profitability, optimal BESS size remains the same for single stage and multiple stages. Additionally, and depending on the ruleset used as part of dispatch adaptability, smaller BESS sizes have greater potential to gain advantages from dispatch adaptability.

As demonstrated thus far, the use of SP to solve for DD is based on k-means algorithm price clusters C developed from the entire historical electricity market clearing price dataset $P_{t,e}\ \forall\ t, e$. Similarly, the TD3 algorithm was given access to the entire dataset of tuples $\langle F_{t,e}, V_{t,e}, P_{t,e}\rangle\ \forall\ t, e$ to learn DD. However, constant fluctuations in $Q_{\theta_1}(S_1, \pi_{\phi_1}(S_1))$ were observed after varying amounts of learning time resulting in non-convergence of $Q_{\theta_1}(S_1, \pi_{\phi_1}(S_1))$. This underfitting behaviour indicates MLP type and size does not have the capacity to generalise well over the entire dataset $\langle F_{t,e}, V_{t,e}, P_{t,e}\rangle\ \forall\ t, e$. Due to computation limitations, the MLP ANN remained unchanged. To improve convergence, the TD3 algorithm access was condensed to a smaller subset of historical data (one month of data). The risk of overfitting is reduced in DRL through exploration via stochastic policy. Furthermore, the exploration policy is used as a state variable for subsequent stages thereby reducing overfitting risk further through the addition of new replay buffer training samples after each training iteration.

The model-free BCR results of (5.1) are shown in Fig.5.5 for single stage and multiple stages using Rule 1. Inclusion of dispatch adaptability (i.e. multiple stages) through model-free formulation increases BCR value for each BESS size, again demonstrating the value of modelling dispatch adaptability when sizing BESS. Conversely to the model-based BCR case, single-stage model-free BCR is largely greater than or equal to 1 with only the 10 MWh single stage BESS size not permissible. Overall, BCR values for model-free are greater than those of model-based with the optimal BESS size the same for both. The optimal BCR value for BESS size 70 MWh for single stage and multiple stages is 1.30 and 1.95 respectively. It can be reasoned that BCR values for model-based and model-free cases could converge further if the TD3 algorithm was able to train over the entire dataset (N_d equal to 463 days of data). However, both methods suggest 70 MWh as the optimal

BESS size which reinforces the results. For purely informational purposes, BCR estimation using MLP ANN trained on 1 month of data evaluated on the entire dataset (N_d equal to 463) is also presented in Fig.5.5 where no BESS sizes are permissible. Clearly an MLP ANN trained on a 1-month dataset is not sufficient to evaluate over the entire dataset. The BCR evaluation over the entire dataset (N_d equal to 463) is not outlined in Fig.5.5 to suggest meaningful BCR values but rather to indicate level of improvement required in ANN architecture to gain parity with model-based BCR. Although the model-free formulation trained/evaluated over 1-month dataset shows promising BCR results, training over entire dataset would give greater confidence in final BCR value. However, the trained/evaluated model-free formulation under the smaller training set of 1-month is capable of capturing dispatch adaptability as part of BESS sizing. This suggests that an improved ANN architecture trained over the entire dataset could yield a more reflective BCR value.

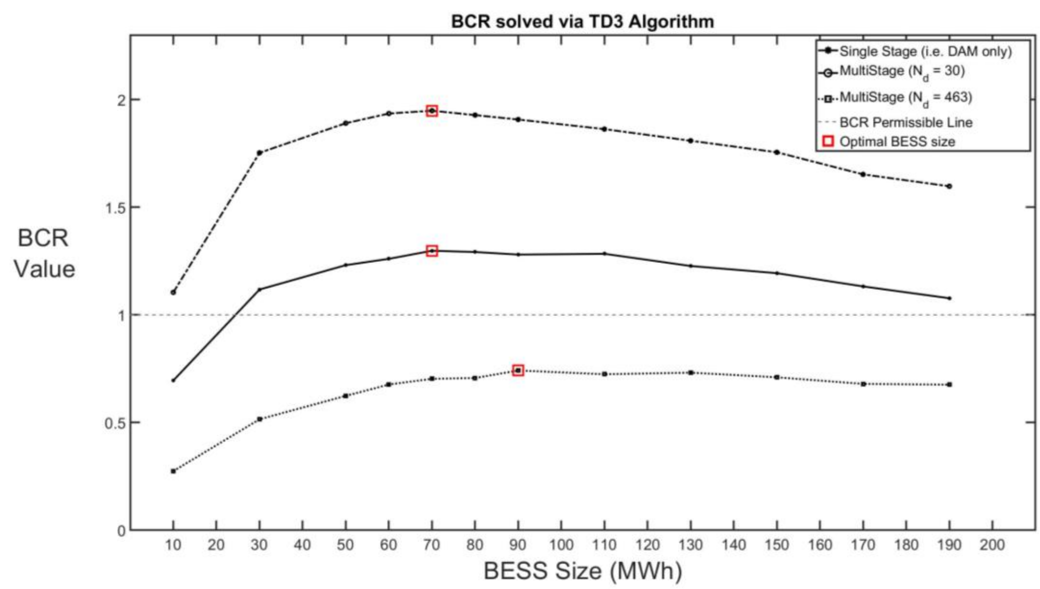

Fig.5.5. – BCR values for different BESS sizes of model-free formulation solved via TD3 Algorithm for single stage and multistage. N_d at 463 is evaluation over entire dataset. All BESS sizes on or above BESS permissible line are deemed acceptable.

Another useful component of analysis when integrating dispatch adaptability is examining bid/offer quality of optimised BESS sizing models. Rephrasing this as a question: are optimised BESS sizing models selecting good dispatch decisions to maximise the expected benefit for a particular BESS size? This type of question only presents itself under stochastic dynamic optimisation problems. Applying this question to the model-based formulation used in this chapter would yield little insight as it is solved using a linear deterministic equivalent stochastic program. Therefore, model-based formulation bid/offer quality is only related to the accuracy of electricity price scenarios Ps_n used, which are solely based on historical electricity market clearing prices without perfect foresight (see Section 5.5.1). Contrastingly, the model-free formulation does not rely on scenarios. Only historical information available at a decision epoch is inputted into the MLP ANN, allowing the Actor to learn a dispatch strategy based on this input and not from historical electricity clearing prices. Hence, the choice of Actor MLP ANN input affects its ability to select dispatch-adaptable high reward bids/offers. The bid/offer quality for a 70 MWh BESS size is shown in Fig.5.6 (d) for an example trading day (i.e. e value for 2nd April 2019) from historical dataset. The normalised MLP ANN inputs for the same trading day are shown in Fig.5.6 (a) for demand net wind grid forecast ($F_{t,e}$) for DAM and IDMs, in Fig.5.6 (b) for market energy volumes traded ($V_{t,e}$) and in Fig.5.6 (c) for market clearing prices ($P_{t,e}$). Looking at the Day-Ahead Market dispatch decisions Fig.5.6 (d), very few bids/offers are established which is in contrast to the volumes of energy normally traded by market participants within DAM compared to IDMs. Market participants reduce their risk by establishing bids/offers in the highly liquid DAM. This element of risk is not incorporated into model-free formulation. However, even without this risk element, favourable trades within DAM are not achievable. The DAM MLP ANN singular input (demand net wind grid forecast) has a low capability of capturing the complex reward structure of DAM and subsequent markets. The combining factors of risk-free bid/offer establishment and lack of suitable available DAM MLP ANN inputs from I-SEM results in the DAM MLP ANN unable to suggest meaningful trades and therefore defers establishment of energy positions until later markets. Improved bid/offer establishment is shown in markets after DAM as a result of the greater number and diversity of ANN inputs for subsequent markets. As DAM is the first market, it does not have access to previous market data (i.e. price, volumes, bids/offers) which has shown to improve bids/offers in IDMs. This improvement in

IDM bids/offers is due to the inclusion of previous market clearing prices ($P_{t-1,e}$) as a proxy input to IDMs MLP ANN. Ultimately, the parallel between $P_{t-1,e}$ and $P_{t,e}$ is akin to knowing the market clearing price beforehand, which follow similar peak trough paths as can be seen in Fig.5.6 (c). This allows the MLP ANN at time t to use

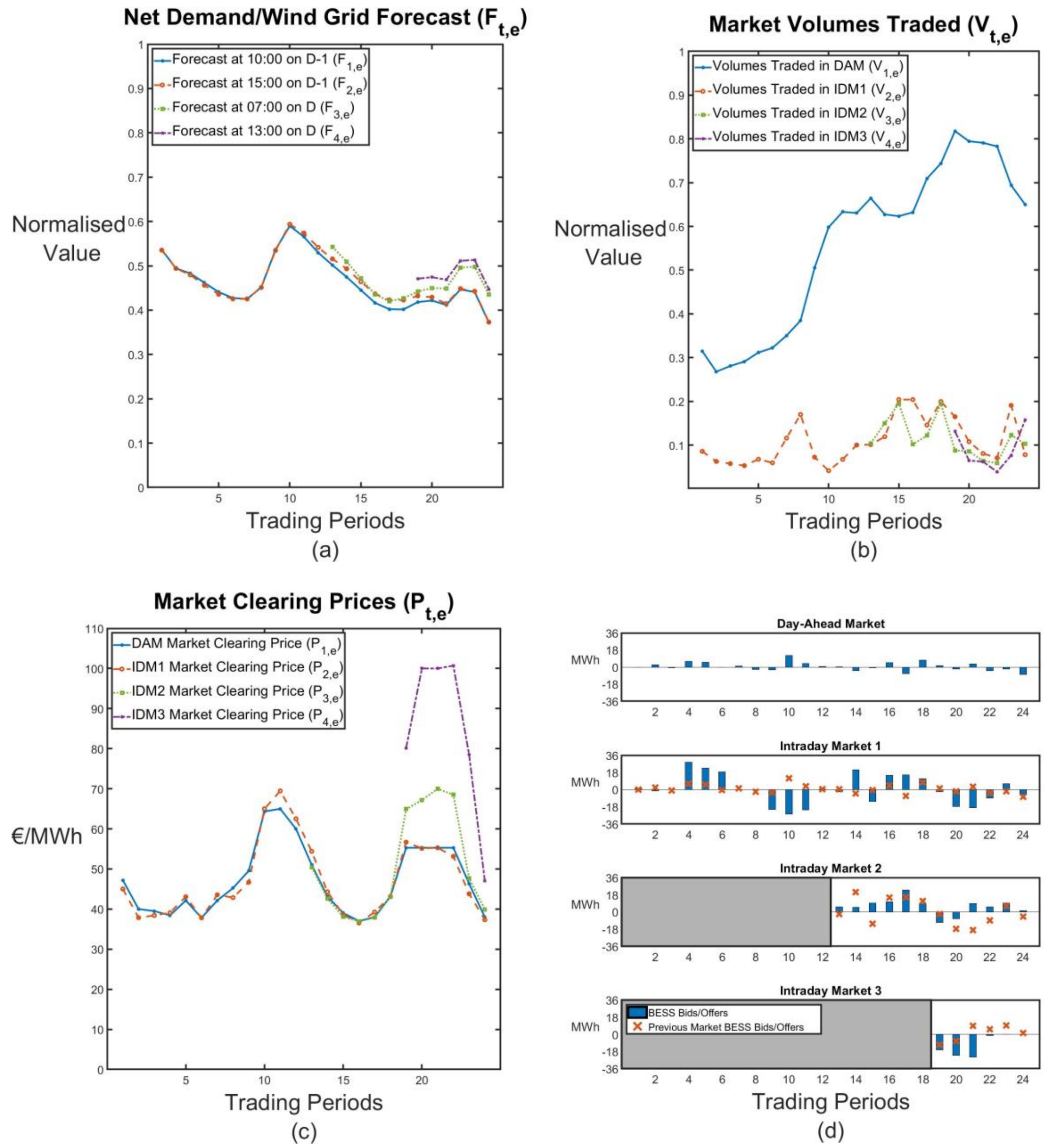

Fig.5.6. – Illustration example of trading day 2nd April 2019 for a 70MWh BESS where (a) is the ANN input demand net wind grid forecast which shows changed forecast as real time approaches, (b) is the IDM ANN input (for $t \leq 3$) market volumes traded which is available after closure of each market showing higher liquidity for DAM, (c) is the IDM ANN input (for $t \leq 3$) market clearing prices which is available after closure of each market showing increased clearing prices for later markets IDM2 and IDM3, (d) recommended dispatch decisions by ANN output for each market.

$P_{t-1,e}$ to inform itself of potentially good decisions. This is demonstrated further for IDM1 in Fig.5.6 (d) where the BESS is charged between trading period 4 and 6 only to be discharged at trading period 9, 10 and 11. This represents good decisions based on the eventual electricity market clearing price peaks and troughs of $P_{2,e}$ shown in Fig.5.6 (c). This learned bid/offer behaviour is key for BESS which rely on market electricity clearing price peaks troughs to perform arbitrage for generating revenue. Not only do MLP ANNs require establishing good decisions corresponding to eventual market price peaks and troughs (i.e. within market arbitrage), good decisions must also take advantage of dispatch adaptability which is based on eventual price differentials between markets (i.e. cross market arbitrage). Good dispatch adaptability decisions are estimated by the TD3 algorithm through learning the state S_t to state S_{t+1} transitions based on the ANN input dataset.

To help reduce errors in estimating state to state transitions, other MLP ANN inputs are required in addition to proxy input $P_{t-1,e}$. Two datasets are utilised for this purpose and further improve on the ability of proxy input ($P_{t-1,e}$). The first is demand net wind grid forecast $F_{t,e}$ where changes closer to real time can suggest a movement from proxy input ($P_{t-1,e}$). For example, if $F_{2,e}$ was underestimated before the closure of IDM1 only for improved forecast accuracy (wind grid forecast reduced) before the closure of IDM2, then the market clearing price ($P_{3,e}$) is likely to increase from that of proxy input ($P_{2,e}$). The second dataset used as part of IDM MLP ANN input is the previous market energy volumes traded ($V_{t-1,e}$). Here, high volumes of trades in IDM markets are an indication that the market participant's energy position within DAM is not suitable anymore. Typically, this is infrequent as the liquidity levels within IDM remain lower than DAM. However, when IDM energy traded volumes increase there is a movement of participants from their established positions which can be a further indication of differences between proxy input $P_{t-1,e}$ and eventual $P_{t,e}$. An example of cross market arbitrage is shown in Intraday Market 2 Fig.5.6 (d), where MLP ANN for IDM2 is taking advantage of a price differential to perform dispatch adaptability. This is achieved through buying back energy sold in IDM1 for trading periods 20, 21 and 22. Initially, IDM1 bids/offers correlated well to peaks (trading periods 9, 10, 11, 20, 21 and 22) and troughs (trading periods 4, 5, 6, 16, 17 and 18) as the DAM clearing price performed adequately as a proxy for the IDM1 clearing price. However, before the closure of IDM2, demand net wind grid forecast $F_{3,e}$ started to increase (in this instance caused by reduced wind forecast) suggesting a possible rise in market clearing prices for the latter half of the trading day in subsequent markets. Therefore, IDM2 Actor MLP ANN suggests a buyback of energy sold in IDM1 for trading periods 20, 21 and 22. This turned out to be a good decision as the clearing price for trading periods 20, 21 and 22 did increase for IDM2 and IDM3. Ensuring IDM2 bids/offers remained close to zero at IDM2 closure allowed the BESS to avail of much higher clearing prices of IDM3, and therefore maximise expected benefit. The goal of bid/offer quality analysis is to show if market Actor MLP ANNs are making good decisions on the whole. Ultimately, not all dispatch decisions will be the right one as Actor MLP ANN makes decisions based on imperfect knowledge along with estimating likely transition to subsequent states. One such situation is the choice to discharge at trading period 19 for IDM3 in Fig.5.6 (d). Once $P_{4,e}$ information becomes available after IDM3 closure, discharging at trading period 22 instead of trading period 19 would have been a better decision. However, the action taken by IDM2 Actor MLP ANN for trading period 19, 20 and 21 can be seen as a corrective action from the dispatch decisions made in IDM1 and shows that the MLP ANN used in this research is capable of dispatch adaptability.

Ideally, a model-free approach should be sought as the appropriate solution method for sizing BESS. This reduces the need to produce accurate models of realisations, thereby permitting BESS sizing on purely raw historical data alone. However, the MLP ANN used in this research is not sufficient. To that end, a model-based approach must be recommended as the more appropriate BESS sizing model when compared to the model-free approach used in this research. Nevertheless, an improved ANN architecture could warrant the use of model-free over model-based. A further advantage of using model-free method is that once a BESS is installed, the learned Actor MLP NN can be used as the dispatch strategy when BESS becomes operational without the need to rely on further modelling of clearing prices.

5.7 CONCLUSION AND FUTURE WORK

The inclusion of dispatch adaptability in BESS sizing models using model-based and model-free methods is shown to improve the profitability for both methods. This is a welcome addition to the BESS sizing research field as previously-proposed BESS battery projects which were deemed unviable could become viable if dispatch adaptability is included in the modelling process. Under the assumptions used here, the optimal storage size for a 36/-36 MW BESS operating solely in Day-Ahead Market and Intraday Markets 1 to 3 within Integrated Single Electricity Market of Ireland is 70MWh. While profitability for both model-based and model-free methods increases with the inclusion of dispatch adaptability, the optimal BESS size remains the same. This is also a welcome result as it demonstrates the robustness of the solutions, along with utilising dispatch adaptability solely for determining project viability. Furthermore, the level of dispatch freedom directly affects the amount of dispatch adaptability achievable, which in turn directly affects the realisable BCR value. Increasing dispatch freedom has a greater influence on smaller BESS sizes. The use of model-free methods has shown promise when training on smaller datasets but requires further ANN development to reduce underfitting and allow training on datasets greater than one month. The MLP ANN inputs for model-free formulation perform well in IDM especially using previous market clearing price as a proxy input for subsequent market clearing price. Due to the limited data available from I-SEM before the closure of DAM, the demand net wind grid forecast does not perform well when used singularly as an MLP ANN input.

Expanding the MLP ANN architecture in terms of size and type is required so that training can happen over the entire dataset. Some promising approaches are Convolutional Neural Networks combined with the necessary computation capabilities. These ANNs have more capacity than MLP networks to represent complex information. While the selected MLP ANN inputs performed well for IDMs, other inputs should be considered moving forward. For example, projected market clearing price information could be used as part of MLP ANN input, especially for DAM. Moreover, rather than modelling projected market clearing prices, the inputs to that model could be directly inputted into MLP ANN, thereby utilising the full ability of model-free optimisation. Normally, market participants submit pairs (price and quantity) when trading in electricity markets. As part of this research only quantity values are employed. To improve on this research, the price portion of submitted bids/offers should be included in decision outputs. In doing so will add an element of risk to the decision-making process including energy position establishment, which could help alleviate the lack of dispatch decisions seen in the DAM. Lastly, allowing total dispatch freedom (i.e. no constraints) is possible if the balancing market is modelled as an extra stage after IDMs. Market participants will get paid/pay-out at the balancing market clearing price. Therefore, the balancing market could be used as a penalty for using non-technically feasible bids/offers. This would be more representative of a realistic trading environment.

CHAPTER SIX

6 CONCLUSION

At the beginning of this study, two research questions were asked regarding the formation of planning objectives Investment Scale, Investment Timing and Dispatch Adaptability as part of BESS sizing. Within Chapter 1, the Research Objectives (RO) were set out in such a way as to actively seek answers to those questions. Herein lies a conclusion on the successfulness of this dissertation's research objectives in answering the research questions.

Research Question 1: *Is it possible to form the planning objectives Investment Scale, Investment Timing and Dispatch Adaptability as part of optimising energy capacity size for new BESS installation seeking maximum profit?*

Subsequent to the research conducted throughout this dissertation, it is concluded that the planning objectives Investment Scale, Investment Timing and Dispatch Adaptability can be incorporated as part of BESS sizing. This deduction is based on the successful completion of research objectives and results described herein. Consequently, the improvements made throughout thesis, make BESS sizing more applicable as a planning tool for BESS project developers, such as those seeking BESS installations in Fig.1.1.

As part of RO1.1, competing objective functions under two MOO methods called Rating Method and Paired Comparison were used as an approach to incorporate Investment Scale as part of BESS sizing. This approach was simulated for a microgrid as part of RO1.2 and was described in Chapter 3. In doing so, it was found that the Rating Method performed best when selecting BESS size in knee regions near maximum DW, which was designated as the area of greatest interest. An added bonus of the Rating Method is that it can select optimal BESS size at maximum DW when less significant knee regions are present. This approach gives an appropriate balance between forming the planning objective Investment Scale and maximising profit. The significance of these results is that Rating Method is capable of forming the planning objective Investment Timing as part BESS sizing which is in answer to the first planning objective of Research Question 1.

RO2.1 modelled the separation of BESS dispatch (i.e. operational) and BESS sizing decisions (i.e. planning) through employing Reinforcement Learning as the operational model solution method and Global Optimisation for the planning model as an approach to from the Investment Timing planning objective as part of BESS sizing. As per RO2.2 and completed per Chapter 4, the aforementioned approach was trialled on data from the Integrated Single Electricity Market (I-SEM) Day-Ahead Market for the operational model, while the planning model utilised various future BESS CAPEX and degradation scenarios. It was found that splitting BESS operational decisions and BESS planning decisions into two different models is an effective technique. The effectiveness can be seen in the ability of the planning model to sample value functions from the operational model, thereby removing the need to simultaneously solve operational decisions and temporal BESS sizing decisions. This resulted in a more tractable planning model where a solution was determined via Global Optimisation. Also, the operational model need only be solved once, as it is sampled subsequently by the planning model, thereby allowing different scenarios to be tested. All in all, through the use of split models, it is possible to incorporate the planning objective Investment Timing as part of BESS sizing. This is supportive of an answer to the second planning objective of Research Question 1.

Completion of RO3.1 utilised model-based (Stochastic Programming) and model-free (Deep Reinforcement Learning) stochastic optimisation methods as a means to form the planning objective Dispatch Adaptability as part of BESS sizing. This was tested on historical Day-Ahead and Intraday Markets electricity clearing prices from the I-SEM as part of RO3.2, which is documented in Chapter 5. Through this, it was found that model-based approach of SP outperformed the model-free approach of TD3. However, it is not clear that such a broad statement can be made about model-free and model-based approaches on the results gained in Chapter 5. The advantages of model-free methods are well known and are gaining popularity.

As already noted, an improved ANN architecture for model-free approach as part of future work (discussed later) may produce better results. That being said, the results of the SP model-based approach show that the planning objective Dispatch Adaptability can be incorporated as part of BESS, while the TD3 model-free approach shows promise when trained on a limited sample set and relatively simple ANN. This provides a positive answer to the last planning objective of Research Question 1.

<u>Research Question 2</u>: *Are there any circumstances where the inclusion of planning objectives Investment Scale, Investment Timing and Dispatch Adaptability as part of BESS sizing helps overcome shortcomings of existing sizing approaches?*

As outlined within the Introduction, the purpose of including planning objectives as part of BESS sizing is to ensure that a built BESS project is the right BESS project, and aligns a BESS project with any goals set out before execution. However, it is important to note any findings from this thesis which have the potential to alleviate other shortcomings facing the BESS sizing community. These include undesirable outcomes that existing BESS sizing approaches can produce.

On completion of RO2.3 in Chapter 4, it was discovered that the maximised NPV objective function under all chosen scenarios returned a value of zero with a BESS size of 0 MWh, which is a shortcoming of using NPV as an objective function. This portends that no available BESS size installed at year 1 would operate with a profit. Therefore, it is not possible to size a BESS under these circumstances. In comparison with reviewed literature, previous works have not reported 0 MWh as the optimal BESS size for any application. These historical outcomes are questionable at best, given the quantity of research undertaken in this area and the nascent stage of BESS deployment. Nevertheless, if a researcher is faced with the prospect of 0MWh as the optimal BESS and all things being equal, the next logical question should be: when will it be possible to size a BESS for my given application? The approach taken within Chapter 4 to forming the planning objective Investment Timing as part of BESS sizing can be used answer this question.

The findings associated with RO3.3 within Chapter 5 showed that BESS operating simple arbitrage within the Day-Ahead Market was not enough to make optimally sized BESS project profitable when solved using Stochastic Programming. Therefore, under this circumstance, BESS is optimally sized (positive BCR value) but project is deemed unprofitable (BCR value is less than one). This result is possible when using BCR as the objective function but not possible when using NPV as the objective function. Arbitrage is a hallmark of existing BESS sizing literature. However, similar to the questionable point made regarding Investment Timing, previous works only report optimal BESS sizes that are profitable and report none that are unprofitable. There is somewhat of a caveat here, in that BCR is less popular as an objective function. As with any project, if cost can be maintained constant and revenues improved then profitability increases. This is what cross-market arbitrage achieves. Researchers sizing a BESS for arbitrage in Day-Ahead Market using BCR objective function should seek to use cross-market arbitrage if the initial optimal BESS size (positive BCR value) is unprofitable (BCR value is less than one). The approaches taken within Chapter 5 to incorporating the planning objective Dispatch Adaptability as part of BESS sizing can be used for this purpose.

None of the findings as part of research concerning Investment Scale planning objective within Chapter 3 gave any indication of being able to overcome shortcomings facing researchers using existing sizing approaches.

Contribution to Knowledge

First and foremost, this thesis's initial original contribution to knowledge is uncovering the fact that existing BESS sizing approaches are lacking in their ability to be used as a planning tool. This knowledge was gained via the literature review within this dissertation which used FEP framework as a lens to review existing BESS sizing approaches. Without this method of investigation into literature, the problem of BESS sizing planning objectives would have gone unnoticed. Furthermore, this problem is not inconsequential. Taking a look as Fig.1.1, it is clear that within Europe alone there is a large current predicted future uptake of BESS installations. Such projects require BESS sizing to be more aligned with project planning. Another school of thought is that there is little point in having BESS sizing approaches available which do not go some way to furthering the development of actual BESS projects.

This thesis's next original contribution to knowledge is the forward movement of BESS sizing approaches from specifically focused goals as shown in literature, towards being more functional and adaptable for project planning purposes. This was achieved through formation of planning objectives Investment Scale, Investment Timing and Dispatch Adaptability as part of BESS sizing optimisation. Through the development of BESS sizing approaches as part of this research, it is now possible to size BESS:

1. which does not suffer scale issues resulting from ever greater diminishing returns of larger BESS sizes,
2. where the timing of the investment can be chosen optimally rather than assuming "here and now" investment,
3. where the operational strategy employed to simulate BESS dispatch is more reflective of actual BESS use and adaptability.

<u>Wider Impact of this Research</u>

First and foremost, this research will have greatest impact on communities of BESS project developers undertaking BESS projects as those outlined in Fig.1.1. Likewise, for all other BESS project developers worldwide undergoing similar projects. These developers seek BESS sizing approaches which are suited to successful project planning. This is where the BESS sizing approaches developed in this thesis are well suited to the aspirations of such developers.

It must be remembered that uptake and predicted uptake of BESS installations throughout the world is predominantly a result of increased penetration of renewable generation as part of overall electricity mix. It is possible to combine these sets of technologies, which results in dispatchable and controllable electricity. Therefore, one could surmise that the success of renewable generation reaching high penetration levels is directly linked to uptake of BESS projects, which in turn is linked to how successfully BESS projects are planned.

Given that this thesis focused on including planning objectives as part of BESS sizing, the impact of this research could go some way to influencing renewable generation penetration in the future.

For researchers who in the traditional sense use BESS sizing as an experimental proving ground, the results of this dissertation show that forming planning objectives as part of their BESS sizing problems can be useful. This implies that researchers need not ignore the results of this work but rather embrace it as a means for solving problems of their own concern. This represents a significant shift in thinking as researchers are somewhat detached from planning objective matters, as evidenced by the literature review of this thesis.

The findings of this thesis show that there is potential to opening pathways for a new BESS sizing research area, namely forming planning objectives as part of BESS sizing. This is inferred through the numerous potential planning objectives within FEP toolkits that have yet to be researched and/or incorporated as part of BESS sizing. Also, the confines of this thesis is only a flavour of what could be researched in terms of planning objective as part of BESS sizing. The approach taken in this dissertation, along with results achieved, is significantly different compared with traditional sizing approach, and therefore warrants further research into forming planning objectives as part of BESS sizing as a whole.

Future Work and Recommendations

The Dispatch Adaptability planning objective used as part of Chapter 5, requires its ANN to be improved significantly as already mentioned in Section 5.7. One approach may be to change the architecture type from MLP to Convolutional Neural Network, which has gained recent success in image and pattern recognition applications. Other neural network inputs should be considered, such as forecasted electricity market clearing prices. Also, expanding the approach to include balancing markets is another key aspect, as this will be an even more accurate reflection of market rules and therefore will give a truer reflection on BESS capability when sizing.

As mentioned at the beginning of this work through a thought-provoking question: how can one take confidence in sizing a BESS correctly unless the objective function contains all project goals (i.e. planning objective) either directly or indirectly? The modelling choices as part of this work remained cognisant of the fact that the end goal should be for a singular BESS sizing approach incorporating all planning objectives of the user. Therefore, future work should maintain splitting apart operational decisions (i.e. BESS dispatch) and planning decisions (i.e. BESS size and time) as this is a sound choice. The operational model in Chapter 4 (which is reinforcement learning) should be replaced with deep reinforcement learning model from Chapter 5, albeit with improved ANN Dispatch Adaptability planning objective as previously mentioned as part of future work. Doing so would combine the planning objectives Dispatch Adaptability and Investment Timing. Furthermore, the planning model in Chapter 4 should be augmented to multi-objective Rating Method used in Chapter 3. This augmentation would convert the multi-objective problem from linear to non-linear. Capturing all the suggested changes above would ensure that all three planning objectives would form part of a singular BESS sizing approach. The results of this should be sought in future work.

As already mentioned within research impact, the FEP framework has numerous potential planning objectives which could be explored as part of future research. Two such planning objectives that were included as part of this study's literature review, but not modelled as part of BESS sizing, are Location and Capacity (Power). Firstly, to form the planning objective Location as part of BESS sizing will require the inclusion of power system modelling as part of the BESS sizing objective function. This would then inform the optimisation model of what the benefit and cost of each location on the grid is, and optimise accordingly. Secondly, to form the planning objective Capacity (Power) as part of BESS sizing, a more holistic method of modelling electricity market interactions of other participants is one method of choice. This would capture the negative connotations of too large a Capacity Power size in one market, thereby putting "downward pressure" on such a design variable.

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