UTRECHT UNIVERSITY

THESIS SUBMISSION
MSc Energy Science — GEO4-2510 — 30 ECT

Dynamic Stacking of Energy & Power Portfolios on the Dutch Market

An investigation into revenue potential considering Day-Ahead, FCR and Imbalance Settlement in the Netherlands

---

Supervisor:

Dr. Elena Fumagalli
e.m.fumagalli@uu.nl

Second Reader:

Prof. dr. Madeleine Gibescu
m.gibescu@uu.nl

Author

Natasha Garrood
n.c.garrood@students.uu.nl
Student ID: 4972368

Company Supervisor

Milan Milinković
milan@spectral.energy

Word Count:

9328

Tuesday 31st January, 2023

Abstract

The thesis is written with Spectral, an Amsterdam-based Energy Consultancy who manage assets for several clients with flexibility to trade electricity products due to portfolios of energy storage and renewable energy systems (ESS & VRES) at commercial sites such as business parks. The cost of investment for these assets is high, meanwhile, grid connections are limited and therefore self-sufficiency is becoming increasingly necessary. As such, there is growing interest in ways to ensure these assets profitability can be maximised. Recent literature suggests that trading dynamically across multiple markets could increase profits. The aim of the thesis is therefore to build a model whereby any client portfolio of assets can be modelled with accompanying production and load data to find optimal trading strategies across various markets. Spectral has experience trading on the day-ahead and FCR markets, so these will be used as the model starting point, while also considering imbalance settlement payments. The research finds that trading on DA with FCR is the most profitable, with FCR being the primary revenue stream. Furthermore, parameters such as curtailment of VRES, grid import and export limits and battery cycling can also be analysed and provide useful information for further economic analyses such as development of the business case for grid connection up- or down-grades. Further research will include integration of future markets into the model, namely the intra-day, as well as reformulation of the imbalance settlement modelling to include this in part of the optimisation.

Contents

1 Introduction **6**

1.1 Research Question 7

2 Theoretical Background **8**

2.1 Electricity Markets 8

2.1.1 Day-Ahead 8

2.1.2 Frequency Containment Reserve 8

2.1.3 Imbalance Settlement 9

2.2 Stochastic Scenarios 10

2.3 Literature Review 10

3 Methodology **12**

3.1 Stochastic Scenario Modelling 12

3.2 Optimisation & Revenue Calculation 13

3.2.1 SQ1: Modelling Portfolios 14

3.2.2 SQ2: Modelling Market Revenues 19

4 Results **25**

4.1 Model Performance 25

4.2 Portfolio Configuration and Use Cases 28

4.3 Exploration of Stochastic Scenarios 29

4.4 Revenues Across Use Cases 30

4.5 Other Key Indicators 32

4.5.1 Curtailment 32

4.5.2 Weekly Cycle Limits 33

4.5.3 Grid Import/Export Limits 34

5 Discussion **36**

6 Conclusion **37**

7 Acknowledgements **38**

List of Figures

1 SoC Control for FCR Provision 9
2 Portfolio Topology 15
3 Model Overview 26
4 Stochastic Scenarios 30
5 Final Revenue 31
6 Day-Ahead Revenue 31
7 Imbalance Settlement Payments 32
8 Curtailment 33
9 Weekly Cycle Limits and Effects on Revenue 33
10 Grid Connection Limits 34
11 Grid Export Limits and Effects on Revenue 35

List of Tables

1 Distribution and Error Types for Inputs Subject to Stochastic Scenario Generation 13
2 ESS Input Parameters 15
3 ESS Decision Variables 15
4 VRES Input Parameters 17
5 VRES Decision Variables 17
6 Site & Cluster Input Parameters 18
7 Cluster Decision Variables 18
8 FCR Input Parameters 21
9 FCR & SOC management Decision Variables 21
10 Portfolio Configuration. 29

Abbreviations

aFRR	Automatic Frequency Restoration Reserve
BRP	Balance Responsible Parties
DA	Day-Ahead
ESS	Energy Storage Systems
FCR	Frequency Contaiment Reserve
IB	Imbalance Settlement
LER	Limited Energy Resource
MILP	Mixed Integer Linear Program
PTU	Programme Time Unit
TSO	Transmission System Operator
VRES	Variable Renewable Energy Systems

1 Introduction

Unlike many commodities, electricity markets are further complicated by the fact that electric energy is a real-time product [1]. As a result, supply and demand must be constantly temporally matched. Historically, this was achieved through conventional, dispatchable, generators on the supply side. Nowadays, increasing penetration of variable renewable energy systems (VRES) has considerably reduced the flexibility this gave.

VRES are less flexible, i.e., less able to provide power adjustments to compensate for imbalance between supply and demand, due to their dependence on variable primary resources[2, 3]. Furthermore, VRES have very low marginal costs and therefore reduce average electricity prices through the merit order effect [4]. This reduces operational hours of conventional generators. Simultaneously, social and political pressure favours VRES over traditional power sources. In the Netherlands, a target of 95% emission reductions on 1990 levels by 2050 has been set [5]. Therefore, the reduction of flexibility on the supply-side is two-fold, both through increased penetration of VRES, and the threat this causes to conventional power plants.

On the demand-side, a shift is also occurring, with the development of 'prosumers' who both produce and consume energy and therefore can offer flexibility through demand response programs (DRP). This is achieved in large part through energy storage systems (ESS), especially lithium-ion batteries. Prosumers can optimise their portfolios of VRES and ESS for revenue creation in a variety of ways. For example, energy arbitrage, whereby energy is sold when prices are high and bought when prices are low.

Use of ESS to participate on electricity markets is far from a novel concept. In more recent years, increasing profitability through stacking has also been researched. Stacking is a method by which profitability can be increased through using the ESS for multiple applications [6]. Previous literature suggests that the most profitable approach is dynamic stacking, whereby multiple applications can be served simultaneously with variable capacity allocations [7]. Applications could be behind the meter approaches such as increasing self-consumption and peak-shaving as well as front of the meter such as operating simultaneously on various electricity markets or providing ancillary services. Similarly, several studies have looked at optimising bidding strategies on various markets for VRES [8], however, in all these studies the focus is often in increasing potential profitability in order to overcome the high investment costs, and focus on a single asset such as one battery or one wind park. No such study has been found which considers a portfolio of ESS and VRES assets each with their own power production, curtailment and storage constraints, examining the Dutch market specifically.

Increasingly, large-scale consumers in the Netherlands are facing rejections for grid connection requests due to grid congestion and the slow and expensive process of upgrading networks being unable to keep up with growing electricity demand [9]. This, alongside energy prices rising in cost and volatility, exemplifies the need for at least some degree of independence from the national grid. In order to do so while keeping aligned to carbon emissions reduction policies, a business case for a portfolio of VRES and ESS is required. Therefore, the aim of the research is to build a model which can take existing portfolios of VRES and ESS assets, and optimise for revenue by trading on various electricity markets, specifically, the day-ahead (DA), and frequency containment reserve (FCR) markets are chosen for the optimisation problem. Imbalance settlement (IB) payments are also considered post-optimisation. Due to the complexity of the modelling, only revenues are considered at this stage, while later work will integrate investment and operating costs in order to calculate profits.

1.1 Research Question

Specifically, the research will answer the following question:

> *What is the potential revenue for portfolios of VRES and ESS assets by trading dynamically on the DA and FCR markets and considering IB payments in the Netherlands?*

The research is divided into various sub-questions as follows:

1. *How can the operation of VRES and ESS assets be modelled as mixed integer linear programming (MILP) problems to trade energy and power products dynamically while considering constraints of these assets?*
2. *How can the functioning of DA and FCR markets as well as IB payments be modelled as MILP problems?*
3. *Using various case studies, what revenue potential is there for market participants trading on these two markets?*

2 Theoretical Background

2.1 Electricity Markets

In Europe, electricity is primarily traded through the EPEX SPOT platform, accounting for 30% of European electricity consumption [10]. European market coupling allows trading across borders throughout Europe, and the Netherlands benefits from interconnections both with neighbouring countries and through the NorNed, BritNed and COBRA cables to Norway, The UK and Denmark respectively [11]. Different markets have different requirements for trading, with some variation on participation rules from country to country. The traded product may be power or energy and time horizons vary from market to market. Furthermore, despite market coupling, prices on different markets can vary from region to region if interconnections are congested. This paper will focus on the DA and FCR markets due to Spectral's prior knowledge of trading on these markets and their already proven profitability. IB payments are considered post-optimisation to find final revenue after deviations from DA trading schedules.

2.1.1 Day-Ahead

The DA market is traded in one hour periods for the next day. Producers and retailers place bids for their production or consumption in the traded period, this is known as their 'e-program'. Bids are placed before noon and once products are locked in, a bid ladder is constructed of all the production and consumption bids, as priced by the participant for specific volumes. Where supply and demand meet, the market clearing price is set. Participants are paid or charged at this price for the accepted production or consumption volume, the price can be negative, therefore in certain conditions participants are paid to consume. Any supply bids above the market clearing price or demand bids below it are rejected. After clearing of the DA, market participants may also trade on intra-day (ID) markets at 15 minute intervals to account for any imbalance between their forecast e-program and forecast consumption/production. This is because deviation from the e-program leads is charged at the imbalance settlement price after delivery.

2.1.2 Frequency Containment Reserve

Reserve capacity is divided into three products, the FCR, and the automatic and manual frequency restoration reserves (aFFR and mFRR). The FCR product is traded on a purely capacity market, available capacity is traded and a reservation price is paid, regardless of whether it is activated. Meanwhile, aFFR and mFRR have both reservation and activation prices. As a result, aFFR and mFRR could be more profitable, however, there are greater barriers to entry for these markets since, if the reserve is activated, then power must be provided for longer time horizons than that of the FCR. The majority of clients at Spectral have lithium-ion batteries for ESS, and it is difficult to obtain permits to provide capacity on FRR markets with the size of battery available, since the TSO is concerned about state of charge constraints being reached. For this reason, the model will focus on the FCR market.

The TSO is responsible for ensuring that production meets demand in real time. This is achieved initially through the activation of reserves acquired via the FCR market, which contain any frequency deviations, before FRR reserves are activated in order to restore it to the nominal level of 50 Hz. On the FCR market, participants must be able to reach rated power within 30 seconds of activation, and capacity is traded in blocks of 4 hours. The minimum accepted bid is 1 MW and the maximum is 25 MW. These bids must also be symmetric, meaning that participants must be able to provide upward or downward frequency containment. In the Netherlands, power provision for FCR is proportional to the size of the bid, up to a maximum power provision equal to the bid when the change in frequency is +/- 0.2 Hz.

For limited energy resources (LERs), such as batteries, state of charge management is also allowed. This is so that the battery can continue to provide FCR provision without either depleting or reaching it's maximum state of charge. State of charge management involves effectively changing the set point from which power provision is provided, through either charging or discharging as required. This is illustrated in figure 1 where discharging occurs around 8500 and 8700 minutes to prevent the batteries maximum state of charge being reached. Despite this, you see that the power provision continues to match frequency deviations.

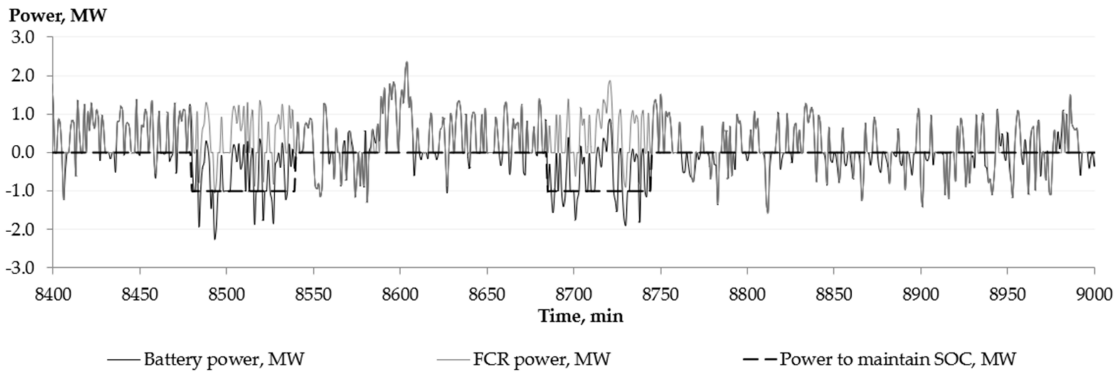

Figure 1: SoC Control for FCR Provision. Adapted from [12]

If a frequency deviation of +/- 0.2 Hz occurs for 15 minutes or more, or proportionally longer at a lower frequency, then the 'alert state' is activated. In the alert state, the resources must be able to provide continuous power for 15 minutes at the bid level. After this time, they may have up to two hours of recovery time where no FCR provision is required. During an alert state, the FCR providing-assets must stop all other activities (such as trading on other markets or SOC management). Alert states occur very rarely, less than 5 times per year, but adds a great deal of computational complexity. For this reason, it is not considered in this model.

The auction takes places every day for the following delivery day and is procured through a common merit order list [13]. If a participants bid is accepted, they are paid the reservation fee. The capacity may or may not be required depending on what deviation from e-programs occurs.

2.1.3 Imbalance Settlement

In real-time, the market is considered short when the actual level of generation is lower than consumption. The TSO balances by purchasing extra energy at the upward price. This is usually a higher price than the DA price since it contains a premium for flexible generators as well as the higher marginal cost for production [14]. Conversely, when the market is long because production outweighs demand, the TSO sells back excess energy to flexible generators at the downward price [14]. This is lower than the price paid on the DA market so in both cases a system cost is generated through imbalance.

The IB fee is calculated at 15 minute intervals and market participants are charged the product of the volume of imbalance from their e-program and the imbalance fee (separate upward and downward fees apply for short or long positions respectively). Across Europe their are two pricing rules for IB, the single and dual pricing schemes. In the Netherlands, the single pricing scheme is used. According to the single pricing scheme, when both the market and the individual are long or short, they are penalised since they increase the size of the market imbalance and the related system costs. Conversely, profits can be made when individuals oppose the market imbalance and therefore help to reduce imbalance system costs [15].

2.2 Stochastic Scenarios

The decision variables of the model can be broadly categorised into two phases. The first phase is the planning or forecasting phase, this is determined in part by uncertain inputs such as wind or solar generation and market prices. The second is the actual operation phase. The actual operation phase is determined through the optimisation based on the planning phase variables, and can be seen as the control strategies for the ESS and VRES assets. This will then also be used for imbalance settlement calculations. More detail on the variables and how they are calculated is provided in later sections.

Since we cannot perfectly forecast, for example, wind generation or market prices, we overcome uncertainty by taking historical profiles of these inputs, and using them as the basis to create stochastic scenarios. For example, if we have an available wind generation profile, e.g., for the year 2019, we then apply a distribution and offset the actual profile by a given value for a range of quantiles across the distribution. In this way, we produce a number of stochastic scenarios from the original input. Further detail on stochastic scenario generation is provided in the methodology section 3.1.

2.3 Literature Review

Energy arbitrage through trading in various markets has been extensively studied in recent years, in particular with the rise of VRES penetration which is positively correlated to rising ESS capacity [16]. The body of research investigating operation in single markets in the Netherlands and globally is vast, but often reaching the conclusion that high investment costs outweigh potential revenue [17, 18, 19, 20, 21]. Some exceptions do occur, however, for example [22] found a positive business case for a wind-farm coupled to an ESS trading on the DA markets. The case study was in Italy, so while there is some market coupling, it cannot be assumed that the same results would be obtained in the Netherlands.

Since a significant amount of literature does conclude that single market applications are not profitable enough to outweigh investment costs [19, 20, 21], the concept of dynamic stacking (serving multiple applications simultaneously with variable capacity allocations [7]) for increasing revenue has come more into focus [6, 7]. Despite this, there is a great deal of focus on residential markets both for singular home energy management optimisation strategies [23, 24], or through the use of aggregator companies [25]. However, far less literature exists for commercial participants, who have different load profiles to residential users, and so no conclusions for these market participants can be drawn.

MILP has been widely used as an effective optimisation technique for modelling revenue from various electricity markets. [26] applies it to find a positive business case for dynamic stacking on ancillary service markets for the PJM market area in the United States. In [27] MILP is employed to model a wind farm and ESS participating on energy and reserve markets in Denmark, again with significant increase in profitability through simultaneous participation in both markets. Building on this work, [28] finds that the conclusions still hold when uncertainty is added to the model through scenario generation using the Monte Carlo simulation and Roulette Wheel Mechanism's. Similar results are found for the German market area, with [7] achieving positive business cases for ESS participating in spot markets and frequency regulation services. In the Netherlands, [29] achieved a positive business case for trading on the Dutch DA market and steering according to IB prices, however, focusing on Hydrogen-Bromine Flow batteries. [30] found similar results with a portfolio of one battery, a solar PV park and load, trading on the Dutch DA market, again achieving positive business cases. Although, the FCR market is not considered in either study.

Other approaches include dynamic programming approach, whereby the model is broken down into various sub-models and solved recursively. This approach is employed in [31] to optimise for revenue through peak shaving, frequency regulation services and arbitrage. However, dynamic programming has largely been replaced by MILP in the last decade since the problem can be modelled more efficiently resulting in lower computation time, which is particularly important with rising time horizons [32]. For this reason, MILP will be employed as the modelling technique for this thesis.

In conclusion, there is a growing body of literature supporting the business case for trading on a combination of markets, in particular for the DA and FCR markets or the DA market with steering according to IB settlement prices. However, to the authors knowledge no such literature exists which both focuses on the Dutch market and considers both the DA and FCR markets, and IB settlement payments.

3 Methodology

As mentioned in section 2.2, the model can be thought of in two phases, the forecasting/planning phase, and the operation phase. In general, the forecasting phase is determined through generation of stochastic scenarios from historic input profiles of e.g. market prices or wind generation in a given year. These stochastic scenarios are then used to determine bidding strategies on the various markets, which in turn determines control strategies (charging, discharging, curtailment) for VRES and ESS assets. The actual operation of assets may deviate from the e-program determined for the day-ahead market, since frequency changes, and therefore power provision on the FCR market, cannot be forecast. As a result, imbalances are determined post-optimisation to derive imbalance settlement payments. The final revenue is therefore the combination of trading on DA and FCR along with IB payments (which could be a revenue or a cost).

Modelling techniques are inspired by a wide range of sources as discussed in section 2.3. In particular, [29] was useful for modelling the DA market revenue, while [33] and [34] acted as good bases for the FCR market revenue. The methods and equations described in the following subsections are an outcome of reviewing the literature and assessing which equations would be suitable to use in the model. These markets and assets have all been modelled in various ways, but it was necessary to ensure that all assets and markets could be integrated and that all equations used would fit within constraints of the model. For example, since it is a linear optimisation, it was necessary that all equations found in the literature were either linear or could be made linear using mathematical techniques such as the 'big-M' constraint, as is done to model power flow for the ESS model in section 3.2.1.2 (see equations 10 and 11).

In the following sections, more detail is provided on 3.1; scenario generation and 3.2; the model structure and optimisation problem. This is divided into two parts, 3.2.1; the operation of VRES and ESS assets and how these are arranged into client portfolios, and 3.2.2; the modelling of market revenues.

3.1 Stochastic Scenario Modelling

For a given year, the actual load profile ($L_{actual,t}$), actual available power profile ($P_{\text{VRES, avail, }actual,t}$) and actual prices (${\mathbb{P}_{\text{actual,t}}}^{DA/FCR/IB}$) are considered as inputs, along with error distributions for these profiles. The available power profile is between 0 and the rated power of the VRES, and is the maximum power that the asset can generate at each time step if no curtailment occurs. From these profiles, stochastic profiles for the load, power and prices are derived as outlined below.

The most basic way to offset the original profiles is with the 'Random Forecast Off-Setter'. For this, a randomly generated offset value is applied to the input profile value at each time-step. The forecast mean is derived as the mean value of the forecast, which has been generated from the actual input profile as per equation 1. Scenarios are later generated by applying an error on top of this forecast mean.

$$F_{mean} = Actual + Offset \tag{1}$$

In later research, a 'Daily Forecast Off-Setter' will be developed, whereby the random value is only assigned to the first time-step of each day. Then, linear interpolation is applied to all other time steps of that day to mimic the effects of forecast drift. The random offset is applied only to the first time step of each day so that the forecast mean differs from the actual input mean by a given offset. Conversely, with the 'Random Forecast Off-Setter', the resulting forecast mean for each profile will end up being similar. This is a limitation of the current model but provides an idea of what will be possible in future model development.

Error values are determined dependant on the type of distribution chosen. We assume a normal distribution for all inputs as per table 1. The user will provide a list of desired quantiles (for example, 0.1, 0.5, 0.9) from which error values can be determined. Based on the quantile input, a standard deviation multiplier for what value that quantile occurs at is returned. (In the case of normal distributions, for an empirical distribution, quantile 0.5 would refer to the median value in the input profile, 0.0 the min value and 1.0 the max value). These error values are used to offset F_{mean}.

Table 1: Distribution and Error Types for Inputs Subject to Stochastic Scenario Generation

Input Profile	**Distribution**	**Error Type**
Available Wind/Solar Power Profile [MW array]	Normal	Relative
Load [MW Array]	Normal	Absolute
Market Price [€/MW or €/MWh array]	Normal	Absolute

Using F_{mean} and the quantile offsets (error values), the forecast values can be calculated. The method is different depending on the input. For market prices and load forecasts, the absolute error applicator is used as per 2. For generation forecasts, a relative error applicator is used which takes into account the fact that error values increase with increasing forecast mean. For example, for solar generation the error is largest at peak generation close to noon, while the error is zero at night when there is no generation. This is shown in equation 3. Together, the various generated forecasts make up a given stochastic scenario. For the case studies of this report, we assume that each scenario has an equal probability of occurring.

$$F_{[quantile]} = F_{mean} + QO_{[quantile]} \tag{2}$$

$$F_{[quantile]} = F_{mean} + |F_{mean}| \cdot QO_{[quantile]} \tag{3}$$

where:

$F_{[quantile]}$: Forecast Value for given quantile
F_{mean}: Forecast Mean
$QO_{[quantile]}$: Quantile Offset for given quantile

3.2 Optimisation & Revenue Calculation

The MILP optimisation is run for the DA and FCR markets as per equation 4, whereby z denotes the weighted average of the stochastic revenues according to the probability of each scenario. The DA bid is determined by the optimisation, while the FCR bid is an input parameter, therefore, stochastic scenarios are not generated for the FCR market. Further details are provided in subsection 3.2.2.2.

Post-optimisation, imbalances are derived and imbalance settlement payments are calculated and added to gross revenue to find the final revenue, according to passive imbalance settlement regulations for the Netherlands.

$$\textbf{maximise z}, \; z = \sum_{t=1}^{T}\sum_{s=1}^{S} \mathbb{R}_{\mathrm{t,s}}{}^{DA} + \mathbb{R}_{\mathrm{t,actual}}{}^{FCR} \tag{4}$$

$$\mathbb{R}_{\mathrm{t,\ actual}} = \mathbb{R}_{\mathrm{t,\ actual}}{}^{DA} + \mathbb{R}_{\mathrm{t,\ actual}}{}^{FCR} + \mathbb{R}_{\mathrm{t,actual}}{}^{IB} \tag{5}$$

where:

T: Time Horizon (1 year), where t is a 15 minute interval of T
S: Scenarios, where s denotes a given scenario
$\mathbb{R}$: Revenue (€)

For each level of the client portfolio, various constraints apply, from VRES and ESS assets up to grid connection constraints at the cluster and portfolio level, as is explained in the following sections.

3.2.1 SQ1: Modelling Portfolios

Client portfolios will consist of different assets each with different rated powers, capacities and so on. The model must be built in such a way that different combinations of assets can be fed into the model as input parameters.

3.2.1.1 Portfolio Topology

A client portfolio consists of a pre-defined selection of VRES and ESS assets which, along with a load, make up a site. A cluster consists of a collection of sites with 1 grid connection, and a portfolio consists of a selection of clusters. This topology can be seen in figure 2.

The decision to model client portfolios as per the outlined topology is based on real client portfolios which Spectral already manage. One such example would be a residential area with generating assets (such as solar panels) sharing a grid connection. Each house in the area would be considered a site with an individual load profile and assets, while together the residences make up a cluster, with one grid connection. A group of such residential areas in close proximity and with the ability to trade electricity would make up a portfolio. These portfolios are considered producers since asset generation outweighs load. It is beneficial to model the individual sites as such because home-owners will want to see data specific to their own homes, despite the fact that the operation of their assets will be influenced by the other assets in the portfolio. Therefore, the topology needs to be maintained as such even though it would make modelling simpler if the various asset capacities and rated powers were simply added together and treated as single entities.

Similar such topologies are found at business parks, with each business having an individual load but sharing a grid connection with other businesses in the park. Again, business owners are interested in the consumption and generation profiles, as well as ESS behaviour, of their individual 'sites'.

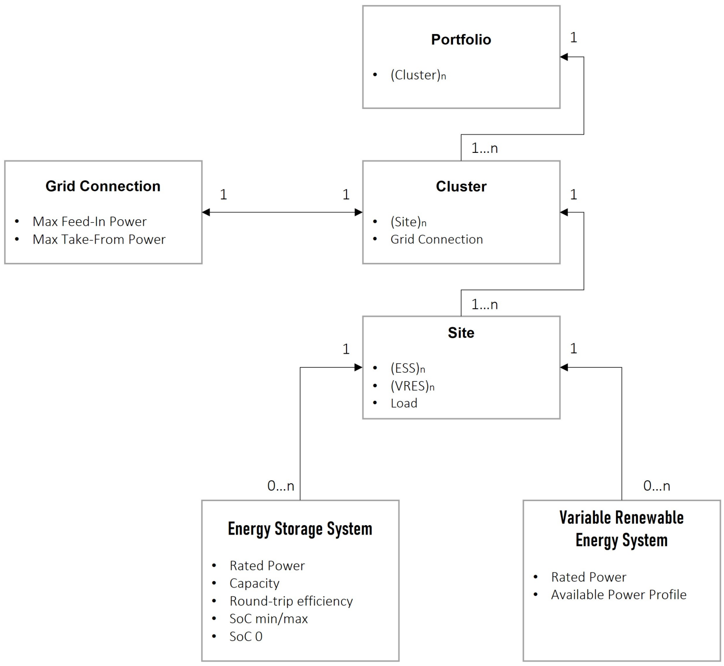

Figure 2: Topology of a portfolio

3.2.1.2 Energy Storage System Model

Input parameters and decision variables for the ESS model are as follows:

Table 2: ESS Input Parameters

Input Parameters	**Symbol**
Maximum charging power [MW]	$P_{\text{max, char}}$
Maximum discharging power [MW]	$P_{\text{max, dis}}$
Capacity [MWh]	Cap_{ESS}
Round trip efficiency	η
State of Charge (min/max)	$SOC_{\text{min/max}}$
Initial State of Charge	SOC_0
Weekly Cycle Limit	C_{lim}

Table 3: ESS Decision Variables

Decision Variables	Symbol	Lower/Upper Bounds
Actual Power [MW]	$P_{\text{ESS},actual}$	$-P_{\text{max,dis}}/P_{\text{max, char}}$
Stochastic Power [MW]	$P_{\text{ESS},s}$	$-P_{\text{max, dis}}/P_{\text{max,char}}$
State of Charge	$SOC_{\text{ESS},s}$	$SOC_{\text{min/max}}$
Charging Power [MW]	$P_{\text{ESS},char}$	$0/P_{\text{max,char}}$
Discharging Power [MW]	$P_{\text{ESS},dis}$	$0/P_{\text{max,dis}}$

The ESS Model is subject to the following constraints:

$$P_{\text{ESS},t,s} = \; P_{\text{ESS},dis,t,s} - \; P_{\text{ESS},char,t,s} \; : \forall \; t, s \tag{6}$$

$$P_{\text{ESS},t,actual} = \frac{\sum_s^S P_{\text{ESS},t,s} * w_s}{\sum_s^S w_s} : \forall t \tag{7}$$

$$SOC_{\min} \leq SOC_{t,s} \leq SOC_{\max}, : \forall t, s \tag{8}$$

$$SOC_{t,s} = \begin{cases} SOC_0 + (P_{\text{ESS,ch},t,s} \cdot \eta_{\text{ch}} - \frac{P_{\text{ESS,dis},t,s}}{\eta_{\text{dis}}}) \cdot \frac{\Delta T}{Cap_{\text{ESS}}} & : t = 1, \forall s \\ SOC_{t-1} + (P_{\text{ESS,ch},t} \cdot \eta_{\text{ch}} - \frac{P_{\text{ESS,dis},t,s}}{\eta_{\text{dis}}}) \cdot \frac{\Delta T}{Cap_{\text{ESS}}} & : t = 1 - T, \; \forall \; s \end{cases} \tag{9}$$

$P_{\text{ESS},t,actual}$ is the actual operation of the ESS system and is determined as the weighted average of $P_{\text{ESS},t,s}$ which is the optimal operation across the various scenarios and will be influenced by that specific scenarios inputs (available power profiles, loads and market prices), and the probability of that scenario occurring. It can be thought of as the determined control strategy for the ESS as a result of the forecasting.

Power can only flow in one direction at any one time. In the case of the ESS, it will either charge *or* discharge. To model for this, auxiliary variables must be introduced to allow the following constraints to be applied.

$$P_{\text{ESS},dis,t,s} <= \; M \cdot \omega \;\; : \forall \; t, s \tag{10}$$

$$P_{\text{ESS},char,t,s} <= \; M \cdot (1 - \omega) \;\; : \forall \; t, s \tag{11}$$

where M is the maximum allowable value of P, in this case the rated charging or discharging power, and ω is the auxiliary binary variable. $P_{\text{ESS},char/dis}$ are bounded between 0 and the maximum charging/discharging powers. The same principle applies to the power flow at the portfolio level, since at grid connections, power should either be flowing into or out of the grid. The decision is taken to model power discharge from the battery and power flow into the grid as the positive elements of the overall power, since the objective is to maximise revenue and therefore the greater the portfolio power, the greater the power which is fed into the grid and therefore has the potential to generate revenue (making the assumption that prices are usually positive as has historically been the more common case).

The weekly cycle limit, C_{lim}, is used to battery degradation. One full cycle is considered a full charge and discharge, therefore, constraint 12 is applied to ensure battery cycling per week does not exceed the weekly limit.

$$(P_{\text{ESS,ch},\tau} \cdot \eta_{\text{ch}} + \frac{P_{\text{ESS,dis},\tau,s}}{\eta_{\text{dis}}}) \cdot \frac{\Delta T}{Cap_{\text{ESS}}} \leq C_{\text{lim},\tau} : \forall \; t, s, \quad \tau \supseteq T^t \tag{12}$$

where:

τ : The weekly super-set interval of the 0.25 hourly t

3.2.1.3 Variable Renewable Energy System Model

For VRES assets, the input parameters include technical specifications as well as an available power profile, that is, the maximum possible power generation of the asset per time step if no curtailment occurs.

The VRES asset input parameters and decision variables are outlined in tables 4 and 5 below.

Table 4: VRES Input Parameters

Input Parameters	**Symbol**
Available Power Profile [MW array]	$P_{\text{VRES, avail}}$
Rated Power [MW]	$P_{\text{VRES, max}}$

Table 5: VRES Decision Variables

Decision Variables	Symbol	Lower/Upper Bounds
Stochastic Power [MW]	$P_{\text{VRES},s}$	$0/P_{\text{VRES, max}}$
Expected Power [MW]	$P_{\text{VRES},expected}$	$0/P_{\text{VRES, max}}$
Actual Power [MW]	$P_{\text{VRES},actual}$	$0/P_{\text{VRES, max}}$

Similarly to with the ESS, a control strategy must be determined for the VRES asset which may include curtailment. Therefore, the actual power of the system could be less than the actual available power profile. Additionally, stochastic available power profiles are generated from the actual available power profile for the asset to account for forecasting errors in generation as described in section 3.1.

$$P_{\text{VRES},t,actual} <= P_{\text{VRES, avail},t,actual} : \forall t, s \tag{13}$$
$$P_{\text{VRES},t,s} <= P_{\text{VRES, avail},t,s} : \forall t, s \tag{14}$$

To calculate the actual power (i.e. the control strategy including any curtailment), the 'expected' power generation of the VRES asset is derived as the weighted average of the stochastic scenarios power generation as per equation 15. The 'actual' power generation of the asset ($P_{\text{VRES},t,actual}$) is then the minimum between the expected power generation ($P_{\text{VRES},expected}$) and the actual available power profile ($P_{\text{VRES, avail},t,actual}$) as per 16. This is because at some time steps the expected power generation may overestimate the actual available power input, therefore, the minimum between the two must be selected.

$$P_{\text{VRES},t,expected} = \frac{\sum_s^S P_{\text{VRES},t,s} \cdot w_s}{\sum_s^S w_s} \tag{15}$$
$$P_{\text{VRES},t,actual} = \mathbf{min}[P_{\text{VRES},t,expected}, P_{\text{avail, VRES},t,actual}] \tag{16}$$

In order to model this as a MILP problem, another auxiliary binary variable is required where 1 signals that the expected power was overestimated, and so $P_{\text{avail, VRES}t,actual}$ should be used, else 0 and $P_{\text{VRES},t,expected}$ is used. This is enforced via constraints 17 and 18. M again represents the maximum allowable value for P, in this case, the rated power of the VRES asset. Then, the remaining four constraints ensure that the minimum is selected as per equation 16.

$$P_{\text{VRES},t,expected} - P_{\text{avail, VRES},t,actual} <= M \cdot \omega \tag{17}$$
$$P_{\text{avail, VRES},t,actual} - P_{\text{VRES},t,expected} <= M \cdot (1 - \omega) \tag{18}$$
$$P_{\text{VRES},t,actual} <= P_{\text{avail, VRES},t,actual} \tag{19}$$
$$P_{\text{VRES},t,actual} <= P_{\text{VRES},t,expected} \tag{20}$$
$$P_{\text{VRES},t,actual} >= P_{\text{avail, VRES},t,actual} - M \cdot (1 - \omega) \tag{21}$$
$$P_{\text{VRES},t,actual} >= P_{\text{VRES},t,expected} - M \cdot \omega \tag{22}$$

3.2.1.4 Sites, Clusters & Portfolios

As per subsection 3.2.1.1, VRES and ESS assets make up a site. In turn, a collection of sites make up a cluster, which is defined as a collection of sites sharing a grid connection. A collection of clusters which can exchange power then make up a portfolio. This is modelled according to the following constraints, for both power per stochastic scenario and actual power.

Table 6: Site & Cluster Input Parameters

Input Parameters	**Symbol**
Load [MW array]	L_{site}
Grid Import Limit [MW]	$P_{\text{cluster, import}}$
Grid Export Limit [MW]	$P_{\text{cluster, export}}$

Table 7: Cluster Decision Variables

Decision Variables	Symbol	Lower/Upper Bounds
Stochastic Power [MW]	$P_{\text{cluster},s}$	-$P_{\text{cluster, import}}$/$P_{\text{cluster, export}}$

$$P_{\text{site},t,x} = \sum_{t=1}^{T} P_{\text{ESS},t,x} + P_{\text{VRES},t,x} - L_{\text{site},t,x} : \forall t, x \tag{23}$$
$$P_{\text{cluster},t,x} = \sum_{t=1}^{T} P_{\text{site},t,x} : \forall t, x \tag{24}$$
$$P_{\text{portfolio},t,x} = \sum_{t=1}^{T} P_{\text{cluster},t,x} : \forall t, x \tag{25}$$

where:

x : any s of S scenarios, or *actual*

3.2.2 SQ2: Modelling Market Revenues

The second research question relates to modelling the electricity markets as MILP problems. These markets were selected because all three are already well-established in terms of market participation and relative ease of access to market participants compared with, for example, supply of automatic frequency restoration reserves (aFRR), which have higher technological and administrative barriers to entry [35].

3.2.2.1 Day-Ahead Market

For the DA market, the model assumes an 100% acceptance rate on all bids. This is because participants are price-takers and put in 0-price bids to ensure they are below the market clearing price. The optimisation goal is to maximise the 'stochastic' revenue, that is, the weighted average of different scenarios according to the probability of each scenario occurring. The only input parameter is the actual day ahead price (${\mathbb{P}_{\mathrm{t,actual}}}^{DA}$), from which stochastic prices (${\mathbb{P}_{\mathrm{t,s}}}^{DA}$) are generated.

$$ {\mathbb{R}_{\tau,\mathrm{s}}}^{DA} = {\mathbb{P}_{\tau,\mathrm{s}}}^{DA} \cdot \bar{P}_{\mathrm{portfolio},\tau,s} \cdot \Delta T : \forall\ t, s, \quad \tau \supseteq T^t \tag{26} $$

where:

τ :	The hourly super-set interval of the 0.25 hourly t (since DA prices are €/MWh)
$\bar{P}_{\mathrm{portfolio},\tau,s}$:	The mean power across every 4, 15-minutes intervals of $P_{\mathrm{portfolio},t,s}$
ΔT:	Time period = 1 hour

The decision for the actual energy bid to be made at the day prior to delivery is calculated as the weighted average of $P_{\mathrm{portfolio},t,s}$, where power (MW) is equal to energy (MWh) since the resolution is hourly:

$$ E_{\mathrm{DA},t} = \frac{\sum_s^S \bar{P}_{\mathrm{portfolio},\tau,s} \cdot \Delta T \cdot w_s}{\sum_s^S w_s} \tag{27} $$

Then, the 'actual' revenue can be calculated as the actual DA price multiplied by the energy bid. This is used later and imbalance revenues or payments applied to calculate the final revenue.

$$ {\mathbb{R}_{\mathrm{t,actual}}}^{DA} = E_{\mathrm{DA},t} \cdot {\mathbb{P}_{\mathrm{t,actual}}}^{DA} : \forall\ t \tag{28} $$

3.2.2.2 Frequency Containment Reserve

Frequency containment bids are power bids made in four hour blocks. The optimal bidding strategy for a particular asset is determined via a different model which is outside of the scope of this research. The bid is then used as an input parameter, alongside historical data for frequency deviations (Δf) in order to model the actual power that needs to be supplied by the asset according to equation 29 & 30. Note that although it is rare, Δf can exceed +/- 0.2 Hz, however, in this instance, the value is clipped with these as the minimum and maximum, to correspond to delivery of the full FCR bid. This is because even if the frequency deviation is greater, the FCR providing asset is never required to deliver more power than is bid.

$$\Delta f = f_t - f_{nominal} \tag{29}$$
$$P_{\text{FCR},t} = \frac{\Delta f}{\Delta f_{nominal}} \cdot P_{\text{FCR max}} : \forall t \tag{30}$$

where:

Δf :	Change in frequency, clipped to a min/max of +/- 0.2 Hz
$f_{nominal}$:	Nominal frequency = 50 Hz
$P_{\text{FCR},t}$:	Actual Power Provision for FCR
$P_{\text{FCR, max},t}$:	Maximum Power Provision for FCR equal to the FCR bid

Additionally, SOC management is required as discussed in section 2.1.2, to ensure the ESS does not reach SOC constraints. As the portfolio could be made up of ESS with different rated powers, the FCR bid is divided amongst the FCR providing-ESS assets. For the rated power, an additional parameter, $P_{\text{ESS, rated}}$, is used since FCR provision must be symmetric, as per equation 31, then the bid is divided as in 32.

$$P_{\text{ESS, rated}} = \mathbf{min[}P_{\text{max, char}},\ P_{\text{max, dis}}\mathbf{]} \tag{31}$$
$$P_{\text{ESS, FCR, max},t} = \frac{P_{\text{ESS, rated}}}{P_{\text{portfolio, rated}}} \cdot P_{\text{FCR, max},t} \tag{32}$$

where:

$P_{\text{ESS, FCR, max},t}$:	Portion of the FCR bid to be supplied by a given ESS
$P_{\text{portfolio, rated}}$:	Sum of the rated powers of ESS's in the portfolio

Adjusted $SOC_{\text{FCR, min/FCR, max}}$ are derived in order to ensure that some capacity is reserved for the unpredictable delivery of FCR power provision. This is calculated as the original minimum plus an additional change in SOC equal to 15 minutes of FCR power provision at the bid level, as is the maximum requirement for LERs.

$$SOC_{\text{FCR, min},t} = SOC_{\text{min}} + \frac{P_{\text{ESS, FCR, max},t} * \gamma_{cap}}{Cap_{\text{ESS}}} \tag{33}$$
$$SOC_{\text{FCR, max},t} = SOC_{\text{max}} - \frac{P_{\text{ESS, FCR, max},t} * \gamma_{cap}}{Cap_{\text{ESS}}} \tag{34}$$

where:

γ_{cap} :	FCR Capacity Reservation Factor = 15/60

Note then that since the FCR bid will vary along the time horizon, $SOC_{\text{FCR, min/max}}$ will also vary, rather than being a simple decimal as is $SOC_{\text{min/max}}$. Similarly, the bounds for the stochastic power of the battery (see table 3) are reduced in order to ensure that some power delivery capability is reserved for the FCR market. Since it is rare that the full FCR bid has to be delivered, a power delivery reservation factor is used.

As per SOC management rules for LERs, the set point from which FCR can be delivered (see figure 1), can only be altered at an interval of 1 minute or more. Therefore, an analysis of frequency changes within a 1 minute interval was performed and a varaince of $\sigma = 8.8$ mHz was derived. As such, with 95% confidence limits we find that a power reservation factor of 13.2% of the FCR bid should suffice as per equation 35. Therefore, the reduced bounds for $P_{\text{ESS, s}}$ are calculated as per equation 36. The input parameters for FCR are summarised in table 8.

$$\gamma_{power} = \frac{3 \cdot \sigma}{f_{nominal}} \tag{35}$$

$$P_{\text{ESS, s, UB/LB}} = +/-\,(P_{\text{ESS, rated}} - P_{\text{ESS, FCR, max},t} \cdot \gamma_{power}) \tag{36}$$

where:

σ: Variability of Δf in one minute = 8.8 mHz
γ_{power} : FCR Power Delivery Reservation Factor = 13.2%

Table 8: FCR Input Parameters

Input Parameters	**Symbol**
Frequency Deviations (Hz)	f_t
FCR Bid (MW)	$P_{\text{FCR, max},t}$
FCR Adjusted SOC (min/max)	$SOC_{\text{FCR, min/FCR, max}}$

Now, in order to determine SOC management, the ESS model must be extended with additional constraints. A theoretical SOC is determined, that is, the SOC if only $P_{\text{DA},t}$ and $P_{\text{FCR},t}$ are considered. Then, if the SOC would exceed $SOC_{\text{FCR, min/FCR, max}}$, the amount of charging or discharging that would be required to ensure they are not violated is implemented ($P_{\text{SOC},t}$). These three power components are then used to calculate the actual changes in state of charge for the ESS. This is outlined in the decision variables table and constraints listed below.

Table 9: FCR & SOC management Decision Variables

Decision Variables	Symbol	Lower/Upper Bounds
Stochastic Power [MW]	$P_{\text{ESS},s}$	36
SOC Management Power [MW]	P_{SOC}	$+/-3 \cdot P_{\text{max, char/dis}}$*
Theoretical SOC	SOC_{theo}	37
Actual SOC	SOC_{actual}	$SOC_{\text{min/max}}$
Change in SOC charging theoretical	$\Delta SOC_{char,theo}$	38
Change in SOC discharging theoretical	$\Delta SOC_{dis,theo}$	39
SOC Management Charging [MW]	$P_{\text{SOC,char}}$	40
SOC Management Discharging [MW]	$P_{\text{SOC,dis}}$	41

* Since the SOC management power could be in opposing direction to the DA and FCR power, this could be up to 3x greater than the rated power of the battery in order for the overall power delivery of the ESS to not exceed its rated power.

The upper and lower bounds for the following decision variables are calculated as follows, similar logic applies for SOC_{theo} as was outlined above:

$$SOC_{theo,\text{LB}} = SOC_{\text{min}} - 2 \cdot \frac{P_{\text{ESS, rated}}}{Cap_{\text{ESS}}} \cdot \Delta T \tag{37a}$$
$$SOC_{theo,\text{UB}} = SOC_{\text{max}} + 2 \cdot \frac{P_{\text{ESS, rated}}}{Cap_{\text{ESS}}} \cdot \Delta T \tag{37b}$$

$$\Delta SOC_{char,\text{LB}} = min(SOC_{\text{FCR, min}}) - SOC_{theo,\text{UB}} \tag{38a}$$
$$\Delta SOC_{char,\text{UB}} = max(SOC_{\text{FCR, min}}) - SOC_{theo,\text{LB}} \tag{38b}$$

$$\Delta SOC_{dis,\text{LB}} = SOC_{theo,\text{LB}} - max(SOC_{\text{FCR, min}}) \tag{39a}$$
$$\Delta SOC_{dis,\text{UB}} = SOC_{theo,\text{UB}} - min(SOC_{\text{FCR, min}}) \tag{39b}$$

$$P_{\text{SOC,char,LB}} = 0 \tag{40a}$$
$$P_{\text{SOC,char,UB}} = \Delta SOC_{char}\text{UB} * \frac{Cap_{\text{ESS}}}{\eta_{char} \cdot \Delta T} \tag{40b}$$

$$P_{\text{SOC,dis,LB}} = 0 \tag{41a}$$
$$P_{\text{SOC,dis,UB}} = \Delta SOC_{dis}\text{UB} * \frac{Cap_{\text{ESS}} \cdot \eta_{dis}}{\Delta T} \tag{41b}$$

The following constraints then extend the ESS to allow FCR market operation and state of charge control to be modelled:

$$SOC_{\text{FCR, min},t} \leq SOC_{t,s} \leq SOC_{\text{FCR, max},t} : \forall t, s \tag{42}$$
$$P_{\text{DA},t} = E_{\text{DA},t} \cdot \Delta T : \forall t \tag{43}$$

The theoretical SOC is determined as if no state of charge control were to be implemented. Note that all power variables are split into charging and discharging components and efficiencies applied, as described in constraints 10 and 11. For simplicity, these are not written out again here.

$$SOC_{theo,t} = \begin{cases} SOC_0 + \frac{\Delta T \cdot (P_{\text{DA},t} + P_{\text{FCR},t})}{Cap_{\text{ESS}}} & : t = 1, \forall s \\ SOC_{theo,t-1} + \frac{\Delta T \cdot (P_{\text{DA},t} + P_{\text{FCR},t})}{Cap_{\text{ESS}}} & : t = 1 - T, \forall\ s \end{cases} \tag{44}$$

If state of charge control charging is required, it is because the theoretical state of charge falls below the FCR adjusted state of charge minimum, and similarly for discharging if the state of charge would go above the maximum:

$$\Delta SOC_{char,theo,t} = SOC_{\text{FCR, min},t} - SOC_{theo,t} \tag{45}$$

$$\Delta SOC_{dis,theo,t} = SOC_{theo,t} - SOC_{\text{FCR, max},t} \tag{46}$$

If $\Delta SOC_{char,theo,t}$ would be positive, then state of control management for charging would not be required, so the actual is found as the minimum between 0 and the $\Delta SOC_{char,theo,t}$. Similarly for the maximum with discharging:

$$\Delta SOC_{char,actual,t} = min[0,\ \Delta SOC_{char,theo,t}] \tag{47}$$

$$\Delta SOC_{dis,actual,t} = max[0,\ \Delta SOC_{dis,theo,t}] \tag{48}$$

By knowing $\Delta SOC_{actual,t}$, $P_{\text{SOC},}$ can be derived from:

$$\Delta SOC_{char,actual,t} = \frac{P_{\text{SOC,char}} \cdot \eta_{char} \cdot \Delta T}{Cap_{\text{ESS}}} \tag{49}$$

$$\Delta SOC_{dis,actual,t} = \frac{P_{\text{SOC,dis}} \cdot \Delta T}{Cap_{\text{ESS}} \cdot \eta_{char}} \tag{50}$$

This allows $P_{\text{SOC},t}$ to be calculated:

$$P_{\text{SOC},t} = P_{\text{SOC,dis},t} - P_{\text{SOC,char},t}, : \forall t \tag{51}$$

Then, with all components of power, the actual state of charge is derived:

$$SOC_{actual,t} = \begin{cases} SOC_0 + \frac{\Delta T \cdot (P_{\text{DA},t} + P_{\text{FCR},t} + P_{\text{SOC},t})}{Cap_{\text{ESS}}} & : t = 1, \forall s \\ SOC_{actual,t-1} + \frac{\Delta T \cdot (P_{\text{DA},t} + P_{\text{FCR},t} + P_{\text{SOC},t})}{Cap_{\text{ESS}}} & : t = 1 - T, \forall\ s \end{cases} \tag{52}$$

Together, these ensure that no technical constraints of the ESS are violated while still acting on both the DA and FCR markets. Finally, revenue is simply calculated as the product of the bid and price:

$$\mathbb{R}^{FCR} = \sum_{t=1}^{T} \mathbb{P}_{\text{t}}^{FCR} \cdot P_{\text{FCR, max},t} : \forall\ t \tag{53}$$

3.2.2.3 Imbalance Settlement

Imbalance energy ($E_{\text{IB},t}$) is calculated post-optimisation as deviation from the DA energy bid. The energy deviation is then multiplied by the upward or downward imbalance settlement price depending on whether the participant produced a surplus or shortage compared with their bid, to determine imbalance settlement payments.

Note that depending on the market position (whether the market is long or short) at a given time interval, the imbalance upward or downward price may be positive or negative to indicate whether payments are made from the participant to the TSO, or from the TSO to the participant respectively.

$$E_{\text{portfolio},actual,t} = \Delta T \cdot (P_{\text{DA},t} + P_{\text{FCR},t} + P_{\text{SOC},t}) : \forall\ t \tag{54}$$

$$E_{\text{IB},t} = E_{\text{DA},t} - E_{\text{portfolio},actual,t} : \forall\ t \tag{55}$$

$$\mathbb{R}^{IB} = \sum_{t=1}^{T} \begin{cases} E_{\mathrm{IB},t} \cdot \mathbb{P}^{IB,up} & : E_{\mathrm{IB},t} < 0 \\ E_{\mathrm{IB},t} \cdot \mathbb{P}^{IB,down} & : E_{\mathrm{IB},t} > 0 \end{cases} \tag{56}$$

4 Results

4.1 Model Performance

One key objective of the research was to produce a model with a high degree of flexibility and a fast run-time despite highly granular input data. For a simple site consisting of a VRES and ESS, the model is able to optimise one year's worth of data at a 15 minute resolution in less than 2 minutes. As the portfolio complexity increases, so does run-time. The most complicated portfolios tested consists of 10 ESS and 9 VRES across multiple sites and clusters. This portfolio optimisation, including DA and FCR market, ran in 19 minutes.

In terms of flexibility, specifically the model has the ability to analyse any desired combination of VRES, ESS, sites and clusters. Furthermore, each of these things, as well as each market revenue, is modelled as a stand-alone unit. This means that choosing which parts to consider in the optimisation problem, as well as integrating future units, can be done quickly and easily. An overview of the model is provided in figure 3, which also includes the units which are currently in development and so have not been discussed in depth in this report, but give an indication of the direction for future work.

Each unit in the figure represents a script containing a python Class. Each Class inherits functions from it's Base Class through the use of Abstract Classes from the 'abc' python package. For example, all market classes require 'revenue' properties, the functions 'add variables' and 'add constraints', and their 'configuration'. The market 'configuration' is a special 'data-class' where the prices (and frequencies in the case of the FCR market) are held.

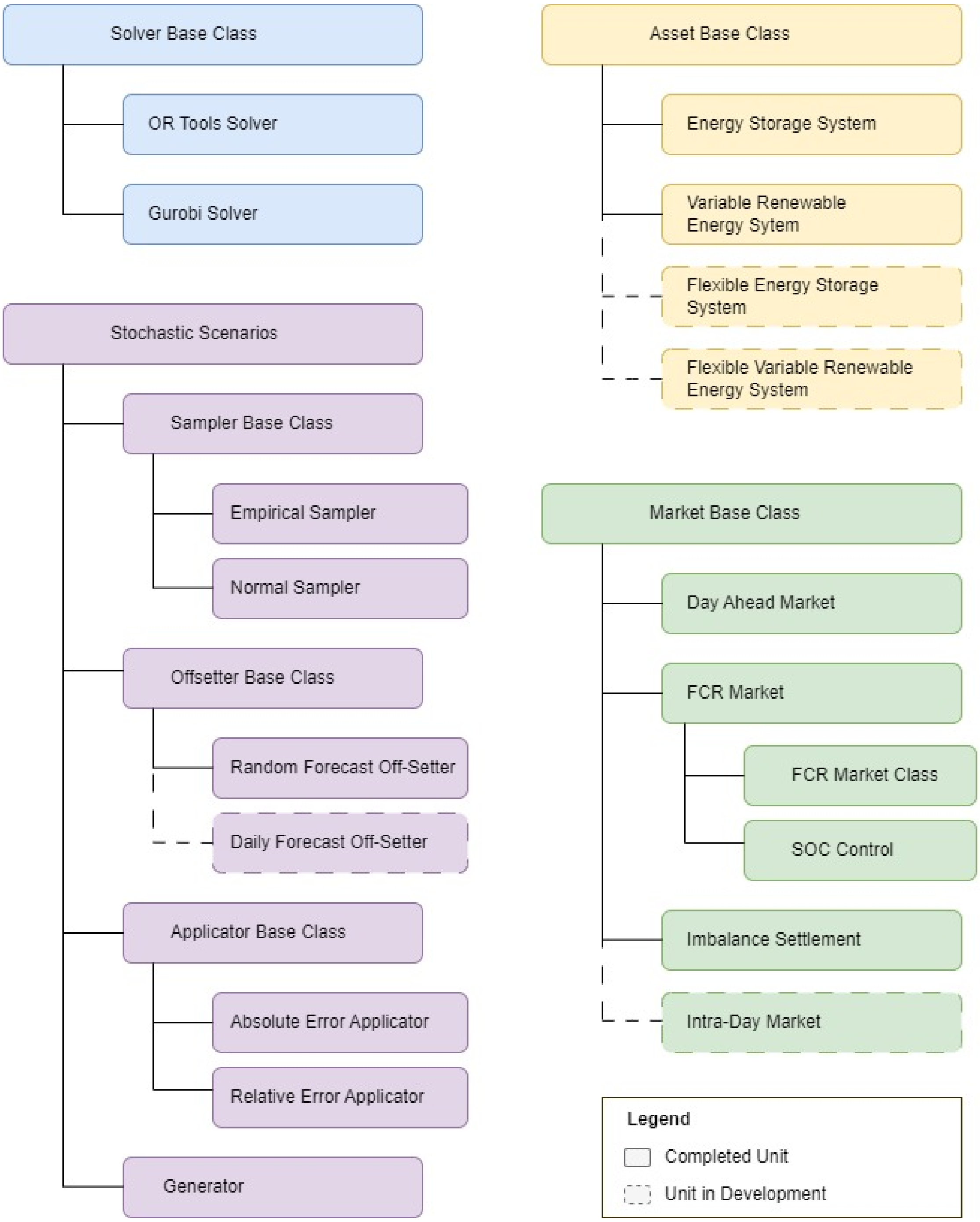

Figure 3: Functional Design of the Model.

For example, the market base class contains the properties and functions, which are inherited into each 'Child Class', such as the DA and FCR markets. In these Child Classes, the specific requirements for revenue calculations and other variables and constraints are implemented. Due to confidentiality agreements, code snippets of these are not included, however a snippet is provided of a 'Fixed Price Market Model' to give an example of how this looks. The Fixed Price Market was developed as a way of testing the model during development stages, and consists of a single feed price and single take price. A code snippet illustrates some elements of this Class below. The ellipses indicate further code which is in the class but not included in the snippet.

```python
# The Fixed Price Market is a Child Class of the Base Market Class
class FixedPriceModel(MarketModel):

    """
    When a Fixed Price Market Model is initialised, the type of solver,
    time dimensions, portfolio and market configurations are called.
    """
    def __init__(
            self,
            solver: ISolver,
            parameters: ModelAxes,
            portfolio_model: PortfolioModel,
            config: FixedPriceMarket,
    ):
        self._solver = solver
        self._params = parameters
        self._portfolio_model = portfolio_model
        self._config = config
        self._revenue_stochastics = None

    # All market classes have a revenue property.
    @property
    def revenue_stochastics(self) -> npt.NDArray[TVariable]:
        return self._revenue_stochastics
    ...

    """
    All market classes have an add_variables function.
    This stochastic revenues variable is unbounded (+/- 'inf') = infinity
    dims = dimensions of the variable
    """
    def add_variables(self):
        time_horizon = len(self._params.horizon.time_steps)
        number_of_scenarios = len(self._params.scenarios)

        self._revenue_stochastics = self._solver.define_num_var_array(
            low_bound=float("-inf"),
            up_bound=float("+inf"),
            name="Fixed_Market_Revenue",
            dims=(time_horizon, number_of_scenarios)
        )
        ...

    """
    All market classes have the add_constraints function.
    For this market, the function states that the revenue is equal to
    the power sold by the portfolio * the feed price
    - the power bought * the take price.
    """
    def add_constraints(self):
        ...
        self._solver.add_constraint(self._revenue_stochastics,
                                    ConstraintType.EQUALS,
                                    time_step *
                                    (self._portfolio_model._power_feed_in *
                                    self._config.energy_feed_price
                                     -
                                     self._portfolio_model._power_take_from *
                                     self._config.energy_take_price))
```

Stochastic scenarios are generated by the generator unit in three stages, as can be seen in figure 3. First, the 'Sampler' class calculates the error values according to the distribution type as specified by the user (see Table 1). Currently, this has been implemented for normal or empirical distributions. Secondly, the 'Off-Setter' applies the offsets. As was discussed in methods section 3.1, this has currently been implemented for the 'Random Forecast Off-Setter', while the Daily Off-Setter is still in development. Thirdly, the 'Applicator' applies the error values to the forecast mean according to the error type, absolute or relative. The 'Generator' script puts these three stages together and applies it to each variable or input which requires stochastic scenarios generation. For example, for the available power profile of a VRES asset, the normal sampler is applied with the relative applicator.

For assets, the base class also contains the 'add variables' and 'add constraints' functions, as well as 'actual electric power' and 'stochastic electric power' properties. The stochastic property will have as many dimensions as there are stochastic scenarios generated. For example, if 3 stochastic scenarios are generated, then there will be 3 possible values per time-step. As described in the methodology, this represents the 'planning/forecasting' phase of the model. Then, the 'actual electric power' can be seen as the control strategy of the asset which is determined as a result of the weighted average of the 'forecast' stochastic scenarios. The ESS and VRES assets have already been implemented and described in the methods. In future iterations of the model, the 'flexible' ESS and VRES will also be completed. These assets are similar except that the rated power (and capacity, for ESS) will be variables rather than input parameters. Therefore, the optimal rated power and capacity for the asset is an output of the optimisation.

As a tool for consultants, this is useful because outcomes for different market and portfolio configurations can quickly be analysed, to assess which markets might be most suitable for particular clients, while also being able to see the behaviour of individual assets, and guide investment decisions for additional assets, or see what impacts would come from additions of potentially new sites purchased into the portfolio.

4.2 Portfolio Configuration and Use Cases

To illustrate the results of the model, a basic use case is constructed consisting of a simple site of 1 ESS and 1 VRES asset. The model is tested using prices and production/consumption data from the year 2020. 4 different ESS configurations were tested with power/capacity ratings:

- 0.5 MW/1 MWh
- 0.5 MW/2 MWh
- 1 MW/1 MWh
- 1 MW/2 MWh

The site was tested both on the DA and DA with FCR. Additionally, a 'Consumer' use case is considered with both VRES production and Load, and a 'Producer' use case. in which load is 0. In all cases, imbalance settlement is considered. The configuration details are outlined in Table 10. Due to GDPR, actual client data cannot be used, therefore a solar profile and commercial load profile are generated using client data which has been anonymized with the use of the 'sklearn decomposition' python package.

Table 10: Portfolio Configuration.

Parameter	**Value**
ESS	
$P_{\text{max}}/Cap_{\text{ESS}}$	*as above*
$SOC_{\text{min/max}}$	0.1/0.9
η	0.95
C_{lim}	7
VRES	
$P_{\text{VRES, max}}$	1.924 MW
$P_{\text{VRES, avail}}$	Typical Dutch Solar Profile [MW]
Other	
L_{site}	Typical Commercial Load Profile [MW]
$P_{\text{cluster, import}}$	1.350 MW
$P_{\text{cluster, export}}$	0.692 MW

4.3 Exploration of Stochastic Scenarios

As described in section 3.1, only the 'Random Forecast Off-Setter' has so far been implemented. An example of the stochastic scenarios compared with the actual scenario is provided in figure 4 for a given day of the optimisation, using quantiles 0.1, 0.3, 0.5, 0.7 and 0.9 to calculate the stochastic scenarios. In the top row are input parameters, available power profile for the VRES asset and DA Prices. The 'actual' line in red is the input parameter supplied by the user, from which stochastic scenarios are generated as described in the previous section.

The bottom row shows two example variables, the portfolio power variable and the DA revenue variable. From each stochastic scenario, there is an optimal variable value for the power or revenue. From these stochastic values, the final 'actual' value is calculated as the weighted average of the stochastic values.

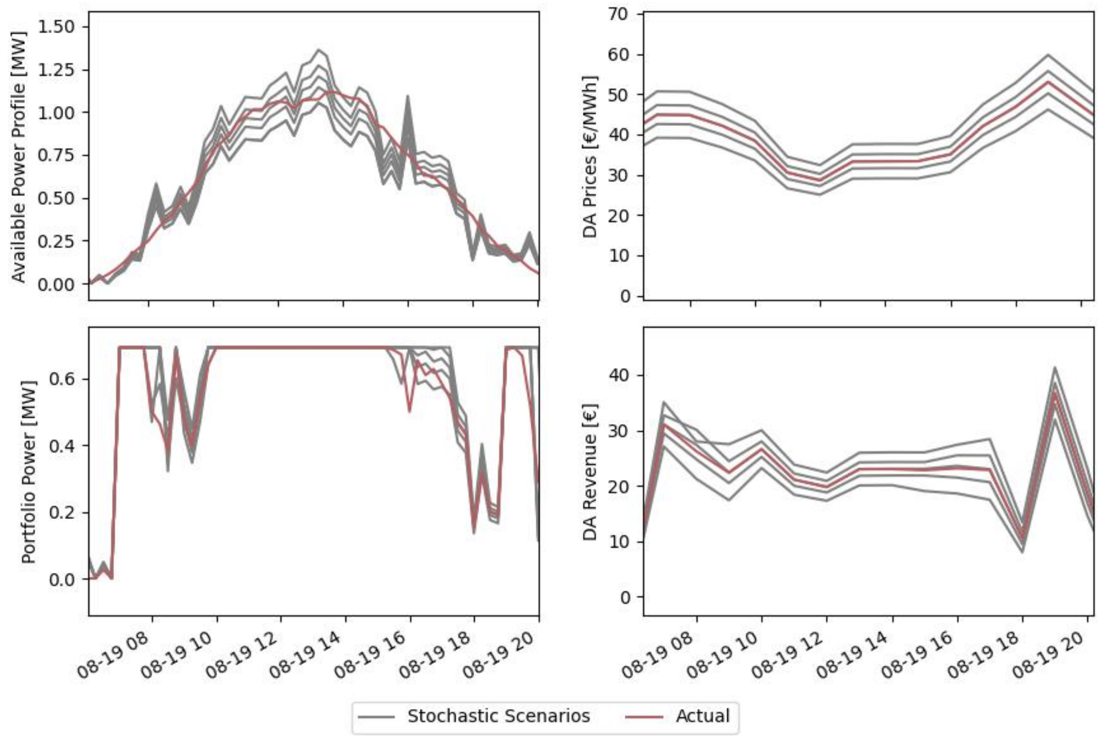

Figure 4: Scenarios for 'Producer' use case, 1/1 ESS. Top, Example Inputs: Available Power Profile and DA Price. Bottom, Outputs: Portfolio Power and DA Revenue. Data is shown for 8 am to 8 pm on August 19 2020. Stochastics are generated based on the quantiles: 0.1, 0.3, 0.5, 0.7 & 0.9.

This figure illustrates how the Random Forecast Off-Setter results in similar forecast means. It also demonstrates the difference in error types as shown by the available power profile, which has relative error, compared to market price, with absolute error. For available power profile, a larger power rating results in a greater spread between the stochastic scenarios, while at lower values the stochastic scenarios are all similar. Conversely, for DA prices, the spread in scenario values is consistent regardless of the magnitude of the value.

4.4 Revenues Across Use Cases

Given the above configuration, final revenues for the 4 use cases (Consumer, Producer and with/without inclusion of the FCR Market) are shown in figure 5.

All use cases produce positive revenue except the consumer not trading on FCR. In the consumer case, consumption exceeds production and so energy must be purchased on the day ahead to satisfy consumption constraints. The 2 MWh capacity ESS's have lower negative revenues since the larger capacities allows them to make greater use of energy arbitrage, charging the battery when prices are lower, and discharging to satisfy consumption requirements when prices are higher.

In the non-FCR cases, the lower final revenue of the 1/2 ESS compared with the 0.5/2, can be attributed to higher IB payments outweighing the slight increase in DA revenue, as shown in figures 6 and 7.

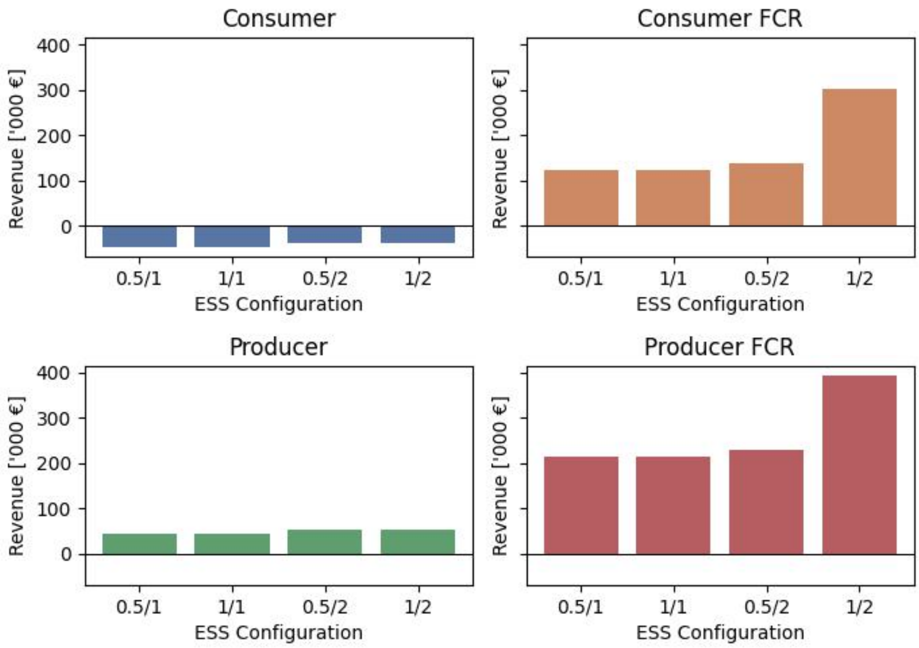

Figure 5: Final Revenue. Clockwise from top left are the consumer, consumer with FCR, producer, and producer with FCR use cases. Y-axis is uniform across all figures.

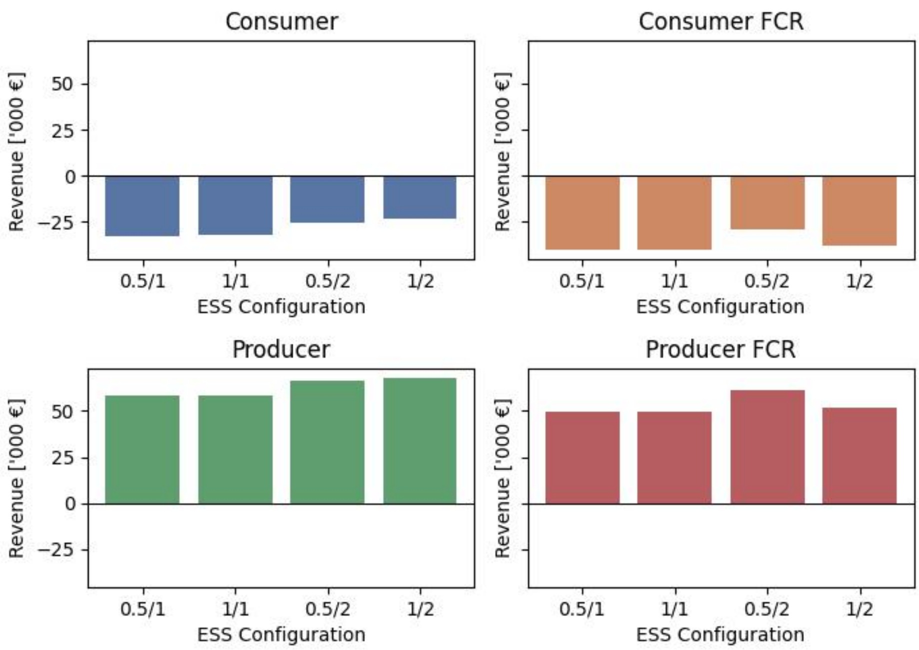

Figure 6: DA Revenue. Y-axis is uniform across all figures.

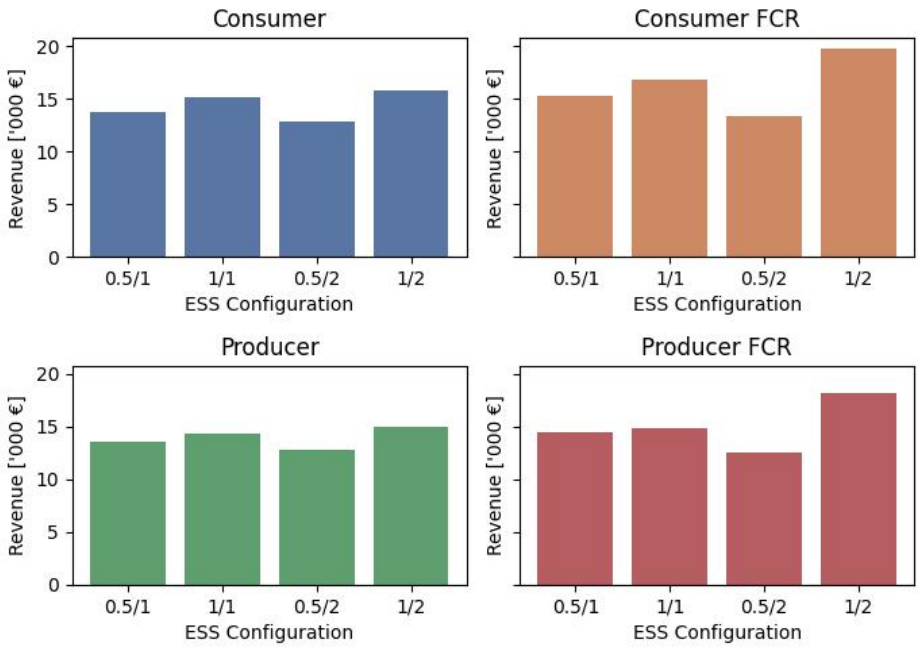

Figure 7: IB Payments. Y-axis is uniform across all figures.

The imbalance settlement is not part of the optimisation problem, but rather, is calculated post-optimisation. It was found that the higher power rating batteries (i.e. 1/1 and 1/2) had higher IB payments than the lower ones, and that when acting on the FCR market, IB payments were higher than when not acting on the FCR market.

FCR Revenue is based on the power bid, regardless of actual power delivery. Since FCR bidding must be in 1 MW blocks, the 0.5/1, 1/1 and 0.5/2 ESS configurations each bid 1 MW and therefore had the same FCR revenue of 1 MW multiplied by the FCR price for that block. This was the maximum bid possible for these ESS assets while still achieving an optimal solution to the optimisation. The 1/2 ESS configuration was able to bid 2 MW and still achieve an optimal solution, therefore, the FCR revenue was doubled for this ESS configuration.

4.5 Other Key Indicators

4.5.1 Curtailment

As well as being able to compare revenues based on different portfolio configurations and market combinations, there are many parameters which can be examined within one use case that could be of interest. One such example is curtailment of VRES assets within the portfolio, as shown in figure 8.

The curtailment figures are useful for further economic calculations (not currently integrated into the model). For example, in the Netherlands renewable generators might be eligible for the SDE+ subsidy at around 70 to 110 €/MWh produced. As a result, figure 8 suggests that the 0.5/2 ESS, which curtails 70 MW less than the 1/2 ESS up to 93 MW less than the 1/1 ESS, could generate somewhere between €5,100 and €10,200 in additional revenue per year. A 0.5/2 ESS is also approximately €100,000 cheaper in terms of CAPEX than a 1/2 ESS

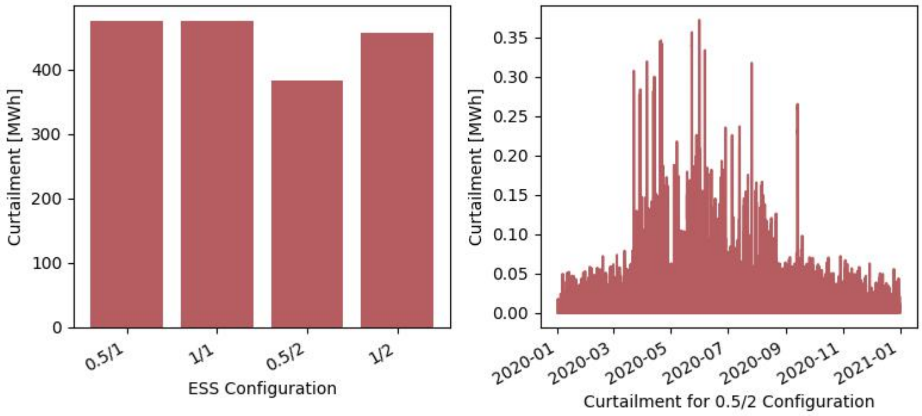

Figure 8: Curtailment in the Producer FCR use case. Left: Across the four ESS configurations. Right: Across the year for the 0.5/2 Configuration at 15 minute resolution.

(internal Spectral estimates, various sources). This information is therefore useful in guiding ESS investment decisions.

4.5.2 Weekly Cycle Limits

In the model, C_{lim} is set by the user as a proxy for limiting battery degradation. Inspection of this parameter shows that this is a limiting factor in all non-FCR use cases. Examining, as an example, the 'Producer" use case for the 1/1 ESS, we can see the effects on revenues of changing this parameter in figure 9.

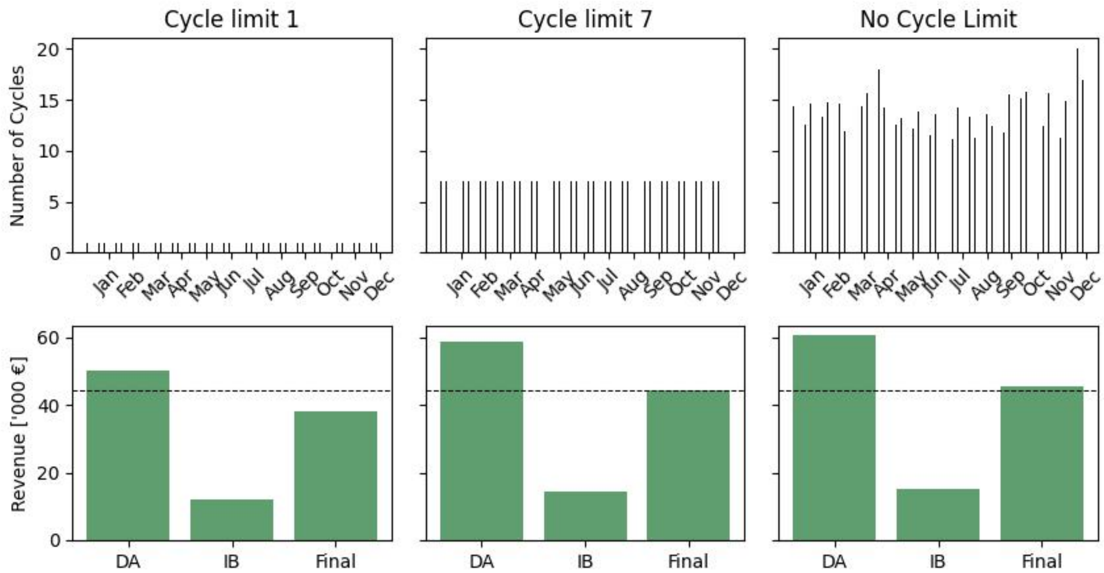

Figure 9: Effects on revenues of weekly cycle limits. Use case is 'Producer' with ESS configuration 1/1. Dotted line indicates final revenue for the original use case, where the cycle limit is 7.

As per the original ESS configuration (see Table 10), a cycle limit of 7 is limiting in almost all weeks of the year. For the 1/1 ESS this resulted in a final positive revenue of €44,000 (Figure 5). Reducing the weekly cycle limit down to 1 results in a reduction in final revenue of close to €6000, a minimal reduction in revenue compared with the benefit of extending battery life. On the other side, if we remove the limit, we see a that the average number of weekly cycles across the year doubles from 7 to 14, with the highest number of cycles in a week being 20. Doubling the average weekly cycles will significantly increase degradation, but only results in a €1000 increase in revenue.

4.5.3 Grid Import/Export Limits

An exploration into the power flow at the grid connection point revealed that while $P_{\text{cluster, import}}$ is non-limiting, $P_{\text{cluster, export}}$ is consistently reached. Since revenues are made on the DA by exporting energy, it follows that increasing $P_{\text{cluster, export}}$ could result in increased revenue. It is worth noting however, that grid capacity increases can be extremely expensive, but these can also be time-dependant. This is an economic rather than technical constraint, a contract is agreed with the DSO whereby the import or export capacity limit can be increased or decreased in certain time-windows. Breaching the agreed limit for the given window will result in fines from the DSO.

On this basis, it is useful to be able to see how often and at which times of year a particular use case reaches $P_{\text{cluster, export}}$, in order to assess the business case for a time-dependant grid capacity upgrade. This is illustrated in figure 10. On the left shows the power flow across 2020 for the original use case. On the right, the grid export limit is doubled and we see that $P_{\text{cluster, export}}$ is still limiting at times, although much less so than in the original case.

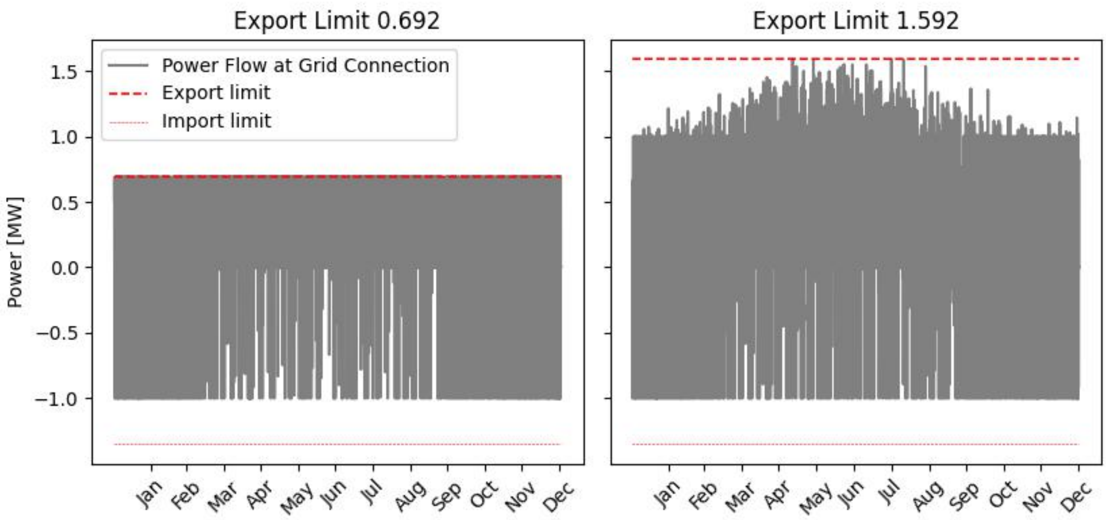

Figure 10: Power flow at the grid connection point. Recall that negative power flow is for imported power. Left: Original configuration. Right: Increased grid export limit to reduce instances of limiting export. Use case is 'Producer' with ESS configuration 1/1

Given the aforementioned costs of grid capacity upgrades, it is useful also to compare these with the impact on revenue. Figure 11 shows the relationship between $P_{\text{cluster, export}}$ and revenue. The grid export scaling factor is a multiplier of $P_{\text{cluster, export}}$ from the original use case, where 1 is equivalent to 0.692 MW.

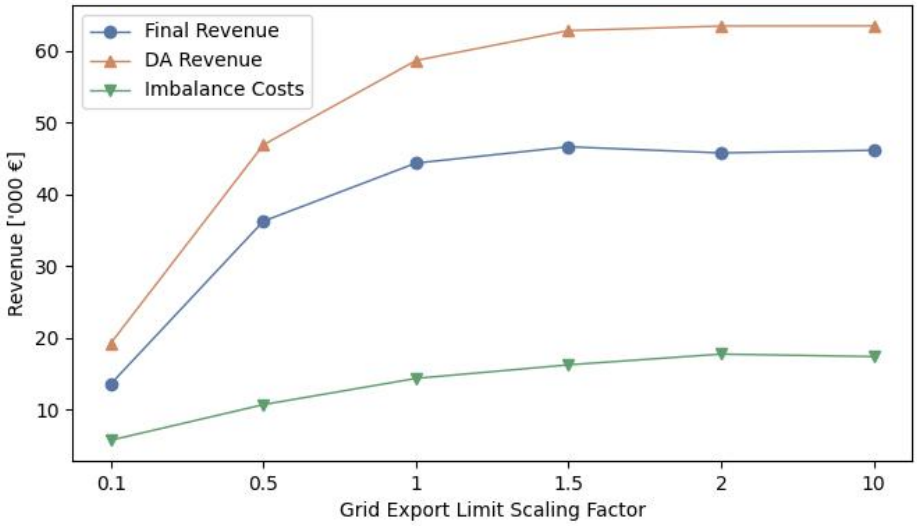

Figure 11: Impact of $P_{cluster,\ export}$ on revenue. The Scaling Factor is a multiplier of $P_{cluster,\ export}$ where 1 is equivalent to 0.692 MW. Use case is 'Producer' with ESS configuration 1/1

Since the additional costs of capacity increases are not considered, we cannot determine the optimal export limit without further economic analysis, however, it is interesting to note the non-linearity of the relationship between revenue and export limit. It is also worth noting that in some cases these results could reveal a potential to increase revenue through decreasing the grid connection limit if it is being under-utilised.

5 Discussion

One major limitation of the model is the currently very crude stochastic scenario generation methods. Implementing the Daily Forecast Off-Setter as discussed in section 3.1 will greatly improve the validity of the model. Secondly, it is a shortcoming of the model that IB is considered, but the intra-day (ID) market is not. In practice, participants trading on the DA market would likely also use ID markets to correct their positions closer to real-time and thus reduce their imbalance. So far, this is not considered, and IB payments are calculated post-optimisation. By adding ID trading and reformulating IB to become part of the optimisation, it is possible that rather than IB payments, both ID and IB participation could result in additional revenue streams. Due to the way in which the model has been built, these are easily implementable, and once completed, will result in a model which has a significant variety of potential uses.

To test the validity of the model, some outcomes were tested against previous research that has been performed by Spectral. Data was only available for the FCR market. When the same year and production profiles are used, previous research estimated a revenue of €168,000, while the model predicted €180,000. The small difference can be almost entirely attributed to the previous research assuming a 95% bid acceptance while the model assumes 100%.

Direct comparisons with existing literature are difficult to make due to the number of differing inputs and configurations to be considered. However, [29] examined trading of a 0.5/1 configuration Hydrogen-Bromine flow ESS on the DA market in the Netherlands for the year 2016. For a given day in May, they achieve revenues on the DA market of around €75. Using a 0.5/1 ESS with no load or production, and price data for 2016 for the same day in May, the model predicts a revenue of €78, remarkably similar to the literature despite quite different modelling approaches.

[36] produced a model which studied revenue potential through trading on the DA market and considering IB payments for 13 wind farms around the UK in the winter of 2017. The prices and regulations differ slightly, however, are similar due to market coupling. If the revenue calculated by [36] is scaled per MW of rated power of the wind farm, then revenues between 48,000 and 98,000 €/MW rated power are achieved. To make a comparison, the same months were used for input prices, and the VRES asset as described in the results section, 4.2, was used. The model achieves revenues between 25,000 and 70,000 €/MW rated power, depending on the ESS configuration used. In the UK in 2017 the prices were on average higher than in the Netherlands, which may account for some of the difference in final revenue. Additionally, the details of ESS used by [36] were not provided, so while further comparisons are difficult to make, it seems as though the model's results are reasonable and well-aligned to literature.

Aside from the potential revenue generated by stacking across various markets, the model also provided insights into parameters such as power flow at the grid connection point. As was discussed in the introduction, Dutch commercial customers are increasingly being denied grid connection requests due to grid congestion. As a result, being able to compare the reduction in peak power flow at the grid connection across different ESS configurations, as well as the times at which the peak is reached, is another useful outcome of the model. Other parameters such as the curtailment across the year are useful if portfolios are eligible for the SDE+ subsidy, and useful further research would include integrating subsidies, operating and investment costs into the model to guide future investment decisions. Additionally, if a client is considering acquisition of a new site, the costs and assets associated with this could then be added into the existing client portfolio and tested to see what potential revenues could be generated as a result of the acquisition.

6 Conclusion

The aim of the research was to build a model which would allow any configuration of portfolio to be optimised for trading across multiple markets, and to see what was the revenue potential through dynamically stacking as compared with acting on singular markets. The model allows a user to run an optimisation for a year or more of data at a high resolution in under 20 minutes even for the most complex portfolios. The use cases tested suggest that dynamic stacking can result in significantly more revenue for a simple site than trading on singular markets, although, further work is required to test overall profitability across more complex sites and portfolios.

For a simple use case, it was found that 1/2 ESS configuration was the most profitable due to the capability of trading an additional 1 MW on the FCR market. However, this ESS configuration also led to higher IB payments. Additionally, many parameters within the portfolio could be studied which form the basis for further economic analysis, such as, the magnitude and timings of curtailment of VRES assets, grid connection limits, and battery cycling. Furthermore, the model has been built in such a way that future market revenues and other cost factors such as capital investment of assets can easily be integrated in future iterations of the model. As such, there is a great deal of potential for further research.

7 Acknowledgements

The work would not have been possible without the collaboration with Spectral. In particular, huge thanks are extended towards Milan Milinković and Thanos Tolis, whose continued support both conceptually and technically allowed me to take the model much further in both complexity and elegance than I would have been able to do alone. Huge thanks also to my academic supervisor at Utrecht University, Dr. Elena Fumagalli, for her encouragement and friendly support throughout the project.

References

[1] T. Brijs, C. D. Jonghe, B. F. Hobbs, and R. Belmans, "Interactions between the design of short-term electricity markets in the cwe region and power system flexibility," *Applied Energy*, vol. 195, pp. 36–51, 6 2017.

[2] T. Brijs, F. Geth, S. Siddiqui, B. F. Hobbs, and R. Belmans, "Price-based unit commitment electricity storage arbitrage with piecewise linear price-effects," *Journal of Energy Storage*, vol. 7, pp. 52–62, 8 2016.

[3] A. Castillo and D. F. Gayme, "Grid-scale energy storage applications in renewable energy integration: A survey," *Energy Conversion and Management*, vol. 87, pp. 885–894, 11 2014.

[4] F. Sensfuß, M. Ragwitz, and M. Genoese, "The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in germany," *Energy Policy*, vol. 36, pp. 3086–3094, 8 2008.

[5] IEA, "The netherlands 2020 - energy policy review," 2020.

[6] S. Englberger, H. Hesse, N. Hanselmann, and A. Jossen, "Simses multi-use: A simulation tool for multiple storage system applications," *International Conference on the European Energy Market, EEM*, vol. 2019-September, 9 2019.

[7] S. Englberger, A. Jossen, and H. Hesse, "Unlocking the potential of battery storage with the dynamic stacking of multiple applications," *Cell Reports Physical Science*, vol. 1, p. 100238, 11 2020.

[8] L. Baringo and A. J. Conejo, "Offering strategy of wind-power producer: A multi-stage risk-constrained approach," *IEEE Transactions on Power Systems*, vol. 31, pp. 1420–1429, 3 2016.

[9] A. Hanemaaijer, M. Kishna, M. Kooke, H. Brink, J. Koch, A. G. Prins, and T. Rood, "Integrale circulaire economie rapportage 2021," 2021.

[10] EEX-Group, "Trading at epex spot," 2021.

[11] TenneT, "International connections," *retrieved from https://www.tennet.eu/our-grid/international-connections-2*, 2022.

[12] E. Groza, S. Kiene, O. Linkevics, and K. Gicevskis, "Modelling of battery energy storage system providing fcr in baltic power system after synchronization with the continental synchronous area," *Energies 2022, Vol. 15, Page 3977*, vol. 15, p. 3977, 5 2022.

[13] ENTSOE, "Frequency containment reserves," *retrieved from* $https://www.entsoe.eu/network_codes/eb/fcr/$, 2022.

[14] S. Clò and E. Fumagalli, "The effect of price regulation on energy imbalances: A difference in differences design," *Energy Economics*, vol. 81, pp. 754–764, 6 2019.

[15] L. Vandezande, L. Meeus, R. Belmans, M. Saguan, and J. M. Glachant, "Well-functioning balancing markets: A prerequisite for wind power integration," *Energy Policy*, vol. 38, pp. 3146–3154, 7 2010.

[16] A. S. Awad, J. D. Fuller, T. H. El-Fouly, and M. M. Salama, "Impact of energy storage systems on electricity market equilibrium," *IEEE Transactions on Sustainable Energy*, vol. 5, pp. 875–885, 2014.

[17] S. A. M. M. Kooshknow and C. B. Davis, "Business models design space for electricity storage systems: Case study of the netherlands," *Journal of Energy Storage*, vol. 20, pp. 590–604, 12 2018.

[18] I. Lampropoulos, M. van den Broek, E. van der Hoofd, K. Hommes, and W. van Sark, "A system perspective to the deployment of flexibility through aggregator companies in the netherlands," *Energy Policy*, vol. 118, pp. 534–551, 7 2018.

[19] K. Bradbury, L. Pratson, and D. Patiño-Echeverri, "Economic viability of energy storage systems based on price arbitrage potential in real-time u.s. electricity markets," *Applied Energy*, vol. 114, pp. 512–519, 2 2014.

[20] D. Zafirakis, K. J. Chalvatzis, G. Baiocchi, and G. Daskalakis, "The value of arbitrage for energy storage: Evidence from european electricity markets," *Applied Energy*, vol. 184, pp. 971–986, 12 2016.

[21] V. Krishnan and T. Das, "Optimal allocation of energy storage in a co-optimized electricity market: Benefits assessment and deriving indicators for economic storage ventures," *Energy*, vol. 81, pp. 175–188, 3 2015.

[22] G. F. Frate, P. P. Carro, L. Ferrari, and U. Desideri, "Techno-economic sizing of a battery energy storage coupled to a wind farm: an italian case study," *Energy Procedia*, vol. 148, pp. 447–454, 8 2018.

[23] T. Terlouw, T. Alskaif, and W. V. Sark, "Optimal energy management of all-electric residential energy systems in the netherlands," Institute of Electrical and Electronics Engineers Inc., 6 2019.

[24] N. B. Brinkel, W. L. Schram, T. A. AlSkaif, I. Lampropoulos, and W. G. van Sark, "Should we reinforce the grid? cost and emission optimization of electric vehicle charging under different transformer limits," *Applied Energy*, vol. 276, p. 115285, 10 2020.

[25] I. Lampropoulos, T. Alskaif, J. Blom, and W. van Sark, "A framework for the provision of flexibility services at the transmission and distribution levels through aggregator companies," *Sustainable Energy, Grids and Networks*, vol. 17, p. 100187, 3 2019.

[26] A. M. Alharbi, I. Alsaidan, and W. Gao, "Optimal scheduling of battery energy storage system performing stacked services," *IEEE Green Technologies Conference*, vol. 2022-April, pp. 110–115, 2022.

[27] P. Hou, G. Yang, P. Enevoldsen, and A. H. Nielsen, "Cooperation of offshore wind farm with battery storage in multiple electricity markets," *Proceedings - 2018 53rd International Universities Power Engineering Conference, UPEC 2018*, 11 2018.

[28] S. Zhan, P. Hou, P. Enevoldsen, G. Yang, J. Zhu, J. Eichman, and M. Z. Jacobson, "Co-optimized trading of hybrid wind power plant with retired ev batteries in energy and reserve markets under uncertainties," *International Journal of Electrical Power Energy Systems*, vol. 117, p. 105631, 5 2020.

[29] N. G. Paterakis, M. Gibescu, W. Kout, and Y. A. Hugo, "Investigation of arbitrage between the dutch day-ahead and imbalance markets as a business case for the hydrogen bromine flow battery," *2017 IEEE Manchester PowerTech, Powertech 2017*, 7 2017.

[30] Y. Tohidi and M. Gibescu, "Stochastic optimisation for investment analysis of flow battery storage systems," *IET Renewable Power Generation*, vol. 13, pp. 555–562, 3 2019.

[31] H. Su, D. Feng, Y. Zhao, Y. Zhou, Q. Zhou, C. Fang, and U. Rahman, "Optimization of customer-side battery storage for multiple service provision: Arbitrage, peak shaving, and regulation," *IEEE Transactions on Industry Applications*, vol. 58, pp. 2559–2573, 2022.

[32] D. Putz, D. Schwabeneder, H. Auer, and B. Fina, "A comparison between mixed-integer linear programming and dynamic programming with state prediction as novelty for solving unit commitment," *International Journal of Electrical Power Energy Systems*, vol. 125, p. 106426, 2 2021.

[33] J. Dalton, "Optimal day-ahead scheduling and bidding strategy of risk-averse electric vehicle aggregator: A case study of the nordic energy and frequency containment reserve markets," *MSc. KTH. School of Electrical Engineering and Computer Science (EECS)*, 2018.

[34] M. van Eck, "Bess investment decisions," *MSc. Utrecht University, Department of Geosciences*, 2019.

[35] O. Borne, K. Korte, Y. Perez, M. Petit, and A. Purkus, "Barriers to entry in frequency-regulation services markets: Review of the status quo and options for improvements," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 605–614, 1 2018.

[36] A. H. Elgamal, G. Kocher-Oberlehner, V. Robu, and M. Andoni, "Optimization of a multiple-scale renewable energy-based virtual power plant in the uk," *Applied Energy*, vol. 256, p. 113973, 12 2019.