Essays on Risk and Profitability in the Future British Electricity Industry

by

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Abstract

This thesis analyses risk and profitability issues in the future British electricity industry through three different studies. The first study develops a novel and fully endogenous portfolio investment model for firms in a competitive electricity industry when they face uncertainties from fuel prices, demand levels, carbon price and renewable penetration. This study finds that both risk aversion and carbon price are crucial factors for investments in nuclear technology.

The second study analyses the impact of the cost of capital on optimal investments. Two distinct costs of capital of a project are considered: one in the pre-development and construction (pre-operation) phase and the other in the operation phase. The pre-operation cost of capital is based on the complex and capital-intensive nature of a project, which prevents potential investors from undertaking them under high costs – this is the first driving force for investment followed by the operation cost of capital. Operation cost of capital is based on a company's ability to generate cash flows that cover debt requirements by varying the debt-equity ratio that a firm can attain. The greater the cash-flow risk, the lower is the level of debt that the firm can include in its financing, and hence, the higher the weighted average cost of capital, given that debt generally benefits from tax shield.

The third study analyses the profit risk of energy storage when it faces fuel-price risk. Specifically, it assesses the future electricity industry with different levels of renewable penetration and storage energy capacity. The study shows that energy storage profits depend on the electricity price risk when it makes profits from arbitrage and reserve provision and also shows that storage profit has a positive correlation with that of other

generators, especially with profits of gas stations, and this correlation is moderated with the level of electricity demand.

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Declaration of Originality

I, Vitali Avagyan, declare that this thesis is solely my own work written with the guidance of my thesis supervisor, Richard Green. All other works are appropriately referenced and acknowledged. All stated views and conclusions are my own, and I bear full responsibility thereof.

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CHAPTER 1: Introduction

Prelude

There are different types of risk and uncertainty in the GB electricity industry. In its strict form, "uncertainty" is a state of a variable where no probability distribution can be assigned to its possible values while "risk" is a state of a variable where the probability distribution of its possible values is known (see, for example, Knight (2012)). Despite their difference in the strict sense, this thesis sometimes uses them interchangeably whenever the precise distinction is not important. For example, "demand uncertainty" indicates that demand intercepts are variable but their distributions are known, whereas "carbon-price uncertainty" is used in its strict sense as scenarios of high and low carbon prices are analysed separately with no probability assigned to them. Even when future fuel-price uncertainty is converted into risk with the help of its projected scenarios for low, central and high price levels given by DECC (2013a), "fuel-price uncertainty" might be used. However, "profit risk" is always used in its strict form as it forms the cornerstone of this thesis. Along with other problems, it presents one of the main barriers to investments in electricity generators of any kind, owing to the fact that there are risk-averse investors (of various degrees) in the British electricity industry. Many of them hold portfolios of different kinds of generating assets: some kinds serve baseload demand while others midload or peakload; some kinds are more exposed to market-price risk while others are hedged against; some kinds are environmentally friendly while others are carbon-intensive.

Unlike other European countries, the UK has already pushed through stricter environmental targets to be met by electricity producers such as Emissions Performance Standards (EPS) for carbon-intensive gas and coal stations. In addition, the 4-year-old government-backed Green

Investment Bank (GIB) was established (with seed money of £3.8 billion) to invest solely in low-carbon projects and to attract private funding by sponsoring only clean projects. It aims to drive down the cost of capital of the project, to make decarbonisation easier to attain and to create lower barriers to market entry.

The financial market trembled right after the UK voted to leave the European Union. This created a legitimate concern about the feasibility of the UK's decarbonisation budget. It was demonstrated, amid great concern, that the UK would be able to meet its binding carbon-reduction conditions, set in the corresponding carbon budgets, even after leaving the European Union (CCC, 2016). However, it came with a recent readjustment of the policy that aimed to set down strategies for closures of unabated coal plants by 2025 (BEIS, 2016a). In addition, since future industry will have more renewables with sporadic outputs, such as wind power (which is more unpredictable than solar that produces electricity under the availability of sun), energy storage deployment has been put on the forefront of the agenda, since it is able to accommodate extra uncertain outputs by renewables and store them for a later use.

However, let us quickly look back a few years to see how the policy was shaped that triggered this path to decarbonisation. In 2010, the government realised that investments in clean technologies would be more sluggish without additional intervention; therefore Electricity Market Reform (EMR) (DECC, 2011) was set in motion to draw up the necessary steps required to foster investments in low-carbon generation with the aim of achieving near complete decarbonisation of the industry by 2050 (80% from 1990 level). It was obvious that the UK decarbonisation would not happen then and there, and it would take further 40-50 years to achieve the required levels. For this reason, EMR set up specific mechanisms to accomplish this. One example is the currently operational Feed-in-Tariff Contract for

Differences (CfD FiT) which was proposed as a long-term contract between a low-carbon generator and the government-owned Low Carbon Contract Company (LCCC) (DECC & LCCC, 2014) with the objective of reducing market risks for those technologies. However, the long-term aim of the government from the late 2020s is to use wholesale market and carbon-price signals to drive investments as all technologies will be mature (DECC, 2012).

At present, these wholesale market price signals are not easy to acquire, as most price quotes are not publicly available. Since 2005, under the British Electricity Trading and Transmission Arrangements (BETTA[1]), English, Welsh and Scottish electricity generators and suppliers can sign bilateral contracts (apart from being able to trade in power exchanges), which give them the freedom to negotiate mutually reasonable short-term or long-term contractual terms (House of Commons & ECCC, 2011). National Grid as an acting System Operator (SO) gets only the final settlements from the contracting parties at the "gate closure" – one hour before the actual delivery of electricity. Currently, 60% of all electricity in the UK is traded bilaterally, which in fact precludes public access to the settlement prices (CMA, 2015b).

Content

In view of the revamp of the British electricity industry, there seems to be an even greater need for investment and profit risk assessment modelling under uncertainties that come from different levels of carbon price, risk aversion and renewable penetration as well as from electricity demand and fuel-price risk. They are important since different technologies have different degrees of exposure to those risks. For example, the consensus is that nuclear is the riskiest investment option among others due to its higher capital-intensive upfront costs and larger deviation of its profit distribution from the expected value. However, the riskiness of

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1 Formerly known as NETA, which did not include Scotland in its single market.

any technology depends largely on how risk is quantified in the model, and therefore different methodologies can yield different results and conclusions.

If profit risk of technologies were easy to quantify, there would not have been many models attempting it. Since the choice of modelling and methodology does matter, it makes a huge difference in how the problems are modelled and analysed. Hence, the need for profit and investment risk analyses and discussion in the context of the UK decarbonisation policy.

Objective

The research objective of this thesis is threefold as it aims to:

1) show how risk aversion, coupled with uncertain renewable output, demand and fuel prices, affects the optimal non-renewable generation portfolio in one endogenous model;

2) quantify the cost of capital of a generating technology (and of a firm of several technologies) and compare the relative riskiness of each technology in the British industry;

3) quantify the impact of fuel prices and weather variation on the profit risks of storage and other technologies.

Methodology

This thesis uses a mixture of approaches in quantifying profit risk of different technologies and draws conclusions from them by elucidating the differences in methodology, assumptions, and results. Two different modelling approaches are used throughout the thesis to model profit risk which depends on the problem types and characteristics. Type and characteristics of a problem allows us to choose a specific modelling technique:

- A calibrated simple Monte-Carlo simulation optimisation merit-order stack model is used for the future British electricity industry in chapters 3 and 4. The construction of the merit-order stack model is detailed in Chapter 3. The choice of merit order stack is convenient for

investment analyses as it gives realistic annual outputs and profits of generators. It is also easy to use in a Monte-Carlo simulation framework. With the use of the merit-order stack, we can construct the price-formation mechanism in the electricity market in a simple way when marginal-cost supply function intersects with an hourly net demand to give hourly clearing prices. It is a straightforward and useful "bird's-eye view" modelling technique where such granular details as plant-level characteristics (start-up or shut-down costs, minimum operating off/on time etc.) are unnecessary. In short, it provides reasonable solutions for equilibrium investment problems (Staffell & Green, 2012).

Equilibrium investment decisions should not be confused with capacity expansion decisions. Capacity expansion decisions are problems that have time as a factor and take existing plants into account whereas the problems of this thesis simplify things assuming that there are fewer plants of each type than the optimal amount. Therefore, a relevant question is to find how much more capacity we need to build in future, given that some generators are subject to specific annual profit variations. These profit variations are induced by uncertainties from yearly fuel prices, hourly renewable outputs, and hourly gross demands under different scenarios of installed renewable capacity, risk aversion level and carbon price level. Fuel prices are modelled with yearly variation although it is understood that they can also have inter-annual variations. However, for the purposes of the thesis, inter-annual fuel-price variations are excluded and instead only annual average levels are considered stochastic. Therefore, in this context, the inter-annual electricity-price variations, to a great extent, depend on variations of hourly gross demand and hourly renewable penetration. This is a reasonable assumption as long as inter-annual marginal cost variations are not great enough to change the merit order of technologies. Assuming they do not change the merit order, hourly gross demand and hourly renewable outputs are modelled in more detail.

Because the models of Chapter 3 and Chapter 4 are computed for many simulations to account for uncertainties, a lot of effort is devoted to making them simpler and quicker while preserving all the essential characteristics of the system under consideration. In particular, historical load-duration curves are constructed from 17 years of data that allow approximation of load distribution at each hour. Some hours are aggregated into tranches whenever average loads within those hours happen to be quite similar. With this method, the sampling from hourly demand distributions is replaced with sampling from tranche demand distributions – total reduction of the number of sampling from 8760 to 362 for each simulation run. The available wind and solar frequency dataset of percentile penetration for each of those 362 tranches allow the construction of the wind and solar load factors for each tranche. After this, the Monte-Carlo simulation framework becomes easy to implement; this starts with sampling from yearly fuel price distributions (that define marginal costs) and from distributions of gross demand and the wind & solar load factors (therefore their penetration levels) for every tranche. This sampling is performed multiple times, and each time with a given renewable capacity vector, risk aversion level, and carbon price by changing the capacity mix of conventional generation until the problem converges to the equilibrium mix.

Merit-order stack has some advantages over other methods as it:

- Eases simulation of the whole complex electricity system into a tractable framework that can be computed in a short time;
- Gives detailed distributions of profits and quantifies investment risk of technologies in an Excel-based user interface;
- Provides a familiar modelling interface that can be complicated further if need be.

- More complicated economic dispatch model is used in Chapter 5 and is applied to representative days that are chosen via clustering of demand, to give enough characteristics for representation of the accuracy of the system. The model is applied to representative days (instead of all days of the year) as, similar to chapters 3 and 4, it is also calculated for many simulation runs. This model is very useful in situations when detailed technical characteristics and hourly operating patterns of plants are important as they are used to calculate the profit risk of both new (e.g. storage) and conventional (e.g. CCGT) technologies. The choice of economic dispatch is convenient as it allows the inclusion of both energy storage and spinning reserve requirement into the optimisation equation, which would otherwise have been harder to incorporate into the models of the merit-order stack of Chapter 3 or Chapter 4. Additionally, economic dispatch is more useful than merit order stack in this context since different start costs of technologies can magnify the price differentials which are essential for energy storage arbitrage revenue. Apart from arbitrage, there are other streams of revenue that storage is capable of getting such as providing ancillary services (e.g. frequency response, black start). The difficulty of considering those services is that they tend to overcomplicate the model. However, the modelling of the spinning reserve by storage is included.

Economic dispatch problems are cost minimisation problems, which aim to minimise the total cost of meeting the system load when operating units are already connected to the system. No transmission constraints or losses are included in these models, as their inclusion would require additional security constraints. In addition, unit commitment problem is not formulated in Chapter 5 as it is computationally challenging, given that many simulations are performed to account for fuel-price uncertainty. It yields shadow prices that are hard to interpret too.

There are many solution methods to economic dispatch problems, depending on the amount of details that can be inserted in the constraints and the objective function. This model has some characteristics of unit commitment but here each type of capacity is continuous and it can start up and shut down anytime to satisfy load instantly as it is assumed to have infinite ramp rates for technologies. Continuous capacity makes prices easier to interpret as shadow prices can easily come out of the optimisation equations which otherwise could have been harder to interpret for integer units of capacity. Assumptions on infinite ramp rates do not incur major problems as the model time granularity is one hour in duration which allows a plant to ramp up or down to a required level, in the meantime. The model is formulated as a linear program and solved in GAMS with CPLEX solver. The main emphasis here is devoted to the modelling of energy storage that makes profits from arbitrage and reserve provision. At each hour, the output should satisfy demand and reserve requirement in the least cost manner and there are no penalties for not satisfying demand as they are put as hard constraints.

Economic dispatch modelling has some advantages over other methods as it:

- Provides detailed operating patterns of each technology on an hourly basis; however, it does not consider that a whole unit can shut down and start up since those problems come under unit commitment models.
- Gives easy-to-use framework to model the impact of fuel prices on technical costs of the generators;
- Is able to exploit representative days in the model for faster processing with a reasonable accuracy of results.

Models of this thesis assume that renewable penetrations are negative demand. This is a pragmatic approach for modelling to happen as dealing with net demand is easier due to the

suppressed number of variables – in this way we have fewer decision variables as we would otherwise have with renewable investment choices in the portfolio. However, portfolio analysis with renewable technologies is important since many companies now hold diverse portfolios with renewables in them. This is an avenue for future research and lies outside of the scope of this thesis.

Assumptions

Models used in the thesis target future industry by trying to depict the state of the industry as it will be. Although the exact date is not crucial, it is fair to assume it encompasses a timeline that is greater than 2025 and smaller than 2030. There is no incremental capacity expansion or delays to build in the models, as the aim of modelling is to give the "status quo post bellum" in future; the models are not dynamic in time (no evolution of the system through time) but solely represent a snapshot of a future industry. In other words, the models represent possible states of the future industry given scenario assumptions of renewable penetration and other projections when it is assumed that recent electricity demand patterns will be preserved. Additionally, it is assumed that no disruptive technology would emerge to replace already established baseload, midload and peaking technologies.

Besides, there are some specific assumptions that need to be presented in more details:

- All models in this thesis assume a perfectly competitive generation market that goes through the pool. Although the trading through the pool constitutes a smaller part of the whole trading balance at present, the expected spot market price tends to drive the contract price. Therefore, calculating spot market prices and inferring contract prices from them is a

reasonable approximation. However, this approximation is valid only for short-term contracts since only then future fuel-price projections can be fed into the contract prices.

- Even now we can observe that electricity prices equal to marginal costs of price-setting technologies, as no unilateral market power has been exercised in recent years by any generator, including even the Big Six[2] and Drax (CMA, 2016). Unilateral market power arises when one specific type of generator withholds its capacity by creating a possibility for the electricity price to jump from a higher merit order to a lower one. However, it is not easy to exercise market power as even if a generator withholds its capacity (assuming that others keep their competitive quantities), the price may not be altered. The amount of capacity withheld should be significant enough to create this price jump across merit orders as a direct outcome of a switch between price-setting technologies. Of course, the aim of raising the electricity price is to make more money – which can be best captured by higher-merit generators or portfolios of higher-merit generators – but the cost of withholding should be offset by its benefits. The opportunity to exercise market power in the pool by withholding output is further complicated by forward output that generators had agreed to deliver when negotiated bilaterally.
- All models assume that there are many identical market participants; they have the same portfolios with the same level of risk aversion. Also, it is assumed that future industry operates without any entry or exit barrier and attracts investors with the same risk profile.
- No interconnection is considered in this study, although the UK currently runs 4-GW interconnection with its neighbours. The inclusion of the interconnection is left for future research. However, due to its forward-looking nature, this study could not overlook profit risk analyses of energy storage, which might gradually pile into the grid-level generation mix.

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[2] British Gas (parent – Centrica plc), EDF Energy (parent - EDF S.A.), RWE npower (parent - RWE AG), E.ON UK (parent - E.ON SE), SSE and Scottish Power (parent - Iberdrola S.A.)

These analyses are carried out in an economic dispatch setting where transmission and system security constraints are omitted.

It is expected that big energy companies will continue to have high market share in the future, which gives them an advantage for making "lumpy" investments. However, as already discussed above, it is unlikely to expect the utilisation of wholesale market power by them. It is acknowledged that the recent government intervention to promote nuclear new build would favour big players since high capital investments can be carried out mostly by those players. This might create a non-homogenous industry, which could be hard to model; hence, these models consider homogenous industry (and market) where generating companies have identical structure. This is a rough approximation of the future industry but useful in providing model solutions with valuable insights. The model solutions are valuable since we obtain profit risks based on prices derived from marginal costs. Profit risk determines which technologies are unfavourable in a competitive model which is likely, to the author's mind, to be preserved under a low or moderate market power.

Contribution

There are many models of the UK electricity system that model uncertainty in detail; however, no model contributes to:

- calibrating profit risk analyses of a portfolio in a fully endogenous setting by quantifying the impact of interlinked uncertainties of risk aversion, carbon price, fuel price, demand and renewable penetration levels in the UK context;
- quantifying the profit risk of technologies with different methods and drawing insights from them;

- modelling of engineering-economic characteristics of an energy storage when it faces risks from fuel price and demand uncertainty by studying its profit correlations with other technologies.

Moreover, there are relatively few models that incorporate (endogenise) risks, and even fewer that endogenise the cost of capital of different assets. This thesis aims to improve these areas via bringing new methods in the literature for investment and profit risk analysis. In particular, it touches upon the following topics:

- Risk aversion - there are many models that study the impact of risk aversion and carbon price in isolation. Although the literature sets aside the link between risk aversion and carbon price level, this thesis is the first to show their intertwined impact on the investment in nuclear generation and provides insights for integrated policy analysis for promoting nuclear investments;
- Fuel price - the impact of fuel-price uncertainty on energy storage is also ignored. Although the literature offers varied modelling approaches for quantifying the impact of fuel-price risk on generators' profits, this thesis is the first to show its potential impact on energy storage and the reasons behind it;
- The UK context – this study brings in some new techniques to study the UK electricity industry. Although the background to the modelling and analyses is the UK, techniques can be successfully applied to different contexts by conforming to the electricity system characteristics of that country.

The author believes the assumptions and simplifications of the presented models do not undermine their merits and they can be useful for policymaking as well as for academic investment analysis as outlined above on pages 23-25.

Scope

While this thesis takes a detailed and constructive look at the decarbonisation challenge of the UK, it confines itself to the following particulars:

- Renewables are treated exogenously to investment decisions. They are modelled indirectly (subtracted from demand) rather than explicitly, although with a thorough discussion of their impact on the profits and capacities of non-renewable technologies. Renewables are left out of the portfolio, since the purpose of this thesis is to analyse the investment decisions in conventional generation. This simplification is adopted to answer the essential research questions of the thesis. Should renewables be included in the portfolio, they would behave like nuclear with high fixed costs and very low operational costs that face variable market prices. This would be the case if the renewables were without subsidies (or subsidised via top-ups on the market price) which is expected to be exercised in future if their costs fall enough. The profit risk of renewables would be largely determined by the impact of renewable penetration on the electricity-price levels and their variability, as the average level of electricity prices will drop and variability will increase under large amount of penetration. This would change if the majority of renewables were subsidised under long-term contract signings. Their revenues would be fixed while the other plants would face low and variable electricity market prices thus allowing renewables to be preferred in the optimal portfolio. However, future research should take into account the inclusion of renewables sources in the portfolio analyses to account for all the effects they might bring since they can alter investment decisions.
- Three types of technologies (Nuclear, CCGT and OCGT) and long-term nuclear contract are considered in Chapter 3, and three technologies in Chapter 4. Only gas price distribution is modelled as an input fuel price in these chapters. This is the only fuel price to

be modelled since technologies considered are gas stations and nuclear plants, and nuclear fuel price variability is considered negligible;

- Five types of technologies (Nuclear, Coal-CCS, CCGT, Biomass and OCGT) are considered in Chapter 5 with their respective sub-categories. In addition to previous chapters, different types of fuels (gas, oil, biomass and coal) are also added;
- Long-term equilibrium analyses rather than system development over time is considered in all models;
- Price-responsive but inelastic electricity demand is calculated with a detailed modelling of the randomness of its intercepts;
- Finite scenarios for risk aversion, carbon price and renewable penetration are considered to contract the computational time of the models;
- Chapter 4 limits its financial analysis to debt covenant requirements and their impact on the cost of capital without modifying either debt or equity rate of return;
- All models use continuously divisible capacity rather than lumpy power stations that have to be turned on or off individually. This is a reasonable approximation for this kind of "coarse-grained" problems which do not require many details to represent the system in a satisfactory way;
- Economic growth in electricity demand is excluded from all models;
- Only one type of storage is modelled in Chapter 5 to give an indication of possible profit risk of storage technologies.

Structure

The thesis consists of three main studies that are united under a single umbrella of profit risk assessment. Profit risks affect total investment, invested capacity mix, electricity prices, to name a few, that form the integral slices of the whole electricity system analysis.

Chapter 2 follows this introduction and presents a general overview of the background to the chapters. Specific literature reviews are presented in the corresponding chapters to facilitate the coherence of the thesis.

Chapter 3 studies quantification of the profit and investment risk in a novel portfolio-optimisation setting. It includes the ins and outs of how electricity prices are formed in a competitive market with the help of merit-order stack model. The electricity price formation is assumed to be carried out in the pool where hourly day-ahead prices are calculated. They are taken as proxies for the actual prices received by the generators, whether in the pool or during bilateral trades. Here it is assumed that generators are not under long-term contracts, and whenever they are (as with nuclear), it is explicitly stated and modelled. The chapter sets out a fully endogenous investment model for different risk-aversion levels considering uncertainties from fuel price and electricity demand. Additionally, it differentiates future scenarios for levels of carbon price and renewable electricity penetration and measures their impact on equilibrium capacity. The results indicate that risk aversion is an essential aspect for defining the capacity mix as it has negative impact on low-carbon baseload generation; a carbon price of at least £54.3 per tonne of CO2 is needed for nuclear technology (without a fixed-term contract) to be included in the portfolio, and nuclear capacity can fall 9.3% with an increase of risk-aversion by 0.05 from the risk-neutral case. The maximum carbon price considered is 80 £/tonne of CO2, and the carbon price needed for any nuclear to be included in the portfolio rises by around £3 per tonne of CO2 for every 0.01 increase in risk aversion

(whenever carbon prices are high enough to favour them). Also, when a fixed-price nuclear contract is included in the portfolio, it acquires around 52% share of baseload technology in the risk-neutral case and around 62% share of baseload technology in the risk-averse cases.

Chapter 4 sets about describing the impact of cash-flow risk on the cost of capital of various technologies, driven by the financing covenants typically used in European projects. Based on the model of Chapter 3, it develops an endogenous model of the cost of capital by bringing in construction and cash-flow risk to determine the debt capacity a project is able to attract, and hence the capital structure of that project. This capital structure is then used to update the cost of capital, which enters the model for another round of looping to update the levelised fixed costs of the project. The chapter uses some external literature sources to derive the cost of capital of technologies during their pre-operation phase. The results indicate that nuclear is the riskiest technology in terms of development with a cost of capital of 10.8%, but is the least risky in terms of its cash flows during the operation phase with a cost of capital of 7.2%. In fact, nuclear has higher absolute volatility than other technologies, consistent with Chapter 3 and the previous literature, but the mean cash flow is much higher thus making it a more attractive option in terms of operation since its coefficient of variation is the lowest. However, as the chapter explains later, this is not enough to boost investments in nuclear due to its high upfront risk.

Chapter 5 quantifies the impact of fuel-price risk on storage revenues, profits by incorporating fuel-price correlation analyses and demand-profile extraction technique. It sets apart the impact of fuel price on storage profits from that of demand uncertainty and gives full information about cross-correlations among profits of all technologies. The underlying model of Chapter 5 is the minimisation model of daily costs and includes some technical characteristics such as start-up and no-load costs. Distribution of profit risk of storage (when

it makes a profit from arbitrage and reserve provision) and other technologies are obtained under uncertainties from fuel price and demand. The results indicate that, with 5 GW of power and 4 GWh of energy capacity, storage makes a mean profit of around 130 million £/year with a standard deviation of around 12 million £/year under low renewables and a mean profit of around 127 million £/year with a standard deviation of around 11 million £/year under high renewables. However, whenever the storage is able to provide more kWh energy (20 GWh) in low-renewable case, it starts to generate a mean profit of around 500 million £/year with a standard deviation of around 51 million £/year.

Chapter 6 presents an overall conclusion of the thesis by bringing up all-important insights arising from thesis chapters, their limitations and future research directions.

CHAPTER 2: General Background

Although Chapter 1 of this thesis provides some glimpses of the background for this thesis, this chapter is designed specifically to shed a broader light on the background of the covered topics. This is only a background, not a literature review as the latter is introduced in the forthcoming chapters as separate contextual pieces. Adherence to this structure is intended to make the thesis more coherent and easier to read.

GB Electricity System

The process of GB electricity system restructuring and privatisation was set in 1989 with the actual procedure effective from 1990. Albeit privatised, the electricity wholesale supply market was not competitive (Green & Newbery, 1992) because it had an effective duopoly which made wholesale prices higher. However, in later years, the market entry barriers were gradually lifted allowing many small and large companies to gain entry and compete.

Before 1990 there was no electricity produced from combined-cycle gas stations (CCGT), despite some electricity coming from gas turbines and oil stations (BEIS, 2016d). After the liberalisation of the industry, investments in CCGT plants increased as some of its legal barriers were removed. As a consequence of this, the coal industry suffered a decline with efficiency rise in nuclear stations adding an extra fuel to the downward sloping path of coal. However, in May 1997, the Labour government came to power and brought energy security to the agenda and tried to revive the coal industry. Some type of gas power plants were temporarily banned (Pearson & Watson, 2012) but it did not slow down investments in gas stations as the "dash for gas" had already begun (Newbery, 1997) which continued its upward trend until 2010 (Figure 1 and Figure 2). .

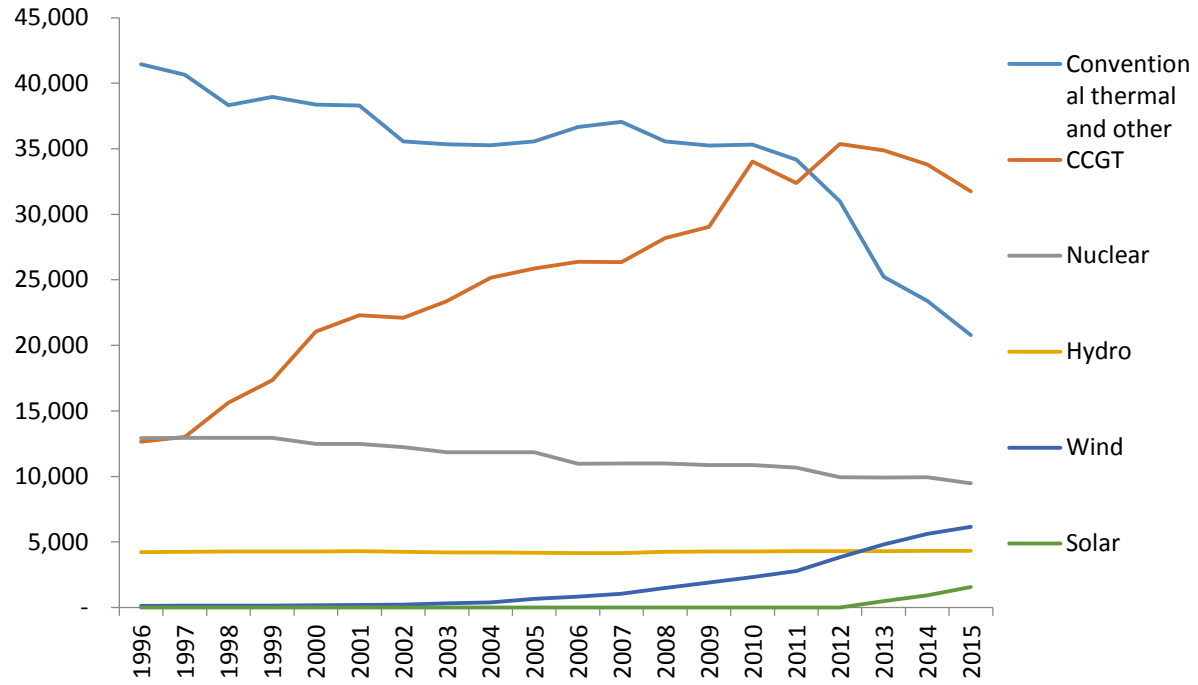

Figure 1: UK Generating Capacity (MW)

Source: BEIS (2016d)

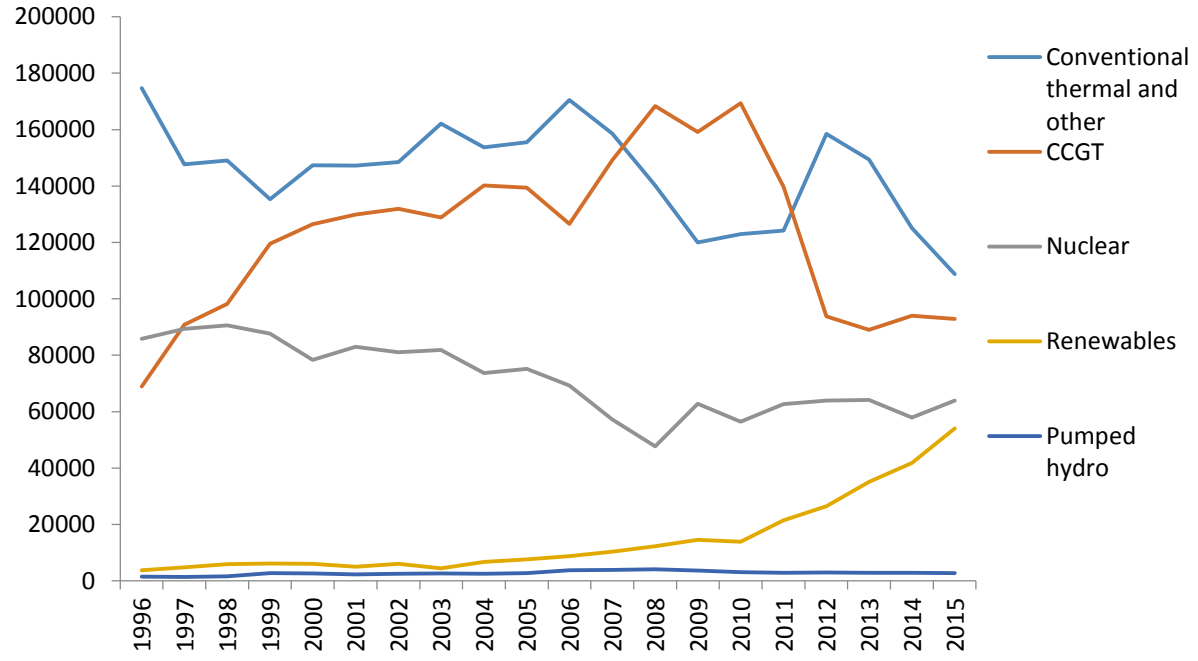

Figure 2: UK Electricity Generation and Supply (GWh)

Source: BEIS (2016d)

The cost of electricity is calculated based on costs of fuel, CO2 emissions, operations & maintenance (O&M) as well as capital costs. Not only generating costs of conventional power plants are rising in line with their carbon emissions, but also their costs are uncertain due to the volatile nature of fossil fuel prices. Fossil-fuel prices create volatile and rising wholesale electricity prices as long as fossil-fuel stations are setting the electricity price and renewable and storage technologies have not overtaken them in capacity. The rationale behind this is that the electricity price is mostly driven by the marginal costs of gas stations (Roques, 2008) that determine the industry supply function. Most commonly it is represented as a piece-wise constant marginal supply function which is derived from the marginal cost functions of individual generators. In a pool, wholesale electricity prices are determined when electricity suppliers and distributors (along with large consumers) bid and offer in power exchanges of APX Power UK[3] (APX Group) and UK N2EX[4] (Nord Pool). Bilaterally traded contracts, on the other hand, are signed outside of those exchanges. They are agreements between parties to deliver the output in future. Physical delivery of these contracts is revealed to the system operator who uses this information to identify any system imbalances that may occur close to real time. Whenever there is such imbalance, the system operator is responsible for balancing the supply and demand in a least-cost manner. Imbalance prices to participating parties – who did not fulfil the contractual obligations – are determined ex-post by Elexon (CMA, 2016).

Most power trading in exchanges is done in a day-ahead market where generators supply their hourly price-quantity pairs of electricity (based on their marginal costs) that need to be delivered on the following day. Whenever all bids and demand schedules are collected from suppliers and buyers, the system operator calculates the clearing price (the equilibrium price)

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[3] https://www.apxgroup.com/trading-clearing/apx-power-uk/

[4] http://www.nordpoolspot.com/Market-data1/N2EX/Auction-prices/UK/Hourly/?dd=GB&view=table

(Figure 3 and Figure 4) as an intersection of supply and demand functions. In addition to the day-ahead market, the intra-day market is also in operation where traders exchange power to prevent potential imbalances that can occur between day-ahead supply and close to real-time demand schedules. This market closes one hour before delivery, and the prices may jump up to the cap level of that power exchange if the electricity demand is extremely high under the available limited production.

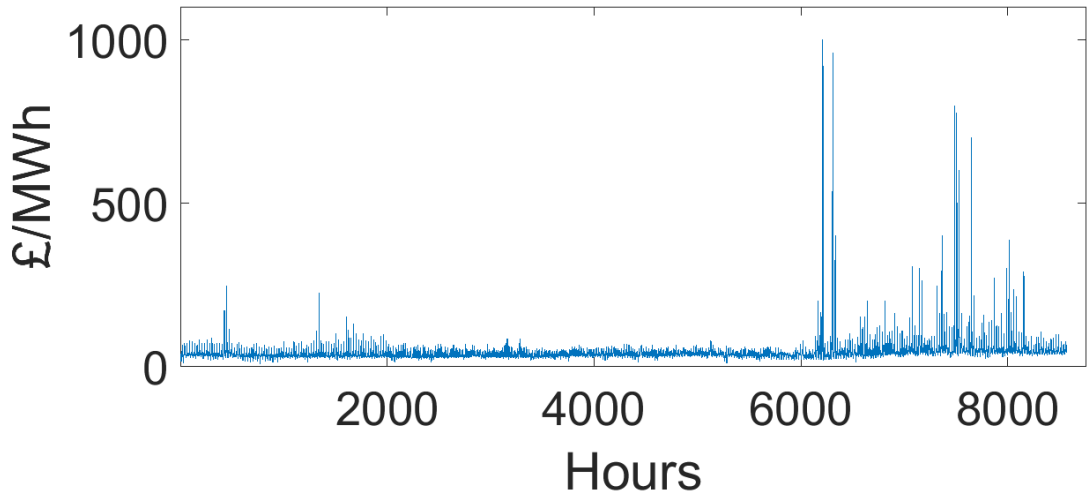

Figure 3: Hourly electricity day-ahead prices in 2016

Source: Nord Pool (2016)

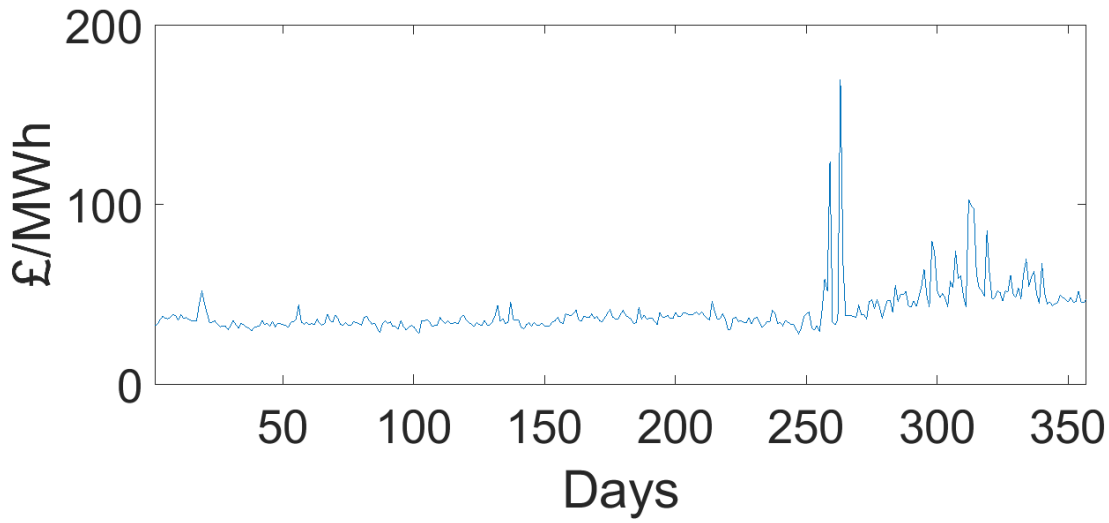

Figure 4: Daily electricity day-ahead prices in 2016

Source: Nord Pool (2016)

However, those price jumps may be limited when a huge amount of renewables coupled with energy storage penetrate the system.

Storage accommodates the extra electricity from renewables in the hours of low demand and supplies back in the hours of high demand. However, stringent regulatory policies have been put forward towards the deployment of energy storage all over Europe (Pöyry, 2014; Ruz & Pollitt, 2016) and storage utilisation has become challenging for some constituents of the electricity chain. Currently, limited rights to storage ownership towards distribution operators and no rights towards transmission operators in the UK hinder significant installations in storage. In addition, storage is surprisingly categorised as "generation" bearing all licensing conditions of a typical generator, which is a clear misrepresentation of its functionality (Castagneto-Gissey & Dodds, 2016). Despite all these regulatory challenges, storage investments might set off very slowly as the interest towards grid-scale storage technologies is on the rise. This is due to storage's ability to benefit from multiple sources of revenue as it is able to utilise electricity price risk to earn arbitrage revenue, be available for reserve provision, and be used for frequency regulation of the load or balance the supply and demand of electricity, to name a few.

GB decarbonisation policy

With the arrival of the mass awareness of "below 2°C" Global Warming, the quest for decarbonisation took a "greener" direction in the GB. Now all discussions were not targeted at the substitution of "dirty" generators with "less dirty" ones but at the possible procurement and utilisation of nuclear and renewable technologies. This is one of the reasons that we have observed a declining slope of CCGT capacity and generation, especially after 2010 (Figure 1 and Figure 2). The other reasons for the decline are the falling electricity demand in recent years, and the impact of coal & gas prices on the running patterns of fossil-

fuel plants (BEIS, 2016e). However, much of the credit goes to the government for its successful recent decarbonisation policies that created an operational market for "green" technologies – the journey until now has not been easy.

Although low-carbon technologies were costly at the beginning, some of the government support schemes helped them compete with conventional technologies. In particular, Non-Fossil Fuel Obligation (NFFO) was framed in the 1989 Electricity Act and took effect in 1990 to support nuclear and renewable generation through the funds collected from the levies on fossil-fuel producers who used to pass them on to final electricity consumers (Mitchel & Connor, 2004). Unlike other European countries, which adopted fixed-price support mechanisms, the UK started auctioning the NFFO contracts through a series of rounds. Although the NFFO was not a great achievement, it created a prospective market for renewables (Gross & Heptonstall, 2010).

In 2002, the NFFO was superseded by the Renewable Obligation (RO) mechanism. The aim of the RO mechanism is to oblige electricity suppliers to acquire Renewable Obligation Certificates (ROC) from "green" generators to satisfy the required proportion of "green" electricity that they supply (*e.g.* ROCs/MWh of 0.348 for 2016-2017). ROCs are tradable certificates, and in case the electricity suppliers are not able to satisfy the "low-carbon" proportion of their supplied electricity, they need to pay a buy-out price (*e.g.* £44.77 in 2016-2017 for each per MWh of "green" electricity not supplied) which is later used to remunerate all "green" suppliers for their pro rata ROCs supplied (Ofgem, 2016b). However, the RO scheme closed for small-scale photovoltaic (PV) projects in September 2015 and for onshore wind projects in April 2016 and is due to completely shut down for new generators in March 2017.

Along with the RO, the government established the Feed-in-Tariff (FiT) scheme in 2010 for small-scale renewable production (PV, wind, hydro, micro-CHP, and anaerobic digestion that are less than 5 MW). On the other hand, Feed-in Tariff with Contract for Difference (FiT CfD), drafted in Electricity Market Reform (EMR) (DECC, 2011) and operational from 2014, is a fixed-price long-term contract between a low-carbon large-scale electricity generator (of more than 5 MW) and LCCC. They are allocated to reduce operational risks of generators. Levy Control Framework (LCF) caps the amount that can be spent on low-carbon support schemes in order to suspend the rise of consumer bills which indirectly support the payment for these schemes (DECC, 2015). FiT CfDs are auctioned but the government sets a fixed Administrative Strike Price (ASP) before each allocation round to represent the maximum support generators can get per MWh of their production. The initial intent was to set ASPs to the similar level as of Renewable Obligation Certificates (ROC) before 2017 since by then generators would still be able to switch between those two schemes. After this grey period, when the ROCs will be phased out and make room for FiT CfD, the ASPs are expected to drop in accordance with the declining generating costs of renewables. As such, strike prices might still be high in future for some technologies such as nuclear (*e.g.* 92.5 £/MWh payable to Hinkley Point C during the first half of its life (BEIS, 2016b) or 85 £/MWh for offshore wind projects that start prior to 2026 (HM Treasury, 2016)). However, the CfD for Hinkley Point C was a product of bilateral negotiations under some political containment; therefore, it cannot be benchmarked against real levels of strike prices for baseload technologies as it is a major project that requires a separate negotiation. In fact, allocation of FiT contracts is competitive in general, which implies that strike prices would not be that high, but competitive allocation could add additional risks on newly built low-carbon technologies (NERA, 2015) since generators are not guaranteed to receive the contracts with any certainty. Although the

initial contracts were allocated at ASP, the later ones were auctioned with the strike price capped at pre-defined ASP. Under CfD, a generator receives (sends) the difference between strike price and reference price from (to) LCCC whenever reference price is less (above) than the strike price. The reference price for baseload technologies is calculated as a volume-weighted average season-ahead price but for the renewable generation it is a volume-weighted average day-ahead price (DECC, 2014b). All electricity suppliers finance the payments of CFD on a quarterly basis under the obligation to pay their metered demand-weighted contribution to LCCC (DECC, 2014c).

Carbon Budgets under the Climate Change Act have been introduced to put the UK on a very "clean" path towards carbon dioxide reductions. Currently, we are in the period of the second Carbon Budget (2013-2017) that requires a carbon emission reduction of 29% from 1990 level. However, the reduction as of 2015 was already around 38%, which is even beyond the required level of 35% in 2020 of the third Carbon Budget (2018-2022). This has clearly set a firmer foot on achieving reductions of 50% in 2025 in the fourth Carbon Budget (2023-2027) (CCC, 2016). Nevertheless, the UK government wants to overdo things via creating unfavourable conditions for unabated coal plants. As a result, they are going to be forced out from the system by 2025 as under a “do-nothing” scenario the system would still have 6 GW of coal capacity in 2025 and can be completely cleared only by 2031 (BEIS, 2016a).

There are also other mechanisms designed to undermine the prospects of polluting plants. One of them is Carbon Price Floor (CPF), which was introduced in April 2013 that puts the carbon price on an upward sloping trajectory. In addition, under the recent Climate Change Levy (CCL) legislation, fossil fuels used to produce electricity, are also taxed thus making per MWh of electricity production more expensive. Taxable rate varies depending on the kind of

commodity used, which can be gas, liquefied petroleum gas, or coal, among others. However, the government announced in the *Budget 2014* that the Carbon Price Support (the difference between CPF and EU ETS price) would be capped at £18 per tonne CO2 until 2019-2020 (HMRC, 2014). This period was later extended to include 2020-2021 (adjustable with inflation) in the *Budget 2016* (HM Treasury, 2016). This cap clearly brings a potential overestimation of carbon-price levels performed in earlier studies.

Another mechanism is Emissions Performance Standard (EPS) that requires Carbon Capture and Storage (CCS) facilities to be installed on new coal plants and annual average CO2 emissions to be limited within 450g CO2/kWh (operational from 2014 and applicable to individual plants instead of a portfolio of plants). However, this applies to the plants with over 50 MWe power capacity that serve baseload demand (DECC, 2011; 2015).

Future Scenarios

Although there are many models that forecast future electricity systems via scenario analysis, future systems will always be unpredictable. National Grid (2016) describes the potential evolution of the system in a few ways. It projects renewable installed capacity in 2020 to be 39 - 47 GW, which can be even more than the installed capacity of fossil fuels under a specific scenario. It outlines that "greener" investments might increase to 51 - 91 GW in 2030, which would be 2 - 3 times the level of fossil-fuel plants' installed capacity of the same year. This scenario would outweigh the current renewable capacity about 2 – 4 times.

In summary, depending on the path the decarbonisation would take – either the least-cost system solution or the long-term environmental solution or consumer-driven market solution or sustainable "green" solution – the investments would vary in type and quantity (Table 1). Carbon Capture and Storage (CCS) technologies are not included in this study, but National

Grid believes they could become viable options in the late 2020s with a gradual rise to about 11 GW in 2040, which would be attributable mostly to CCS-Gas.

	2020		2030		2040	
	low	high	low	high	low	high
Storage	3.1	4.2	3.5	10.7	3.6	18.3
Solar	12.8	16.8	14.7	33.6	10.3	42.3
Wind	18.6	22.2	28.6	47.3	22.6	48.6
Nuclear	7.8	9.0	1.2	10.2	4.6	18.6
Gas	25.4	29.8	24.4	37.6	14.8	38.4

Table 1: Ranges of Installed Capacity (GW) of Major Technologies

Source: National Grid (2016)

Not only future installed capacities are unknown but also the future carbon prices which are based on the EU ETS scheme. As already mentioned, the UK has capped CPS at maximum £18 per tonne CO2 until 2021 first introduced in the *Budget 2014* in March. DECC's Updated Energy and Emission Projections came out in September 2014 and factored in the cap on CPS. It estimated a carbon price of 27.3 £/tonne (in 2014 prices) for 2020 (DECC, 2014). This overestimates more recent studies such as the report by Thomson Reuters Commodities Research and Forecasts (Thomson Reuters, 2016) which indicates that the survey results that they collected yield an EU ETS price of €11.4 per tonne of CO2 in 2020, which translates into £24.9 per tonne of CO2 (in 2014 prices) for the GB. It overestimates Thomas Reuter's own analysis too, which reveals a price of €8.7 per tonne of CO2 translated into £23.3 per tonne of CO2 for the GB. However, there are independent research groups that forecast carbon prices at even higher levels. For example, ICIS Tschach Solutions (2016) reports an expected EU ETS price of about €25 (£15.2 in 2014 prices) per tonne of CO2 in 2020 and about €20 (£12.1 in 2014 prices) in 2025 and 2030. This translates into £33.2 per tonne CO2 in 2020 and £30.1 per tonne CO2 in 2025 and 2030 in the GB (assuming that the £18 cap will still be kept

by then). In addition, CCC (2015) under the cap of £18 estimates a carbon price of £37 per tonne of CO2 in 2025 and £42 per tonne of CO2 in 2030. However, DECC (2014d) forecasts £55.7 per tonne of CO2 in 2025 and £78 per tonne of CO2 in 2030. Some of those assumptions take into account that renewables will replace some fossil -fuel plants and bring lower carbon price levels.

Similar to the projections of carbon price levels, there are also projections on possible fossil-fuel price levels such as the ones by DECC (2014a; 2013a) (Table 2).

	Crude oil (Brent) $/barrel		Natural gas (NBP) p/therm		Coal (ARA) $/tonne	
	DECC (2014a)	DECC (2013a)	DECC (2014a)	DECC (2013a)	DECC (2014a)	DECC (2013a)
2020	96.2	119.7	60.3	73.8	93.5	122.9
2030	120.6	135	76.4	73.8	103.3	122.9

Table 2: DECC's fuel price projections for 2020 and 2030

No doubt, these projections help us better understand future systems but they are all subject to specific assumptions. Therefore, it is hard to point to a specific projection of the future system state and use it as an input to the model. It is acknowledged that fuel prices can be very turbulent as they depend not only on fuel supply and demand but also on other forces such as geopolitics. Those forces can make the static projections void of credibility; hence the models should make every effort to properly model the distribution of fuel prices of the future. Fuel-price distributions should be modelled in a way that would allow any possible realisation of fuel price achievable. For this reason, the models in this thesis calculate fuel-prices as log-normal distributed variables. The parameters of the distribution are chosen based on the projections of DECC and can take any positive values. The chapters also

consider different scenarios of future states but it should be mentioned here that, in particular, the equilibrium solutions in the perfectly competitive setting that the chapters employ bring less capacity than those projected in scenarios of National Grid or others. In particular, Chapter 3 brings 56.2 GW capacity in risk-neutral case, Chapter 4 brings 57.4 GW capacity with endogenous costs of capital while Chapter 5 brings 62.3 GW capacity for close-to-normal yearly profits of technologies. These differences from projections as well as from each other are attributable to the absence of Capacity Market in all chapters and to the absence of Operating Reserve in Chapter 3 and Chapter 4.

Electricity System Models

There are many models of electricity systems. In the 1970s, Anderson's classic paper demonstrated a summary of models that could be used to minimise the overall cost of electricity generation subject to capacity and technological constraints (Anderson, 1972). It gave a broad range of optimisation and simulation techniques that could be used for electricity system analyses, such as linear programming, non-linear programming, dynamic programming, and simulation for different electricity-modelling problems, either short-term or long-term. However, many new solution techniques have been created since then but the categorisation of the electricity modelling problems, in terms of a problem's timeframe, has not changed.

There are short-term and long-term problems. Short-term models are operational problems that can be broadly categorised as either unit commitment or economic dispatch or both (when economic dispatch is considered as a sub-problem of unit commitment (Wood et al., 2013)) which were briefly discussed in the Introduction of this thesis. Unit commitment decisions are typically made by a system operator to determine daily electricity production

schedules and corresponding prices for every hourly increment. These models aim to find the minimum costs for meeting demand requirements given the set of available generating units (Kirschen and Strbac, 2004). Solution techniques to unit commitment problems can be dynamic programming, mixed integer programming, Lagrangian relaxation, or some heuristic algorithms. Despite their “close-to-reality” setup, unit commitment problems suffer from the "curse of dimensionality" and computational intensity if solved directly as mixed-integer or dynamic programs.

Economic dispatch problems, on the other hand, are easier to solve because most of the time they are linear programs. In general, dispatch problems are set after unit commitment decisions have already been obtained. Their aim is to meet the load in the most economical way possible (under some technical constraints). However, there are cases when unit commitment and economic dispatch problems can be combined into one single problem (see for example Conejo *et al.* (2010)).

Recently, some heuristics and time-reduction techniques have been developed to reduce the solution time of energy-system problems. For example, merit-order stack has been shown to be an efficient and practical method (Staffell & Green, 2012) to determine the best combination of running generators based on the merit order of their operating costs (Stoft, 2002; Kirschen & Strbac, 2004) .

Pre-processing of models can also be made more efficient. One method for doing this is to use K-means clustering method – an efficient grouping algorithm that reduces the computational time by contracting the input dataset. In particular, it can be used to reduce the number of days in different years into a small number of representative days that preserve the general characteristics of the daily demand profiles within obtained clusters. A more detailed discussion of this method is presented in Chapter 5.

Long-term problems, on the other hand, are mainly decision problems of capacity expansion over time; therefore, they are out of the scope of this study.

Financing and Investments

Recent approaches on optimisation of electricity generation mix have switched from a single-scenario optimisation to the optimisation of ranges of variables. Ranges of variables create problems that are more realistic but difficult to solve. One way of making it easier is to simulate the system many times by sampling from the unknown ranges of variables and get the probability distribution of the outcomes. This method proves to be very useful in constructing and analysing a portfolio of electricity generation assets when significant factors that affect investments are uncertain. Portfolios can be represented with a trade-off function between risk and return, *i.e.* mean-variance (MV) utility function (Markowitz, 1952). MV framework is easy to implement for perfectly competitive portfolio investment problems in particular, as finding the long-run equilibrium requires setting the portfolio utility to zero while preserving the same level of individual utilities. Optimal solutions bring a combination of technologies that are in line with the risk profile of an investor. It can also bring an umbrella of combinations that are in line with the preferences of different risk-averse investors as some combinations are “high risk - high return” while others are “low risk - low return”. A perfectly competitive optimal solution chooses a portfolio where the expectation and the risk-aversion-adjusted variance of the weighted sum of the assets' profits offset each other. However, finding zero-profit equilibrium assumes all technologies are covering their £/kW-year fixed costs along with their operating costs which makes the distribution of their profits overlap (at least in risk-neutral case). Moreover, MV analysis requires that profits of technologies have elliptic distributions (*e.g.* normal in a special case). This is important for practical purposes as simulated distributions of assets profits or cash flows are close to

normal and their distributions do indeed overlap. This enables the unquestionable use of MV approach in portfolio analysis since if the distributions of assets' profits did not overlap, MV method would mislead and therefore need to be replaced with other risk frameworks such as value-at-risk (VaR), conditional value-at-risk (CVaR), cash-flow-at-risk (CFaR) (Campbell et al.,2001; Benati, 2003).

Actually, Shimon Awerbuch (2000) was the first to apply portfolio theory to electricity generation costs despite the whole body of literature coming after Markowitz's 1952 seminal paper. Specifically, he showed, at that time contrary to common sense, that including more expensive renewables in a portfolio might actually reduce the cost of getting a given risk due to offsetting cost correlations among assets (Awerbuch, 2006).

As mentioned earlier, the optimal portfolios for each generator may vary depending on their idiosyncratic risk-aversion levels. The more the investors are risk averse, the more they prefer to minimise risk versus maximise profit, and these risk-profit preferences can create various optimal portfolios with different plant mixes. Hence, it should be on the policy agenda to consider the relationships of risk aversion, carbon price, profit risk and investment decisions to ensure the presence of different types of technologies in the technology mix of the future industry. The importance of this has already been addressed in previous publications (Gross *et al.*, 2010; Gross *et al.,* 2007) but the role of risk aversion in that equation has not been revealed. Also, in line with the discussion of Gross *et al.* (2010), this thesis quantifies the effect of price risk on debt financing and cost of capital in a novel "Endogenous Cost of Capital" or "P50-P90" framework introduced in Chapter 4. In particular, the cash flows of assets are analysed for risk-neutral investors to derive an endogenous cost of capital of an asset, which is taken to be the reflection of the perceived risk of that asset. Since capital-intensive technologies (such as nuclear) have higher capital costs and hence higher fixed

costs, their cash flows from the operation are much higher (at zero-profit equilibrium) together with their absolute variance of cash flows. However, their relative cash-flow variation (the coefficient of variation) is lower, which brings more debt capacity and less cost of capital by virtue of utilisation of tax shield on debt.

Chapter 4 quantifies the development risk too, relying on some available external data sources such as data of the newly built Hinkley Point C nuclear station, as the successful implementation of this project would lay the foundations for the next generation of nuclear projects. While costs might decline from the first of a kind (FOAK) to the n-th of a kind (NOAK) effective 2030 onwards, it gives good benchmark cost numbers for modelling and analyses when estimating nuclear pre-development & construction costs. Building feasible investments model for different risk-profile investors might assist them in undertaking specific projects commensurate with their risk profiles.

To summarise, the aim of this chapter was to erect the foundations for the upcoming chapters pointing to the areas a reader is expected to delve into. The next two chapters examine two different approaches to optimising profit risk of portfolios of technologies in a merit-order stack model followed by Chapter 5, which quantifies storage profit risk in an economic dispatch model with technical characteristics of included technologies.

CHAPTER 3: Optimal Portfolios for Risk-Averse Generators

Introduction

This chapter asks whether risk aversion level, fuel-price risk, carbon price level and demand uncertainty affect the capacity mix of generating technologies under different scenarios of renewable penetration. It seeks to further explore the magnitude and direction of this impact, in case they are significant. In doing so, this chapter develops and implements a fully endogenous model of capacity investment in the UK in the presence of risks and uncertainties mentioned above.

There are many papers on investment risk analysis of electricity portfolio; however, the need for further analysis still stands firm as the impact of uncertainty on optimal portfolios of risk-averse investments are of paramount importance for a low-carbon world. The proposed methodology in this chapter will reveal the magnitude and the direction of this impact by answering whether there is a systematic under-exposure to specific technologies such as nuclear stations or over-exposure to others such as carbon-intensive gas stations. In particular, this study will analyse this issue in light of fuel-price and demand uncertainty for different renewable penetration scenarios.

The context for the study is the UK electricity industry where the required development and analysis of the model are performed. The model calculates the equilibrium investment capacities in the non-renewable generation where none of the generating technologies makes any super-normal profit. Though a simulation optimisation model with three technological choices is presented, it can be easily generalised to many choices. Those three choices are nuclear, combined-cycle gas turbine (CCGT) and open-cycle gas turbine (OCGT). Coal plants are not included in this study since, according to the decarbonisation directive set

by the UK government (BEIS, 2016a), unabated coal stations have to close by 2025 unless new stations arrive with carbon capture and storage (CCS) facilities or the older ones are upgraded to include them. A deliberate decision was made to model the renewable generation exogenously and exclude them from the portfolios being modelled in order to simplify the scope of the entire thesis. Obviously, there are benefits in including renewable generation in the portfolio, as those portfolios would better reflect the real investment options available to investors as there are already many companies that have a mixture of technologies in their portfolios (BEIS, 2016c). There are also extreme cases though, such as Dong Energy, that has only wind energy in its UK portfolio (Dong Energy, n.d.). The non-dispatchable nature of renewables would complicate the modelling by forcing the consideration of specific low-carbon payment mechanisms. For example, if the renewable share in the portfolio is minute, renewables qualify for small-scale FiT subsidy and if the share is substantial, they qualify for FiT CfD scheme. Also, when making the amount of renewable generation endogenous, we are faced with endogenous variation of net demand. This implies that decision variables for renewable investments affect the distribution of net demand which requires a new method of modelling.

The next principal component of this chapter is thorough analyses and discussions on potential implementations of nuclear projects under uncertainty in the presence of risk aversion and a considerable amount of intermittent output. The importance of this issue is high, as the UK has already embarked on a new nuclear project in Somerset, which could potentially open a new arena for further investments in nuclear power. Nuclear projects, however, usually come with intricate issues of financeability, environmental safety, and political discourse thus creating, among other things, a real conundrum for governments especially when they are in the process of implementing decarbonisation directives. In

particular, this is very pertinent to the UK government, which has set targets to secure the affordable and uninterruptible electricity supply to consumers while creating suitable investment incentives for low-carbon technologies. However, the issue of affordability and security of electricity supply, despite being important cornerstones of the UK decarbonisation policy, lies beyond the scope of this study.

Fundamental features of the underlying model are the analyses of endogenous prices and outputs that interact with uncertainty and risk aversion to determine the optimal amount of invested capacity. Demand and fuel price uncertainties have been incorporated into the model with detailed distributions. As mentioned above, although investments in renewable sources are not modelled directly, their impact on generator's optimal portfolio is quantified secondarily. Since the context of the study is the UK, market power is not discussed in this chapter because the main interest is to harness the benefits of modelling the competitive industry (assumed to subsume ample market players). In the light of this competitive setting, generating companies with symmetric marginal-cost supply functions and an equivalent level of risk aversion level are considered. The rationale for considering a competitive industry lies in the assumption that the UK wholesale market is competitive enough to produce prices close to marginal costs most of the time. This is a valid simplification and a pragmatic choice for modelling. This could perhaps seem an idealised representation of the reality of future but it clearly gives results helpful for policy research and analyses.

The study finds that optimal portfolios are affected by uncertainty in different ways. In particular, demand risk turns out to be the driving force for total investment whereas fuel-price risk happens to be the trigger for the capacity mix. All in all, companies end up increasing their investments in non-baseload technologies under uncertainty while decreasing them in baseload. Importantly, the more a firm is risk-averse, the less the total

invested capacity is when carbon prices are not high enough. Yet, this effect vanishes as soon as carbon prices become high enough as it brings a non-linear relationship between risk aversion and total investment in (non-trivial) optimal portfolios[5]. However, when a nuclear contract is added to the portfolio, nuclear becomes an attractive option irrespective of its risk aversion level; it also produces more diversified portfolios as modelled in Roques (2008).

Lastly, this study demonstrates that an increase in renewable penetration into the system reduces overall investment in conventional technologies by reducing capacity in baseload and increasing it in non-baseload.

One important implication of this study is that long-term fixed-price nuclear contracts will be necessary to incentivise investments in nuclear in the future as far as nuclear will still be sensitive to fuel-price risk and risk aversion. This suggests to policy-makers that perhaps higher carbon price levels are required in the presence of risk aversion if we want nuclear to be a success. This important takeaway can be of great help to policy analysts and designers who are willing to put favourable investment incentives for low-carbon technologies.

The structure of this chapter is as follows: the first section covers literature review, the second compiles modelling and data, the third contains the results and discussions, and the fourth lists the conclusions.

Contextual Literature Review

This study derives optimal portfolios in the framework of mean-variance utility function with a trade-off between risk and return. As already mentioned, Awerbuch (2000) was the first energy economist to apply portfolio theory to energy cost analyses. Later he also showed that it might become cheaper to obtain a specific level of risk by adding high-cost renewables

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[5] An optimal portfolio is considered "non-trivial" if it includes all possible technologies. This is contrary to an optimal portfolio which can be "trivial" only if it excludes at least one technology.

into the portfolio because renewables, unlike conventional generators, do not have volatile operating costs (Awerbuch, 2006). It was thus expected to see some more papers that took generating cost approach in constructing optimal portfolios (Krey & Zweifel, 2006; Vithayasrichareon & MacGill, 2009, 2012; Zhu & Fan, 2010).

Roques *et al.* (2006) showed that profits and costs act differently given exogenous correlations between generation costs and electricity prices; the idea became revolutionary in the energy economics literature changing the focus from cost to profit analysis. Later, Green (2008) examined the impact of a carbon tax and carbon permits on the generators' profit risk by calculating it for endogenous electricity prices but for a fixed capacity mix. Afterwards, Gross *et al*. (2010) showed the importance of electricity price risk (which defines revenue risk) in designing the appropriate policy. They suggest that policy should pay attention to both cost and revenue risk in designing favourable investment incentives. A policy can set long-term contract schemes that reallocate price risk from developers to consumers as the low-carbon support schemes are paid through "consumers' money" that goes to low-carbon developers as a fixed strike price which is in reference to the cost of that low carbon technology.

Fan *et al.* (2010) study investment decisions in the competitive energy market with and without CO2 regulatory scenarios and find that, in the presence of carbon tax, risk-averse firms (risk-averse towards regulatory scenarios) will increase investments in clean technologies having investments that are proportional to their risk aversion levels. They also find that risk aversion brings in investments that lean towards the least profitable scenario. However, they do not include uncertainty from fuel prices, which is one of the important inputs in the model of this chapter. A later study by Ehrenmann & Smeers (2011) showed that risk-aversion creates optimal portfolios likely to include technologies with low fixed cost.

They illustrate their application in a small problem designed for an energy-only and a capacity market. The closest study to this one is Meuner's (2013) where he finds a closed-form solution for optimal portfolios induced by risk-aversion in the mean-variance formulation but he shows no application of it. He finds that there are two possible equilibria: one where overall capacity may increase and the other where overall capacity may decrease depending on risk aversion level. If the load duration curve is flat, peak and overall capacity increase; if the load duration curve is steep, baseload capacity increases and overall capacity decreases. Another similar study is by Tietjen *et al.* (2016) where they find optimal portfolios for combinations of risk aversion and carbon price. However, they do not endogenise the impact of portfolio mix on the electricity price distribution thereby not reaching the actual equilibrium. Unlike the previous study, Delarue *et al.* (2011) showed that modelling actual operating patterns of technologies would change the portfolio mix.

Finally, it has been shown that when nuclear contracts are added to the portfolio, nuclear profit risks decline and render more diversified optimal portfolios (Roques *et al.*, 2008) both in a perfectly competitive market (Green, 2008) and in a non-competitive market (Chin and Siddiqui, 2014).

Model and Data

It is straightforward to find optimal portfolios of technologies when there is no risk aversion and uncertainty. We simply find the intersection points of the screening-curve cost lines of technologies (where the intercept is the fixed cost and the slope is the variable cost). With this method, it is possible to derive yearly duration of each technology runtime and determine their optimal capacities. Given we already know how to find the profit-maximising set of generating plants in a competitive electricity industry in a deterministic world – the

world where the social planner finds its cost-minimising solution – this model asks whether this correspondence is preserved when there are risks and uncertainties in the industry. In order to put this question into context, uncertainties from fuel prices, electricity demand levels and penetration of renewable sources into the system are discussed.

The model is constructed to find equilibrium levels of investments where none of the technologies is making a super-normal profit. Throughout the model, merit-order stack approach is extensively used to construct industry supply function. The supply function is assumed to be piece-wise constant where the constant value of each piece is the marginal cost of a technology. Merit order stack minimises the sum of generators' operating costs (more information is available in Stoft (2002) or Kirschen & Strbac (2004)) yet ignoring operational constraints such as ramping constraints, reserve requirements, transmission system limits, and stable load limits. Despite all these omissions, Staffell & Green (2012), comparing merit order stack to a more detailed model, showed it gives reasonable results for models in terms of annual output and profits.

This study uses endogenous simulation optimisation model by adding capacity choices to a merit order stack (aka "merit order stack with endogenous capacities") to obtain electricity price and profit distributions for the whole duration of the year (see Figure 5).

Demand is price-responsive, and its intercept is calculated for the given slope. Demands are scaled to a common underlying level as no economic growth (demand growth) is considered in the model; this model does not take into account the evolution of the system through time. Available 17 years of hourly demand data are used to construct 17 load duration curves along 8760 hours of a year. However, since the model runtime would have been slower if all 8760 hours were included into the model for simulation optimisation, these hourly data were aggregated to condense the number of hours into *tranches*.

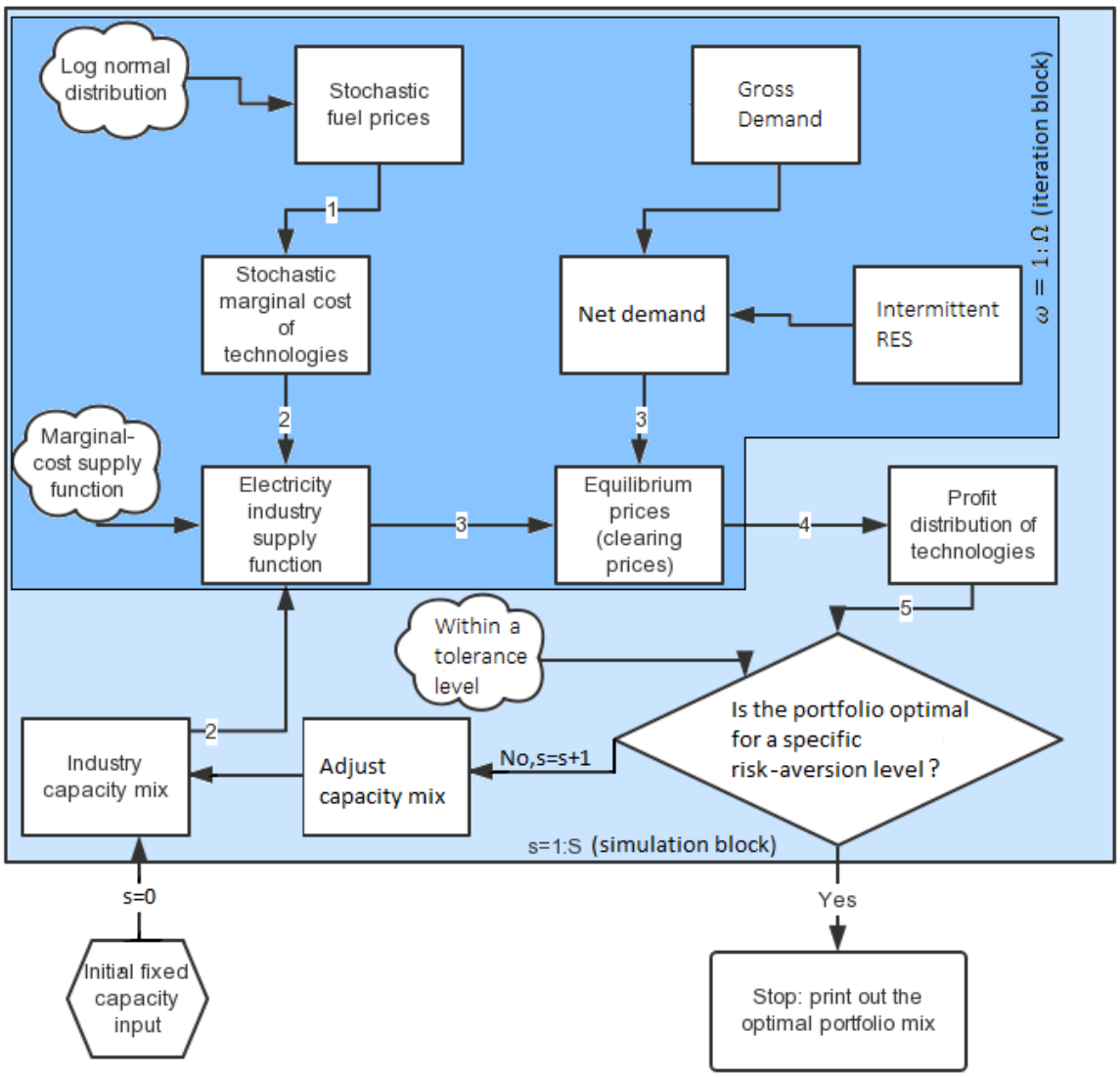


Figure 5: Conceptual simulation model

Source: The author

At first, each year's hourly data are sorted in a descending order in columns, and the average of each row of data is taken across years. Then, whenever the average demands across years (raw averages) are apart from each other within 0.1 GW, they are combined into one tranche (*i.e.* given more weight in modelling). This is done to reduce computations by using load tranches instead of load hours. Overall, 362 tranches along the load duration curve are obtained instead of initially available 8760 hours. However, it is straightforward to approximate a sample yearly load duration curve from our tranche data (see Figure 6).

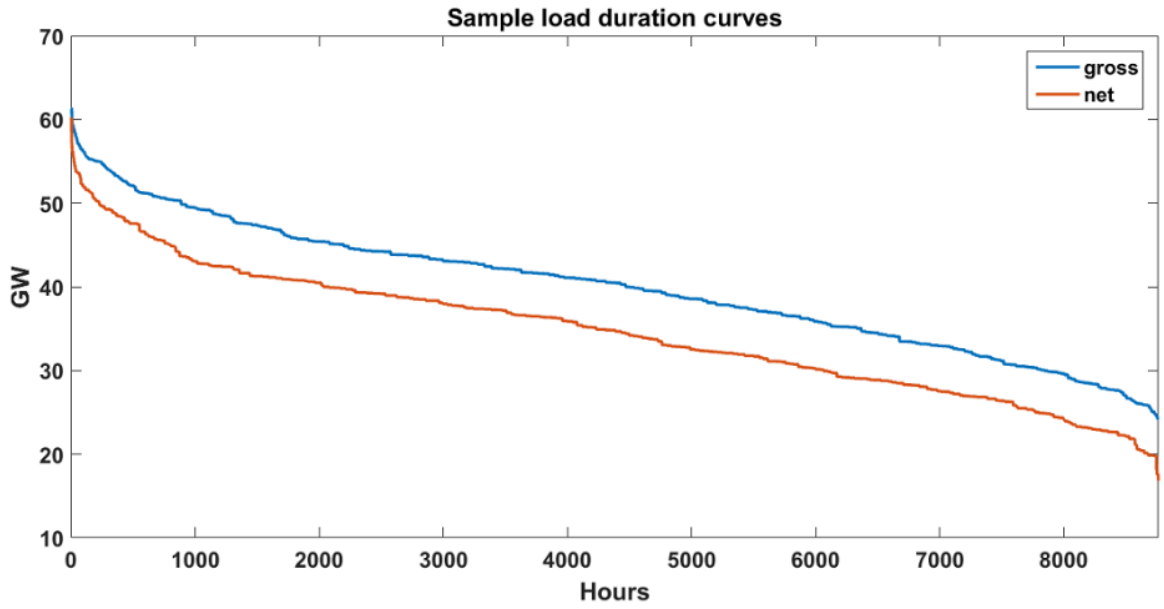


Figure 6: Approximated load duration curves

Source: The author's calculations

The “best” distribution fit is performed to choose the distributions of demands within each tranche where *Akaike Information Criteria* (AIC) is the lowest (Table 3 and Table 4). Distributions with smaller AIC numbers are preferred as a smaller AIC value denotes a better fit to the data (for more information, refer to Gujarati & Porter (2009)). Since it would encompass a lot of space to include all 362 fitted tranche distributions, only the highest and the lowest demand tranche distributions are presented here. Table 3 and Table 4 show the chosen distribution (the second row) via AIC. Brackets after distribution names represent parameters of the given distribution. For an extreme value distribution, the first element is the location parameter and the second is the scale parameter while for a normal distribution the first parameter is the mean and the second is the standard deviation. The rest of the statistics of distributions are provided in the subsequent rows.

Those distributions are then used to create random draws during simulation optimisation (see Figure 7).

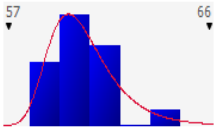
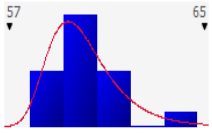
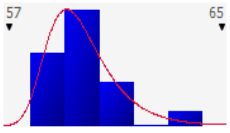
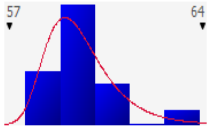
	Tranche 1	Tranche 2	Tranche 3	Tranche 4
Best Fit (Ranked by AIC)	Extreme Value (59.77,1.16)	Extreme Value (59.49,1.09)	Extreme Value (59.25,0.97)	Extreme Value (59.09,0.93)
AIC	63.205	61.8663	57.901	56.4346
Min	-Infinity	-Infinity	-Infinity	-Infinity
Max	+Infinity	+Infinity	+Infinity	+Infinity
Mean	60.4437	60.1133	59.8096	59.6286
Mode	59.7732	59.4864	59.2514	59.0895
Median	60.1989	59.8845	59.6058	59.4318
SD	1.4898	1.3928	1.2404	1.1977
Graph				

Table 3: Fitted Distributions for 4 Highest Demand Tranches

After this, distribution of demand intercepts across a period of one year (362 tranches) is calculated with the help of random vector $\vec{\Delta} \in \mathcal{R}_+^H$ and a vector of fixed hours of $\vec{T} \in \mathcal{R}_+^H$. For each $h = 1, \dots, H$ (where index h stands for a tranche) the demand intercept level and number of hours at that demand intercept level (number of aggregated hours into that tranche) are δ_h and τ_h respectively where δ_h is a random variable drawn from fitted distribution as described earlier. Load factors of renewables are denoted with a random matrix $\Lambda \in \mathcal{R}_+^{hxR}$, while the system installed renewable capacities with column vector $\Phi \in \mathcal{R}_+^{Rx1}$ where R stands for a renewable source.

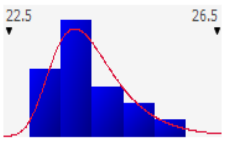
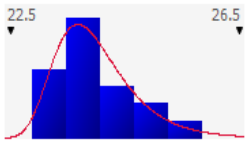
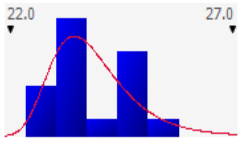
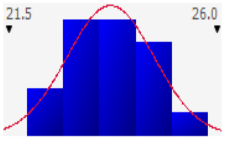
	Tranche 359	Tranche 360	Tranche 361	Tranche 362
Best Fit (Ranked by AIC)	Extreme Value (23.80,0.56)	Extreme Value (23.72,0.54)	Extreme Value (23.49,0.70)	Normal (23.71,0.90)
AIC	38.0898	37.4888	45.0478	48.4951
Min	-Infinity	-Infinity	-Infinity	-Infinity
Max	+Infinity	+Infinity	+Infinity	+Infinity
Mean	24.1265	24.0279	23.8949	23.711
Mode	23.8038	23.7164	23.4928	23.711
Median	24.0087	23.9142	23.7481	23.711
SD	0.717	0.6921	0.8937	0.8994
Graph				

Table 4: Fitted Distributions for 4 Lowest Demand Tranches

Vector of renewable penetration into the system is calculated as $\Psi = \Lambda\Phi$ where components of $\Lambda, \lambda_{h1}, \lambda_{h2} \dots \lambda_{hR}$, stand for stochastic load factors while components of Φ, $\phi_1, \phi_2 \dots \phi_R$, for installed renewable capacity. Solar and wind hourly load-factor data are available for 17 years from NASA's MERRA reanalysis, CM-SAF's and SARAH databases (Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016) that are used at different load levels (Figure 8).

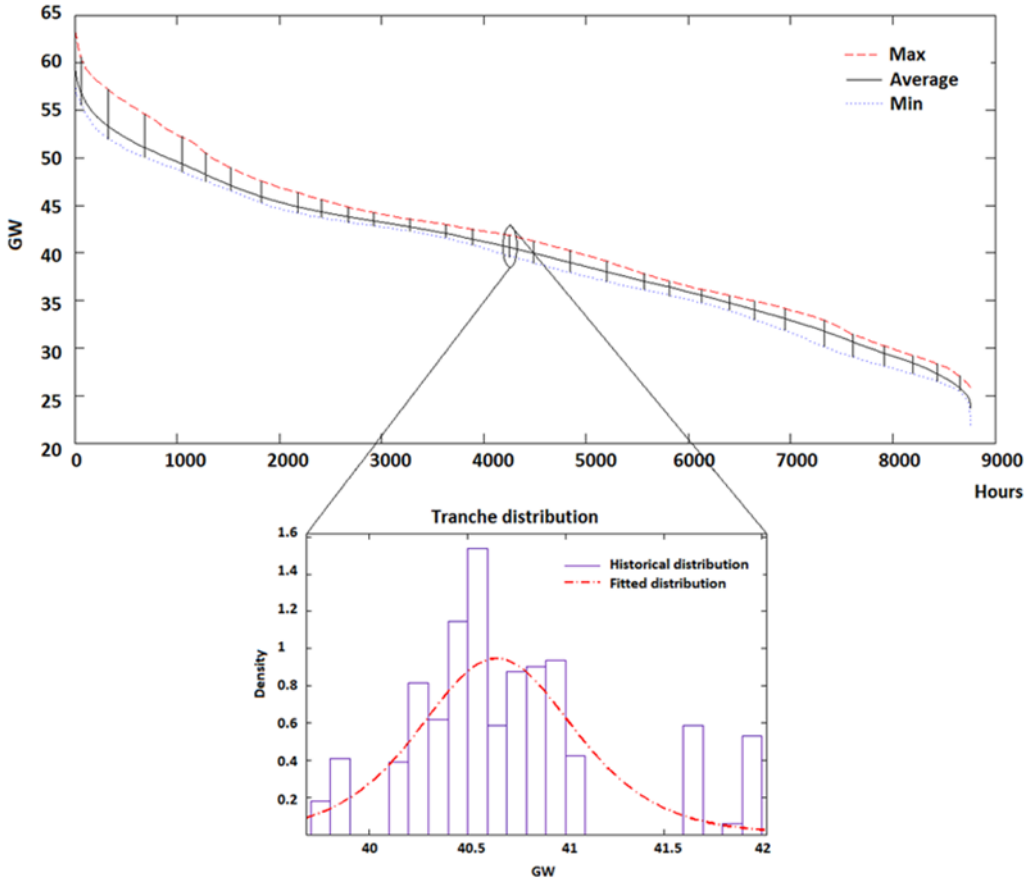


Figure 7: Gross-Demand Tranches and Distributions

Source: The author's calculations

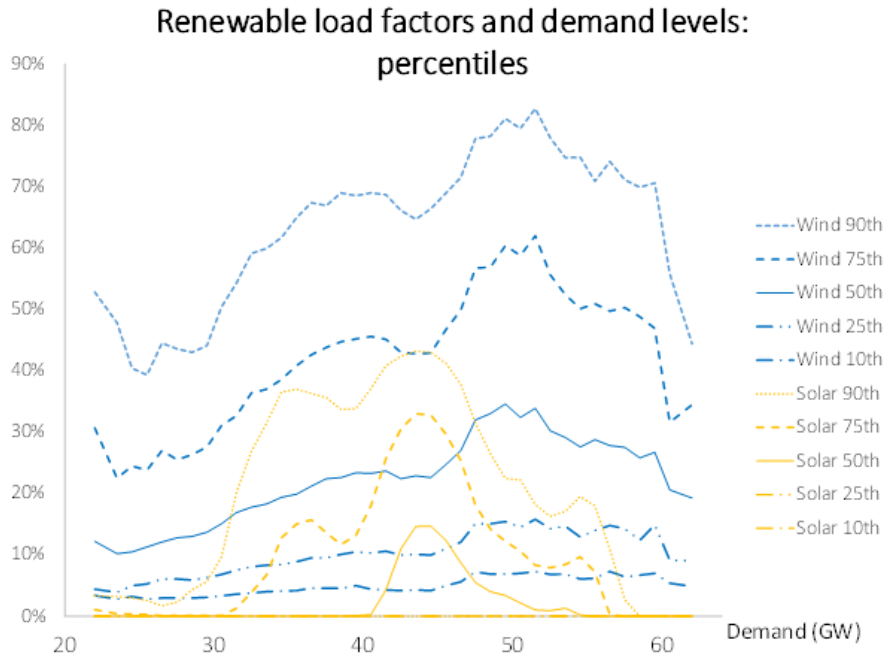


Figure 8: Renewable Load Factors and demand levels: percentiles

Source: The author's calculations

Figure 8 shows that wind is almost evenly distributed across the load giving a range of load factors at different demand levels. In addition, there is a clear trend between high levels of demand and high levels of wind up to 53 GW of the load. On the contrary, solar penetrates in medium ranges of the load; load factors of 100% from solar panels are not achievable in the UK (BEIS, 2016f).Those hourly data were used to construct *general* probability distribution functions – examples of those distributions are depicted in Figure 9 and Figure 10 below[6]. Figure 9 shows probability distribution function for wind load factors when demand is 44.5 GW. Specifically, it shows that wind load factors are mostly concentrated around 10% when demand is 44.5 GW. The area under the curve sums to unity as it covers all possible ranges of load factors. Similarly, Figure 10 shows that, whenever demand is 44.5 GW, solar load factors are mostly less than 12% despite having a bimodal distribution. The second mode is exhibited at around 33% of load factor. It should be mentioned here that these are observed historical values of demand and load factors. The model does not consider wind and solar load factors to have those general distributions whenever demand is exactly 44.5 GW. In fact, those distributions are associated with a demand tranche that has an average demand of 44.5 GW. Therefore, 362 pairs of solar and wind load factor distributions are constructed for each demand tranche. A random sampling from each tranche distribution and associated wind & solar distributions help us construct net demand that needs to be met by conventional generators as described next.

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[6] MatLab functions for creating PDF of general probability function can be found at: https://gist.github.com/vitali87/56f9ef77c4a83acbad01b77e54090c91

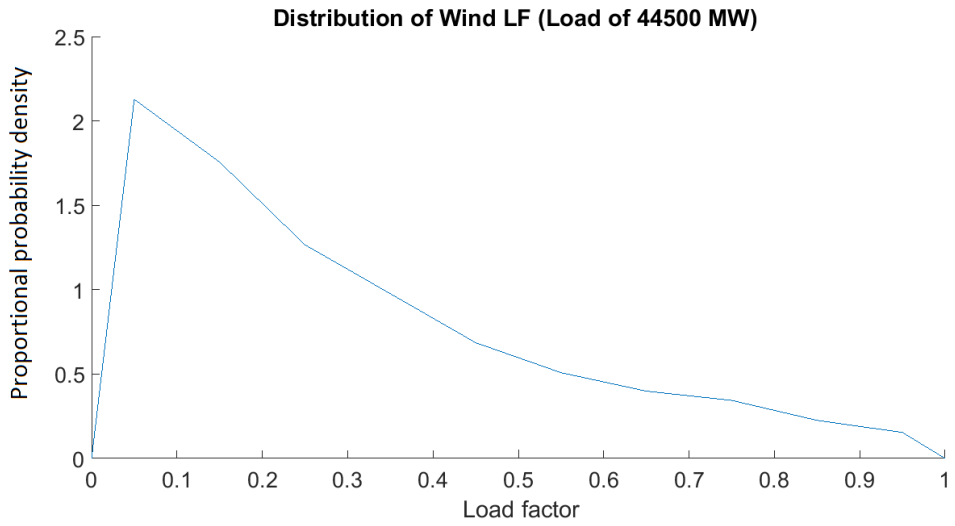

Figure 9: An example of general distribution of wind load factor

Source: The author's calculations

As already mentioned, portfolios with renewable technologies are not considered, and for this reason stochastic renewable output is subtracted from *gross* demand in order to get the *net* demand that needs to be met by conventional generators; hence $\vec{\Delta}^n$ represents matrix of stochastic intercepts of net demand (hereafter *demand*) with elements $\delta_h^n = \delta_h - \psi_h$.

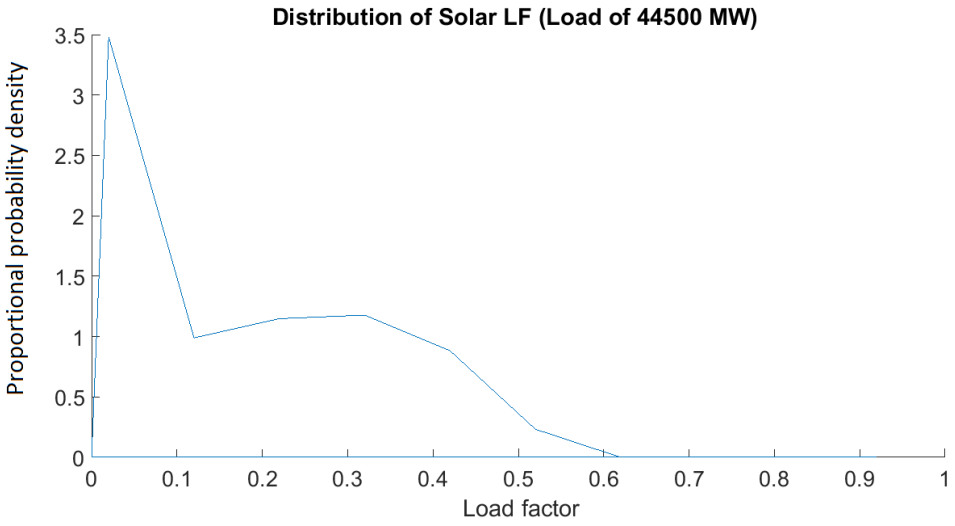

Figure 10: An example of general distribution of solar load factor

Source: The author's calculations

It is assumed that demand functions (and their inverses) are the following linear functions:

$$q_h(p_h) = \delta_h^n - bp_h$$

$$p_h(q_h) = \frac{\delta_h^n - q_h}{b}$$

where b is the slope of the demand which is taken as 0.01 in the model to reflect the price inelasticity of demand. Later it will be shown how the equilibrium price and quantity are obtained from the given supply and demand intersection.

As, in general, it is hard to switch off or constrain nuclear output abruptly when demand is low and renewable generation is high, the model takes this into account to differentiate between inflexible and flexible nuclear technologies[7]. Therefore, n technologies (indexed by $i = 0, \dots, n$) are considered where inflexible nuclear technology is denoted with the index $i = 0$ and the flexible part of nuclear technology with $i = 1$. If net demand is lower than available inflexible baseload capacity, renewable generators curtail their output instead of sending it into the grid; this reduces market price to the negative per-unit subsidy level (the first horizontal line (P_0=m_0) in Figure 11).

Each technology has a fixed cost $c_i \geq 0$, thermal efficiency $0 < \eta_i < 1$ (see Table 5).

Plant types	*Baseload (Nuclear)*	*Midload (CCGT)*	*Peakload (OCGT)*
Fixed cost (£/kW-year)	470	103	72
Efficiency (%)	39.3	48.0	41.0
Expected fuel price (£/MWh$_f$)	3.1	14.9	14.9

Table 5: Plant input data
Source: Parson Brinkerhoff (2011), Mott MacDonald (2010), Arup (2011), IEA & NEA (2010), and EIA (2010)

[7] This is true only for Advanced Gas-cooled Reactors (AGRs) that are widespread in the UK. Pressurised Water Reactors (PWRs) or Boiling Water Reactors (BWRs), on the other hand, are able to follow the load as they can ramp up and down at 5% rated capacity per minute (Pouret et al., 2009).

Vector Y defines capacities with elements $y_i \geq 0$ but for more convenience vector X defines the cumulative installed capacity (with elements $x_i = \sum_{j=0}^{i} y_j$) as the decision variable. The inflexible baseload output (*i.e.* inflexible nuclear output) is denoted by x_0 ($x_0 = y_0$) corresponding to the first horizontal part in Figure 11.

This chapter follows the same methodology as similar studies employ (Green, 2008; Vithayasrichareon & MacGill, 2012) by using log-normal distributions to approximate the distributions of fuel prices. The rationale of using log-normal distribution lies at the heart of its capability to express extreme random levels (thus creating possibilities for downside risk) thanks to its right-hand-side fat tail. Fuel prices of DECC's Low, Central and High cases for 2020 are used (presented in Table 6) to derive parameters of log-normal distributions.

Fuel	*Low*	*Central*	*High*
Oil (£/barrel)	51.2	71.1	89.1
Coal (£/tonne)	55.1	73.0	82.6
Gas (£/therm)	0.251	0.438	0.613

Table 6 : Oil, Coal and Gas Price Projections for 2020[8]

Source: DECC (2013a)

Fuel price of each technology f_i is modelled in the following way:

$$f_i = \exp(\sigma_i z_i + \mu_i)$$

where μ_i and $\sigma_i \geq 0$ are corresponding mean and standard deviation of normally distributed random variable, and $z_i \sim N(0,1)$. Mean and standard deviation of the log-normal distribution are given with the following formulae:

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[8] USD was converted to GBP with a rate of 1.684.

$$\mathrm{E}(f_i) = \exp\left(\frac{1}{2}{\sigma_i}^2 + \mu_i\right)$$

$$\mathrm{SD}(f_i) = \exp\left(\frac{1}{2}{\sigma_i}^2 + \mu_i\right)\sqrt{exp({\sigma_i}^2) - 1}$$

For gas, $\mathrm{E}(f_{gas}) = \exp\left(\frac{1}{2}{\sigma_{gas}}^2 + \mu_{gas}\right) = 0.438$ £/therm.

DECC's lower (0.251) and upper bounds (0.613) are taken as two standard deviations lower and higher points from the central case (0.438). On the one hand, we get $2\mathrm{SD} = 0.613 - 0.438 = 0.175$ and, on the other hand, $2\mathrm{SD} = 0.438 - 0.251 = 0.187$; hence $\mathrm{SD} = (0.175/2 + 0.187/2)/2 = 0.0905.$

Therefore,

$\mathrm{SD}(f_{gas}) = \exp\left(\frac{1}{2}{\sigma_{gas}}^2 + \mu_{gas}\right)\sqrt{\exp({\sigma_{gas}}^2) - 1} = 0.0905$ £/therm.

which leads to:

$$\sqrt{\exp({\sigma_{gas}}^2) - 1} = 0.2066$$

$$\sigma_{gas} = 0.2045$$

$$\exp(0.0209 + \mu_{gas}) = 0.438$$

$$\mu_{gas} = -0.8464$$

The rest of the fuel prices are derived in a similar way. As for nuclear, a tiny variation across its expected fuel price was incorporated but midload and peakload technologies (*i.e.* CCGT and OCGT) are subject to gas price risk.

The marginal cost (£/MWh of electricity) of each technology i (m_i) is given by the ratio of the fuel price (£/MWh of fuel) and its thermal efficiency plus this technology-specific carbon price (£/MWh of electricity):

$$m_i = \frac{f_i^f}{\eta_i} + p_i^c$$

where f_i^f is the fuel price in £/MWh$_f$ derived from f_i ; p_i^c is the carbon price in £/MWh$_e$; η_i is the thermal efficiency of technology i. In particular, m_0 is defined as minus the renewable subsidy, which is implicitly assumed to be for onshore wind only. Negative prices (set by negative marginal costs) reflect the subsidies foregone by renewable generators when their output is curtailed giving them a negative opportunity cost of the generation that sets the price of power.

It is assumed that variation in fuel prices does not change the ordering of $m_0 < m_1 < m_2 < m_3 \ldots$.

For each technology i, the model defines:

$$t_i^l = x_{(i-1)} + bm_i \text{ and } t_i^u = t_i^l + x_i,$$

where $x_{-1} = 0$, noting as well that the following ordering must be preserved (Figure 11):

$$t_0^l < t_0^u < t_1^l < t_1^u < t_2^l < t_2^u < \cdots < t_n^l < t_n^u < +\infty.$$

The equilibrium price (£/MWh) and quantity (GW) pair is then defined in the following way:

$$\left(p_h^*(\delta_h^n), q_h^*(\delta_h^n)\right) = \begin{cases} (p_h(x_i), x_i) \ if \ t_i^u < \delta_h^n < t_{(i+1)}^l \text{ for some } i = 0, \ldots, n-1 \\ (m_i, q_h(m_i)) \ if \ t_i^l \leq \delta_h^n \leq t_i^u \\ (p_h(x_n), x_n) \ if \ \delta_h^n > t_n^u \end{cases}$$

where functions $p_h(q_h)$ and $q_h(p_h)$ are defined earlier.

In the first and third cases of the above equation, demand functions intersect with vertical pieces of the supply functions implying that demand rationing occurs as a result yielding price jumps to make demand equal to the available capacity at that price. Prices may rise as long as it is not profitable to switch on the next type of technology. In particular, for the first vertical-piece case, between inflexible baseload and lowest flexible baseload, the inflexible baseload is still satisfying the net demand while prices are still rising. This continues up to the point

where flexible baseload is profitable to switch on. On the contrary, prices may rise ad infinitum along the fourth vertical-piece case due to limited overall supply.

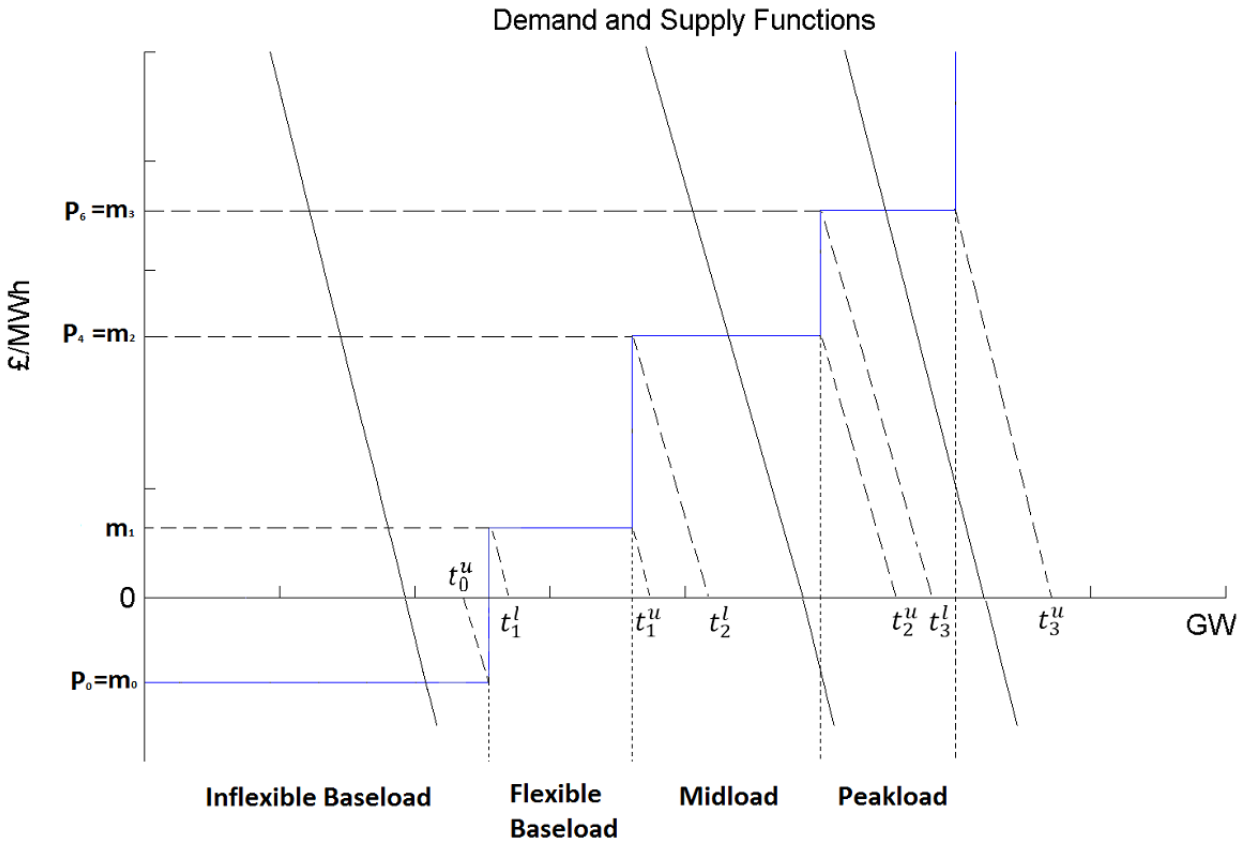

Figure 11: Supply and Demand

Source: The author

In the second case, demand functions intersect with a horizontal piece of the supply function, and the equilibrium price is determined in the usual way by putting the price to be equal to the marginal cost of a specific technology. Moreover, in the second sub-case when $i = 0$, demand is even less than the inflexible baseload capacity implying the price drops to minus the level of renewable subsidy.

The objective of the problem is to find an industry-wide capacity mix that can be broken down into optimal portfolios for symmetric risk-averse companies in order to calculate the equilibrium capacity that gives zero economic utility (zero risk-adjusted profit).

The following quantity:

$$u_h^i = \max\{0, \min\{q_h^*(\delta_h^n) - x_{i-1}, y_i\}\}$$

denotes the actual output (GW) from technology i at net demand intercept level δ_h^n. The total annual output (GWh) of technology i is calculated as $o_i = \sum_{h=1}^{H} \tau_h u_h^i$ while the total annual revenue of technology i as $r_i = \sum_{h=1}^{H} p_h^*(\delta_h^n)\tau_h u_h^i$ thus rendering the total annual pre-fixed-cost profit (in million £) for each technology as $\pi_i = \frac{r_i - o_i m_i}{1000}$.

Portfolio mean-variance utility function (in £/kW) is calculated as $U(x_n) = \mathrm{E}[\sum_{i=1}^{n} \frac{\pi_i - y_i c_i}{x_n}] - 0.5\alpha\mathrm{V}[\sum_{i=1}^{n} \frac{\pi_i - y_i c_i}{x_n}]$, while individual mean-variance utility functions (in £/kW) are calculated as $v(y_i) = \mathrm{E}(\frac{\pi_i}{y_i} - c_i) - 0.5\alpha\mathrm{V}\left(\frac{\pi_i}{y_i} - c_i\right)$ where α is the parameter of risk-aversion.

The simulation optimisation problem without a nuclear contract is described below:

$$\min_{y_i} U^2(y_1, y_2 \dots y_n) \quad (1)$$

subject to:

$$v(y_i) = v(y_k), i = 1, \dots n-1; k > i \quad (2)$$

$$x_i \leq x_{i+1}, i = 1, \dots n-1 \quad (3)$$

$$x_i \geq 0, i = 1, \dots n \quad (4)$$

Equation (1) represents the risk-adjusted portfolio profit per kW, which is set to approach zero. Equations (2) ensures that individual utilities of technologies are equal to each other suggesting that generators would be indifferent across technological choices at that level of investment; *i.e*. there will be no need to change investments across technologies if that combination gives them a zero portfolio utility.

Proposition: *Utilities of individual technologies will be less or equal to the utility of the portfolio at optimum.*

See Appendix 1 for proof.

The proposition suggests there will not be many solutions that will give the same negative level of individual utilities while the utility of the portfolio is zero. Even more, the optimal solution to the problem {(1) - (4)} among "non-trivial" portfolios should be unique as it was repeatedly tested for different starting points, and each time the problem converged to a unique solution if left to run for a considerable amount of time. In addition, for faster convergence, each simulation optimisation was started from the deterministic solutions (found earlier based on the expected level of fuel prices and demand) to help the algorithm reach its optimum faster. The equilibrium capacities turned out not to be very different from the deterministic solutions.

Risk aversion of $0 \leq \alpha \leq 0.1$ is considered for the UK in line with such studies as Roques (2008), Grinold (1996) and Green (2004). Risk aversion is an important ingredient in our model because it reflects the risk tolerance of society in a perfectly competitive market. The assumption is that society has become more risk-averse in terms of tolerance towards profit deviation as investors desire more stable investment profit streams given market uncertainties[9]. Moreover, risk aversion is also important as it represents one of the cornerstones for establishing a transition to sustainable electricity investment.

This study also analyses the impact of the fixed-price nuclear contract on optimal portfolios. The model differentiates between inflexible contracted nuclear and flexible contracted nuclear, *i.e*. both categories $i = 0$ (inflexible nuclear) and $i = 1$ (flexible nuclear) branch into two sub-categories: $i = 0_c$ as contracted inflexible nuclear and $i = 0_m$ as market-facing inflexible nuclear; $i = 1_c$ as contracted flexible nuclear and $i = 1_m$ as market-facing flexible nuclear. Nuclear contract enters portfolio as a separate technology with a contract price calculated as the average revenue of nuclear exposed to market risk.

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[9] However, it should be understood that risk-aversion against *low probability & high impact* events such as the disastrous event of Fukushima Daiichi in 2011 is not considered or discussed.

$r_m = \sum_{h=1}^{H} p_h^*(\delta_h^n)\tau_h u_h^{0m} + \sum_{h=1}^{H} p_h^*(\delta_h^n)\tau_h u_h^{1m}$ represents the total annual revenue of market-facing nuclear, and $o_m = \sum_{h=1}^{H} \tau_h u_h^{0m} + \sum_{h=1}^{H} \tau_h u_h^{1m}$ the total annual output of market-facing nuclear. Similarly, total annual revenue of nuclear contract is calculated as $r_c = \mathrm{P}(\sum_{h=1}^{H} \tau_h u_h^{0c} + \sum_{h=1}^{H} \tau_h u_h^{1c})$ where $\mathrm{P} = r_m/o_m$ is the contract price, and total annual output as $o_c = \sum_{h=1}^{H} \tau_h u_h^{0c} + \sum_{h=1}^{H} \tau_h u_h^{1c}$.

With the above notations, the simulation optimisation problem with contract takes the following form:

$$\min_{y_i} U^2(y_1, y_2 \dots y_n) \quad (5)$$

subject to:

$$v(y_i) = v(y_k), i = 1, \dots n-1; k > i \quad (6)$$

$$\mathrm{P} = r_m/o_m \quad (7)$$

$$x_i \leq x_{i+1}, i = 1, \dots n-1 \quad (8)$$

$$x_i \geq 0, i = 1, \dots n \quad (9)$$

Monte-Carlo simulations are used to solve portfolio problems, and the non-convexity of the problem requires the use of global solvers such as genetic algorithm, which probabilistically searches for the global optimum (see, for example, Goldberg (1989)). Specifically, Palisade's Risk Optimiser solver for Excel is used by running Genetic Algorithm (Population size of 50, Crossover rate of 0.5 and Mutation rate of 0.1) to search for the global optimum given this non-convex problem. The non-convexity arises from the equation of equilibrium price and the quantity pair on page 65 as well as from the equations of output on page 67.

Since the simulation iterations yield approximately normally distributed portfolio profits (Figure 12), the following formula can estimate (with a significance level of 0.05) the number

of iterations needed for the mean of the portfolio profit to be within pre-defined error margin:

$$\Omega = \left(z_{\alpha/2}\ \frac{\mathrm{SD}_e}{\mathrm{EM}}\right)^2$$

where SD_e stands for the estimated standard deviation of the portfolio profit, EM is the error margin, $z_{\alpha/2}$ is the critical value for normal distribution, and Ω is the required number of iterations.

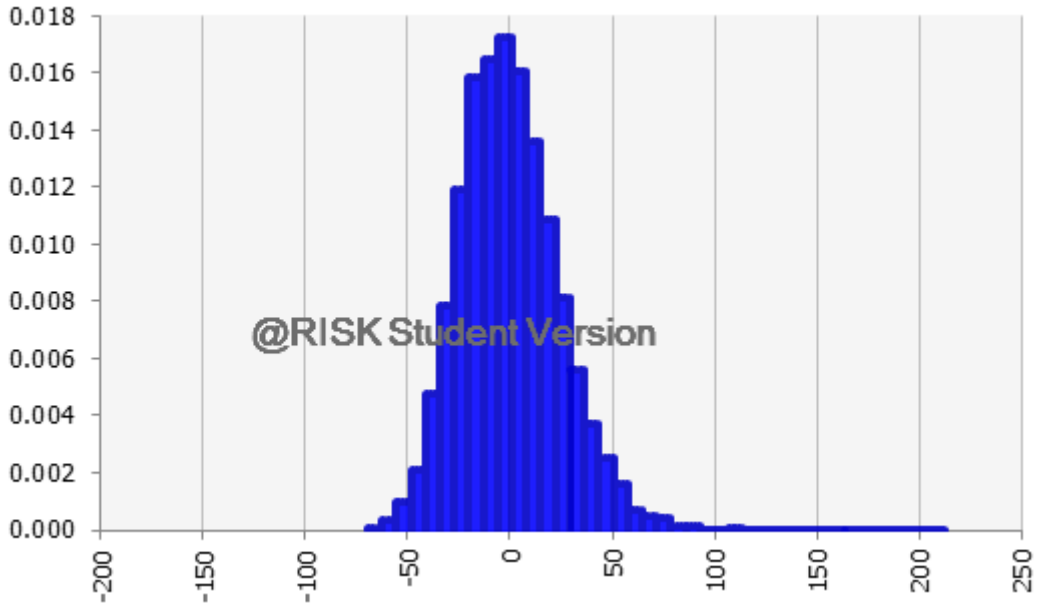

Figure 12: Distribution of portfolio profit at optimum (CP 80, Solar 7 GW, Wind 15 GW)[10]

Source: The model calculations

The error margin of 0.3 million £/GW is considered reasonable which is equivalent to 0.3 £/kW – practically a negligible number for generators' profit considering that the objective value includes penalties as well (discussed below). A standard deviation of SD_e =16.6 was estimated after running the model for 1000 iterations; for estimation purposes, 1000 is a higher number compared to commonly used numbers in some textbooks (see for example

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Winston (2000)). After plugging in all the required numbers in the above equation, it was found that the simulation optimisation problem, conceptualised in Figure 5, therefore requires 11776 iterations per simulation run, and this is the number used throughout all model runs. However, this is the necessary number of iterations for Monte Carlo sampling that achieves the specified error margin. However, since Latin Hypercube sampling method is used instead of Monte Carlo – which is about 3 times more accurate for the same number of iterations than Monte Carlo (Stein, 1987) – the obtained number of iterations is more than enough to achieve this error margin.

Furthermore, since it might be difficult to find strict equalities in equations (2), (6) and (7), they are made as soft constraints by implementing quadratic penalty functions of the following forms:

$$\frac{1}{\rho}[v(y_i) - v(y_k)]^2 \quad (10)$$

$$\frac{1}{\rho}[\mathrm{P} - r_m/o_m]^2 \quad (11)$$

which[11] are added to the value of the objective function. Simulation optimisation is stopped whenever the error tolerance for both objective value and constraints are less or equal to 0.0049. [12]

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[11] $\rho = 10$ for penalty (10) and $\rho = 2$ for penalty (11) are chosen during the implementation to give hierarchically more weight to the 1) convergence of the portfolio utility 2) convergence of the equalities of individual utilities 3) convergence of the contract price to the average revenue of nuclear that is exposed to market risk. This setup allows the model to find optimal portfolios faster within desired error tolerance.

[12] However, in some cases the optimisation is stopped earlier whenever there is no improvement in objective value for a long period while error tolerances are reasonably close to zero.

Results

Effects of Risk-Aversion

The cornerstone of this paper is to show how important risk-aversion coupled with carbon price is in determining the portfolio choices. This is in line with the discussion about the impact of risk-aversion in society. Consistent with the discussion by Tietjen et al. (2016), it is found that the risk aversion reduces total investment when carbon price is low (see Figure 13). In this case, CCGT serves as a baseload as there is no nuclear investment under this carbon price. Risk aversion reduces overall investments mostly (but not greatly) in baseload CCGT as OCGT acts as a price-setter due to low carbon price.

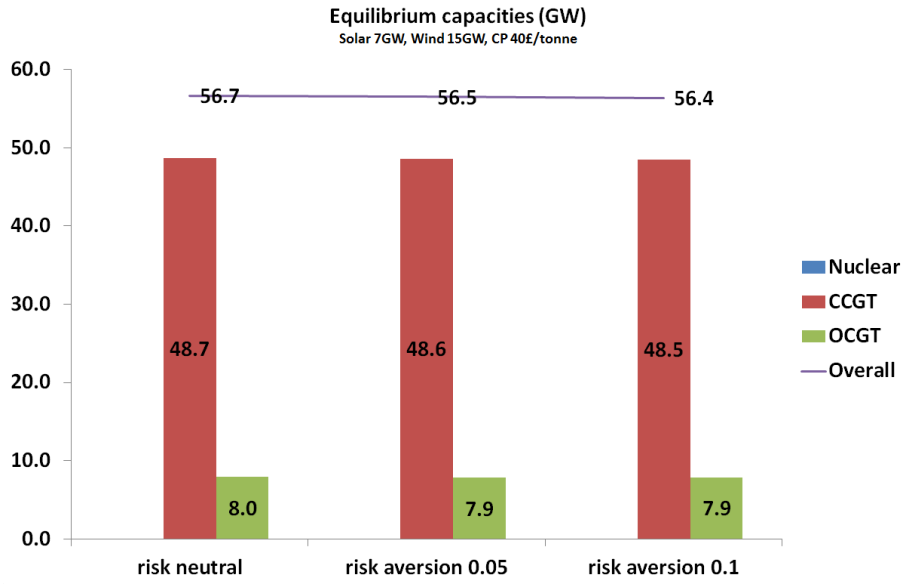

Figure 13: Equilibrium investments under low carbon price

However, when carbon price is high, nuclear acts as baseload (Figure 14) since high carbon prices prevent gas stations from being as profitable as they could be otherwise. Besides, in this case, risk aversion level has different effects on total investments and on investments in OCGT at each different levels of risk aversion (Figure 14).

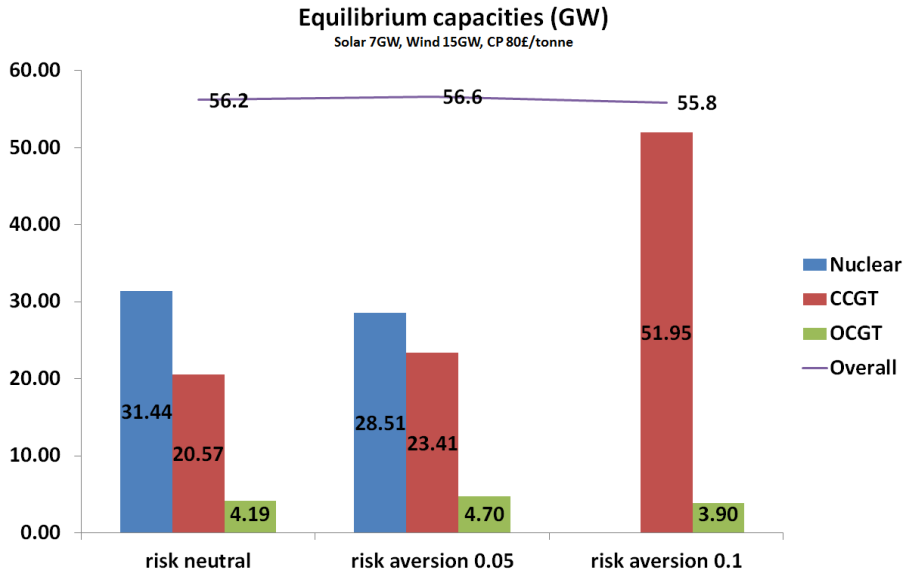

Figure 14: Equilibrium investment under high carbon price

Figure 14 shows that risk aversion not only creates a tremendous impact on portfolio mix by greatly reducing nuclear share (due to the sizeable riskiness of nuclear), but it also pushes total capacity in different directions. Total capacity with risk aversion of 0.05 is higher than that with no risk aversion and also higher than with the same level of risk aversion and a lower carbon price. This might seem counter-intuitive as low carbon price produces lower wholesale prices and higher demand and hence more capacity. However, this happens because nuclear plants are still making so much money in the portfolio that the OCGT and CCGT can afford to lose some money (in relative terms) by increasing their capacities. In other words, due to its riskiness, nuclear shrinks in the portfolio making portfolio utility greater than zero; hence, gas capacity is added (CCGT and OCGT profits are extremely correlated (Table 7)) to push utility down to zero again and bring more total capacity. Table 8 shows that nuclear profits have a high correlation with fuel price. As fuel prices define electricity prices, it brings high variance of nuclear profits that needs to be covered by high profits to meet zero-utility portfolio condition. It is only possible to get high nuclear profits by reducing its capacity. A higher capacity of OCGT increases CCGT profitability given it sets the

electricity price for most of the time. Table 7 shows that nuclear profits have a little correlation with those of gas stations indicating there is a portfolio effect. However, this effect is not enough to counterbalance the nuclear profit variance.

	$\text{Corr}(\pi_{nuc}, \pi_{ccgt})$	$\text{Corr}(\pi_{nuc}, \pi_{ocgt})$	$\text{Corr}(\pi_{ccgt}, \pi_{ocgt})$
risk neutral	0.18	0.13	0.97
risk aversion 0.05	0.14	0.09	0.97
risk aversion 0.1	-	-	0.97

Table 7: Risk aversion and profit correlations

	Nuclear	CCGT	OCGT
Profit variance	1577	156	135
$\text{Corr}(f^{f}_{gas}, \pi)$	0.93	-0.14	-0.17

Table 8: Fuel price and profit correlations

Subsequent increases in risk aversion push nuclear off the portfolio and drive total capacity down. Nuclear leaves portfolio as it is no longer able to offset its own growing variance thus reducing its capacity to zero. However, this is not the reason that total capacity goes down. In fact, total capacity goes down because higher carbon price brings forward higher marginal cost and higher electricity prices therefore lower peak demand. Lower peak demand in its turn reduces peak generator's (OCGT) capacity.

Nonetheless, when long-term fixed-price nuclear contract is added to the mix for high-carbon-price case, more diversified optimal portfolios are obtained (Figure 15). Not surprisingly, the greater the risk aversion, the more the capacity of contracted nuclear. This happens because the nuclear contract has a tiny profit risk compared to the baseload technology (which can be either nuclear or CCGT depending on the level of risk aversion). Interestingly, nuclear contract splits baseload capacity into two parts: one in which there is only contracted nuclear and the other in which there is only baseload capacity (which would

otherwise sum up to the baseload capacity if there were no contracted nuclear in the portfolio (compare Figure 14 and Figure 15)) and what's more, it satisfies the implicitly assumed limited CfD contract positions. The more the investors become risk-averse, the more CfD contracts should be allocated.

Nuclear contract's strike price is put to equal to average revenue of the nuclear technology which is exposed to the market risk. At optimum, average levels of the strike price vary between 70 £/MWh and 73 £/MWh for different levels of risk aversion.

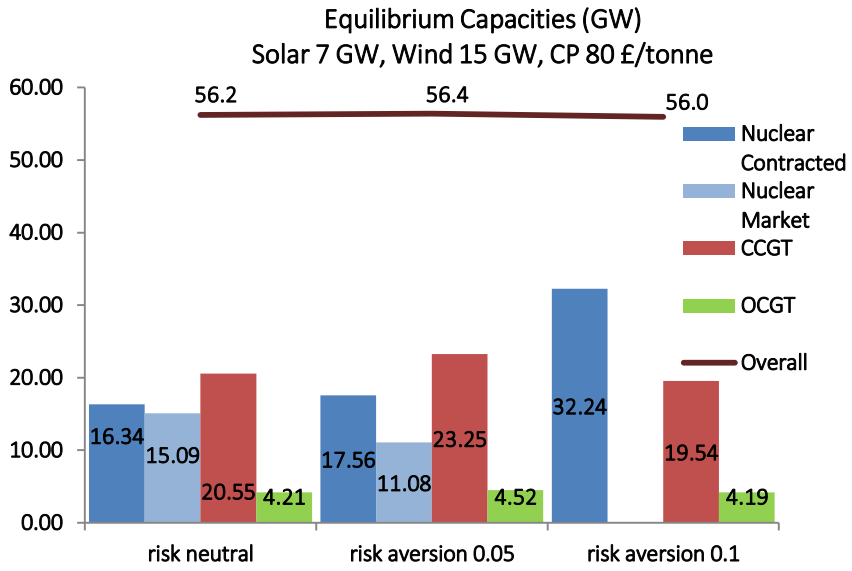

Figure 15: Equilibrium investment (GW) with nuclear contract

The model finds also the equilibrium capacities as a function of carbon price in risk-neutral case (Figure 16). Noticing that baseload technology can switch (without a nuclear contract) with respect to carbon price level, it becomes important to find the carbon price level at which point nuclear comes into the portfolio and acts as a baseload ("*baseload switching point*"). Computations reveal this level as 54.275 £/tonne implying that whenever carbon price is less than this level, CCGT serves as baseload (see Figure 16), as such a price is too low for nuclear to be included in the optimal portfolio mix. Here the reader should be reminded that there is no time component in the model. For each carbon-price level in Figure 16, a

separate equilibrium investment level is calculated as a snapshot of the industry one would expect to have in future under the model assumptions.

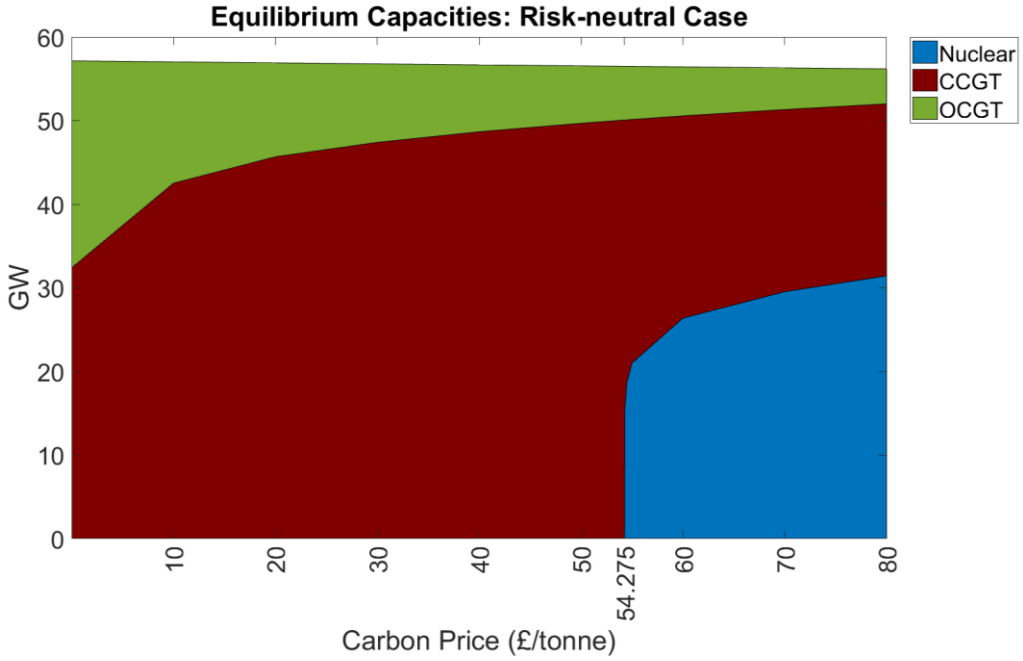

Figure 16: Baseload switching point

In addition, we observe that baseload technology switches with respect to risk aversion *and* carbon price (Figure 13 and Figure 14). The model finds those *"baseload switching points"* with respect to a combination of risk aversion and carbon price is where nuclear capacity leaves portfolio; *i.e*. those are the points on the plane when nuclear is in the borderline of becoming an unattractive investment option.

This problem of finding baseload switching point with respect to carbon price and risk aversion turns out to be bi-level problem, which is not so easy to solve directly. The inner problem of the bi-level problem is the following:

$$\min_{y_i,\alpha} U^2(y_1, y_2, \dots y_n, \alpha) \quad (10)$$

subject to:

$$v(y_i) = v(y_k), i = 1, \dots n-1; k > i \quad (11)$$

$$x_i \leq x_{i+1}, i = 1, \dots n-1 \quad (12)$$

$$0 \leq \alpha \leq 0.1 \quad (13)$$

$$x_i \geq 0, i = 1, \dots n \quad (14)$$

The full bi-level optimisation problem therefore becomes:

$$\min -\alpha \quad (15)$$

subject to:

$$x_1 = \arg\min_{y_i, \alpha} \{\text{problem } (10) - (14)\} \quad (16)$$

$$x_1 > 0 \quad (17)$$

However, for our modelling results, we do not need great precision in solving this bi-level problem directly. Therefore, the problem is relaxed into the following single-level problem:

$$\min_{y_i, \alpha} U^2(y_1, y_2, \dots y_n, \alpha) \quad (18)$$

subject to

$$v(y_i) = v(y_k), i = 1, \dots n-1; k > i \quad (19)$$

$$x_i \leq x_{i+1}, i = 1, \dots n-1 \quad (20)$$

$$x_1 = \xi, i = 1, \dots n \quad (21)$$

where ξ is a user-defined positive small number[13].

Problem (18) - (21) is minimised with respect to α in order to find the minimum level of risk aversion when nuclear is asymptotically zero. The problem seeks to discover the minimum risk aversion because nuclear capacity and risk aversion are reversely connected; higher risk aversion yields lower nuclear investment.

The results for different carbon price levels are shown in Table 9. The second row shows the minimum levels of risk aversion when there is no nuclear investment in the portfolio. Having

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[13] $\xi = 0.01$ is chosen which is equivalent to 10 MW amount of investment in nuclear – a very negligible number.

these levels, the half-spaces (regions) of nuclear availability in the optimal portfolio are easily interpolated (Figure 17).

As future systems would include more renewable capacity than the current levels, this study shows as well how this extra penetration of renewable output affects future investments (Figure 18 and Figure 19).

Carbon price	54.275	60	70	80
Risk aversion	0	0.0190	0.0525	0.0864
Nuclear capacity (GW)	0.0	0.0	0.0	0.0
CCGT capacity (GW)	50.1	50.5	51.2	51.8
OCGT capacity (GW)	6.4	5.8	4.9	4.1
Objective value with penalties	0.0	0.0	0.0	0.0

Table 9: Bi-level optimisation results (relaxed solutions)

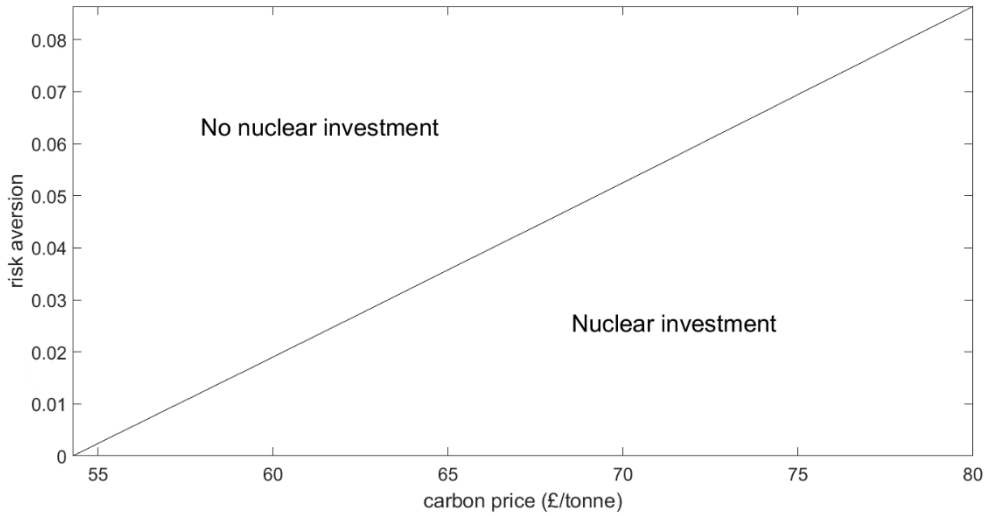

Figure 17: Nuclear availability regions in the optimal portfolio

Effects of More Renewables

In line with DECC (2014d), this study also assumes that there will be double the amount of the current levels of renewable capacity in the 2020s. As expected, the additional renewable

penetration into the system cuts back the total conventional investments since there is already less demand (net of renewables) left to be served. In order to get the combined effect of stochasticity from fuel price, renewable penetration and risk aversion, two cases of carbon price level are separated for every level of risk aversion and renewable penetration.

In the case of high carbon price (Figure 18), investments substantially decrease in nuclear when it acts as a baseload for cases of risk-neutral and risk aversion of 0.05. In this case, the capacity of gas stations increases. This happens because renewable variation extends the gap between gross and net load-duration curves for the most of downward part of load duration curves thus affecting the stations that operate for longer periods, *i.e*. baseload nuclear in this case. As nuclear shrinks in the portfolio, its profits increase which needs to be counterbalanced by an increase in the capacity of gas stations thus pushing their profits down and preserving the zero portfolio utility. In other words, in order to counterbalance the positive utility of a portfolio created by the reduction of nuclear capacity, the capacity of both gas stations increases since per kW nuclear profits are much higher than that of gas stations'. However, when risk aversion is 0.1, there is no investment in nuclear and CCGT acts as baseload and therefore extra additions of renewables reduce their investments which should be offset by an increase in OCGT capacity. This case is similar to the one when there is no nuclear investment under low carbon price (Figure 19) as total investment reduces at the expense of CCGT reduction while investment in OCGT increases.

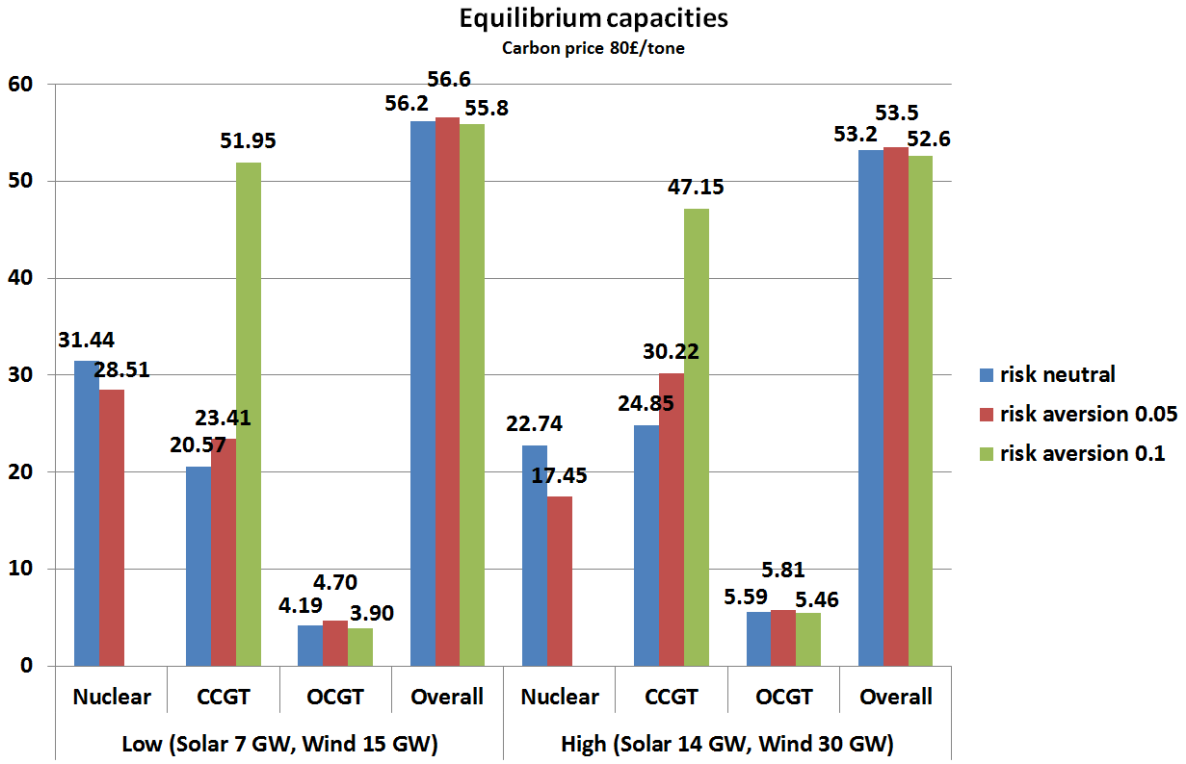

Figure 18: Effect of Renewable Penetration (High-carbon-price case)

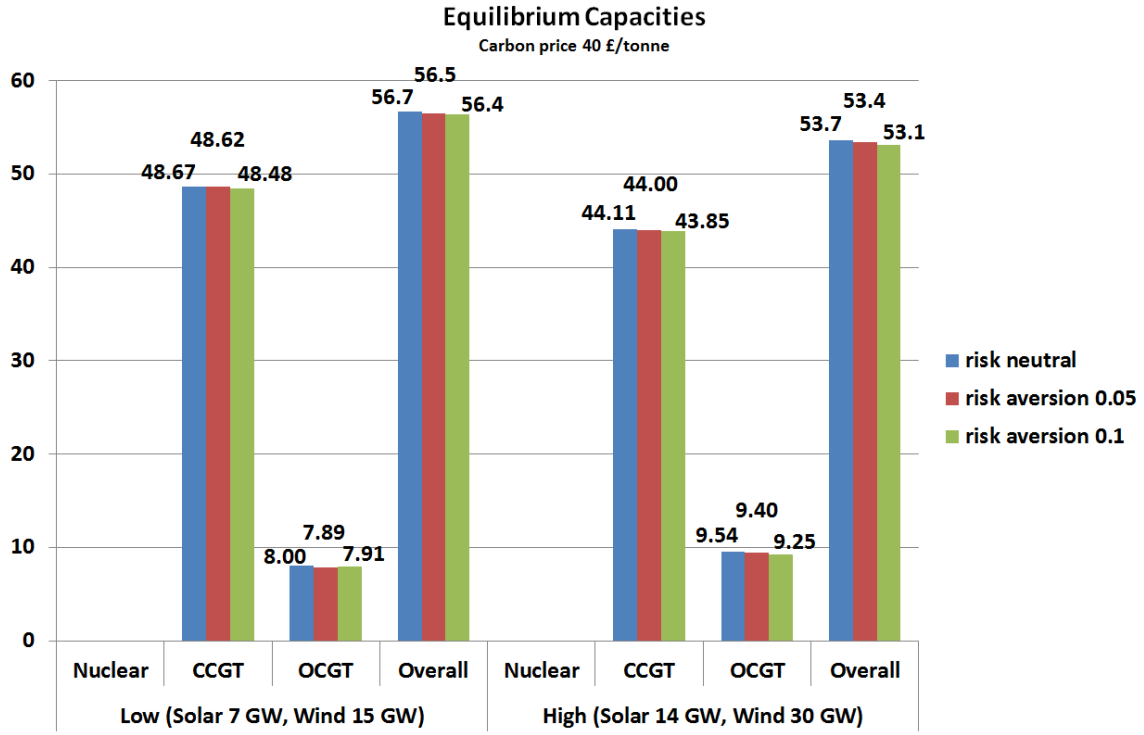

Figure 19: Effect of Renewable Penetration (Low-carbon-price case)

The impact of massive integration of renewables decrease nuclear capacity from 28-39% when it serves as baseload; however, when CCGT serves as baseload (risk aversion of 0.1) the decrease in CCGT capacity is only 9% (Figure 19).

Conclusion of Chapter 3

Using the future UK industry as a context, this chapter develops the first fully endogenous model for calculating the risks of different technologies in a competitive market accounting for risk aversion in the face of uncertain fuel and carbon prices, demand and renewable generation. It brings forward a few key insights worth discussing.

As demonstrated in Chapter 2, future carbon price projections are very uncertain. This is why this chapter considers two separate cases for carbon price – low and high. This chapter is not interested in projecting a possible carbon price that modelling and analyses should be based on. A mere representation of distinct low and high prices is enough to understand the dynamics of investments in the UK electricity industry, and these dynamics turn out to be quite different for each case. Most notably this distinction is crucial for investments in nuclear. On the one hand, low carbon prices are beneficial for gas stations that emit carbon dioxide and therefore are less penalised and, on the other hand, low carbon prices yield low electricity price, ceteris paribus, and low electricity prices yield low nuclear profits, which are not enough to offset their profit variance. These are the main factors for not having an investment in nuclear in the optimal portfolio in the low-carbon-price case. In particular, the modelling suggests that the level of carbon price should be at least 54.275 £/tonne of CO2 to make nuclear an attractive option. However, the minimum level of carbon price still does not guarantee nuclear investments as this level rises with the rise of risk aversion. Particularly, a minimum additional carbon price of 3 £/tonne of CO2 will be required for every 0.01 increase

in risk aversion. This sends a clear message to policy-makers about the importance of risk aversion when designing carbon-price policy.

On a related note, low gas prices are not desirable for nuclear as they reduce the electricity price while its cost is relatively fixed. On the contrary, high gas prices are desirable for nuclear as this means that electricity prices are also high given that gas stations are still price-setters. However, high risk aversion undermines nuclear investment greatly, and if this is further coupled with future low levels of carbon price (which is plausible given the recent introduction of a cap on the Carbon Price Support), this could be bad news for the prospects of nuclear. This should be the main rationale for allocating long-term *FiT CfDs* to nuclear technologies and not the actual market risk *per se*. These incentives would be very important for nuclear in the event of high risk aversion, as they will reduce revenue risk of the nuclear and bring them into the optimal portfolio. Unless some projects are pushed through by the government under these schemes, it seems there would be no future for nuclear.

Additionally, although Green (2008) showed that it is possible to add a much higher proportion of nuclear capacity to an optimal portfolio when a nuclear contract is included, this chapter shows that a contract does not actually add more capacity under low risk aversion but only takes more than half of the portion of the baseload capacity while preserving the total capacity. Moreover, the nuclear contract is even able to take some portion from baseload CCGT when risk aversion is high enough as market-facing nuclear is absent from the optimal portfolio.

Finally, the model presented here is not intended to predict the actual future levels of carbon price, fuel price or renewable capacity but rather to give more reference cases thus enabling us to separate “winners” and “losers” among generators. As the analysis shows, nuclear can be a loser but it can also be a winner if it is able to secure a long-term fixed-price contract.

However, a future system will include more renewable electricity and this will create even more challenges for policy-makers in promoting nuclear as more renewables render more nuclear profit variation. But, as with the coal plants, if the government decides to stop the operation of unabated gas stations, this might also reintroduce the interest towards nuclear technology, among others.

CHAPTER 4: Cash-Flow Risk, Cost of Capital and Investment Decisions in the UK Electricity Industry

Introduction

Electricity companies make large investments in power stations, often partly funded by debt, and repay them from their (uncertain) cash flows. In project finance, the link between cash flows and the ability to repay debt is project-specific, whereas, in corporate finance, the company's ability to cover this debt depends largely on its whole balance sheet. Nevertheless, both cases bear the risk of default, which can happen when companies are unable to generate sufficient cash flows to cover debts. As a result, companies create a solvency cushion via accepting limits on the amounts of debt they take even though the tax shield given to debt makes it a cheaper source of finance than equity (see, for example, Donaldson & Fox (2000)). The more uncertain the cash flows, the lower the proportion of debt hence the higher the cost of capital. This effect could vary between power stations as they face different levels of construction and operation risks during their lifetime. The aim of this paper is to quantify this effect in the context of the UK electricity system.

Currently, the UK electricity retail market is mostly dominated by large vertically integrated companies (the *Big Six*) that also hold portfolios of generating sources (Ofgem, 2016a, 2016d). However, in contrast to the retail sector, the wholesale electricity market is quite competitive despite the presence of these big players. As discussed earlier, there has not been any significant exercise of wholesale market power in recent years. This chapter, similar to Chapter 3, builds on this fact assuming a reasonably competitive generation market will continue to operate in future. Thus, this chapter builds an equilibrium model of investment (when the cost of capital is endogenously calculated) for a perfectly competitive case.

Correspondingly, all assumptions made in Chapter 3 are preserved here. Fuel prices are assumed to follow a log-normal distribution with parameters derived from the projections of DECC (2013). Similarly, demand is modelled in the same way as a fitted distribution of a tranche (refer to Chapter 3 for more details). However, only one carbon price is analysed, *i.e.* 80 £/tonne which corresponds to the high-carbon-price case. This allows nuclear to be present in the optimal portfolio. There is no risk aversion considered here (*i.e.* the modelling is performed in a risk-neutral setting) as the aim of this chapter is to quantify the risk exposure of technologies with the help of their cost of capital. Comparative analyses of the results of Chapter 3 and Chapter 4 are presented thoroughly to pinpoint the essential differences in modelling approaches between the two chapters.

This chapter separates two types of investors in the electricity system: stand-alone generators and energy companies (hereafter *firms*). A stand-alone generator has only one generating asset at its disposal, which can be either nuclear, CCGT or OCGT. However, a firm has a combination of distinct types (a portfolio) of generating assets and aims to construct a portfolio with non-zero combinations of those assets whenever possible. This distinction is important to understand the portfolio effect that could be harnessed when considering a firm that has one cost of capital for an entire portfolio of assets. This is examined against independent power producers with one generating asset that can have not only one cost of capital for the whole duration of the asset's lifetime but also different costs of capital during asset's pre-development & construction phase and operation phase.

This chapter quantifies the impact of construction and operation risk on the cost of capital of each technology and the impact of that cost of capital on their (and firms') investments decisions in a closed-loop simulation optimisation model derived from the model of Chapter 3. As in Chapter 3, the equilibrium capacities of technologies (computed for zero economic

profit thus allowing them to make only accounting profit) are used to get equilibrium cash flows from which the cost of capital is endogenously derived which then affects the equilibrium capacities. Like a financial firm, a power generator (and a firm) is also exposed to a cash-flow risk, and the realised amount of cash-flow uncertainty can be treated as an indicator of its financial distress or bankruptcy (default). Power generators (generating firms) have their own unique volatility (idiosyncratic risk) that is present in their cash flows, and they usually perform tests on whether the left tail of their cash-flow distribution meets debt lenders' financial requirements (covenants) for securing external funds (see, for example, LaGattuta *et al.* (2000)). This study takes benchmark numbers from the energy credit industry of Europe to evaluate the maximum debt capacity generators (and firms) are able to take based on their cash-flow risk.

This chapter is structured in the following way: firstly, the contextual literature review is introduced, and then the model is presented followed by the data and assumptions. Next, the results are discussed followed by the conclusions.

Contextual Literature Review

Cost of Capital in the UK Electricity Industry

There are three types of investors in electricity industry: a utility[14], a private investor and an institutional & strategic investor. Each group has a different expected level of cost of capital (Helms *et al*., 2015). While studying the future of the UK electricity industry in a perfectly competitive setting, the previous chapter calculated endogenous equilibrium capacities for a fixed cost of capital. However, this chapter shows that a fixed cost of capital does not completely reflect the actual amount of invested capacity thus supporting some studies that

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[14] Although *utility* does not have a unique meaning in different countries, this chapter puts it under the same category as a vertically integrated energy company that owns a portfolio of both generation and supply.

have already demonstrated this important issue in different contexts. For example, Green & Staffell (2013b), who modelled the impact of State Aid for nuclear power stations in Great Britain for the European Commission, showed the effect of different costs of capital on the evolution of capacity mix, and Roques *et al.* (2008) showed that a higher cost of capital favours portfolios of gas stations while lower cost of capital favours nuclear.

CMA (2015a) performed a thorough analysis on the cost of capital of the UK energy sector. It separated three categories of companies: a stand-alone generator that owns one generating asset; a retail supply company that owns only supply; and vertically integrated energy company that owns both generation and supply. It calculated that the pre-tax weighted average cost of capital (WACC) in the UK is 7.9 – 9.7% for a stand-alone generator. This is 0.2% higher than a vertically integrated energy company's WACC, although they both have a similar cost of equity of 9.6 – 10.3%. The pre-tax cost of debt is 5.5-7% and 5-6%, while the post-tax WACC is 5.8% – 7.1% and 5.6 – 6.9% respectively for a generator and a firm (for the gearing ratio of 0.2-0.4 and the average corporation tax rate of 0.27). However, for nuclear projects OECD & NEA (2015) report 5% pre-tax cost of debt because of their low operational risk, and 7.5% cost of capital because of their high opportunity cost of capital. Nonetheless, it is acknowledged that the investors of energy infrastructure projects sometimes necessitate higher WACCs by adding hurdle premium rates of 5.28 – 7.45% (the exact number depends on the equity premium) onto the computed cost of capital to reflect the pessimistic margin of the discount rate attached to the unsystematic risk of a project (Meier & Tarhan, 2007).

Pre-operation and Operation WACC, IRR and Hurdle Rate

A project from construction to commissioning stages bears different risks to investors. For instance, nuclear construction risk is among the highest due to its complexity while its operation risk is among the lowest due to its low-marginal-cost profile.

As a rough guide, one may divide the fixed cost of a technology by its variable cost to determine the relative investment risk of that technology, *i.e.* the higher the ratio, the bigger the investment risk. However, apart from the investment risk, there are other risks a nuclear project is exposed to. Particularly, OECD & NEA (2015) emphasise three common sources of risk for nuclear projects: 1) electricity-price risk, 2) construction risk and 3) load-factor risk, which jointly induce the variability of the cost of capital. The model of this chapter includes all these three risks; however, one kind of load-factor risk, due to technical faults that prevent stations from running at their designed load-factor level, is not modelled; rather, it is assumed that all stations are capable of running at 85% availability. Moreover, endogenous risk of nuclear station running at (slightly) reduced output is included to accommodate surplus wind power (refer to Chapter 3 for more information).

It is incumbent upon companies to have a low cost of capital of a project in order to undertake it. Whilst the cost of capital is the weighted cost of owned funds and post-tax borrowed funds, hurdle rate is the minimum acceptable rate of return a company is willing to consider for its investment purposes. On the other hand, internal rate of return (IRR) is the rate that makes the net present value of a project's future cash flows zero. Therefore, the higher the IRR, the more attractive a project is but it should be greater or equal to its project-specific hurdle rate to be an acceptable investment option.

For endogenising the cost of capital of technologies in the pre-operation period, this study relies heavily on some external reports: firstly on the European Commission (2014a) report for nuclear pre-operation WACC, secondly on the EWEA (2013) and NERA (2015) study for gas stations.

There are also other reports that provide comparison benchmark numbers between WACC, hurdle rate and internal rate of return (IRR). For example, the KPMG report (European

Commission, 2014b) reports an overall nuclear IRR of 9.4-10% and an IRR of 9-13% during its construction phase (*e.g.* Akkuyu plant in Turkey that has 0.7 debt share and $9.3 billion debt financing (OECD & NEA (2015)). As already mentioned, the operation period of nuclear is less risky therefore a less internal rate is expected as can be seen from WSP & Parsons Brinckerhoff (2016) report on an IRR of 6-9.5% for the most reactor types (*e.g.* large SMR or PWR-AP1000).

As for the hurdle rates, NERA (2015) assumes pre-tax hurdle rate of 9.7-13.6% for new nuclear projects while Oxera (2011) reports 11% and DECC (2013b) 9.5%. Nuclear is not the only technology that is costly and risky as there are other technologies that have comparable hurdle rates such as biomass with 10-13.2% (NERA, 2015), 11% (Oxera, 2011), 14.4% (ARUP, 2010) or coal-CCS with 11-14.9% (NERA, 2015), 14.5% (Oxera, 2011) and 13.5% (ARUP, 2010). However, the acceptable rates are lower for OCGT and CCGT at 7.8-11.8% (NERA, 2015), 7.5% (Oxera, 2011; DECC, 2013b). On the other hand, a study by NERA (2015) has found the risk-adjusted hurdle rate, where risks come from electricity price, contract allocation, policy, fuel and carbon price, is in the range of 10.5-17.4% for nuclear project which is in agreement with the European Commission's (2014b) rate of 11.7% for Hinkley Point C.

Cash-Flow Risk and Capital Structure

Two streams of literature address risk in different ways; the first stream does it from the optimisation/ operations-research perspective while the second from finance/economics. From the first stream, *e.g.* Ehrenmann & Smeers (2011, 2013) showed the importance of heterogeneous cost of capital in optimisation models confirming that the project-finance nature of many investment projects brings a project-specific cost of capital. The second stream, on the other side, has focused on studies that link cash-flow risk to capital structure

(*e.g.* Bradley *et al*. (1984), Leland (1994) and Strebulaev (2007) *etc*.). Another example is Dudley & James (2015) who showed that low cash volatility allows firms to take more debts; but the riskier the cash flows are, the more restrained the firms become in taking debts. The energy economics stream, in particular, tries to connect those theories in the context of energy problems. For instance, Green & Staffell (2013a) took account of the impact of cash-flow risk on the cost of capital in evidence to the UK government on whether it was appropriate to have the same per-MWh price for all wind farms irrespective of their expected output.

Although the classical theory of Modigliani & Miller (1958) demonstrates the irrelevance of the leverage when there are minor financial costs associated with it, Bradley *et al.* (1984) showed that optimal capital structure, in fact, depends on the significance of corporate borrowings. Later, Lelend (1994) showed that optimal capital structure and debt are directly associated with firm's risks and bankruptcy costs. As the electricity sector is also subject to capital-expenditure and cash-flow risk, then firms can easily be exposed to financial distress and, in some cases, even to a bankruptcy.

As the problem of capital structure is very complex, it is not surprising to see competing theories explaining it. First, the *Pecking Order Theory* (Myers & Majluf, 1984; Myers, 1984) asserts that firms hierarchically prefer to 1) use their internal money and 2) borrow external money, and whenever those two options have been exhausted (and there is still a shortfall of money), they 3) finance themselves through the equity issuance. This theory further assumes whenever a firm is in need of larger funding (which can be more than its inner resources) it takes on more debt. More debt implies more information transparency among a firm's agents. Second, the *Trade-off Theory* posits that riskier cash flows lead to a financial distress; therefore, firms weigh debt riskiness against debt benefit, which can bring a utilisation of tax

shield to debt or resolve the inner agency conflicts (Graham & Leary, 2011). The *Dynamic trade-off theory*, an extension of the latter, says that occasional adjustment of capital structure is optimal (Fischer *et al*., 1989). However, Strebulaev (2007) using a calibrated dynamic trade-off model, showed that delays of changes in capital structure can create sub-optimal leverages when it is readjusted due to market frictions. On the contrary, Leary & Roberts (2005) had already shown that firms incur readjustment costs to achieve the optimal balance range. Recently, Danis *et al.* (2014) found that whenever firms are close to their optimal capital structure, the link between profitability and leverage is positive but whenever they are further apart, the link is negative. DeAngelo *et al.* (2011), on the other hand, showed that firms intentionally divert from their optimal capital structure to issue transitory debt – the difference between the actual and the target debt – to finance their investments. On the other hand, Denis & McKeon (2012) showed that firms issue debt to cover their operating needs instead of paying dividends.

All these analyses are important for this chapter, as it will be shown that operating income risk together with construction risk is one of the main drivers for limiting debt capacity contingent upon zero or near-zero readjustment costs.

Risk Measure, Debt Covenant and Financeability

Risk measures, such as value at risk (VaR_{λ}) or conditional value at risk ($CVaR_{\lambda}$) (Artzner *et al*., 1999; Rockafellar & Uryasev, 2000; Andersson *et al.*, 2001), have profoundly penetrated the risk-analyses sector of banking & finance. Their wide use and extension are credited mainly to the *RiskMetrics* firstly introduced by JP Morgan in 1994 (JP Morgan, 1994). However, since most of these methods had been developed for the banking & finance industry, a new but

similar method, namely cash flow at risk ($CFaR_{\lambda}$)[15], was established for non-financial firms especially for such heavy-capital industry sectors as energy (LaGattuta *et al*. (2000), Stein *et al*. (2001)). In an energy context, LaGattuta *et al.* (2000) showed the limits of an isolated financial-ratio analysis in the power industry of 1991 and 1999 (for more information about single ratio analysis on vertically integrated energy companies of the UK, see Appendix 3) demonstrating that whilst cash flows are volatile (measured with $CFaR_{\lambda}$), a financial ratio such as debt-to-assets ratio or interest cover ratio (ICR) might not be volatile and thus cannot represent the actual level of risk.

Firms' investment decisions are affected by their financial performance as Chava & Roberts (2008) showed in their study. They show that financing frictions are the key connectors of a firm's financeability to its investment decisions. However, they studied the effect of the *breach* of debt covenants on investment. In contrast, this chapter examines the effect of satisfying the *minimum level* of debt covenant on investment, *i.e.* when firms adhere to the minimum debt-service cover ratio (DSCR) both in an average year and in a year with relatively low profits. Typical numbers of cash-flow distributions for long-term DSCR for European projects are 1.4 for P50 and 1.2 for P90 (Tindal, 2011; Fitch, 2015a, 2015b). By imposing this covenant on a generator (a firm) – when it satisfies both debt holders and equity holders from its volatile operating cash flows – the equilibrium state (*i.e.* a state that includes equilibrium values of the cost of capital, invested capacities, debt levels, debt share *etc.*) can be calculated as described in the next section.

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[15] Non-financial companies calculate CFaR at maximum 0.05 quantile level due to long periods under consideration that almost wipe out tail effects (Pergler & Rasmussen, 2013).

Modelling

This chapter develops a simulation optimisation algorithm based on the model of the previous chapter. This model also uses a merit order stack to calculate electricity prices and generators' outputs over a year with stochastic demand, renewable generation and fuel prices where capacity is endogenously calculated. That capacity mix is then readjusted (looped) in the light of risks and returns faced by generators[16].

This study calculates the social optimum with a risk-aversion of zero in order to achieve a mean-variance utility of zero. The cost of capital during operation (induced by plants' cash-flow risk) that generators are covering is endogenous. While the construction cost of capital for nuclear plants is derived exogenously, it is semi-endogenously calculated for thermal stations as uplift on top of the cost of capital during operation. The model loops between the cash-flow risk (that defines max debt a firm can exercise), debt-equity ratio (that determines the maximum leverage a firm can attain while utilising tax shield to debt), cost of capital (which changes the annualised fixed costs of generators), capacity mix (which is affected by the generators' annualised fixed costs), profit risk (and therefore cash-flow risk) (determined through operating patterns of the given capacity mix) (Figure 20).

Project's pre-development time and cost for technology i are denoted respectively with τ_i^p (years) and c_i^p (£/kW). Total pre-development costs at k-th loop ($C_i^{(po)k}$) at the start of the project are calculated as a discounted sum of yearly pre-development costs:

$$C_i^{(po)k} = \sum_{\tau=1}^{\tau_i^p} \frac{c_i^p/\tau_i^p}{(1+W_i^k)^\tau} \quad (1)$$

[16] For more details, refer to Chapter 3 and, specifically, to the model (1) - (4).

where W_i^k is the weighted average cost of capital during pre-development & construction period at k-th loop defined as:

$$W_i^k = \begin{cases} w_i^k + \varphi_i, & i \in i_d \\ w_i^F, & i \in i_x \end{cases}$$

Here w_i^k is the operation WACC of technology i at k-th loop; φ_i is the WACC premium during pre-development & construction (fixed uplift of construction WACC over operation WACC); w_i^F is the exogenously calculated WACC during construction; i_d is the set of all "endogenous" plants (which have endogenous construction WACC); and i_x is the set of all "exogenous" plants (which have exogenous construction WACC).

The total construction cost is calculated as a sum of discounted yearly construction costs:

$$c_i^{(co)k} = \sum_{\tau=1}^{\tau_i^c} \frac{c_i^c / \tau_i^c}{(1 + W_i^k)^\tau} \tag{2}$$

Here $c_i^{(co)k}$ represents discounted overall construction cost at the beginning of the project construction at the k-th loop; c_i^c per kW construction cost; τ_i^c construction length.

In order to get the overall construction cost at the beginning of the project (*i.e.* at the beginning of the pre-development phase), all $c_i^{(co)k}$ are discounted for τ years and summed:

$$C_i^{(co)k} = \sum_{\tau=1}^{\tau_i^p} \frac{c_i^{(co)k}}{(1 + W_i^k)^\tau} \tag{3}$$

The total electricity production, at the beginning of the project, is obtained as a discounted production of electricity which was calculated at the beginning of the operation:

$$\mathrm{EL}_i^k = \frac{\sum_{\tau=1}^{T_i} \frac{8760\delta_i^k}{(1+w_i^k)^\tau}}{(1+W_i^k)^{\tau_i^p+\tau_i^c}} \tag{4}$$

Here EL_i^k is the overall discounted electricity production of plant i at the k-th loop, T_i is the plant operating period, and δ_i^k is the endogenous average-lifetime load factor (net of plant availability) at the k-th loop.

After this, the k-th-loop levelised pre-development cost is calculated as $C_i^{(po)k}/\mathrm{EL}_i^k$, and levelised construction cost as $C_i^{(co)k}/\mathrm{EL}_i^k$.

Fixed costs for each technology at the k-th loop is calculated as fixed operating and maintenance costs plus annual repayment of capital cost and half of decommissioning & waste disposal costs adjusted for the number of hours the generator was on load:

$$\mathrm{FC}_i^k = \frac{F_i^{om} + \frac{C_i^{(po)k} + C_i^{(co)k}}{\mathrm{EL}_i^k} + \frac{\mathrm{DW}_i}{2}}{8760\delta_i^k} \tag{5}$$

where F_i^{om} is the levelised *fixed operating and maintenance* costs (which includes not only the *fixed operation and maintenance* costs, but also the insurance and connection & use-of-system charges) of technology i, and DW_i is the levelised decommissioning and waste-disposal costs[17].

The capital investment at the onset of the project commission is calculated in the following way:

$$\mathrm{CI}_i^k = (C_i^{(po)k} + C_i^{(co)k})(1+W_i^k)^{\tau_i^p+\tau_i^c} \tag{6}$$

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17 Decommissioning and waste-disposal costs are treated as half-fuel and half-fixed cost.

The project cash flow is derived from the project's Earnings Before Interest, Tax and Depreciation & Amortisation (EBITDA_i) defined as:

$$\text{EBITDA}_i^k = r_i^k - m_i^k \times o_i^k - c_i^{O\&M} - I_i - \text{SC}_i \tag{7}$$

where, for each of technology i and loop k, r_i^k is the annual revenue; m_i^k is the marginal cost; o_i^k is the total annual output[18]; $c_i^{O\&M}$ is the fixed operation and maintenance costs; I_i is the insurance payments; and SC_i is the connection & use-of-system charges[19].

Earnings Before Interest, Tax at the k-th loop (EBIT_i^k) is the measure of cash flow which is obtained after subtracting yearly depreciation from EBITDA_i:

$$\text{EBIT}_i^k = \text{EBITDA}_i^k - \text{DA}_i^k \tag{8}$$

Here DA_i^k is Depreciation & Amortisation at the k-th loop calculated as a straight-line depreciation of a technology over its given operating lifetime[20]:

$$\text{DA}_i^k = \frac{\text{CI}_i^k - \text{RV}_i}{T_i} \tag{9}$$

where RV_i is the residual value of an asset (a plant).

Financiers' typical requirements for debt service are that 1) median cash flow is at least $\gamma_{P_{50}(\text{EBIT}_i^k)}$ times the annual interest payment with principal repayment (Equation (10)) and 2) the λ quantile of operating cash flow is at least $\gamma_{P_{\lambda_i}(\text{EBIT}_i^k)}$ times that payment (Equation (11)) (Tindal, 2011; Fitch, 2015a, 2015b):

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18 Formulae for r_i^k, m_i^k, o_i^k are given on pages 64 and 67.

19 Fixed O&M, insurance and connection & use-of-system charges are not affected by different levels of WACC because they are given in yearly basis.

20 Generally, fixed cost of a long-lasting asset (such as a generator) in a firm's balance sheet is capitalised and therefore depreciated yearly.

$$\mathrm{P}_{50}(\mathrm{EBIT}_i^k) \geq \gamma_{P_{50}(\mathrm{EBIT}_i^k)} D_i r_{D_i} \frac{(1+r_{D_i})^{\eta}}{(1+r_{D_i})^{\eta}-1} \tag{10}$$

$$\mathrm{P}_{\lambda_i}(\mathrm{EBIT}_i^k) \geq \gamma_{P_{\lambda_i}(\mathrm{EBIT}_i^k)} D_i r_{D_i} \frac{(1+r_{D_i})^{\eta}}{(1+r_{D_i})^{\eta}-1} \tag{11}$$

Here D_i is overall debt of technology i; r_{Di} is the annual interest rate on that debt; η is the tenor of the asset; $\mathrm{P}_{50}(\mathrm{EBIT}_i^k)$ is the median of EBIT_i^k; and $\mathrm{P}_{\lambda_i}(\mathrm{EBIT}_i^k) = \{x \in \mathbb{R}: \mathrm{P}\left(\mathrm{EBIT}_i^k \leq x\right) = \lambda_i\}$.

From equations (10) and (11), we can get the maximum debt that a project (a firm) is able to attract:

$$D_i^{(\max)k} = \frac{1}{r_{D_i}\frac{(1+r_{D_i})^{\eta}}{(1+r_{D_i})^{\eta}-1}} \times \min\left(\frac{\mathrm{P}_{50}(\mathrm{EBIT}_i^k)}{\gamma_{P_{50}(\mathrm{EBIT}_i^k)}}, \frac{\mathrm{P}_{\lambda_i}(\mathrm{EBIT}_i^k)}{\gamma_{P_{\lambda_i}(\mathrm{EBIT}_i^k)}}\right) \tag{12}$$

After all these, new operation WACC can be derived from the capital structure when maximum debt is exercised:

$$WACC_i^k = \frac{D_i^{(\max)k}}{\mathrm{CI}_i^k} r_{D_i}(1-\varpi_i) + \frac{\mathrm{CI}_i^k - D_i^{(\max)k}}{\mathrm{CI}_i^k} r_{E_i} \tag{13}$$

Here ϖ_i is the tax rate, and r_{E_i} is the equity rate of technology i. For the subsequent loops ($k = k+1$), the cost of capital during operation is updated as $w_i^k = WACC_i^{k-1}$, and calculations restart from equation (1) (See Figure 20).

The model posits that the riskier the cash flows of the firm (equations (8) and (9)), the lower the proportion of maximum available debt (equation (12)), and therefore the higher the cost of capital (equation (13)). Whenever the cost of capital is adjusted, it affects the annualised fixed cost of each generating technology (equation (5)) thus changing both the overall amount of equilibrium capacity and the zero-profit capacity mix. Whenever this happens, the

distribution of electricity prices, revenues (therefore profits and cash flows) change, and the model loops between capacity, cash flows, the maximum debt-equity ratio and the cost of capital to reach the equilibrium level of investment (Figure 20).

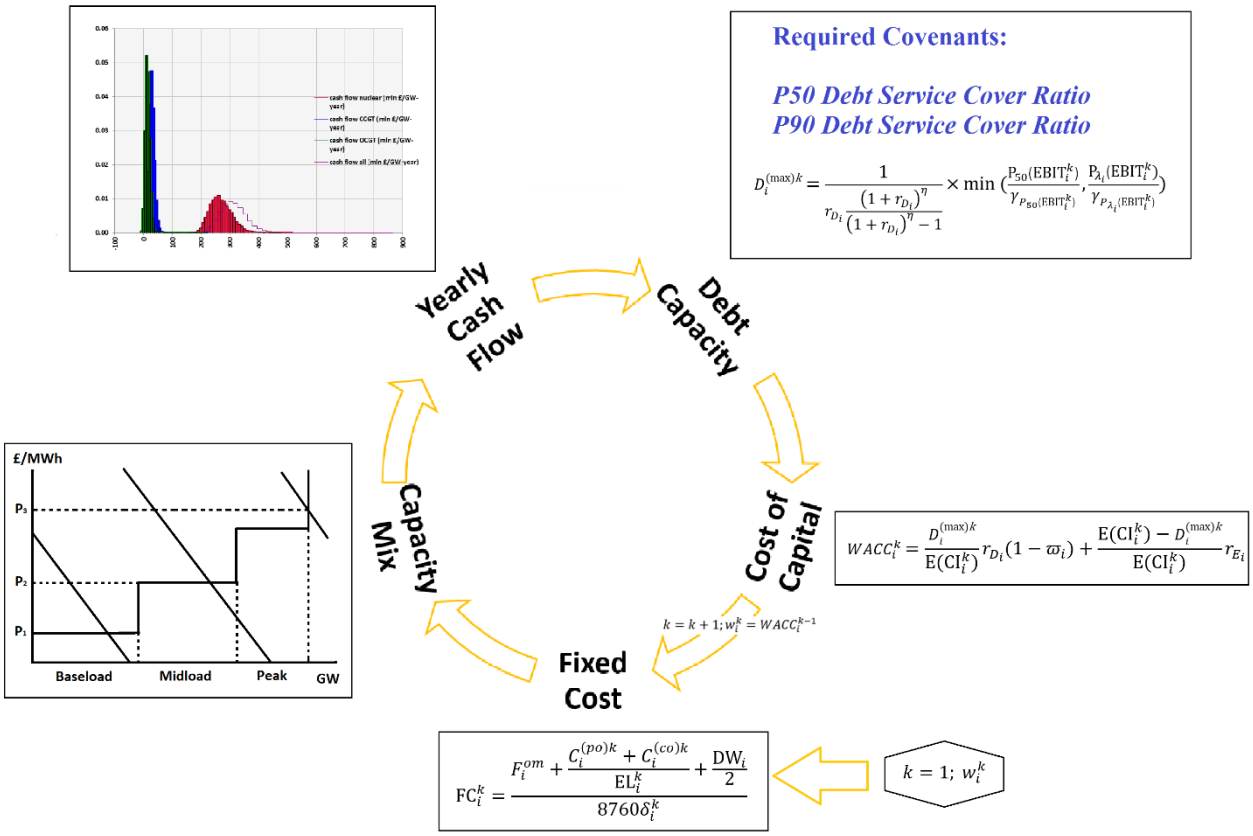

Figure 20: Conceptual Simulation Model
Source: The author

Data and Assumptions

This chapter relies on DECC's (2013b) yearly £/kW central pre-development and construction costs data and European Commission's (2014b) data on Hinkley Point C to calculate the capital investment costs. Specifically, it assumes that nuclear has a 6-year pre-development and a 7-year construction period. Hinkley Point C nuclear station's £24.5 billion construction cost and estimated £34 billion capital at the end of construction phase (including interest during construction) renders a cost of capital of 10.8% which is used in the model both for construction and pre-development phases of a nuclear project. This cost of capital is

assumed to have already absorbed the construction and pre-development risks of a nuclear project. Of course, the actual cost of capital during pre-development and construction phases may be different depending on the contract type between the owner and the developer. For example, if a contractor takes responsibility for delivering the full package ("turnkey" contract), then the cost of capital during pre-development and construction will tend to be similar since one company (therefore one WACC) is responsible for the full-package delivery.

	Nuclear	CCGT	OCGT
Pre-development costs (£/kW)	210	10	20
Pre-development period (year)	5	2	2
Construction cost (£/kW)	4100	600	300
Construction period (year)	7	3	2
Operating lifetime (year)	60	25	25
Operation & Maintenance costs (£/MW/year)	72000	22000	9900
Insurance payments (£/MW/year)	10000	1990	960
Connection & use-of-system charges (£/MW/year)	7400	6840	3440
Decommissioning costs (£/MWh)	2	0	0

Table 10: Model input data

Source: DECC (2013b), European Commission (2014b)

On the contrary, the cost of capital could be different in cases when the responsibilities were split between two or more companies. If there are two parties involved, one might be responsible for the development of the nuclear island (and its expanded system) while the other for the development of the turbine island (and its expanded system). Although acknowledging that the pre-development costs, compared to construction costs, are better established in practice, *i.e.* have negligible variability in their costs compared to their construction cost, they are likely to have more risks for not proceeding with the project. If this happens, they can be written off since many risks that involve political and environmental issues, possibility of not getting a contract during allocation rounds or the risk related to not getting the final project approval or not securing insurance, can lift the pre-development risks up to the level of that of the construction phase.

Unlike nuclear stations, pre-development & construction WACC of gas stations is calculated semi-endogenously by hauling cost of capital up by 50 basis points from pre-development & construction phase to their operation phase. This is based on the similar assumptions for offshore wind farms (EWEA, 2013) and solar projects (NERA, 2015). While EWEA points to this 50-basis-point differential only, the survey performed by NERA (2015) shows that there is a perceived risk range of 50-100 basis points for the differential between pre-operation and operation phases in solar projects. Considering that gas stations are more mature technologies than wind and solar, the lower bound of this differentials (*i.e.* 50 basis points), is considered here.

Table 10 presents the input data to the model collected from the mentioned sources. One exception is nuclear construction time, which is assumed to be 7 years in this study instead of 6 as proposed by DECC (2013b) because according to the numbers provided by the European Commission (2014b), Hinkley Point C is going to take longer to build.

Whenever a firm is able to construct a "non-trivial" portfolio – a portfolio that includes all possible non-zero weighted combinations of assets – it commits to it. A firm's cash flow is calculated as the weighted sum of cash flows of all underlying assets. Further, firms repurchase (replace) an asset and continue applying yearly depreciation whenever the asset's operating time expires; residual value RV_i in equation (9) is put at zero. The cost of equity and cost of debt for a generator and a firm are taken as the midpoints of their respective ranges reported by CMA (2015a) (Table 11). It is worth observing that the cost of debt is higher for a generator than for a firm, since it has only a single source of revenue stream, which prevents from counteracting the unfavourable cash flow it might produce during a bad year. In contrast, a firm has different sources of cash flows enabling it to offset one adverse cash flow by another (favourable) one. Since CMA (2015a) does not differentiate between a stand-alone generator and a company which holds a combination of generators, this study assumes a firm's pre-tax cost of debt, cost of equity and tax rate are the same as for the vertically integrated energy companies which hold a portfolio of generation and supply (Table 11).

However, unlike the CMA, this study assumes corporation tax rate of 18% as it targets future British electricity industry, where lower levels of the tax rates will be set; corporation tax rate will decline down to 18% in 2020 (PwC, 2016) (Table 11).

WACC Components	Firm	Generator
Cost of Equity	0.0995	
Pre-tax Cost of Debt	0.055	0.0625
Tax rate	0.18	

Table 11: WACC components

Source: CMA (2015a)

Similar to the previous chapter, the analyses for future industry are performed with a carbon price of 80 £/tonne and a renewable capacity of 22 GW (15 GW of wind and 7 GW of solar). It should be noted that 80 £/tonne allows nuclear to make enough money to be included in the optimal portfolio.

Results and Discussions

Cash flows of a generator (or a firm) are derived when on average it makes a zero economic profit in the risk-neutral case (see Figure 21 and Figure 22 that show the distribution of profits and cash flows of power stations calculated based on the underlying model of this chapter).

As can be seen from Figure 22, nuclear makes huge cash flows compared to gas stations. This is not surprising given its capital-intensive pre-development & construction phases, as investors are guaranteed to have big future cash inflows for their committed significant initial cash outflows. Moreover, despite nuclear cash flows being more volatile compared to cash flows of gas stations, it is the preferred option even for the most risk-averse investors since its cash-flow distribution almost absolutely dominates the cash-flow distributions of gas stations; its coefficient of variation is the lowest of all (Table 12).

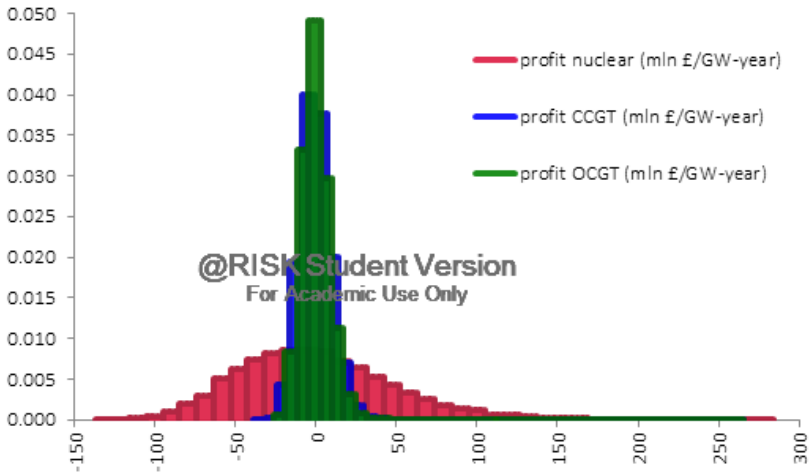

Figure 21: Profit Distributions of Technologies

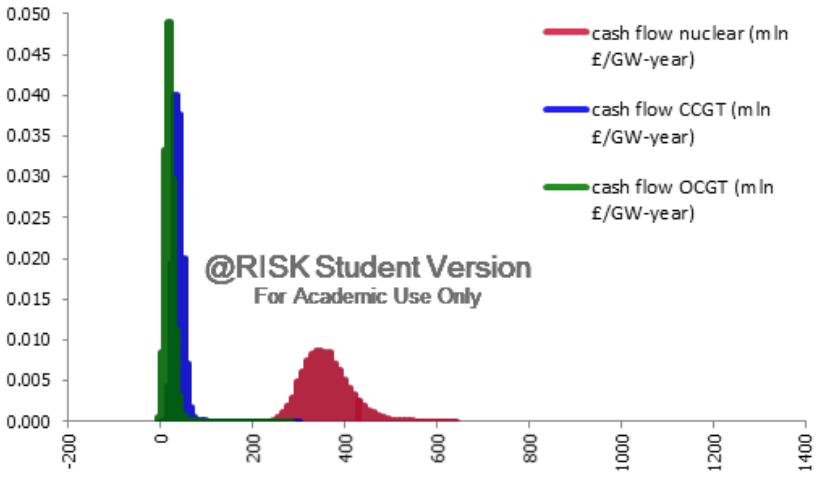

Figure 22: Cash-Flow Distributions of Technologies

In general, whenever there is an absolute dominance, the mean-variance method of ranking the assets in a portfolio may not be precise due to the presence of non-overlapping distributions.

Simulated results	Nuclear	CCGT	OCGT	Firm
Mean of cash flows (£/kW)	360	39	20	34.7
Median of cash flows (£/kW)	355	38	20	33.9
P90 of cash flows (£/kW)	303	27	10	23.5
Variance of cash flows $(£/kW)^2$	2294	106	87	101.9
Mean load factors	1	0.67	0.07	-
Coefficient of variation	0.13	0.26	0.47	0.34
Mean Fixed Costs (£/kW/year)	553	96	48	-

Table 12: Simulation Statistics for Optimal Solutions

Other methods, such as $CFaR_{\lambda}$, VaR_{λ} or $CVaR_{\lambda}$, can be used instead but the *P90-P50* method (Equations (10), (11) and (12)) can also address this issue from the perspective of a financial analyst while sharing some similarities with other risk measures. It is similar to $CFaR_{\lambda}$ whenever the mean and the median of cash-flow distributions are close to each other (see Appendix 3 for CFaR calculation). This near absolute dominance of nuclear cash flow over others is the reason why total operating risk (and WACC) of nuclear is lower than that of the others (Table 12 and Table 13) despite its higher variance around its mean (Table 12). On the contrary, the pre-development & construction risk is higher for nuclear than that of gas stations (3rd column in Table 13).

	Different-WACC Case					One-WACC Case		
	Operation WACC	Construction WACC	Project's Total Lifetime WACC	Capacity (GW)	Debt Share	WACC	Capacity (GW)	Debt Share
Nuclear	0.072	0.108	0.078	17.7	0.57	0.073	24.7	0.56
CCGT	0.084	0.089	0.085	31.6	0.33	0.084	24.6	0.32
OCGT	0.088	0.093	0.089	8.1	0.25	0.088	8.1	0.24
Firm	-	-	-	-	-	0.083	Nuclear – 0 CCGT – 49.2 OCGT – 8.3	0.30

Table 13: Equilibrium WACC, Capacity and Debt Share

DECC's assumed cost of capital (10%) to value the riskiness of projects irrespective of their type and phase should not be used as it is high for the operation phase and low for the pre-

development & construction phases of nuclear projects (it is higher for all phases of gas stations as well) (Table 13).

Since it has been shown that a higher cost of capital favours portfolios of gas stations, and a lower cost of capital portfolios of nuclear stations (Roques, 2008), it is not surprising to see that the cost of capital of 10% brings no nuclear investment and replaces it completely with CCGT (Table 14).

Besides, the 7th column of Table 13 shows that only one WACC for the whole duration of the asset lifetime (endogenously calculated) might not be an accurate measure, although the aim is to show one cost of capital that can reflect the risk from both pre-operation and operation phases. This WACC is calculated when the model's cost of capital for both pre-operation and operation phases have the same endogenous WACC. This endogenously calculated single WACC for the whole lifetime of the asset is biased towards the operation phase as operation dominates pre-operation in duration thus pushing down the cost of capital to the level of the operation WACC and giving the nuclear stations a big advantage over others.

	Equilibrium (GW)	Debt Share
Nuclear	0	-
CCGT	48.6	0.41
OCGT	8.6	0.31
Firm	Nuclear - 0 CCGT – 48.6 OCGT – 8.6	0.40

Table 14: Equilibrium Simulation Results for the Cost of Capital of 10%

Furthermore, this one WACC does not show the pre-development & construction risks of a project. In fact, if we compare invested capacity for cases of different WACC and one WACC, we can observe that nuclear capacity increases by 7 GW when moving from different-WACC case to one-WACC case (5th and 8th columns of Table 13).

One way to show the comparative riskiness of an asset with a single WACC is to combine the equilibrium pre-operation and operation WACCs in such a way that the new WACC would be able to reflect the total riskiness of the asset from the beginning to the end of the asset's lifetime. For example, it can be done through "*project's total lifetime WACC*" defined as the time-weighted WACC across "different" WACCs of the asset (from pre-development to construction and to operation):

$$\text{WACC}_i^l = \frac{W_i^* \tau_i^p + W_i^* \tau_i^c + w_i^* T_i}{\tau_i^p + \tau_i^c + T_i}$$

Here, $WACC_i^l$ is the total project lifetime WACC for technology i; W_i^* is the equilibrium pre-development & construction WACC; w_i^* is the equilibrium operation WACC (see the 4th column of Table 13).

This WACC better represents total riskiness of a technology as a single number; however, it still indicates nuclear is the least risky option when the whole asset lifetime is considered. This shows investors a long-term incentive to acquire nuclear capacity due to its low operation risks. However, the capital-intensive nature of nuclear pre-operation phase hinders its prospects. Indeed, nuclear pre-development & construction risks are high enough to undermine its lower operation risk. This low operation risk is not able to offset the negative impact that the capital-investment risk has brought forth. For this reason, the optimal portfolio contains only 17.7 GW nuclear capacity, which is less than CCGT capacity (5th column in Table 13).

This has an important corollary: pre-development & construction risk (measured with pre-development & construction WACC) is the first most important factor for investments. We can observe this in our example when comparing WACCs during pre-operation and investments; *e.g.* higher pre-operation nuclear WACC brings lower nuclear investments, and lower CCGT pre-operation WACC brings higher CCGT investments. However, this does not mean that the pre-operation WACC is the sole determinant for the investments – it is the first determinant before operation WACC. In order to illustrate this, let us compare solutions of Chapter 3 and Chapter 4 of this thesis (Figure 23).

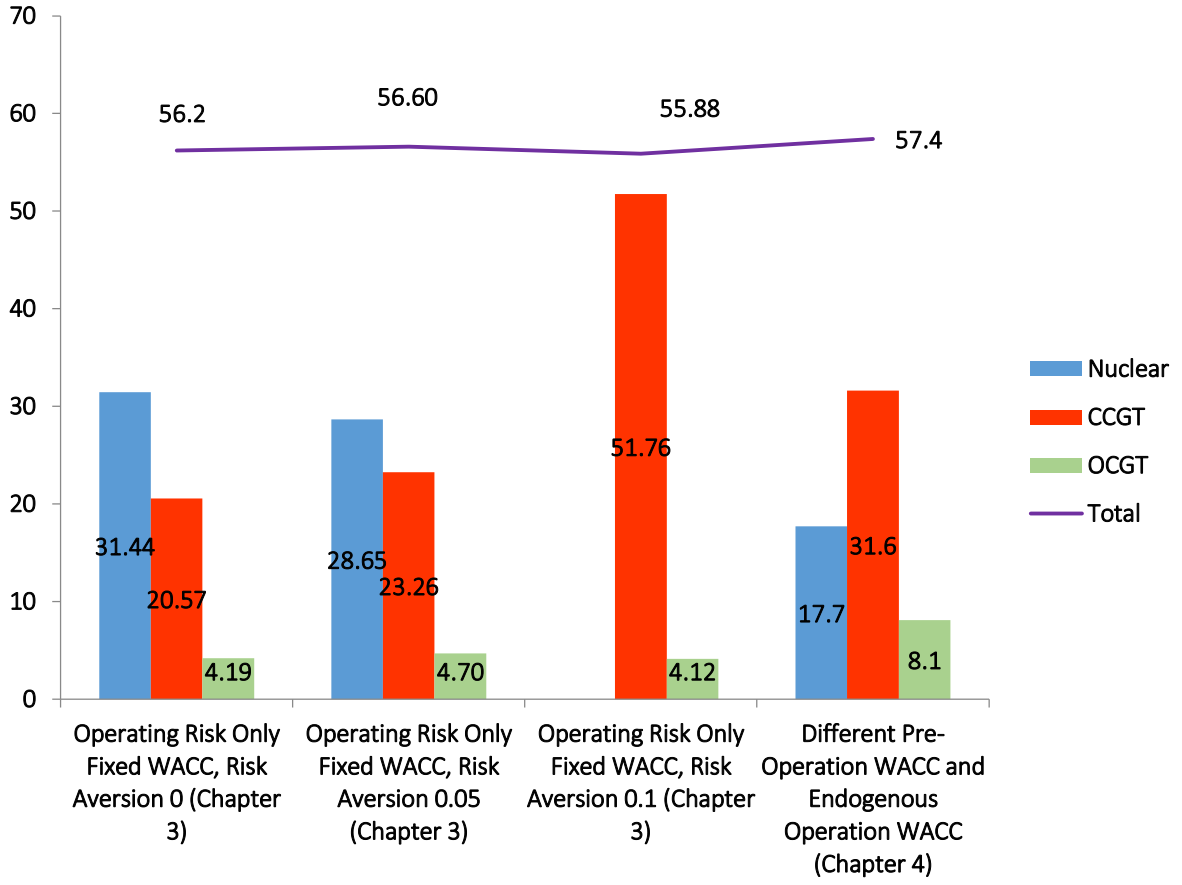

Figure 23: Equilibrium Investments from Chapter 3 and Chapter 4 (CP 80 £/tonne)

We can observe from the Figure 23 that the pre-development & construction risk does indeed change the equilibrium capacity mix in favour of gas stations when comparing with

the risk-neutral case or with the case of risk aversion of 0.05. In Chapter 3, the driving force for investments was operation risk only. In this chapter, it is 1) pre-operation risk and 2) operation risk (this hierarchical order is important).

This implies that excluding pre-development & construction risk overestimates investments in nuclear and underestimates it in others. The risk aversions in the results of Chapter 3 show the investor's risk attitude towards investing in a portfolio (that gives zero portfolio utility) where technologies are subject only to operational risk. The zero-utility portfolio of Chapter 4 is constructed in the risk-neutral case when pre-operation risk and operation risk of the underlying assets are considered.

It is worth mentioning that were a carbon price of 40 £/tonne (low carbon price) modelled here, the model would have rendered less profit distribution for nuclear due to low electricity price distribution. Less profits for nuclear would have rendered less nuclear capacity (and perhaps zero capacity if fixed costs of nuclear were high). If at equilibrium, the level of nuclear capacity turns out to be positive, it will have the highest cash-flow distribution among others as is the case with high-carbon-price. Once more, it would mean that nuclear is preferable in operation risk among other plants. The analogy of the discussion as in the high-carbon-price case will follow from here: operation WACC of nuclear will still be lower than that of gas stations as well as lower than its construction WACC. Therefore, the different-WACC case would yield less equilibrium nuclear capacity than one-WACC case similar to the ones presented in Table 13. This will again imply the construction risk superiority over the operation risk.

The model of Chapter 4 calculates a few more results. As nuclear availability is 85%, it operates as baseload plant due to the fact that the stochastic net demand is always higher than its available capacity (Table 12). However, gas stations have load-factor variability

because they serve the net demand in the merit order whenever this net demand is higher than the available capacity of nuclear (Figure 24 & Figure 25). Figure 24 shows the load factor distribution for CCGT which is confined between 0.64 and 0.71 with the 5th percentile of 0.66 and the 95th percentile of 0.6867. Those numbers are reasonable for mid-merit stations as they are not supposed to operate all the time. Similarly, the load factor of OCGT stations (Figure 25) is confined between 0.045 and 0.1 with a 5th percentile of 0.05983 and 95th percentile of 0.07892. This is again not surprising to see OCGT operate very few hours during the year as it acts as a peak-load plant. It should be noted that those figures do account for availability, i.e. they are load factors for the available capacity of technologies. Availability for thermal plants is assumed to be 85% each. Expected load factors are 0.67 and 0.07 for CCGT and OCGT respectively (see 6th row in Table 12). These load factor distributions are used to calculate the levelised cost of electricity as well as the fixed cost of each technology.

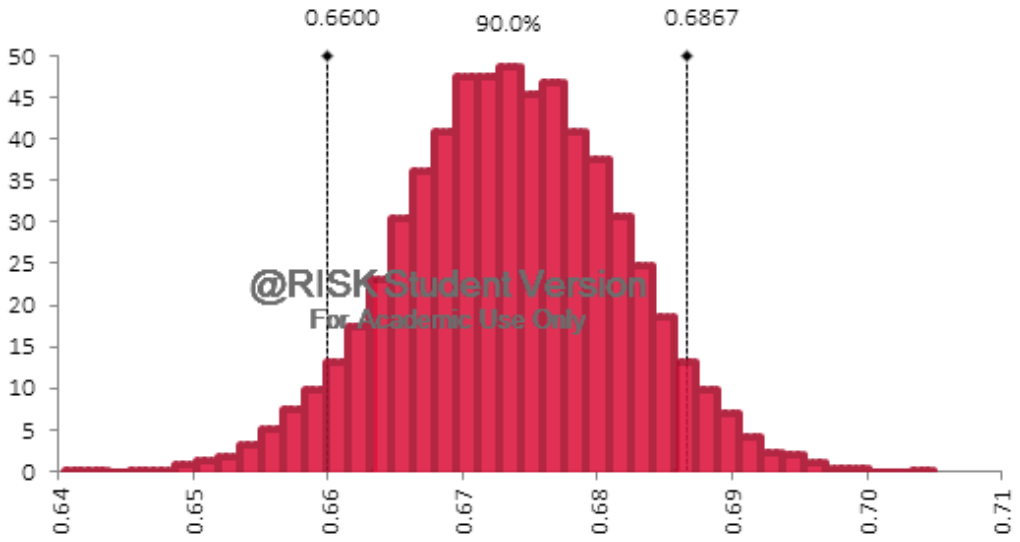

Figure 24: Load-Factor Distribution of CCGT

In addition to all the analyses performed above, a separate looping is performed for a firm, since it has a lower cost of debt than individual technologies. A firm has a cash flow as the

weighted sum of cash flows of its portfolio assets. Optimal portfolio for a firm contains no nuclear (Table 13) as the obtained single cost of capital (0.083) is too high for nuclear.

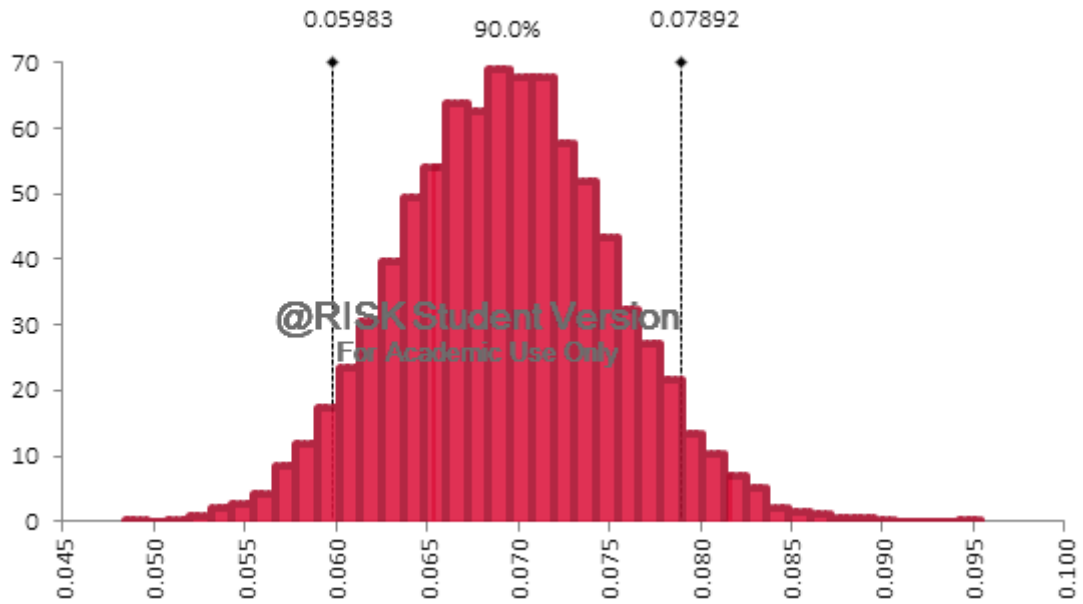

Figure 25: Load-Factor Distribution of OCGT

Consequently, if we were to use the DECC's cost of capital of 0.1 for a firm, we would have underestimated its ability to include more total capacity in the mix and overestimated its ability to take more debts (Table 13 and Table 14).

Conclusion of Chapter 4

This chapter assesses the extent to which greater cash-flow risks lead to a lower debt-equity ratio and a higher cost of capital during operation, and how far this reduces investment. Specifically, it shows that cash-flow risks have a noticeable effect on the operation cost of capital. The project total lifetime cost of capital, calculated as the time-weighted average cost of capital across pre-operation and operation periods, is introduced as a measure of the relative riskiness of a project from start to finish. However, it should be used with a caution, as it does not explain the difference in capacity investments. In fact, capacity investments are

influenced firstly by the cost of capital during pre-development & construction phase and secondly by the cost of capital during operation phase for a given carbon price level. The cost of capital during pre-operation phase is important, as investors are not inclined to commit to risky development projects, whereas the cost of capital during operation phase is important too as investors do not like cash-flow volatility and therefore constrained finances.

In addition, the average level of cash flows (and hence the proportion of fixed costs) is as important as their variability, *i.e.* coefficient of variation is a better measure of riskiness across assets than the comparison of their respective mean and variance when ranking the assets in a MV framework. The results of this study could seem counter-intuitive at first as it finds that nuclear becomes the least risky option among all technologies in terms of operation. This happens partly because a high level of carbon price (80 £/tonne) is considered in order to make nuclear profitable. No scenario analysis around carbon price is performed as it is assumed that carbon price is known a priori. The study finds also that the operation WACC is the second trigger for investment after pre-development & construction WACC. This implies that nuclear long-term contracts do insure nervous investors against political risk and allow governments the possibility to offer above-market prices to favoured generators, but the benefits of insurance against normal cash-flow risks (and total lifetime risk) of nuclear may have been exaggerated. The key problem the investors face with a nuclear project is its high pre-operation risk triggered by its high capital requirements and complex arrangements.

This study also suggests that if there were no pre-operation risk, then the optimal portfolio would favour nuclear (which is expected as carbon price is high enough) because it has the lowest cost of capital or, in other words, because it has the lowest coefficient of variation. This implies we should not use MV approach to find the equilibrium investments when cash

flows are considered as MV ranks the underlying assets based on their profit's mean *minus* risk-adjusted variance, whereas the methodology proposed here ranks the assets based on their profit's standard deviation *divided* by the mean. Of course, depending on the optimisation problem, they may often bring the same solutions but there can be cases that the solutions differ.

In future research, it is important to include adjustable cost of debt and cost of equity. When cash flows become volatile, while projects are able to secure debt financing, debt rates may go up in line with cash-flow risks. On the other hand, if projects have a less cash-flow risk, which allows them to take more debts, the systematic risk of that type of projects goes up which leads to a higher cost of equity. All these interrelationships should be considered when adjusting the cost of capital at each model loop.

Additionally, it would make analyses more thorough if a sensitivity analysis on lower tax rates for nuclear were considered when it can benefit from lower effective tax rates due to capital allowances. In addition, incorporating tax credits into the calculations of tax rate could be another avenue of future research.

CHAPTER 5: Energy Storage Profit Risk under Stochastic Fuel Prices

Introduction

The primary focus of this chapter is to analyse profit risk faced by short-term diurnal electricity storage facilities when they utilise hourly electricity price variations to make arbitrage profit and provide operating reserve. Future British electricity industry will face high shares of renewables that will introduce a volatile system detrimental for the electricity grid. The Capacity Mechanism tailored with a policy might be in place to ensure a security of electricity supply to consumers. Although this could be done in different ways, one way is through massive deployment of storage (Grünwald *et al*., 2011). In this study, storage profit risks are calculated based on arbitrage and reserve provision. Income from any other services, the impact of large-scale storage on conventional generating capacity and the overall cost and viability of storage, are beyond the scope of this study.

Storage can be a profitable investment option if enough policy incentives are provided in the near future. There are clear potential benefits from utilisation of storage such as significant reduction in carbon emissions (Edmunds *et al*., 2014) or cutbacks of annual system costs of more than £10 billion in 2050 (Strbac *et al*., 2012). Besides, not only can energy storage balance supply and demand in the grid, but also benefit from intra-hour arbitrage opportunity providing also, among others, energy frequency response, operating reserve and power & voltage stabilisation.

There are many power system optimisation models that include energy storage. In particular, there are some studies which include future fuel price scenarios to calculate arbitrage revenue of storage. For example, Dunbar *et al*. (2016) use merit-order stack model to calculate arbitrage revenue using “Gone Green” scenario by National Grid. However, to the

best of the author's knowledge, there is no model that includes a detailed distribution of fuel prices to model their impacts on profits of storage.

This chapter introduces a simulation optimisation model, developed on the model of Green & Staffell (2015) which combines the electricity dispatch module[21] (to generate hourly prices and operating patterns of technologies) and the investment module (to find the long-run equilibrium capacity mix). The dispatch module of this chapter re-runs the model in a Monte Carlo simulation setting to find the impact of fuel price variation. The dispatch module uses marginal-cost supply function (with operating reserve requirement) to get hourly electricity prices. A storage facility is included in this model enabling it to charge and discharge whenever needed to make an arbitrage profit and provide a reserve in the short run. The investment module finds the competitive capacities when all type of generating technologies are making close to zero economic profit. This model, compared to the models of Chapter 3 and Chapter 4, includes more technologies – more types of nuclear, CCGT and OCGT plants as well as biomass plant and coal plant with carbon capture and storage (CCS) facility.

The impact of fuel prices is simulated using endogenous electricity prices, by carrying out repeated runs with different levels of fuel price to estimate profits of technologies. This creates distributions of the profits faced by storage provider and by generators of different kinds similar to the discussions in Chapter 3 and Roques *et al.* (2006).

The results indicate storage has no correlation with yearly average gas price in the low renewable case. However, we observe low but significant positive correlation when storage energy capacity is increased or when renewable capacity goes up. The main source of storage revenue is electricity price risk, which is utilised for arbitrage and reserve provision. It is shown profit risks are reasonably low around their mean. However, since there is uncertainty

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[21] The module includes such technical constraints as ramping, start-up and no-load costs.

around their capital costs, the profits from arbitrage and reserve provision may not suffice to cover those costs. Additionally, this study finds that storage profit positively correlates with profits of other stations, especially with gas stations. However, this correlation lessens with the penetration of more renewables.

Contextual Literature Review

There are three types of electric energy storage technologies – electrical, electrochemical and mechanical - that vary in size and functionality (Luo et al., 2015). Energy storage can be of any size, and its size and operating pattern can affect the electricity price. For example, high-energy supercapacitors are electrochemical direct storage technologies that provide fast response to the system and are generally less than 100 kW in size. On the other hand, pumped hydro storage is a mechanical storage that provides a slow response but fast enough compared to most power stations. Sioshansi *et al.* (2009) demonstrated storage device could influence electricity prices if it is big enough (*e.g.* greater or equal than 1 GW for PJM[22]) thus altering prices while making arbitrage profit. They also showed that fuel prices have a significant impact on arbitrage value of marginal storage (Sioshansi *et al*., 2009).

As long as there will be a high level of renewable technologies in the future, they will affect the arbitrage profit of storage. Dunbar *et al*. (2016) showed that massive deployment of renewables suppresses electricity price jumps, therefore, diminishing arbitrage opportunities. However, apart from getting arbitrage revenue and providing system balance, storage is also able to increase its revenue stream via additional services. For example, batteries (*e.g.* li-ion, flow, lead-acid, nickel-metal hydride or nickel-cadmium) and supercapacitors (*e.g*. high-energy or high-power) are fast responsive devices used for frequency regulation (see *e.g*. Ekman *et al*., 2010). Staffell & Rustomji (2016) showed that storage can indeed expand its

[22] PJM interconnector organises the transmission of the wholesale electricity across many states in the USA ranging from Illinois to New Jersey.

revenue exposure; with a single algorithm, based on the models of Lund *et al*. (2009) and Connolly *et al*. (2011), they showed that storage revenues could be increased as much as threefold when providing both reserve and arbitrage. However, they find storage is not economical from an investment point of view suggesting other revenue streams or cost reductions would be necessary to evaluate the viability of its role in the future technological mix.

While round-trip efficiency is very important, its detailed modelling depends on the particular problem aims. Some models, similar to this one, use fixed round-trip efficiency (Figueiredo & Flynn, 2006; Black & Strbac, 2006) whereas others use time-dependent round-trip efficiency (Barbour *et al*., 2012; Bruce *et al*., 2016; Bruce *et al*., 2014). The round-trip efficiency – in the context of time dependency – can be described via a function of charge and discharge that changes depending on time and the required level of storage output. Not only time-dependent round-trip efficiencies are different, but also there is a big difference in technology-dependant round-trip efficiencies as this efficiency can be the smallest in hydrogen batteries (around 45%) and the biggest in super capacitors (around 92%) (Staffell & Rustomji, 2016). However, this chapter does not require detailed modelling of time-dependent or technology-dependant round-trip efficiency as it includes one representative storage without technological characteristics pertaining to granular levels of any engineering design.

Zakeri & Syri (2015) updated cost data of storage and performed uncertainty and sensitivity analysis on the levelised cost of storage electricity. They also analysed various components of total capital and life cycle cost and found that median total capital costs are among the

highest for Hydrogen-FC (2950 £/kW) and ZEBRA (3072 £/kW)[23] technologies while average annualised life-cycle costs are among the highest for nickel-cadmium batteries (766 £/kW/y), vanadium-redox flow batteries (642 £/kW/y) and lead-acid batteries (588 £/kW/y)[24]. However, the levelised cost of electricity is the highest for lithium-ion batteries (561 £/MWh). Since storage cost structures are not yet economical from an investment point of view, policy becomes a huge factor in promoting storage technologies. Although storage can benefit from revenues from reserve provision and arbitrage, it seems that they will not be enough to cover their capital costs. However, some mature storage technologies such as pumped hydro have secured their place in the portfolio mix with a pre-tax hurdle rate of 8.4-10.3% and post-tax nominal hurdle rate of 8.4-10% (NERA, 2015). In contrast, new types of storage devices are still struggling to penetrate because of their high investment and policy risks. However, policies directed to promoting storage technologies are crucial not only for storage but for the whole system. One such an example can be found in Strbac *et al*. (2012), where they performed scenario analyses of system savings for a different combination of installed storage capacity and found that should storage cost decline in line with their massive instalments, marginal system savings would also drop.

The value of storage can be defined as the amount of system cost savings credited to storage (Strbac *et al.*, 2012, Del Granado *et al*., 2016) or the amount of revenue it produces based on electricity price fluctuations (Sioshansi *et al*., 2009; Dunbar *et al.*, 2016). The value of energy storage can vary as much as 22-330 £/kW; many papers use exogenous electricity price forecasts to evaluate this value (Dunbar *et al*., 2014; Lund *et al*., 2009; Khani *et al.*, 2014). The range of value of storage is such a high number because some devices are not only used for

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23 Euro/GBP exchange rate of 0.91 as of 11/10/2016.

24 Those numbers are for bulk energy storage technologies that have 8 hours of discharge time, 250 cycles per year and interest rate of 8%.

energy arbitrage but also for frequency regulation or provision of power in case of unplanned plant shutdowns or blackouts (Denholm *et al*., 2010).

Fuel prices, operating costs and storage value are related. Strbac *et al*. (2012) showed in their scenario analyses that high fuel prices increase storage value (mostly due to savings in operating costs) while low fuel prices decrease it as operating technologies become cheaper options to satisfy the system needs.

There are many studies on the profitability of energy storage as well. For instance, Ekman & Jensen (2010) concluded that electricity spot prices were not volatile enough in Denmark to provide an opportunity for arbitrage profit of storage. In their study, they assumed only a marginal amount of storage. Together with electricity price volatility, the perfect foresight of this price patterns is necessary for storage revenue to schedule its charge and discharge patterns of operation. For instance, Dunbar *et al*. (2016) found that high wind penetration induces great variability of low electricity prices and narrows down the proportion of high price spikes pivotal for storage revenue.

Model and Data

1. Profit-Store Model[25]

SETS

Set of all generators	$g \in G, g = \overline{1, \bar{g}}$
Set of consumer (pseudo) generators	$c \in C, C \subset G$
Set of storage generators	$b \in B,\ B \subset G$
Set of real generators	$r \in R, R = G \backslash C$
Set of pure generators	$p \in P, P = R \backslash B$

[25] You can find the GAMS code in the following link:
https://gist.github.com/vitali87/1153cd8c3df25477083dc3f3d772fa17

Set of demand clusters	$\bar{d} \in D, d = \overline{1,\bar{d}}$
Set of hours in a day (cluster)	$t = \overline{1,24}$
Index of random fuel price	$j = \overline{1,\bar{j}}$
Index of year	$y = \overline{1,\bar{y}}$
CAPACITY	
Capacity of generator g (GW)	Cap_g
Online capacity of generator g on day (cluster) d at hour t (GW)	O_{rtd}
Capacity of type g generator started on day (cluster) d at hour t (GW)	$\overline{w}_{gtd}$
Capacity of type g generator shut down on day (cluster) d at hour t (GW)	$\underline{w}_{gtd}$
Storage availability in generator b on day (cluster) d at hour t (GWh)	L_{btd}
GENERATION	
Minimum power requirement of generator g	$\underline{\rho}_g$
Start-up time of generator p (hours)	τ_p
No-load fraction of generator p	ϱ_p
Average thermal efficiency of generator p	η_p^a
Incremental thermal efficiency of generator p	η_p^i
Output of generator g on day (cluster) d at hour t (GWh)	u_{gtd}
DEMAND	
Consumption of storage generator b on day (cluster) d at hour t for fuel index j (GW)	S_{btdj}
Proportion of cluster d in year y	β_{yd}
Net demand on day (cluster) d at hour t (GWh)	D_{td}

COST

Operating fuel cost of generator p for fuel index j (£/MWh)	f_{pj}^{o}
Start-up fuel cost of generator p for fuel index j (£/start)	f_{pj}^{s}
No-load carbon emissions of generator p (kg/MW/h)	ζ_{p}^{n}
Carbon emissions on start-up of generator p (kg/start)	ζ_{p}^{s}
Incremental carbon emissions of generator p (kg/MWh)	ζ_{p}^{i}
Variable operations and maintenance cost of generator p (£/MWh)	c_{p}^{om}
No-load cost of generator g for fuel index j (£/MW/h)	c_{gj}^{n}
Start-up cost of generator g for fuel index j (£/start)	c_{gj}^{s}
Incremental cost of generator g for fuel index j (£/MWh)	c_{gj}^{i}
Total operating cost of generator g on cluster d at hour t for fuel index j (million £)	c_{gtdj}

RESULTS

Shadow price[26] of electricity demand (£/MWh)	λ_{d}
Shadow price of operating reserve (£/MWh)	λ_{r}
Revenue of generator g at year y for fuel index j (million £)	v_{ygj}
Profit of generator g at year y for fuel index j (million £)	π_{ybj}

MISCELLANEOUS

Spinning reserve requirement (GW)	Q
Carbon price (£/MWh_e)	φ

Table 15: Nomenclature of the model elements (decision variables are in green)

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[26] Shadow price (marginal price of the electricity demand) is the Lagrange multiplier associated with the equation of the electricity demand. It represents the change in total cost attributed to the change in the right hand side of the demand equation (for more information on Lagrange multipliers and duality, refer to Luenberger & Ye (2016)).

The Profit-Store model is derived from the Unit Commitment Capacity Optimiser (UCCO) developed by Staffell & Green (2012). UCCO model is a mixed integer problem with individual generating plants but the Profit-Store model is a linear model with continuous capacity. Both models include start-up, no-load and incremental costs and minimise the total cost of meeting national electricity net demand for a specified time period allowing some generating capacity to switch on and off at each time interval to meet demand and reserve requirement in a least-cost manner. The model solves for representative days (clusters) found by k-means clustering method (for more thorough discussion, refer to section 3 of this chapter). Solving the model for the day-by-day operation of the storage is appropriate for a short-term storage; however, it will not be for seasonal storage technologies.

A year comprises distinct weighted combinations of 150 clusters, and these combinations distinguish inter-annual variability of each year. Weights are computed based on the number of appearances of that cluster in a given year, therefore it is possible for some clusters to have zero weights in that year.

Figure 26 conceptualises the dispatch module of the Profit-Store model. Generators' input data (*stage 1*) include all generating capacity found during the pre-dispatch module. When renewable capacity is low, investment module represents a scenario where all technologies have enough capacity to make a near-zero economic profit. When renewable capacity is high, the capacity of each technology is adjusted to reflect the similar level of pre-fixed-cost profits obtained during the low-renewable case (Table 16).

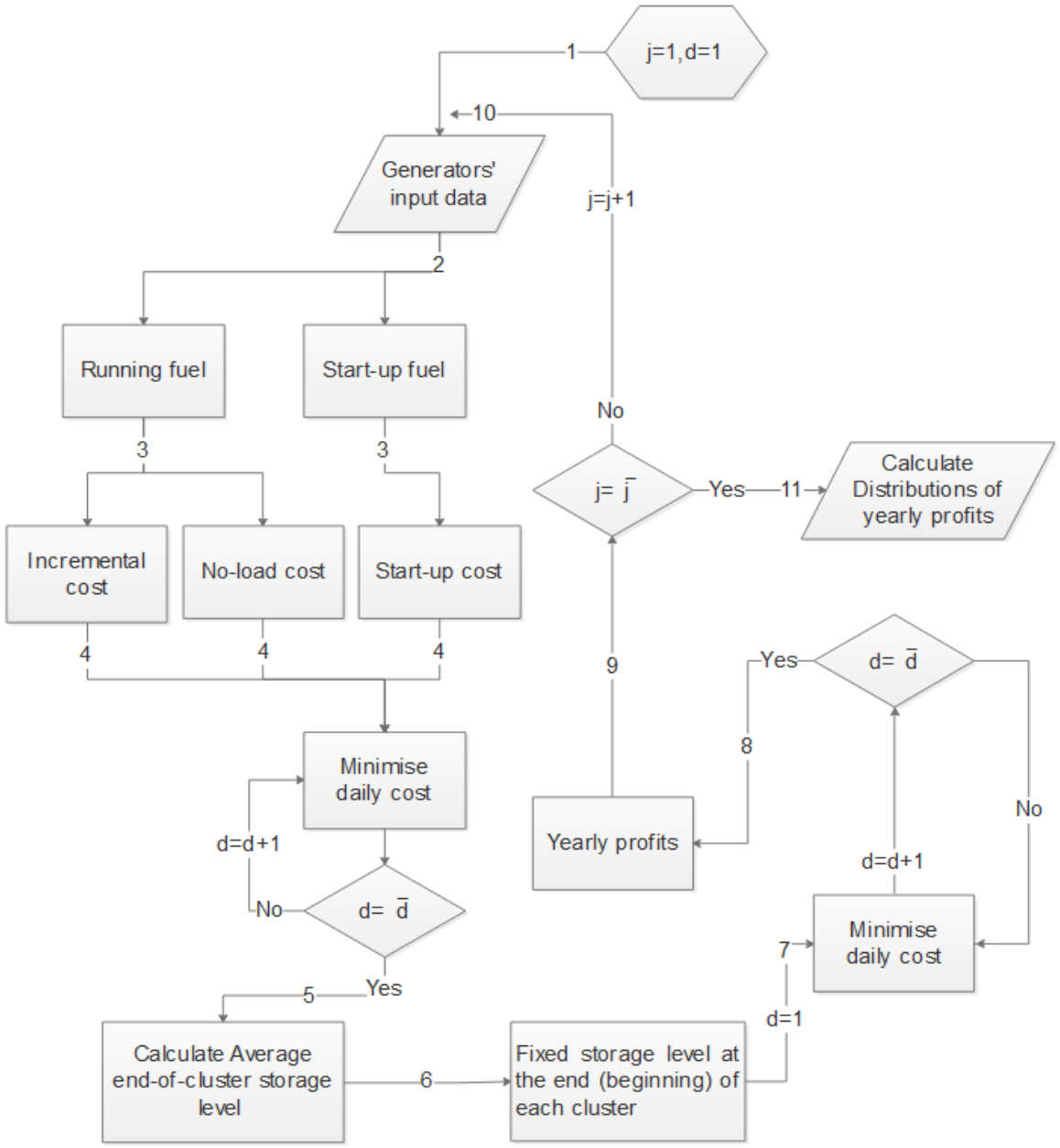

Figure 26: Flowchart of Dispatch Module of Profit-Store Model
Source: The author

Stage 1 includes minimum power requirement, fixed, no-load, incremental and start-up costs as well as no-load, incremental and start-up carbon emissions. Random fuel prices (the detailed modelling is presented in section 4 of this chapter) are generated based on DECC's high, central and low scenarios (DECC, 2013a). Upon generation, they feed into stage 2 of the dispatch module (Figure 26). Average efficiency, no load fraction, incremental efficiency (defined as the ratio of average efficiency and 1 minus no-load fraction) and variable

operation and maintenance costs are also included in order to update no-load, incremental and start-up costs (*stage 3*) via running and start-up random fuel costs (*stage 2*). Next, the optimisation model is run for $\bar{d}$ times (*stage 4*) to calculate the average end-cluster level of storage across all clusters (*stage 5*) for the current fuel price. Since the problem is to calculate the yearly profit of storage, the end (beginning) level of storage is approximated with its average level across all clusters (*stage 6*). This is done to avoid cluster-to-cluster (*i.e.* day-to-day) jumps of the start/end level of storage enabling the model to optimise for one cluster at a time (*stage 7*) via constraining all start/end levels of storage to its average level. After optimising for all clusters, yearly profits of technologies are calculated (*stage 8*).

This method reduces the original problem significantly; 150 weighted clusters (representative days) are used instead of 13*365+4*366=6209 distinct daily profiles of 17 years.

This chapter considers a scenario with five technologies (nuclear, coal-CCS, CCGT, biomass and OCGT) where overall conventional installed capacity (with spinning reserve) is around 62 GW (7 GW solar, 5 GW onshore and 10 GW offshore wind), and individual technologies are making near-zero economic profits contingent on average fuel prices (Table 16).

	Low renewables		High renewables	
Technology (1st sub-category for each)	*Installed Capacity (MW)*	*Profit before fixed cost (£/kW-year)*	*Installed Capacity (MW)*	*Profit before fixed cost (£/kW-year)*
Nuclear	9022	509	9500	496
Coal-CCS	4522	263	4200	253
CCGT	33729	85	32000	81
Biomass	9544	19	8500	33
OCGT	5509	68	3000	73
Overall	*62326*		*57200*	

Table 16: Pre- and post-renewable installed capacities and profits

For differentiation purposes, 3 sub-categories of nuclear, coal-CCS, biomass and OCGT, as well as 15 sub-categories of CCGT generators, are added, and they all differ mainly in their efficiency rates.

High renewable scenario (14 GW solar, 10 GW onshore and 20 GW offshore wind) of the right side of Table 16 was obtained during multiple runs of the model when capacities of pure generators were adjusted based on their profit levels derived from the average fuel prices. If during the high-renewable case a generator made a profit different from the low-renewable case, its capacity was adjusted and the model was run again. This process was iterated until similar levels of profits (before fixed costs) were obtained (Table 16). After this stage was complete, dispatch module of the model (Figure 26) was initiated where the equilibrium installed capacity of each type of generator was inputted into the model.

The Profit-Store model has technical constraints which are included to mimic the actual engineering characteristics of technologies. For example, there are minimum power requirements for each type of generator beyond which it shuts down. The system spinning reserve requirement is 3 GW, which is used to provide balancing of any supply disruptions on the load.

Nuclear acts as a baseload technology and runs throughout a year. If there is an excess electricity production from wind coupled with low demand, wind electricity is spilt out to prevent an expensive nuclear shutdown. On the other side, demand response is modelled (from commercial and residential sectors) with the help of price spikes that act as an offsetting mechanism against demand increase. The load is shed (at great expense) when generation and operating response cannot satisfy existing demand. Storage technology is modelled to have 5 GW of power capacity and 4 GWh (and 20 GWh) of energy capacity with a fixed roundtrip efficiency of 0.9.

2. Mathematical Model

Output by all generators goes to demand and rechargeable storage:

$$\sum_{g=1}^{G} u_{gtd} = D_{td} + \sum_{b=1}^{B} S^{I}_{btd}, \forall t, d \tag{14}$$

Storage cannot absorb more than its energy capacity:

$$0 \leq S^{I}_{btd} \leq \text{Cap}_{b}, \forall b, t, d \tag{15}$$

Capacity online is at least demand level plus operating reserve but price-based demand response reduces demand level:

$$\sum_{r=1}^{R} O_{rtd} \geq D_{td} + Q - \sum_{c=1}^{C} u_{ctd}, \forall t, d \tag{16}$$

There are maximum and minimum capacity requirements for all plants at each point in time:

$$\underline{\rho}_{r} O_{rtd} \leq u_{rtd} \leq O_{rtd}, \forall r, t, d \tag{17}$$

$$O_{gtd} \leq \text{Cap}_{g}, \forall g, t, d \tag{18}$$

Online storage capacity cannot exceed storage availability of previous period:

$$O_{btd} \leq L_{b(t-1)d}, \forall b, t, d \tag{19}$$

Generators can start and shut down at each period:

$$\overline{w}_{gtd} \geq \begin{cases} O_{gtd} - O_{g(t-1)d}, \forall g, t, d \\ 0, \qquad\qquad \forall g, t, d \end{cases} \tag{20}$$

$$\underline{w}_{gtd} \geq \begin{cases} O_{g(t-1)d} - O_{gtd}, \forall g, t, d \\ 0, \qquad\qquad \forall g, t, d \end{cases} \tag{21}$$

The hourly changes of storage level are described with the following equations:

$$L_{btd} = L_{b(t-1)d} - u_{btd} + S^{I}_{btd}\eta_{b}, \forall b, t, d \tag{22}$$

$$0 \leq L_{btd} \leq \text{Cap}_{b}, \forall b, t, d \tag{23}$$

The no-load, start-up and incremental costs are modelled through random fuel prices[27]:

$$c_{pj}^{n} = \frac{f_{pj}^{o}}{\eta_{p}^{a}} \varrho_{p} + \varphi \zeta_{p}^{n}, \forall p, j \tag{24}$$

$$c_{pj}^{s} = \frac{1}{\eta_{p}^{a}} \tau_{p} f_{pj}^{s} + \varphi \zeta_{p}^{s}, \forall p, j \tag{25}$$

$$c_{pj}^{i} = c_{p}^{om} + \frac{f_{pj}^{o}}{\eta_{p}^{i}} + \varphi \zeta_{p}^{i}, \forall p, j \tag{26}$$

The generation cost at each point in time equals the sum of no-load cost, start-up cost and incremental cost of technologies:

$$c_{gtdj} = c_{gj}^{n} O_{gtd} + c_{gj}^{s} \overline{w}_{gtd} + c_{gj}^{i} u_{gtd}, \forall g, t, d, j \tag{27}$$

The objective function minimises the sum of all no-load, start-up and incremental costs from all generators:

$$Min \sum_{d=1}^{\bar{d}} \sum_{g=1}^{\bar{g}} \sum_{t=1}^{24} c_{gtdj}, \forall j \tag{28}$$

Electricity price in each hour is calculated as a sum of a shadow price of meeting demand (14) (λ_d) and a shadow price of meeting spinning reserve requirement (16) (λ_r). Storage makes profit both from arbitrage and reserve provision, yet other generators make revenue only from generation[28]. It is worth pointing out that shadow prices (and therefore electricity price) are derived from the equations (14) and (16) where the storage participates as a consumer and a generator. Therefore, the storage, as well as other generators, contributes to shaping the electricity price.

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27 NB: $c_{bj}^{s} = 1$, $c_{cj}^{s} = 0$ and $c_{bj}^{i} = 0$ for $\forall j$

28 It is acknowledged that pure generators could also benefit from reserve provision (*i.e.* earn $(O_{ptd}^{*} - u_{ptd}^{*})\lambda_r$ for each hour) but it is not included in the model; in very few cases capacity online is greater than output for pure generators thus bringing very small additional revenues.

$$v_{ypj} = \sum_{d=1}^{\bar{d}} \beta_{yd} \sum_{t=1}^{24} (u^*_{ptd}\, \lambda_d) \tag{29}$$

$$v_{ybj} = \sum_{d=1}^{\bar{d}} \beta_{yd} \left(\sum_{t=1}^{24} (u^*_{btd} - S^*_{btdj})\lambda_d + L^*_{btdj}\lambda_r \right) \tag{30}$$

$$\pi_{ygj} = v_{ygj} - \sum_{d=1}^{\bar{d}} \beta_{yd} \sum_{t=1}^{24} c_{gtdj} \tag{31}$$

3. Clustering of Demand Data

Before the optimisation model is solved, clustering of 17-year hourly net demand data (1995-2011) into 150 representative days is performed. A "representative day" (a cluster) is computed via combining similar days into one "day" to get a daily pattern while preserving some characteristics of the included days. Hourly demand data are taken from the National Grid website (National Grid, 2016). The objective of clustering is to reduce the computational time of the model. Acknowledging the fact that too much reduction of a number of days into clusters might undermine the variability of daily demand and load structure, 150 clusters were chosen to get a realistic picture of the British electricity load (Figure 27). It is worth mentioning that the storage makes money on hourly variations of electricity price via arbitrage and by providing reserve on each representative day – it is a diurnal storage as opposed to seasonal. Since the beginning level of storage is fixed on every representative day, it does not matter which days are put in succession in the optimisation model, since the daily storage profit is optimised based solely on the daily demand profile of a given representative day. Once profits of daily energy storage are optimised, it is easy to calculate yearly energy storage profit as a weighted sum of those daily energy storage profits.

k-means demand clustering methodology is carried out as described in Green *et al*. (2014) to reduce the number of days from 6209 (for 17 years) into 150 clusters[29].

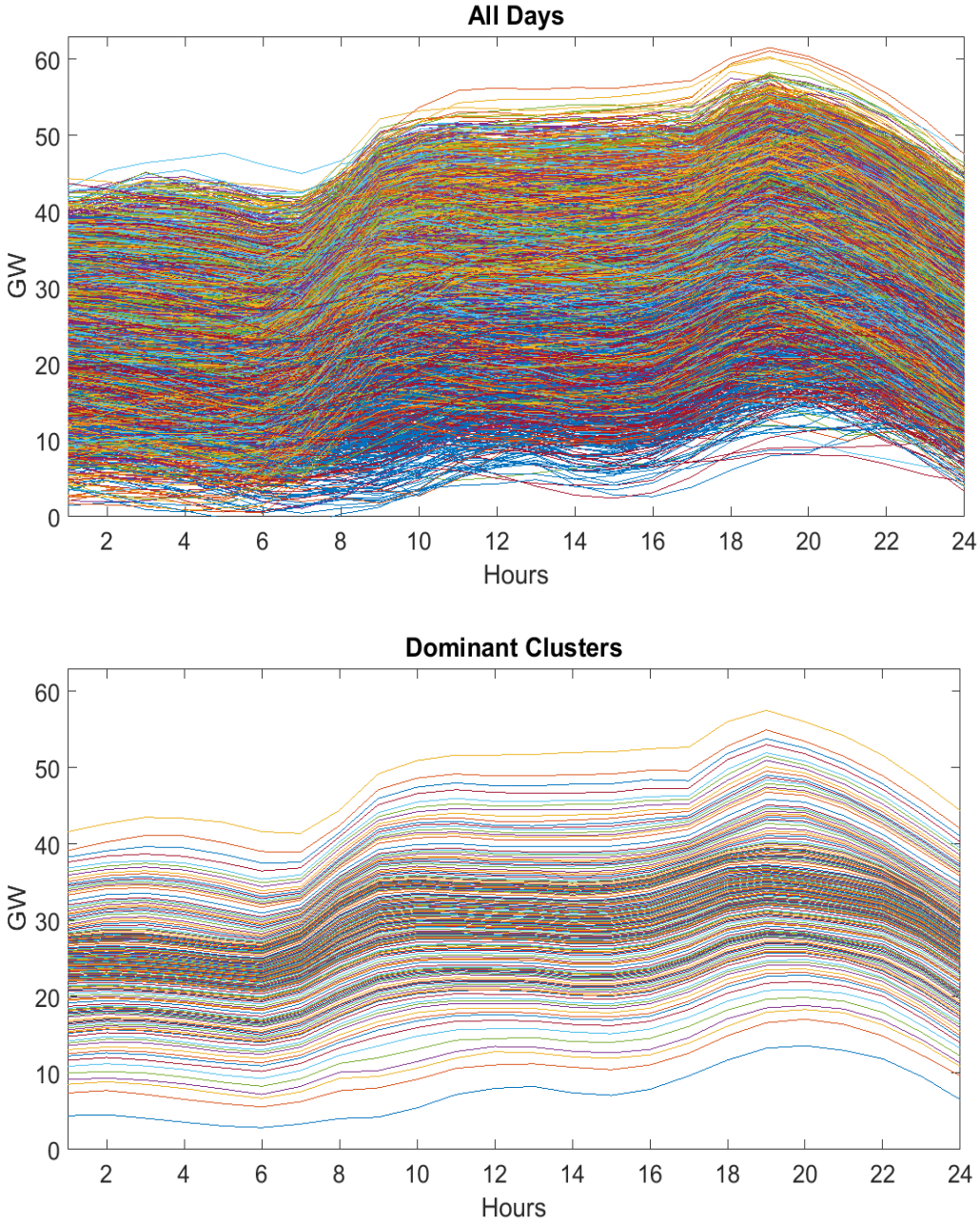

Figure 27: Results from Dominant Clustering Method

Green *et al*. (2014) report that there are several ways to cluster demand: cluster centroid; representative day within a cluster; random day in a cluster; filtered days in a cluster; simple average in a cluster; dominant hourly changes and common hourly changes in a cluster. It is

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29 You can find the MatLab code for cluster generation in the following link: https://gist.github.com/vitali87/433ea55e514f7d4a503578f1b6c088d0

shown by them that the latter three methods provide more accurate results than the others. Hence, dominant profiling method was chosen for the calculations of this chapter (Figure 27). At the core of dominant profile lie the changes between subsequent hours of a day in a cluster. When a subset of days in a cluster for a specific hourly change has the same sign as the mean hourly change, they are called "dominant" days. The hourly profile within a cluster is produced by taking the average of hourly changes for each column of hourly changes across all "dominant" days. This principle is applied to all 23 columns of the matrix of hourly changes to get all hourly profiles of a cluster.

4. Correlated Fuel Prices

Correlations among fuel prices were calculated with the help of Gaussian Copula[30]. It produces correlated variables very close to their respective theoretical values as can be seen from simulated cross-correlations, simulated means and standard deviations (Table 17) as well as from bivariate correlation plots (Figure 28, Figure 29 and Figure 30) and multivariate correlation plot (Figure 31).

	Theoretical Correlations		
	Gas	*Oil*	*Coal*
Gas	1.00	0.94	0.84
Oil	0.94	1.00	0.85
Coal	0.84	0.85	1.00

	Simulated Correlations		
	Gas	*Oil*	*Coal*
Gas	1.00	0.94	0.84
Oil	0.94	1.00	0.86
Coal	0.84	0.86	1.00

	Theoretical Mean	Simulated mean	Theoretical SD	Simulated SD
Gas (£/MWh$_{th}$)	14.95	15.05	3.09	3.03
Oil (£/MWh$_{th}$)	44.91	45.10	5.98	5.90
Coal (£/MWh$_{th}$)	11.00	11.03	1.04	1.02

Table 17: Theoretical and Simulated Fuel Price Data

The theoretical correlation between gas and oil prices is approximated based on correlations of yearly average prices of natural gas from UK Heren NBP Index and BP crude oil. However,

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30 You can find MatLab code for random fuel price generation in the following link: https://gist.github.com/vitali87/b89d837d59a7f9a533141bc280ff2e1e

the correlations between gas, oil and coal prices are very similar across indices (apart from North American indices of Alberta and Henry Hub) (Table 31 in Appendix 4) thus, there would have been no practical difference in the choice of index for the correlation analyses.

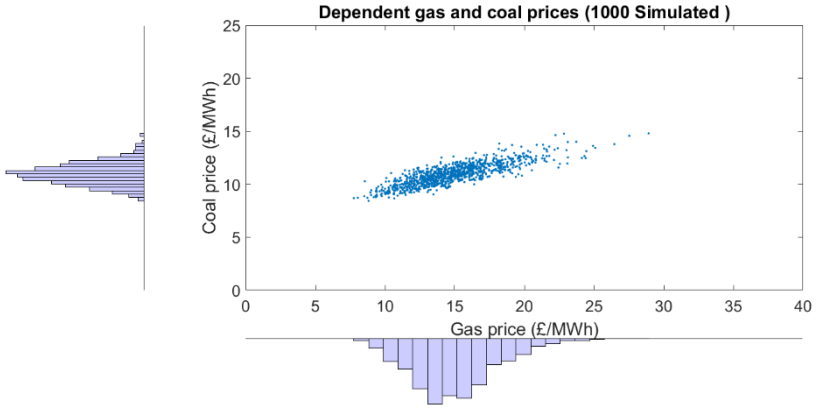

Figure 28: Bivariate correlation between gas and oil prices

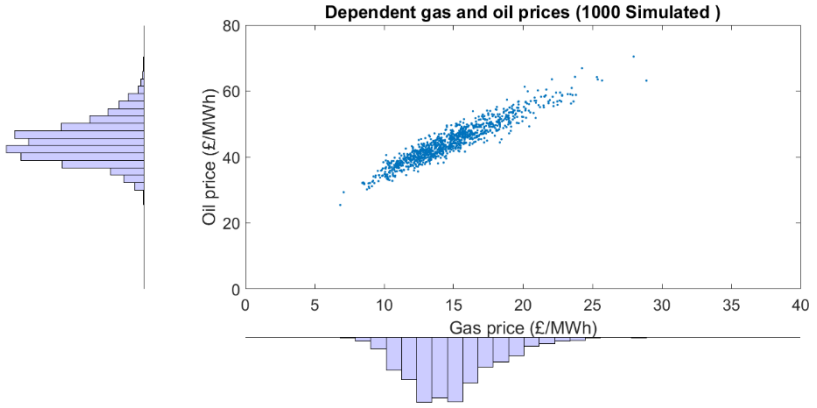

Figure 29: Bivariate correlation between gas and coal prices

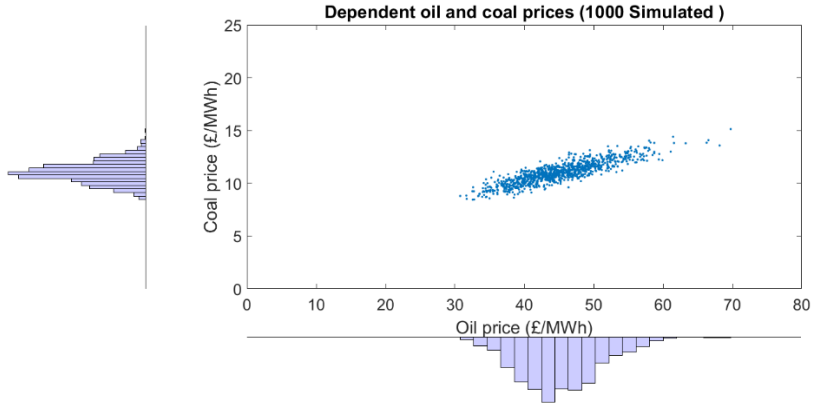

Figure 30: Bivariate correlation between oil and coal prices

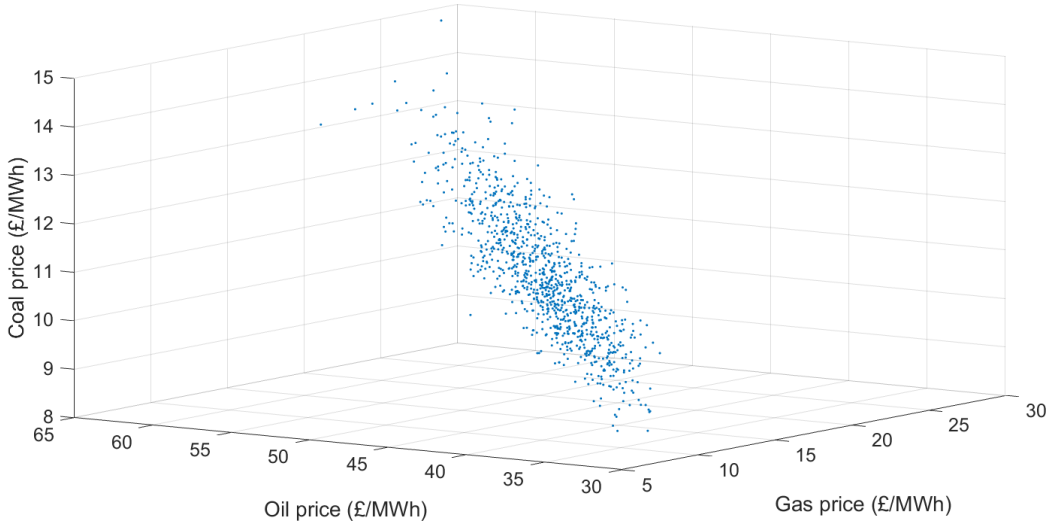

Figure 31: Multivariate distribution among gas, oil and coal prices

Results and Discussion

As expected, the results show almost no difference in average hourly electricity prices between low and high renewables cases (Table 18) because capacities of technologies were adjusted to allow them to make similar profits. Despite the presence of high shares of renewables, the fundamental structure of the market does not change (as we can see from Figure 32); as long as gas stations set the electricity price, gas and electricity prices will be highly correlated.

	Low Renewables (4 GWh)	*High Renewables (4 GWh)*	Low Renewables (20 GWh)
Mean	77.1	76.8	74.6
Median	68.3	66.6	68.8
SD	47.4	66.5	37.8
Minimum	44.0	-326.5	44.5
Maximum	865.0	1081.0	864

Table 18: Descriptive Statistics of Hourly Electricity Price (£/MWh)

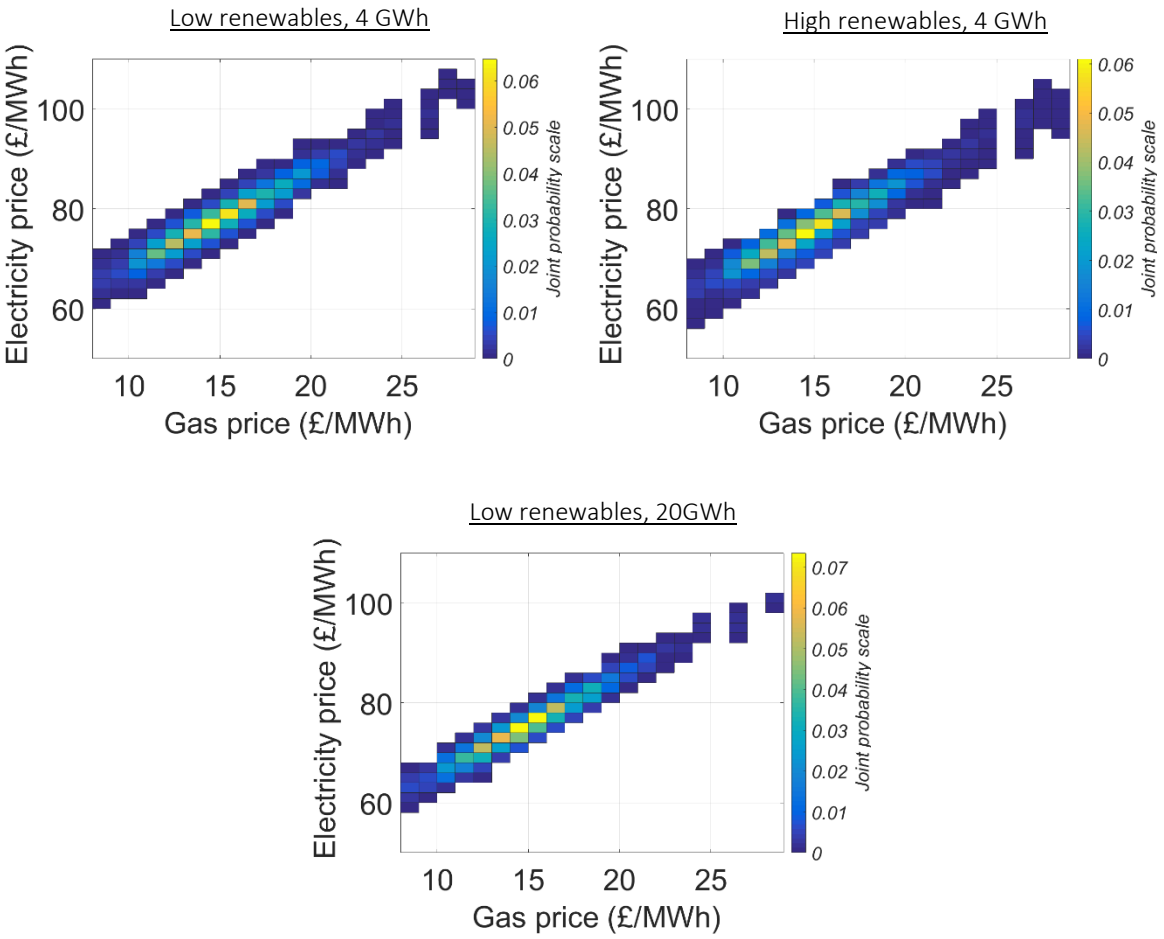

Figure 32: Joint probability distribution of gas and electricity price

Also, it is not surprising to find a low but a significant correlation between yearly average electricity price and yearly storage profit (Figure 33, Table 19, Table 20 and Table 21) and very high correlation between within-year standard deviation of electricity price and yearly storage profit (Figure 34, Table 19, Table 20 and Table 21). This happens due to the arbitrage revenue (around 1/4 of all revenues) and the revenue from reserve provision (around 3/4 of all revenues) that storage is able to generate which are highly dependent on electricity price fluctuations.

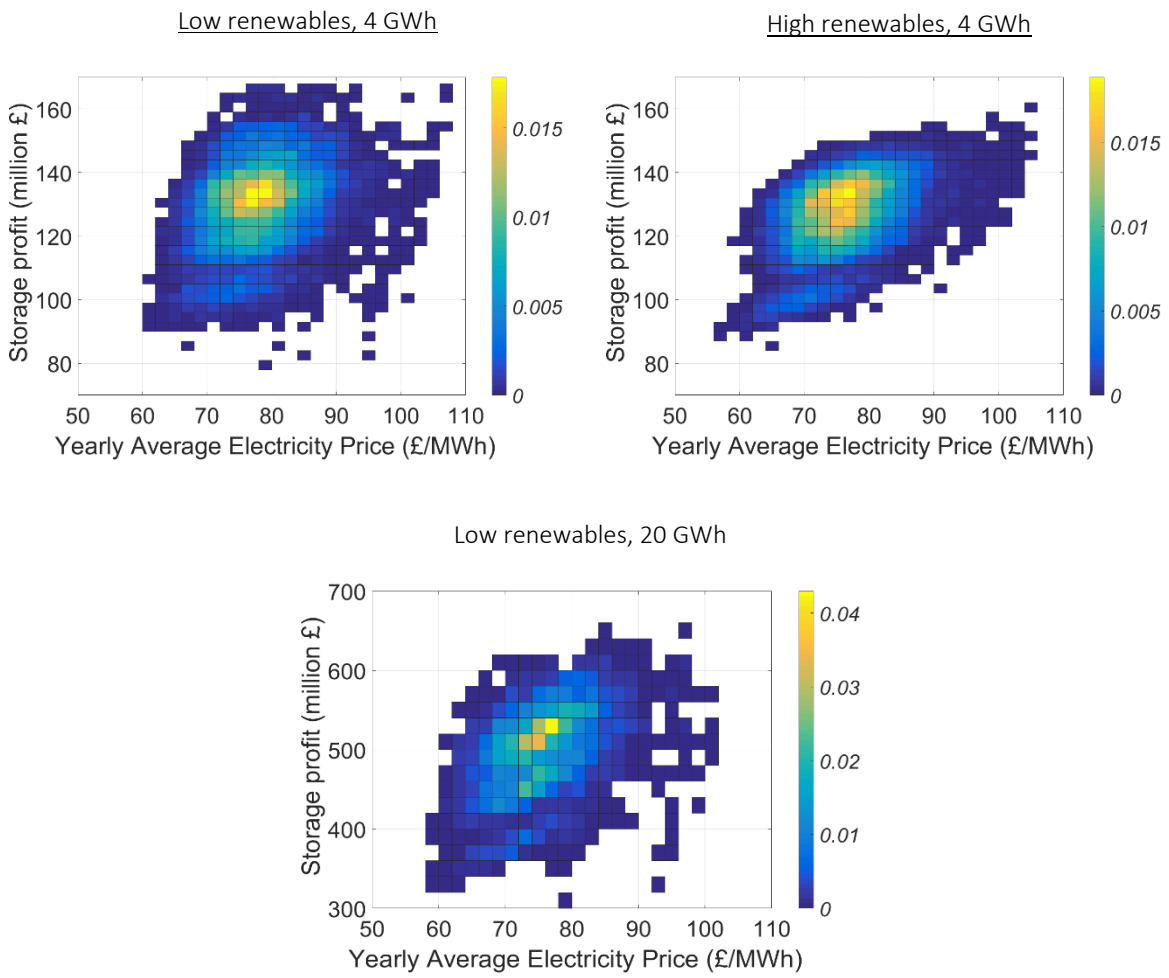

Figure 33: Joint probability distribution of electricity price and storage profit

However, it was unexpected to see no correlation between yearly gas price and yearly storage profit for the case of low renewables (Figure 35, Table 19).

		Profit						Price		
		Nuclear	Coal-CCS	CCGT	Biomass	OCGT	Storage	Gas	Elec.	SD elec.
Profit	Nuclear	1.00								
	Coal-CCS	0.90	1.00							
	CCGT	0.00	0.16	1.00						
	Biomass	0.19	0.25	0.42	1.00					
	OCGT	-0.12	0.06	0.99	0.40	1.00				
	Storage	0.31	0.42	0.88	0.26	0.83	1.00			
Price	Gas	0.96	0.81	-0.29	0.06	-0.40	0.04	1.00		
	Elec.	1.00	0.90	-0.01	0.19	-0.12	0.30	0.96	1.00	
	SD elec.	0.34	0.46	0.90	0.31	0.84	0.99	0.07	0.34	1.00

Table 19: Correlation matrix of technology profits, gas price, electricity price and standard deviation of electricity price (with low renewables, 4GWh)

		Profit						Price		
		Nuclear	Coal-CCS	CCGT	Biomass	OCGT	Storage	Gas	Elec.	SD elec.
Profit	Nuclear	1.00								
	Coal-CCS	0.90	1.00							
	CCGT	0.07	0.24	1.00						
	Biomass	0.28	0.39	0.76	1.00					
	OCGT	0.02	0.19	1.00	0.76	1.00				
	Storage	0.44	0.52	0.71	0.44	0.68	1.00			
Price	Gas	0.95	0.80	-0.25	0.03	-0.29	0.22	1.00		
	Elec.	1.00	0.90	0.08	0.29	0.03	0.44	0.94	1.00	
	SD elec.	0.51	0.59	0.75	0.55	0.72	0.99	0.28	0.51	1.00

Table 20: Correlation matrix of technology profits, gas price, electricity price and standard deviation of electricity price (with high renewables, 4GWh)

		Profit						Price		
		Nuclear	Coal-CCS	CCGT	Biomass	OCGT	Storage	Gas	Elec.	SD elec.
Profit	Nuclear	1.00								
	Coal-CCS	0.90	1.00							
	CCGT	-0.03	0.11	1.00						
	Biomass	0.18	0.20	0.21	1.00					
	OCGT	-0.20	-0.04	0.98	0.21	1.00				
	Storage	0.43	0.50	0.81	0.15	0.70	1.00			
Price	Gas	0.97	0.84	-0.26	0.12	-0.42	0.22	1.00		
	Elec.	1.00	0.90	-0.03	0.18	-0.20	0.43	0.97	1.00	
	SD elec.	0.38	0.46	0.86	0.11	0.76	0.98	0.17	0.38	1.00

Table 21: Correlation matrix of technology profits, gas price, electricity price and standard deviation of electricity price (with low renewables, 20GWh)

This happens as yearly average gas price does not reflect electricity price fluctuations within that year. We would experience a positive relationship between them only if the correlation between yearly average electricity price and within-year standard deviation of electricity price (Figure 36) were strong enough to bring about this effect; it is not strong enough for low renewables with 4 GWh energy capacity.

Figure 37 - Figure 39 show profit distributions of storage for each year's weather pattern as each year has one set of wind, solar and demand. However, we cannot establish the relationship between weather-corrected storage profit and net demand from those

distributions. In order to show it, storage profit of each year based on average fuel price was plotted against net demand (Figure 40).

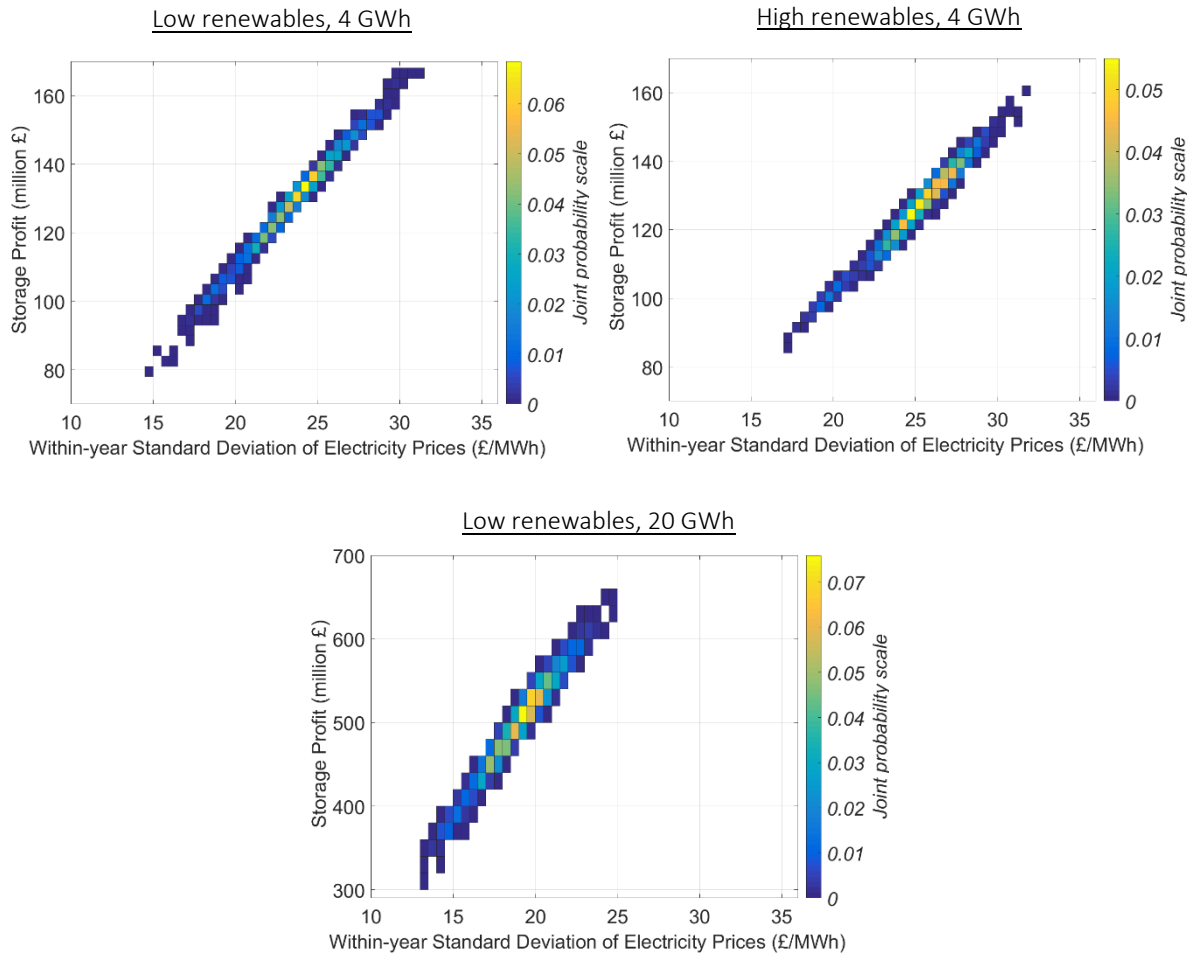

Figure 34: Joint probability distribution of electricity price risk and storage profit

		Correlation of yearly net demand with					
			Correlation of storage profit with				
Scenario	*t two-tail critical value (significance level of 0.05)*	Storage Profit	Nuclear	Coal-CCS	CCGT	Biomass	OCGT
Low Ren. (4GWh)	*0.514*	*0.791*	*-0.863*	*-0.820*	*0.794*	-0.507	*0.810*
High Ren. (4GWh)		*0.769*	*-0.532*	*-0.549*	0.398	*-0.663*	0.402
Low Ren. (20GWh)		*0.809*	*-0.750*	*-0.688*	*0.750*	*-0.515*	*0.791*

Table 22: Significance of Correlation Coefficients

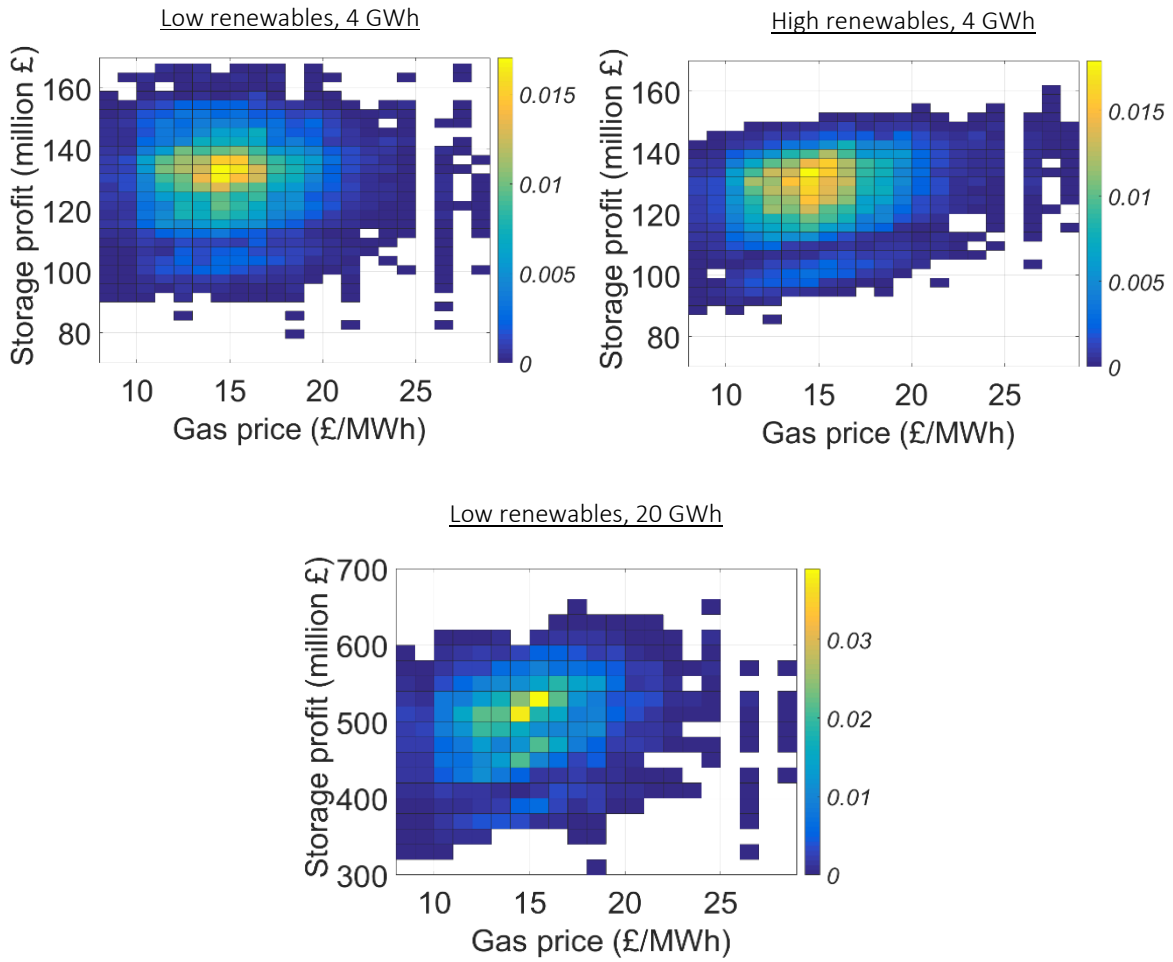

Figure 35: Joint probability distribution of gas price and storage profit

Since only 17 years of data were used (which might not yield a statistically significant correlation between net demand and storage profit), the significance of correlation is demonstrated in the third column of Table 22. The significant positive correlation between yearly electricity demand and yearly storage profit can be assumed with 95% confidence.

Next, it is shown that fuel-price uncertainty for different years (*i.e.* for different levels of net demand) yields the following correlations among profits of storage and other technologies shown in Table 23 - Table 25. Biomass and storage profits are negatively correlated because of the electricity price risk. This is because biomass has the worst merit order due to its highest level of generating cost among all technologies; it is the most expensive technology due to the highest variable operations and maintenance cost, no-load and incremental costs,

fuel costs, start-up costs & carbon emissions as well as one of the lowest average and incremental thermal efficiencies.

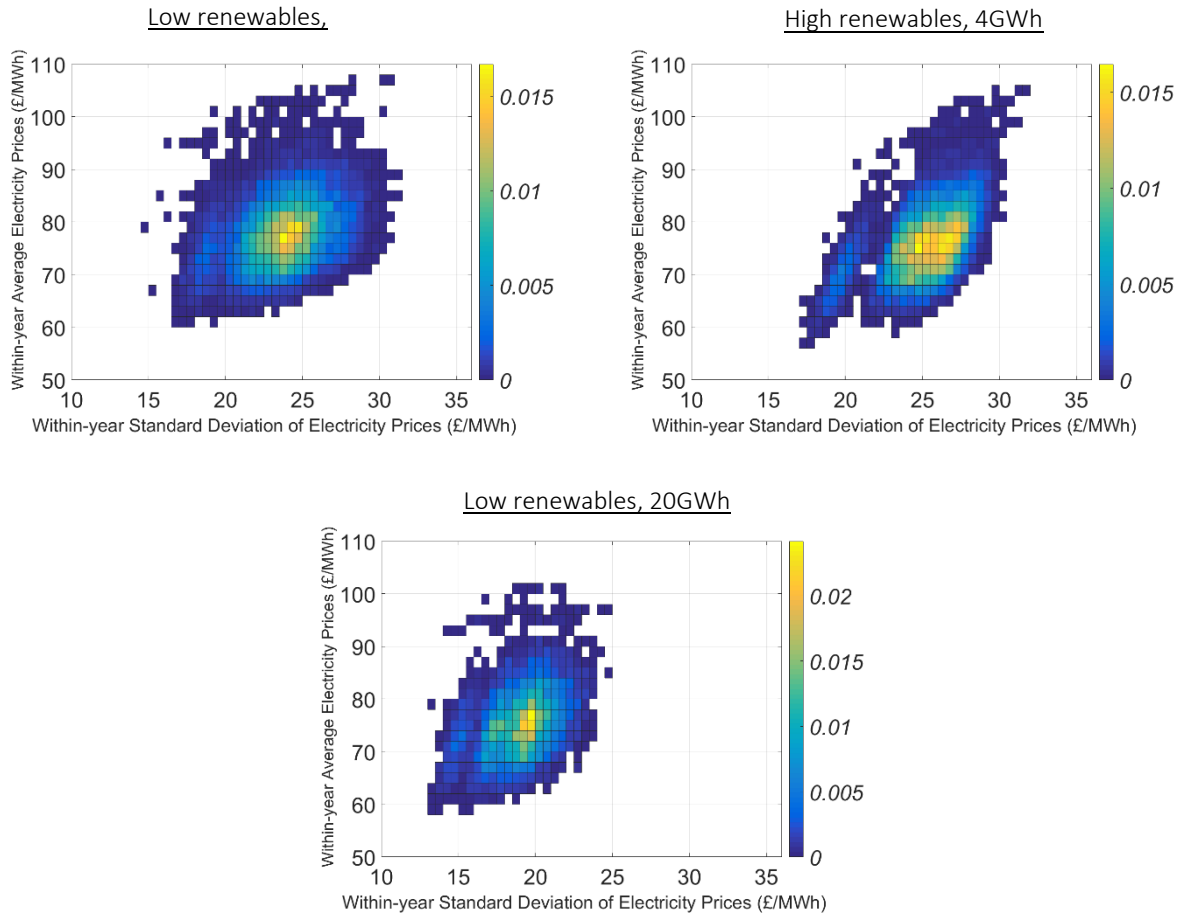

Figure 36: Joint probability distribution of yearly standard deviation of electricity price and yearly average electricity price

There is a very high positive correlation between biomass fuel and its generation cost, and whenever biomass fuel costs are high, its generation cost is also high, and hence the biomass profit is low. Whenever biomass fuel prices are high, electricity price fluctuations are also high because of the presence of high-demand clusters (peak demands) in a given year when biomass sets the price of electricity above the marginal costs of gas stations. Accordingly, high (low) jumps of biomass fuel prices lead to high (low) biomass generation cost, which leads to low (high) biomass profit. However, high (low) biomass generation cost leads to high

(low) electricity price risk as well, which leads to high (low) storage profits; therefore, profits of electricity storage and biomass become negatively correlated.

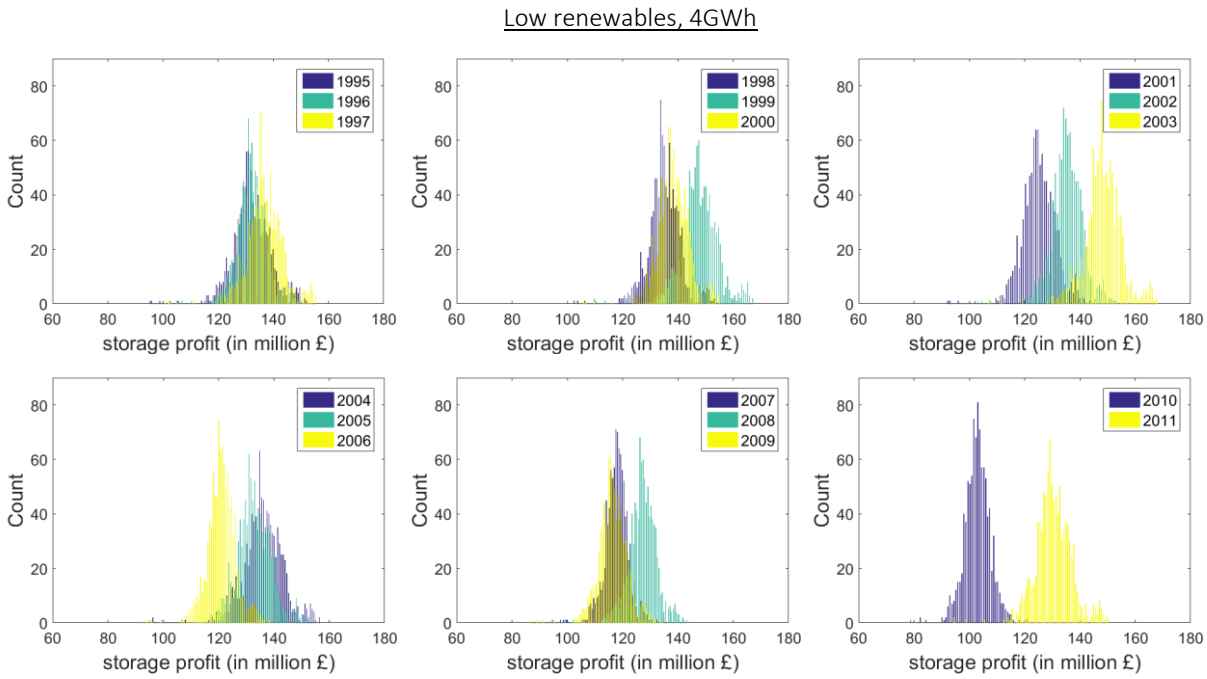

Figure 37: Distribution of storage profit in different years with low renewables (4GWh)

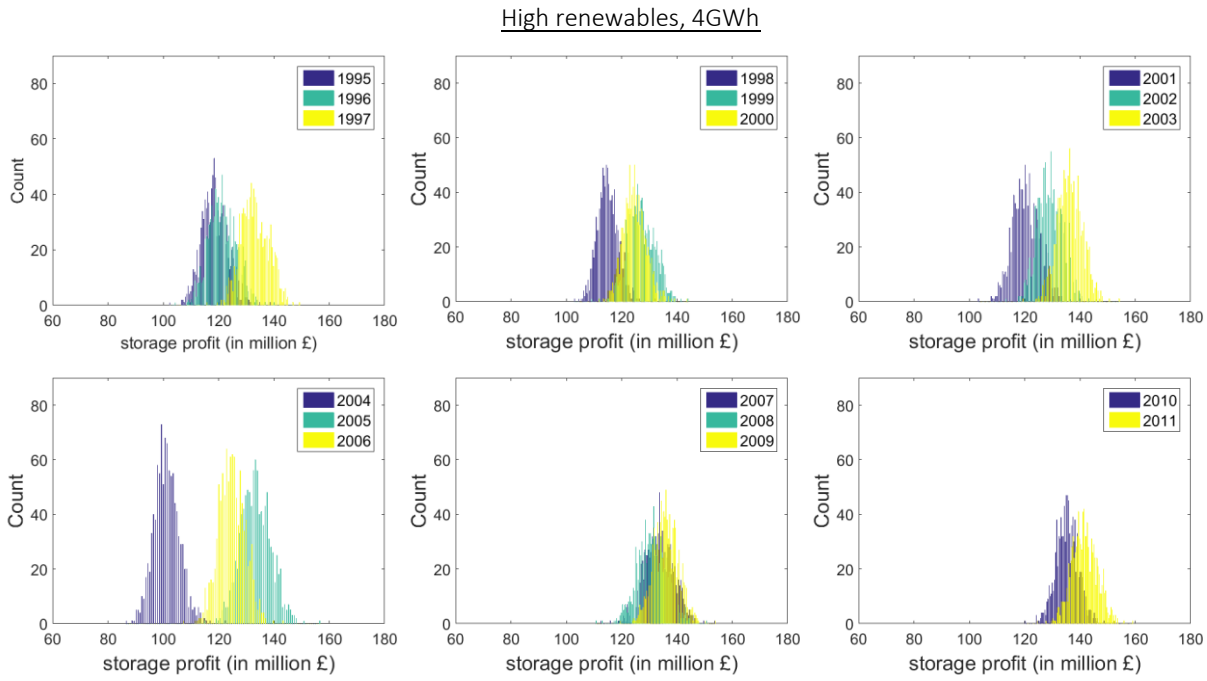

Figure 38: Distribution of storage profit in different years with high renewables (4GWh)

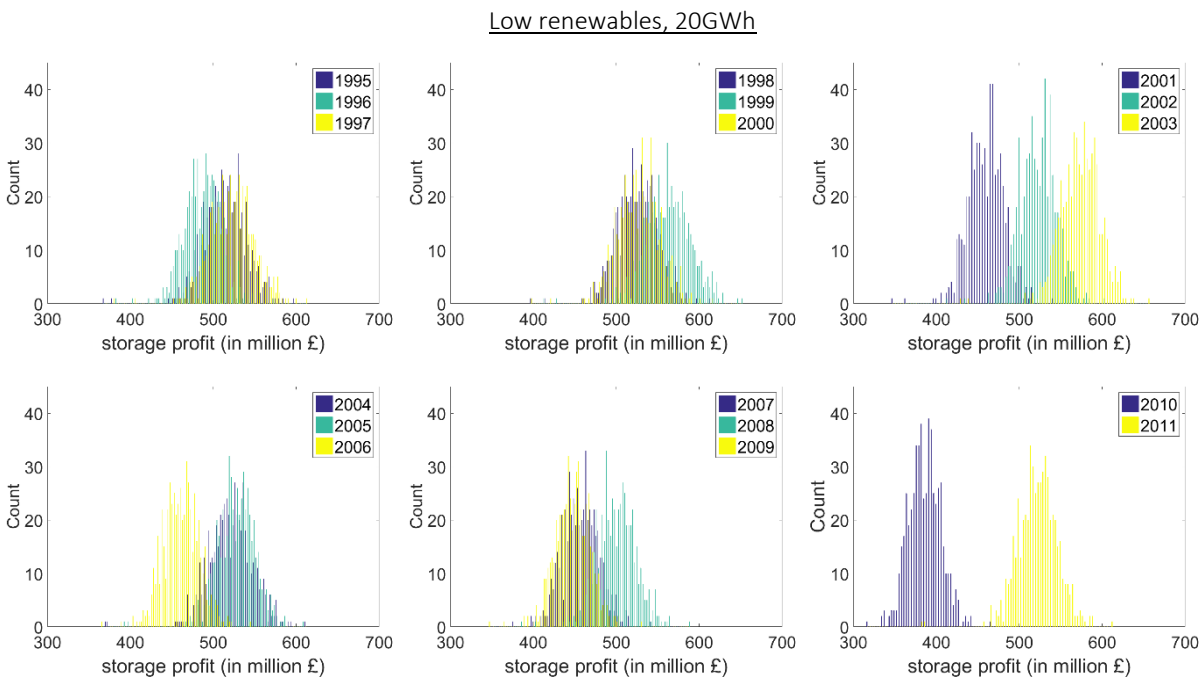

Figure 39: Distribution of storage profit in different years with low renewables (20GWh)

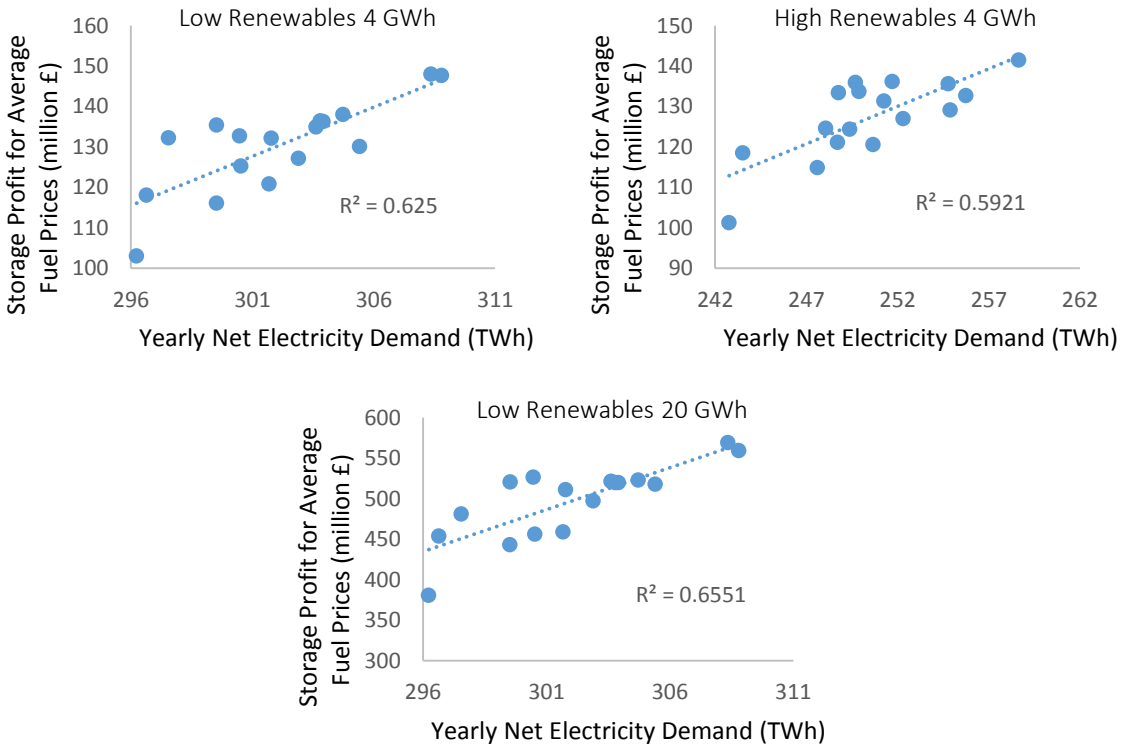

Figure 40: Scatterplot of Net Demand and Storage Profit for 17 Years of Data

Low Renewables, 4GWh		Correlation of Storage Profit with Profit of				
Net Demand (TWh)	*Year*	*Nuclear*	*Coal-CCS*	*CCGT*	*Biomass*	*OCGT*
308.79	1999	0.16	0.26	0.87	-0.90	0.81
308.35	2003	0.14	0.23	0.88	-0.86	0.81
305.41	2011	0.19	0.25	0.87	-0.79	0.78
304.73	2000	0.24	0.30	0.82	-0.89	0.73
303.91	2004	0.18	0.25	0.88	-0.71	0.81
303.79	1997	0.22	0.29	0.85	-0.82	0.78
303.62	1998	0.23	0.30	0.84	-0.78	0.76
302.89	2008	0.28	0.30	0.79	-0.85	0.68
301.78	1995	0.22	0.28	0.86	-0.78	0.78
301.68	2006	0.32	0.34	0.78	-0.81	0.65
300.53	2001	0.27	0.30	0.82	-0.81	0.73
300.47	2005	0.22	0.26	0.85	-0.86	0.75
299.53	2002	0.28	0.31	0.80	-0.85	0.69
299.52	2009	0.30	0.32	0.79	-0.74	0.68
297.55	1996	0.29	0.33	0.79	-0.84	0.70
296.63	2010	0.42	0.42	0.67	-0.77	0.53
296.23	2007	0.44	0.42	0.73	-0.63	0.55

Table 23: Profit correlations of storage and other technologies for different demand patterns, facing fuel-price risk (low renewables, 4GWh)

High Renewables, 4GWh		Correlation of Storage Profit with Profit of				
Net Demand (TWh)	*Year*	*Nuclear*	*Coal-CCS*	*CCGT*	*Biomass*	*OCGT*
258.6	2011	0.58	0.55	0.46	-0.74	0.37
255.7	1997	0.47	0.50	0.61	-0.79	0.55
254.9	2002	0.55	0.55	0.51	-0.75	0.43
254.8	2010	0.70	0.66	0.27	-0.65	0.17
252.3	1999	0.47	0.48	0.60	-0.78	0.53
251.7	2003	0.63	0.61	0.41	-0.70	0.33
251.3	2008	0.48	0.50	0.60	-0.80	0.54
250.7	2001	0.58	0.56	0.51	-0.69	0.43
249.9	2007	0.55	0.55	0.54	-0.72	0.46
249.7	2009	0.63	0.62	0.39	-0.69	0.31
249.4	2000	0.78	0.75	0.17	-0.52	0.09
248.8	2005	0.68	0.66	0.39	-0.61	0.32
248.7	1996	0.56	0.56	0.53	-0.66	0.46
248.1	2006	0.59	0.58	0.49	-0.71	0.41
247.6	1998	0.79	0.73	0.18	-0.50	0.07
243.5	1995	0.66	0.64	0.38	-0.64	0.29
242.8	2004	0.79	0.74	0.25	-0.37	0.16

Table 24: Profit correlations of storage and other technologies for different demand patterns, facing fuel-price risk (high renewables, 4GWh)

Low Renewables, 20GWh		Correlation of Storage Profit with Profit of				
Net Demand (TWh)	*Year*	*Nuclear*	*Coal-CCS*	*CCGT*	*Biomass*	*OCGT*
308.79	1999	0.51	0.52	0.63	-0.33	0.49
308.35	2003	0.53	0.52	0.51	-0.52	0.38
305.41	2011	0.51	0.48	0.61	-0.29	0.42
304.73	2000	0.55	0.54	0.58	-0.26	0.42
303.91	2004	0.49	0.48	0.61	-0.31	0.47
303.79	1997	0.53	0.52	0.61	-0.18	0.46
303.62	1998	0.57	0.56	0.52	-0.37	0.38
302.89	2008	0.62	0.58	0.49	-0.28	0.31
301.78	1995	0.48	0.47	0.63	-0.35	0.48
301.68	2006	0.67	0.62	0.42	-0.20	0.20
300.53	2001	0.63	0.58	0.48	-0.07	0.27
300.47	2005	0.52	0.48	0.56	-0.48	0.37
299.53	2002	0.57	0.54	0.50	-0.48	0.31
299.52	2009	0.70	0.64	0.36	-0.16	0.16
297.55	1996	0.69	0.64	0.38	-0.12	0.21
296.63	2010	0.71	0.65	0.37	-0.25	0.15
296.23	2007	0.79	0.71	0.30	0.09	-0.02

Table 25: Profit correlations of storage and other technologies for different demand patterns, facing fuel-price risk (low renewables, 20GWh)

Columns 4-8 of Table 22 show the moderation effect of demand in defining the strength of the relationship between the profit of storage and profits of other technologies. Actually, this means that on average a rise in electricity demand brings a rise in storage profit (Figure 40 and column 3 of Table 22) while profits of nuclear and coal-CCS become less and less likely to rise with the rise of storage profits (column 4 and 5 of Table 22)[31]. On the contrary, whenever, on average, electricity demand declines, storage profit also declines while profits of nuclear and coal-CCS become more and more likely to decline with the decline of storage profit. Using the same analogy, demand becomes a positive moderator between profit of storage and profits of gas stations. However, unlike low renewable cases when demand significantly influences the relationship between storage profit and profits of gas stations,

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31 NB: Correlation of storage profit and biomass profit is not significant in low renewable (4 GWh) case: it can be zero thus implying no amplifying effect of demand on the relationship between profit of storage and biomass. However, this effect exists in high renewable case and low renewable case with 4 GWh storage capacity.

there is no such a significant moderation effect between storage profit and profits of gas stations when renewable penetration is high (columns 6 and 8 of Table 22).

Since capacities are adjusted when moving from low renewable case to high, electricity prices stay almost the same. However, the high renewable case brings about 5 GW more nuclear into the mix while it takes away about 5.5 GW from other types (Table 16). This allows nuclear stations to set electricity prices more frequently (and less frequently high-cost biomass sets the price whenever it runs) than before thus creating more risk around the electricity price. Because of the lower marginal cost of nuclear (that sets the price more frequently) compared to CCGT, CCGT profits decline and therefore poorly correlate with the electricity price risk as they prefer to run whenever CCGT or a lower-merit-order station (*e.g.* biomass) sets the price (right side of Figure 41).

Although higher electricity price risk is always good news for storage (Figure 34), it is not so good when it is unable to fully utilise it. It is possible to have negative prices when net demand is less than the inflexible baseload production (compare min and max levels in Table 18). Whenever electricity produced by renewables is very high coupled with low demand in the system, some portion of renewable electricity is absorbed – "soaked up" as it is generally referred to – by storage (up to its full capacity) and the rest is spilt out to prevent grid overload as inflexible baseload is still up and running. Thus, unfortunately for storage, it is not able to capture this extra (spilt) electricity further under those cheap (and even negative) electricity prices. Hence, the variability of electricity prices does indeed go up with more renewables but storage can only benefit from the variability across positive electricity prices. However, this variability across positive prices (due to upward price jumps) is not enough for storage to make as much profit as it does in the low-renewable case (compare column 7 in Table 26 and Table 27).

	Nuclear	*Coal-CCS*	*CCGT*	*Biomass*	*OCGT*	*Storage*
Mean	1535.7	397.1	191.9	59.8	125.1	130.4
Median	1528.3	394.3	191.6	58.0	125.0	131.5
SD	135.0	44.7	30.2	18.1	24.1	12.4
Minimum	1133.3	252.8	82.0	28.1	34.9	78.4
Maximum	2198.9	627.5	299.9	121.5	212.8	167.9
Coefficient of variation	0.09	0.11	0.16	0.30	0.19	0.10

Table 26: Descriptive statistics of generators' profits (million £) in low-renewable case, 4GWh

	Nuclear	*Coal-CCS*	*CCGT*	*Biomass*	*OCGT*	*Storage*
Mean	1574.9	355.7	172.9	93.5	73.0	127.2
Median	1567.4	353.6	172.8	84.1	73.0	128.5
SD	142.2	41.7	28.9	29.8	13.3	10.6
Minimum	1132.4	213.6	61.2	25.7	23.8	86.5
Maximum	2259.3	563.7	249.4	175.7	109.0	159.2
Coefficient of variation	0.09	0.12	0.17	0.32	0.18	0.08

Table 27: Descriptive statistics of generators' profits (million £) in high-renewable case, 4GWh

	Nuclear	*Coal-CCS*	*CCGT*	*Biomass*	*OCGT*	*Storage*
Mean	1477.1	368.8	152.1	31.3	88.2	500.9
Median	1470.3	366.2	152.2	28.2	88.0	507.3
SD	132.9	43.6	24.4	13.0	18.9	50.8
Minimum	1095.7	232.1	66.9	2.9	18.3	315.1
Maximum	2070.4	581.5	238.2	83.4	156.0	657.1
Coefficient of variation	0.09	0.12	0.16	0.42	0.21	0.10

Table 28: Descriptive statistics of generators' profits (million £) in low-renewable case, 20GWh

In the light of this effect, we do not observe a significant difference in average or median storage profits between different levels of renewable cases (Table 26, Table 27). Nevertheless, storage still benefits from these price jumps unlike gas stations, and this decreases the correlation between profits of storage and gas stations (compare intersections of row 8 and columns 5 and 7 in Table 19, Table 20 and Table 21).

Table 19, Table 20 and Table 21 show, among others, that gas price negatively correlates with profits of gas stations while having no correlation with storage profit. The former happens because of the dependence of gas stations' marginal cost on gas price.

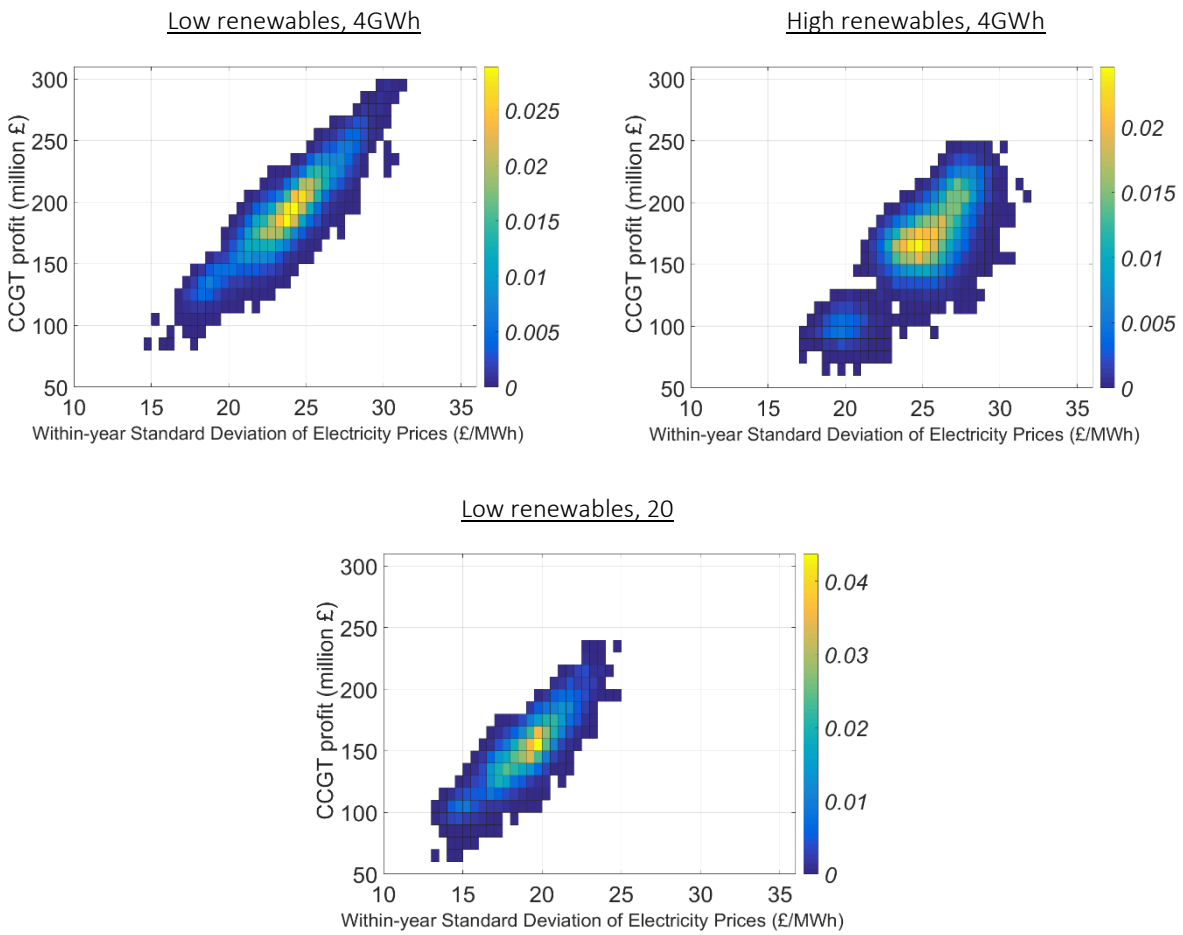

Figure 41: Joint probability distribution of electricity price risk and CCGT profit

Although average levels of yearly gas prices are negatively correlated with yearly profits of gas stations and positively correlated with yearly electricity prices, they do not determine the key electricity price risk faced by storage. It is not the average level of electricity or gas price that define the profit of storage and the generating profit of gas stations but the electricity price variation (Figure 34 and Figure 41). This is the main reason storage profit is highly correlated with the profits of the gas stations. Additionally, electricity price and storage profit are positively correlated since the mean and standard deviation of the electricity price are also positively correlated (Figure 36).

Conclusion of Chapter 5

This chapter provides evidence of the role of storage in an energy-system transition towards low-carbon pathway while also supplementing the existing mostly technical analysis. It shows that if storage is included in the mix, it can greatly benefit from the electricity price variation by making profits from reserve provision and arbitrage while facing risks from fuel price and demand. Storage is able to make a mean yearly profit of about £127-130 million (with 4 GWh of energy capacity) with a standard deviation of about £11-12 million. However, when it is able to provide more energy (20 GWh), average yearly profits rise to about £500 million with a standard deviation of about £51 million. Storage profit variation is reasonably low which should, therefore, attract many investors contingent upon its ability to recover its capital costs.

Storage profit is not correlated with the yearly average level of gas price in low-renewable case but it has a slight positive correlation when storage is able to provide more energy. The high-renewable case brings a slight positive correlation between storage profit and yearly average gas price. Besides, storage profit has a positive correlation with profits of other stations which is moderated by the electricity demand level.

Profitability of storage depends largely on its installed capacity and available energy capacity. However, it can only generate a profit of 26-100 £/kW/yr (depending on its energy capacity) when utilising arbitrage and reserve provision. This can be on the margin to cover the depreciated capital costs[32] of some storage systems such as of fast-response batteries (112 £/kW/yr) (National Grid, 2015), of lithium-ion batteries (90 £/kW/yr), of flywheels (100 £/kW/yr) (Manuel, 2014). This implies if batteries are to be implemented in a grid scale, then they must utilise other revenue services such as frequency regulation. However, 26-100

[32] Depreciated capital costs do not include interest payments. Here they are also calculated for the equipment lifespan instead of equipment lifecycle.

£/kW/yr may cover depreciated capital costs of some large-scale storage systems such as pumped hydro (20-32 £/kW/yr) (Kannan *et al.*, 2007; Locatelli *et al.,* 2015) and compressed-air energy storage (8.6 – 14.3 £/kW/yr) (Locatelli *et al.,* 2015). However, since they are very capital-intensive systems with a long operational lifetime, they need to not only cover their yearly-depreciated capital costs but also get multiple revenue streams (*e.g.* from balancing) because their upfront capital investment costs would require higher returns.

To sum up, a profit-maximising investor should ponder over many questions on a future system – whether it will contain higher shares of renewables, or whether electricity prices will be volatile enough for storage profit. Storage will immensely benefit from arbitrage revenue and reserve provision. However, if a massive amount of storage is added to the grid, they will smooth out the electricity price jumps, which are important for their revenues. Hence, if investors are willing to generate high profits, they should invest in storage as soon as possible, as it is not as ubiquitous in the system as it is expected to be in 20 years' time. Nevertheless, if not now, there will always be a potential for reserve provision, balancing and ancillary services for the late-majority investors. Hence, it would be crucial to consider the utilisation of multiple and additional revenue sources in future energy storage research as storage would be abundantly present in the system.

CHAPTER 6: Conclusion of the Thesis

In a nutshell, this thesis improves existing models and simultaneously provides novel solutions using already well-known investment and profit-quantification approaches in the electricity industry. Some results are surprising and some are not; however, in general, they open up new streams of research in the domain of energy systems modelling.

As George Box would say, “all models are wrong, but some are useful”, the models built in this thesis are “wrong”. Nevertheless, at least they are useful, as their aim is to help target audiences better understand the risk quantification in electricity systems by looking at variables and uncertainties of different kinds.

Of course, there are multiple ways of solving the same problem. However, there is a subtle distinction on what constitutes a “proper solution” as, generally, a solution should go beyond revealing specific numbers for answers. In fact, “proper solutions” are meant to deliver a message that those numbers contain since it is absurd to believe any model is even capable of providing precise estimates for future energy vectors. In reality, what does matter is the ability to project possible scenarios of the future and foresee the implications that can be drawn from them. However, sometimes the results are deemed “unreasonable” at first glance while further analyses reveal that they are “more than reasonable”, given the fact that we tend to overlook some important facts and over-simplify the relationships among variables thus creating a possibility to come to nothing.

Energy economics is not confined to only mathematical equations and reasoning but is much broader in its scope as it models the whole energy system which includes many elements of both human and non-human nature. Unfortunately, this creates difficult tasks for energy system modellers when they try to represent the relationships of the reality in one single compact model.

Bearing these in mind, one might question the practice of creating more and more electricity-system models that are both “wrong” and context-specific. This thesis partially addresses this issue by demonstrating that, indeed, methods, techniques and assumptions do affect the results and misrepresentation of the reality, but these are unavoidable pitfalls. The author believes the most important thing is to define the problem’s boundaries, present assumptions and set granularity dimensions in order to clarify the interpretability of the results. And, yes, it is true that the models presented in this thesis greatly simplify the reality, but the aim is clear – to help energy economists and policy-makers better understand the future systems and analyse them based on likely prognosis of their future states.

No doubt, we will progressively see more models on energy systems in years to come, and some of them with a particular focus on electricity systems. However, “the best model” will always be the “actual reality” which is all but impossible to describe in equations as over-parametrising or under-parametrising some phenomena would create biases in models and results. Nevertheless, with the arrival of new computing power and modelling technologies, the detailed representation of reality might be increasingly easier to calculate and illustrate.

In view of this big picture, this thesis fills some specific gaps. Albeit different in nature, those contributions form a broader theme of the risk and profitability analyses of the UK system. These assumptions and modelling approaches bring us to some overarching conclusions drawn from the content of the thesis.

The content of the thesis is about the future UK electricity industry. The word "future" is the key here as it combines all three chapters to form a holistic view of a possible future electricity industry. Despite the unknown outlook of the electricity industry, this thesis attempts to model it in face of its upcoming challenges.

On a high level, the thesis tries to establish which technologies are risky and, more importantly, why and to what extent they are risky. Chapter 3 and Chapter 4 address the riskiness of conventional technologies with particular emphasis on the riskiness of nuclear and reasons behind it. The chapters find that nuclear is risky and justifies long-term contractual support for them. Chapter 5 addresses the riskiness of short-term diurnal storage and reasons behind it. The chapter finds that storage makes a reasonable profit with a reasonably small risk also providing some insights on a portfolio effect that storage can have on the profits of other technologies. This high-level picture can be broken down into a few crucial takeaway points.

The first takeaway point combines the reasons behind the challenges of nuclear profit risk. On its path to decarbonisation of the energy industry, the UK has embarked on building a new nuclear power plant, Hinkley Point C. It is not only an important source for a secure electricity supply but it also cements the UK's links with France (by courtesy of EDF) and China (by courtesy of China General Nuclear). The details as to why Hinkley Point C got such a generous deal are yet unclear but what is clear is that this deal adds more fuel to the fire when it comes to the discussion of the place of nuclear in the future and of its survival in a competitive market environment if not supported by the government.

The models of Chapter 3 and Chapter 4 show the competitiveness issue of nuclear. Policy on carbon pricing is one of the fundamental drivers for its promotions, which should be designed in relation to investors' risk attitude assessment. However, this relationship is not enough to promote nuclear investments, as most investors can be hesitant about putting huge amounts of money aside in anticipation of making great profits in future. As it gradually becomes clear in Chapters 3 and Chapter 4, the failure should not be attributed to external events (such as the disaster of Fukushima Daiichi) but because of the market

implications of nuclear competitiveness. Indeed, supporting nuclear investment by the government might fire some interest and lead to a nuclear "renaissance" but it seems nuclear is not able to compete with the falling costs of renewables. This problem is exacerbated especially when carbon prices are not rising high enough to rule out carbon-intensive technologies.

Risky nuclear profits are another factor that impedes its investments. Therefore, this gives rise to the allocation of nuclear contracts that mitigates its risk exposure. However, as further research shows in Chapter 4, the emphasis should be placed not only on mitigating nuclear market risk but also pushing investment costs down whenever carbon prices are high enough that allow them to make enough money. This is simply because investors are mainly concerned about their initial cash outflows that nuclear requires and then only about profit risk that nuclear may face in a market (assuming that no contract is allocated to nuclear and that carbon prices are high enough). Of course, the governmental guarantees will trigger interests in nuclear, which unfortunately may create unequal competitive conditions for investors with less capital; this, in turn, will raise the market concentration index in the electricity industry and we may experience a market, which is a long away from the perfectly competitive one. The perfectly competitive generation market lowers long-run electricity prices. Lower electricity prices are always good for consumers and help to achieve one of the goals in the UK Energy Trilemma.

The results obtained in the chapters can be interpreted as the "upper" bounds on what we might expect to see in the future. Since the generating market will never be fully competitive, there will always be barriers to entry for small companies as lumpy investments favour big players. Additionally, it will include many different technologies not studied in this thesis. These models also simplify the reality greatly as the actual investments do not

happen incrementally but in heavy lumps. For instance, nuclear plants are built in a couple of hundreds of MW of capacity all at once which gives a clear advantage to the rich.

In regards to why renewables are treated exogenously from investment decisions, there are "pros and cons" to this that needs a separate discussion. These non-dispatchable renewable technologies will definitely form some part of the optimal portfolio of energy companies in future. Will they alter the invested capacity in conventional technologies? Perhaps they will, but it is a very complex question to answer without a proper modelling and analyses, and therefore further research should be carried out to understand it better. Will the support with FiT CfD contracts make them more appealing than conventional generators? They may well be, but there will always be a need for more flexible generators that provide not only system reserve but also system inertia. This thesis is not about renewables, but their impact is well acknowledged as the sensitivity analyses of Chapter 3 detail. They show that high level of renewables affects nuclear investments. This happens due to the volatile nature of net demand, which makes prices and profits riskier.

However, if we consider cash-flow risk analyses instead of profit-risk analyses, we may conclude that the riskiness of nuclear cash flows (and therefore profits) is not a significant factor when carbon prices are high enough. In fact, the cash-flow distribution of nuclear dominates the cash-flow distribution of other technologies making it a more attractive option among them. Of course, high capital investments of nuclear eliminate many small players, and the big ones are left to worry only about development and construction risk.

The second takeaway on the thesis analysis of the “future” is from the utilisation of electricity storage as it is highly likely that the future will include grid-level electricity storage. Envisioning that electricity storage is already installed and connected to the grid, the thesis looks at its profit risk. Sources for storage profit are electricity price arbitrage and

reserve provision. The analyses show that electricity storage integrates well with other technologies while making decent profits with small risk. It relies on hourly electricity price fluctuations to make a profit. Some portfolio effects can be drawn from this analysis. When constructing a portfolio with energy storage and gas stations, investors should consider that there is a significant profit correlation between them; therefore, they should be put separately in optimal portfolios. Further research should be performed to construct a portfolio of gas and storage stations to see if it holds.

Before we go into detailed discussions of each model, it should be noted that this chapter started by mentioning modelling issues in general along with mention of electricity systems modelling in particular. In short, these models are "wrong" but the insights are precious. The findings, policy implications, limitations and possible future work arising from each chapter are discussed separately in the following sections:

Assessment of Chapter 3

Chapter 3 provides an easy framework for portfolio analysis of generating assets in a perfectly competitive setting. It creates fully endogenous risk-averse portfolios of different technologies when fuel prices, electricity demand, renewable penetration and carbon prices vary. It shows that nuclear technology is highly sensitive to risk aversion and carbon price. In order to make nuclear an attractive investment option in the portfolio mix, not only a carbon price of at least 54.275 £/tonne but also an increase of carbon price of at least 3£/tonne for every 0.01 increase in risk aversion would be necessary to achieve this. In addition, this chapter shows that nuclear investments decrease by 9.3% when risk-neutral investors are substituted by investors with risk aversion of 0.05. Moreover, when there is twice more wind and solar capacity in the system (30 GW wind and 14 GW solar), nuclear investments decline by 27.7% in the risk-neutral case and 38.8% for the case of risk aversion

of 0.05, accompanied by an increase of investments in gas stations. However, whenever a nuclear contract is added to the mix, more than a 52% share of baseload capacity is taken by them while preserving the total capacity, and this share increases with an increase in risk aversion.

Chapter 3 also points out that the carbon price and risk aversion are linked when analysing investment prospects of nuclear; the "right" policy should estimate the possible trajectory of investors' risk aversion to design a necessary trajectory for the carbon price. In addition, in case the carbon price is not at the required level to stimulate nuclear investment, a contract can easily cushion this by providing more than half of the baseload generation.

While this study limits itself to three capacity choices they can be easily extended to many choices if need be. Although it is easy to observe that nuclear investment is an increasing concave function of the carbon price for values greater than 54.275 £/tonne, more scenarios of risk aversion and carbon price are required to confirm this relationship. More scenarios are required also to show that nuclear investment is a decreasing concave function of risk aversion while the amount covered by the contract is an increasing convex function of risk aversion.

This study reveals that there are some clear interdependencies that need closer examination as they have opened up new research directions such as mathematical proofs of these actual relationships and inclusion of other factors in the model. One possible extension could be the study of the Capacity Mechanism – another decarbonisation initiative already implemented by the UK government under which many technologies will be paid for availability on demand in order to fill the imbalances of supply.

Moreover, market power is not considered in this study as it is imperceptible in the British electricity wholesale market (CMA, 2015a), but might be worth examining in other contexts.

Assessment of Chapter 4

Chapter 4 presents a financial model for valuing risk of different projects through their cost of capital. Even though the literature points out that there is a clear distinction between the cost of capital during pre-development & construction and the cost of capital during operation, it does not attempt to quantify them separately in one single model. For this reason, this chapter tries to include them in a model and analyse their respective impacts on investments.

While the operating risk of technologies is endogenously calculated through cash-flow risk, their pre-operation cost of capital is exogenously derived from two credible sources, EWEA (2013) and NERA (2015), that show there is at least 0.5% differential between the pre-operation and operation cost of capital for the wind and solar projects; this differential is assumed to be preserved for gas stations too. Those two sources have been superimposed to eliminate any assessment bias against a specific technology.

Furthermore, this chapter contributes to the literature by presenting a modelling methodology, called *P90-P50,* where the capital structure is derived from uncertain cash flows of projects that adhere to the financing covenants of the debt lenders' requirements to secure adequate debt capacity. Actually, it shows that not only cash-flow risk is important in determining the riskiness of an asset, but also its mean value; in other words, the coefficient of variation, defined as a ratio of standard deviation and mean of cash flow, is the correct measure for ranking the cash-flow distributions of assets to determine their relative operational risks. In particular, the coefficient of variation of nuclear cash flow (0.13) yields a cost of capital of 7.2% during operation while the coefficients of variation of CCGT (0.26) and OCGT cash flows (0.47) give a cost of capital of 8.4% and 8.8% respectively. Taking the analyses even further, this study shows that this relatively lower cost of capital for nuclear

alone is not enough to promote nuclear investments as it has higher than others' pre-operation cost of capital which hugely affects its investment. In the model, the inclusion of distinct pre-development & construction and operation cost of capital reduces nuclear investments by 28.3% (while preserving the total capacity) in comparison to the investments with only one endogenous cost of capital for all phases. Therefore, this implies that there is a hierarchical impact of the cost of capital on investment decisions; investors first consider the development & construction costs of a project before computing its operational benefits since the initial high-cost & lump-sum capital investments undermine low-risk & high-yield revenues that a project can generate in the future. This also implies that a policy designed to reduce the cash-flow risk of a nuclear project is not market-driven but merely behavioural since the project's lifetime cost of capital of nuclear is the lowest. However, contracts with a strike price above average market price could be issued to attract apprehensive investors.

This study has some limitations. Firstly, it derives the cost of capital of each technology without changing the rate of debt and equity with respect to leverage. Actually, if the proportion of debt increases, financial leverage of a project also increases, which leads to a higher systematic risk (beta) and a higher cost of equity. Since the cost of equity becomes higher, the total cost of capital may change in any direction depending on whether the tax benefits of debt increase offset the cost increase of equity. Also, when cash flows become more volatile, financiers require higher debt rates as remuneration for taking this extra risk. Secondly, this study does not endogenise the cost of capital of nuclear technology during pre-development & construction phase and takes a hybrid stance for the cost of capital of gas stations during pre-development & construction, considering that the stations exercise a 0.5% higher cost of capital during pre-operation phase over their endogenously calculated cost of capital during their operation phase. Thirdly, tax rates both during pre-operation and

operation phases for all technologies are taken to be the same, and any tax relief to different technologies is not reflected in those rates.

In future work, these issues could be addressed.

Assessment of Chapter 5

Chapter 5 quantifies the impact of fuel-price risk on the profitability of storage when it makes profits from arbitrage and reserve provision. It presents a cost minimisation model of five different technologies when all of them are making close-to-normal profit both in low- and high-renewable scenarios. Specifically, it develops a comprehensive model with plants' technical characteristics and utilises the inclusion of representative days of net demand (to reduce computational time) by substituting the existing 17 years of daily electricity profiles by only 150 profiles.

The results suggest that the most important variable in defining the profitability of storage is the electricity price risk measured as a standard deviation of electricity price. In particular, the results show that electricity price risk and storage profit have a correlation of 0.99 both in low- and high-renewable cases when 4 GWh of energy is available, and a correlation of 0.98 in the low renewable case when 20 GWh of energy is available.

It should be noted that the policy needs to promote storage technologies as profits of around 26 £/kw-year (4 GWh of energy capacity) and 100£/kw-year (20 GWh of energy capacity) seem not to be enough to cover their annualised fixed costs. There should be either additional services that storage can generate money from or specific policies that support investments with the aim of capturing the value of storage ability to reduce overall system costs.

This study has some limitations too. Firstly, it does not differentiate between different types of storage technologies and their technical characteristics. Those differences could be

deemed important given that batteries are small-sized and fast-response devices while pumped-hydro storage and CAES systems are large in size and slow in response time. Their arbitrage and reserve profits will be different since fast-response storage can benefit more from price fluctuations and less from reserve provision while slow-response storage can benefit more from reserve provision than from arbitraging on frequently fluctuating electricity prices. Secondly, it does not include energy balancing (that really needs a stochastic model) which is left out for simplicity; however, should they be included, revenue streams of storage and their operating patterns might change.

As a future research, it would also be important to study the interaction between energy storage and other sources of flexibility such as detailed inclusion of demand-side response to help policy-makers better understand the role of storage in the future technology mix. Another possibility could be to look at the impact of storage in shaping the long-run equilibrium capacity mix when it is included in the portfolio mix.

Closing Statements

As of the fourth quarter of 2016, the share of renewable generation was about 22.2% of all nationwide electricity generation in the UK while the share of coal, gas and nuclear were 9.3%, 45.2% and 20.3% respectively. These numbers were achieved with a massive depletion of coal generation (and some of their replacements by gas) by around 50% from the fourth quarter of 2015 (BEIS, 2017). With this tempo, it seems that the UK renewable targets for 2030 and 2050 can easily be met as long as the country is on track for achieving its carbon-emission reduction targets. Obviously, this high penetration of renewables will create risks to nuclear technologies and the need for storing the excess electricity in the "best" possible way.

Although currently there is only 4 GW of capacity that connects GB to its neighbouring countries (Ofgem, 2017), the future system might see more investments in this infrastructure to transfer electricity across borders. Whether it is a cheaper option to import electricity instead of firing some stand-by "dirty" generators or to keep excess capacity in reserve and not to export abroad is a question for future research. Whether or not it would be beneficial to export electricity depends on many factors but notably on the opportunity cost of storing the electricity for later use.

If this thesis were to be continued, first and foremost, it needs to include international trade (*i.e.* interconnection) since this would help us better understand the UK's role in the whole European network when it would be on its way to becoming a benchmark decarbonisation-driven system admired by everyone.

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Appendix 1: Proof of Proposition

Proposition: *Utilities of individual technologies will be less or equal to the utility of the portfolio at optimum.*

Proof: Imagine, we have a portfolio of two equilibrium capacities, y_1^* and y_2^* and uncertain profits of $\pi_1$and π_2. At optimum we would have:

$$\mathrm{E}\left(\frac{\pi_1^* + \pi_2^* - y_1^* c_1 - y_2^* c_2}{y_1^* + y_2^*}\right) - 0.5\alpha \mathrm{V}\left(\frac{\pi_1^* + \pi_2^* - y_1^* c_1 - y_2^* c_2}{y_1^* + y_2^*}\right) = 0 \quad (A11)$$

$$\mathrm{E}\left(\frac{\pi_1^*}{y_1^*} - c_1\right) - 0.5\alpha \mathrm{V}\left(\frac{\pi_1^*}{y_1^*} - c_1\right) = \mathrm{E}\left(\frac{\pi_2^*}{y_2^*} - c_2\right) - 0.5\alpha \mathrm{V}\left(\frac{\pi_2^*}{y_2^*} - c_2\right) = b \ (A12)$$

We need to show that b takes non-positive value at optimum.

From equation $(A11)$ we get:

$$\mathrm{E}\left(\frac{\pi_1^*+\pi_2^*-y_1^* c_1-y_2^* c_2}{y_1^*+y_2^*}\right) - 0.5\alpha \mathrm{V}\left(\frac{\pi_1^*+\pi_2^*-y_1^* c_1-y_2^* c_2}{y_1^*+y_2^*}\right) = \frac{1}{y_1^*+y_2^*}\mathrm{E}(\pi_1^*) + \frac{1}{y_1^*+y_2^*}\mathrm{E}(\pi_2^*) - \frac{c_1 y_1^*}{y_1^*+y_2^*} - \frac{c_2 y_2^*}{y_1^*+y_2^*} - \frac{0.5\alpha}{(y_1^*+y_2^*)^2}\mathrm{V}(\pi_1^* + \pi_2^*)=0 \quad (A13)$$

$$\mathrm{E}(\pi_1^*) + \mathrm{E}(\pi_2^*) - c_1 y_1^* - c_2 y_2^* - \frac{0.5\alpha}{y_1^* + y_2^*}\mathrm{V}(\pi_1^* + \pi_2^*)=0 \quad (A14)$$

From equation $(A12)$ we get:

$$\mathrm{E}\left(\frac{\pi_1^*}{y_1^*} - c_1\right) - 0.5\alpha \mathrm{V}\left(\frac{\pi_1^*}{y_1^*} - c_1\right) = \frac{1}{y_1^*}\mathrm{E}(\pi_1^*) - c_1 - 0.5\alpha \frac{1}{(y_1^*)^2}\mathrm{V}(\pi_1^*) = b \ (A15)$$

$$\mathrm{E}\left(\frac{\pi_2^*}{y_2^*} - c_2\right) - 0.5\alpha \mathrm{V}\left(\frac{\pi_2^*}{y_2^*} - c_2\right) = \frac{1}{y_2^*}\mathrm{E}(\pi_2^*) - c_2 - 0.5\alpha \frac{1}{(y_2^*)^2}\mathrm{V}(\pi_2^*) = b \ (A16)$$

Therefore,

$$\mathrm{E}(\pi_1^*) - c_1 \mathrm{y}_1^* - \ 0.5\alpha \frac{1}{\mathrm{y}_1^*} \mathrm{V}(\pi_1^*) = b\mathrm{y}_1^* \ (A17)$$

$$\mathrm{E}(\pi_2^*) - c_2 \mathrm{y}_2^* - 0.5\alpha \frac{1}{\mathrm{y}_2^*} \mathrm{V}(\pi_2^*) = b\mathrm{y}_2^* \ (A18)$$

If we sum left and right sides of equations $(A17)$ and $(A18)$ and rearrange, we will get:

$$\mathrm{E}(\pi_1^*) + \ \mathrm{E}(\pi_2^*) - c_1 \mathrm{y}_1^* - c_2 \mathrm{y}_2^* = b(\mathrm{y}_1^* + \mathrm{y}_2^*) + 0.5\alpha \frac{1}{\mathrm{y}_1^*} \mathrm{V}(\pi_1^*) + 0.5\alpha \frac{1}{\mathrm{y}_2^*} \mathrm{V}(\pi_2^*) \ (A19)$$

If we substitute $(A19)$ into $(A14)$, expand variance of sum and reshuffle, we will get:

$$b = \frac{-0.5\alpha \frac{1}{\mathrm{y}_1^*} \mathrm{V}(\pi_1^*) - 0.5\alpha \frac{1}{\mathrm{y}_1^*} \mathrm{V}(\pi_2^*) + \frac{0.5\alpha}{\mathrm{y}_1^* + \mathrm{y}_2^*} \mathrm{V}(\pi_1^*) + \frac{0.5\alpha}{\mathrm{y}_1^* + \mathrm{y}_2^*} \mathrm{V}(\pi_2^*) + \frac{0.5\alpha}{\mathrm{y}_1^* + \mathrm{y}_2^*} 2\mathrm{corr}(\pi_1^*, \pi_2^*) \sigma_{\pi_1^*} \sigma_{\pi_2^*}}{\mathrm{y}_1^* + \mathrm{y}_2^*} \ (A110)$$

Since $y_i \geq 0$, we need to prove only that the numerator is non-positive. The numerator of Equation $(A110)$ is equivalent to:

$$-0.5\alpha \frac{1}{\mathrm{y}_1^*} \sigma_{\pi_1^*}^2 - 0.5\alpha \frac{1}{\mathrm{y}_2^*} \sigma_{\pi_2^*}^2 + \frac{0.5\alpha}{\mathrm{y}_1^* + \mathrm{y}_2^*} \sigma_{\pi_1^*}^2 + \frac{0.5\alpha}{\mathrm{y}_1^* + \mathrm{y}_2^*} \sigma_{\pi_2^*}^2 + \frac{0.5\alpha}{\mathrm{y}_1^* + \mathrm{y}_2^*} 2\mathrm{corr}(\pi_1^*, \pi_2^*) \sigma_{\pi_1^*} \sigma_{\pi_2^*} \ (A111)$$

which can be transformed into:

$$-0.5\alpha \frac{\mathrm{y}_2^*}{\mathrm{y}_1^*(\mathrm{y}_1^* + \mathrm{y}_2^*)} \sigma_{\pi_1^*}^2 - 0.5\alpha \frac{\mathrm{y}_1^*}{\mathrm{y}_2^*(\mathrm{y}_1^* + \mathrm{y}_2^*)} \sigma_{\pi_2^*}^2 + \frac{0.5\alpha}{\mathrm{y}_1^* + \mathrm{y}_2^*} 2\mathrm{corr}(\pi_1^*, \pi_2^*) \sigma_{\pi_1^*} \sigma_{\pi_2^*} \ (A112)$$

Again, since $y_i \geq 0$ and $0 \leq \alpha \leq 0.1$, we can reduce the above into:

$$-\frac{\mathrm{y}_2^*}{\mathrm{y}_1^*} \sigma_{\pi_1^*}^2 - \frac{\mathrm{y}_1^*}{\mathrm{y}_2^*} \sigma_{\pi_2^*}^2 + 2\mathrm{corr}(\pi_1^*, \pi_2^*) \sigma_{\pi_1^*} \sigma_{\pi_2^*} \ (A113)$$

Since we have that:

$$-(\sqrt{\frac{\mathrm{y}_2^*}{\mathrm{y}_1^*}} \sigma_{\pi_1^*} - \sqrt{\frac{\mathrm{y}_1^*}{\mathrm{y}_2^*}} \sigma_{\pi_2^*})^2 = -\frac{\mathrm{y}_2^*}{\mathrm{y}_1^*} \sigma_{\pi_1^*}^2 - \frac{\mathrm{y}_1^*}{\mathrm{y}_2^*} \sigma_{\pi_2^*}^2 + 2\sigma_{\pi_1^*} \sigma_{\pi_2^*} \leq 0 \ (A114)$$

$$-\frac{y_2^*}{y_1^*}\sigma_{\pi_1^*}^2 - \frac{y_1^*}{y_2^*}\sigma_{\pi_2^*}^2 \leq -2\sigma_{\pi_1^*}\sigma_{\pi_2^*} \quad (A115)$$

we can substitute $-\frac{y_2^*}{y_1^*}\sigma_{\pi_1^*}^2 - \frac{y_1^*}{y_2^*}\sigma_{\pi_2^*}^2$ in $(A113)$ with its upper bound obtained from $(A115)$:

$$-2\sigma_{\pi_1^*}\sigma_{\pi_2^*} + 2\text{corr}(\pi_1^*, \pi_2^*)\sigma_{\pi_1^*}\sigma_{\pi_2^*} \quad (A116)$$

Since $\sigma_{\pi_i} \geq 0$ and $\text{corr}(\pi_1^*, \pi_2^*) \leq 1$, $(A116)$ is definitely non-positive and therefore b is non-positive. The proof can be easily generalised to n technologies.

Appendix 2: Limitations of a Single Ratio Analysis

To show the limitation of a single ratio analysis, we examine the following key ratios that are commonly used in energy practice:

1. Debt-to-assets (Figure 43)
2. ICR (Figure 42)
3. Debt-to-EBITDA (Figure 44)
4. Debt-to-capital (Figure 45)
5. Debt-to-equity (Figure 46)

These are not the exhaustive list of ratios for analysing a firm's financial stability. However, they give a good indication of their performance with respect to cash-flow[33] risk. Specifically, if we look at the juxtaposition of ICR (Figure 42) and debt-to-equity ratio (Figure 46) (or debt-to-capital (Figure 45) for Centrica, we would be able to observe that the firm is the riskiest in the first case and the highest in the second – a typical situation a firm should try to avoid. However, looking only at debt-to-EBITDA ratio (Figure 44), we can observe that Centrica performs decently.

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[33] As a general observation, firms recently are performing poorly in terms of interest coverage which already raises the issue of financeability.

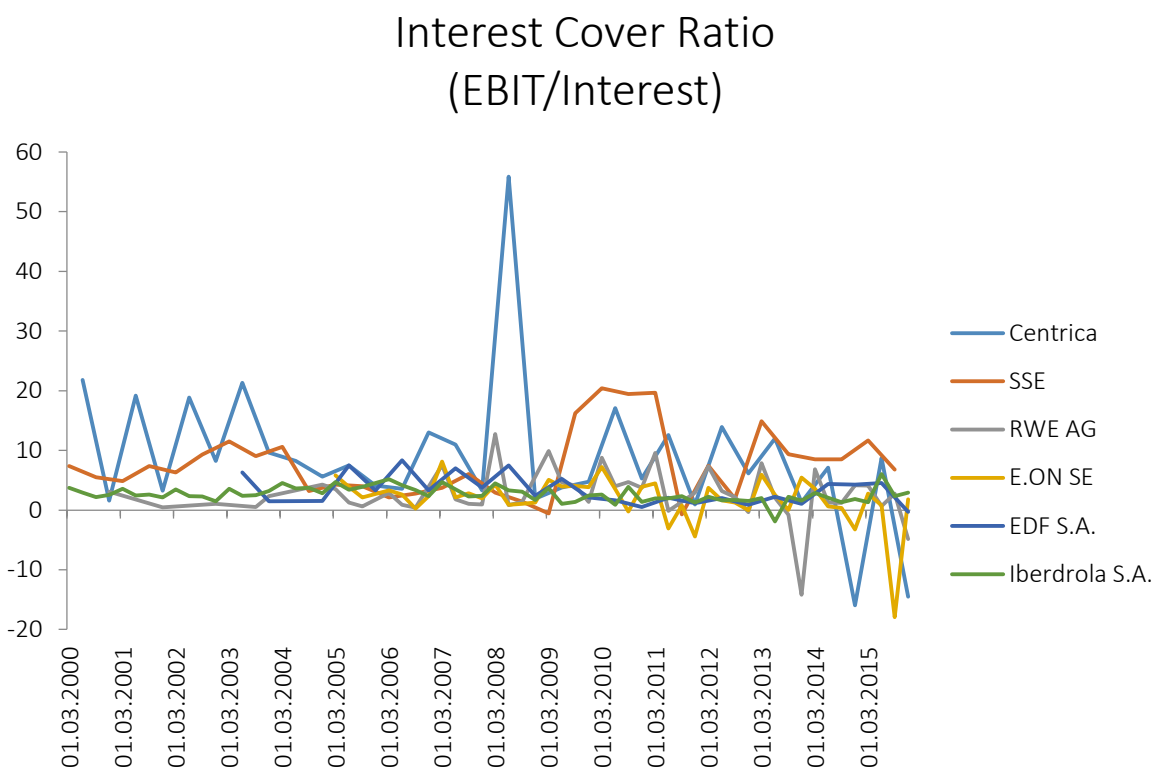

Figure 42: Interest Cover Ratio

Source: Bloomberg terminal

"Commonly known as Interest Coverage Ratio. Ratio used to determine how easily a company can pay interest on outstanding debt. EBIT (earnings before interest and taxes) is also commonly known as Operating Income. Calculated as EBIT / Total Interest Incurred" (Bloomberg)

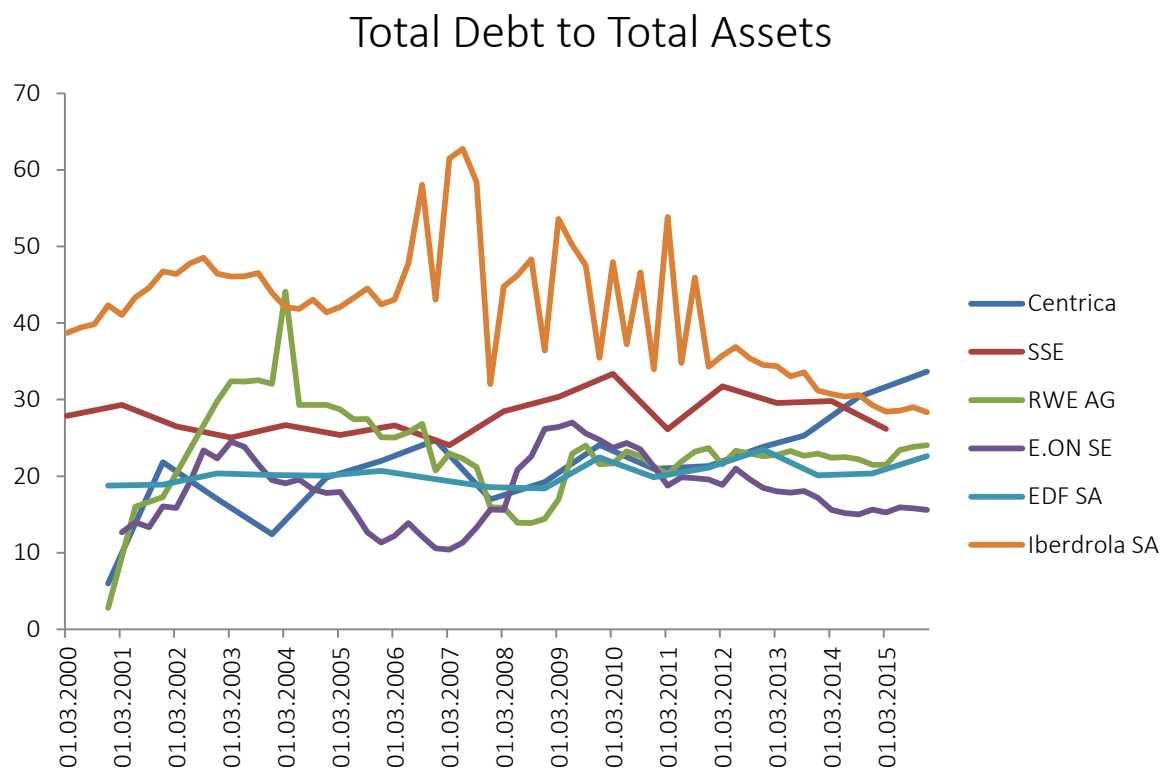

Figure 43: Debt to Assets Ratio

Source: Bloomberg terminal

This is one of the ratios for financial leverage.

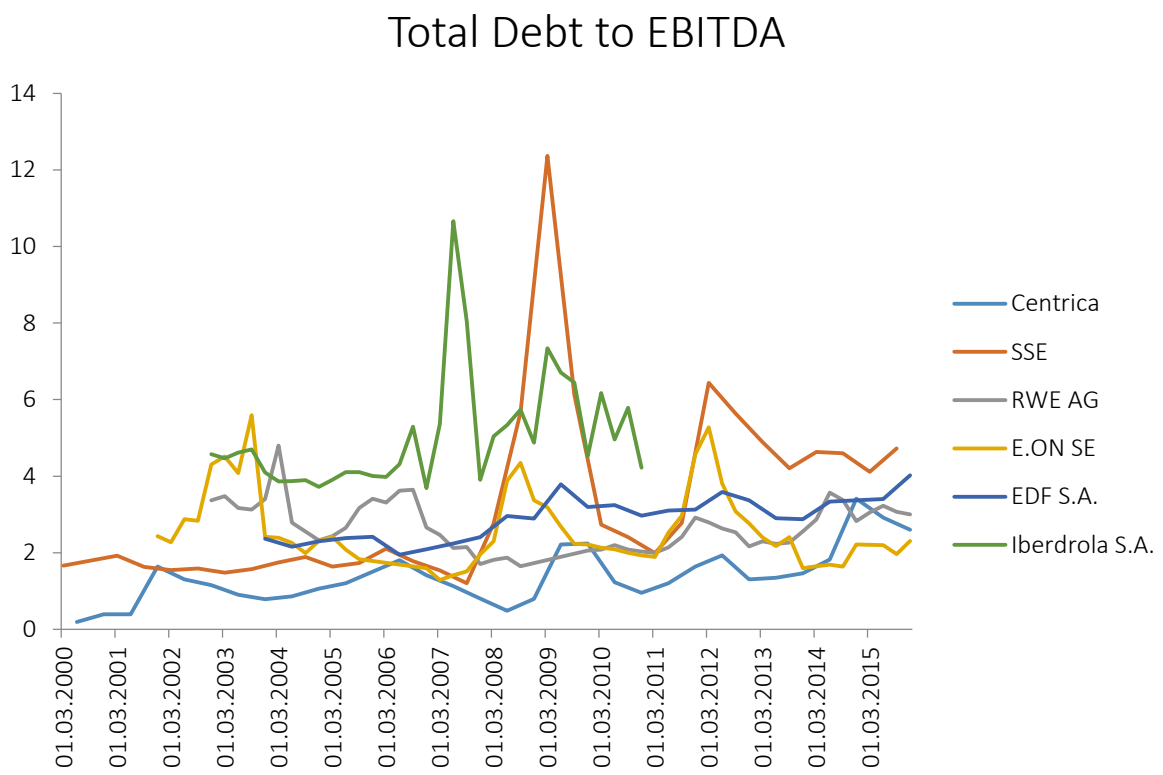

Figure 44: Debt-to-EBITDA ratio

Source: Bloomberg terminal

"Measure of a company's ability to pay off its incurred debt. This ratio gives the investor the approximate amount of time that would be needed to pay off all debt, ignoring the factors of interest, taxes, depreciation and amortisation. Calculated as Total Debt / Trailing 12 Month EBITDA" (Bloomberg).

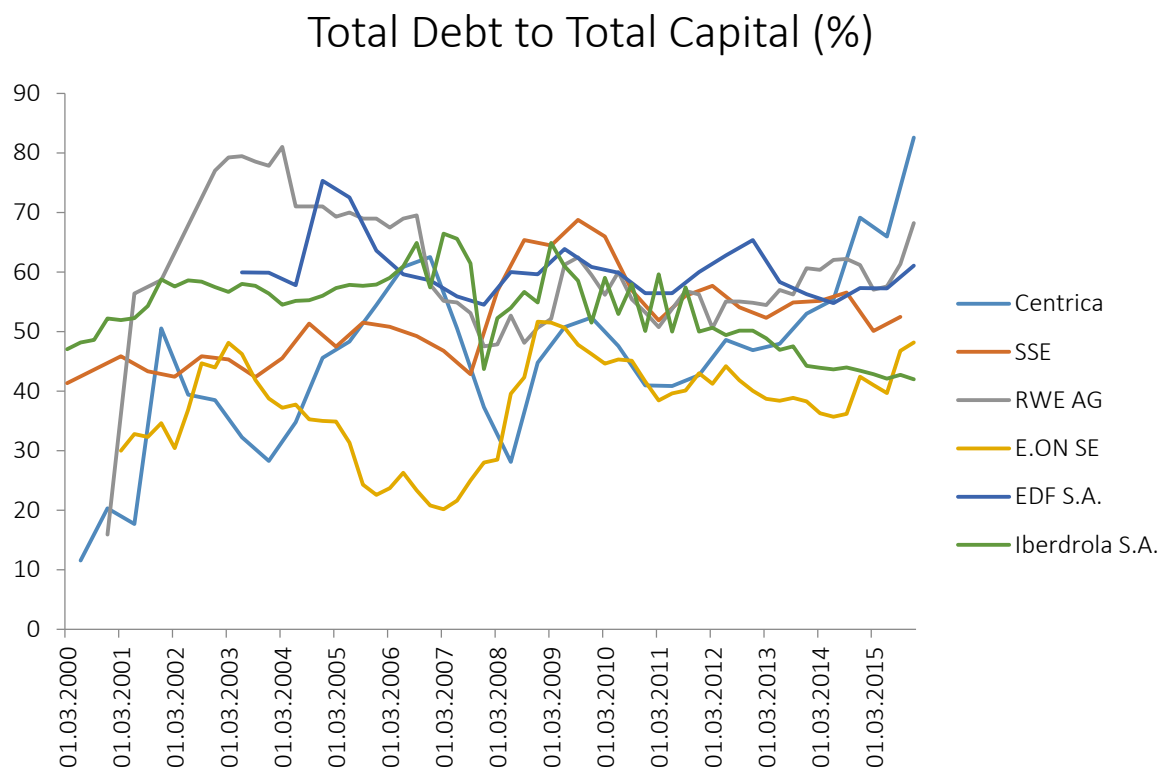

Figure 45: Debt-to-Capital ratio

Source: Bloomberg terminal

"Measure of a company's financial leverage that presents its total debt as a percentage of total capital. Calculated as Total Debt x 100 / Total Capital" (Bloomberg).

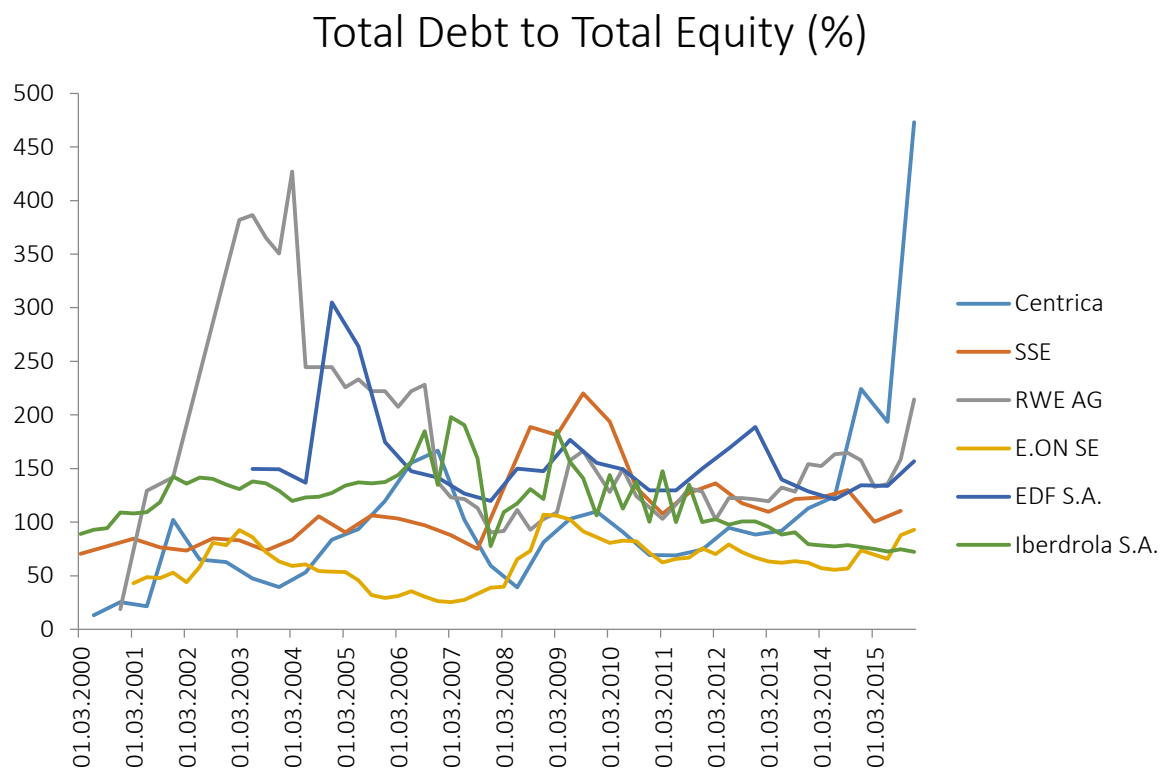

Figure 46: Debt-to-Equity ratio

Source: Bloomberg terminal

"Total debt divided by total shareholders' equity. Calculated as (Short and Long Term Debt / Shareholders' Equity) *100" (Bloomberg).

Appendix 3: Financial Covenants and CFaR

This appendix refers to Chapter 4.

If $P_{50}(EBIT_i^k) = E(EBIT_i^k)$ in equations (10) and (11), this is equivalent to having $(\gamma_{E(EBIT_i^k)} - \gamma_{P_{\lambda_i}(EBIT_i^k)})$ proportion of interest payment less than $CFaR^k{}_{\lambda i}$ (see calculations and Figure 47 below):

$$E(EBIT_i^k) \geq \gamma_{E(EBIT_i^k)} D_i r_{D_i} \frac{(1+r_{D_i})^\eta}{(1+r_{D_i})^\eta - 1}$$

$$P_{\lambda_i}(EBIT_i^k) \geq \gamma_{P_{\lambda_i}(EBIT_i^k)} D_i r_{D_i} \frac{(1+r_{D_i})^\eta}{(1+r_{D_i})^\eta - 1}$$

$$(\gamma_{E(EBIT_i^k)} - \gamma_{P_{\lambda_i}(EBIT_i^k)}) D_i r_{D_i} \frac{(1+r_{D_i})^\eta}{(1+r_{D_i})^\eta - 1} \leq E(EBIT_i^k) - P_{\lambda_i}(EBIT_i^k) = CFaR^k{}_{\lambda i}$$

Then, if maximum debt is exercised, we would get:

$$D_i^{(max)k} = \frac{CFaR^k{}_{\lambda i}}{(\gamma_{E(EBIT_i^k)} - \gamma_{P_{\lambda_i}(EBIT_i^k)}) r_{D_i} \frac{(1+r_{D_i})^\eta}{(1+r_{D_i})^\eta - 1}}$$

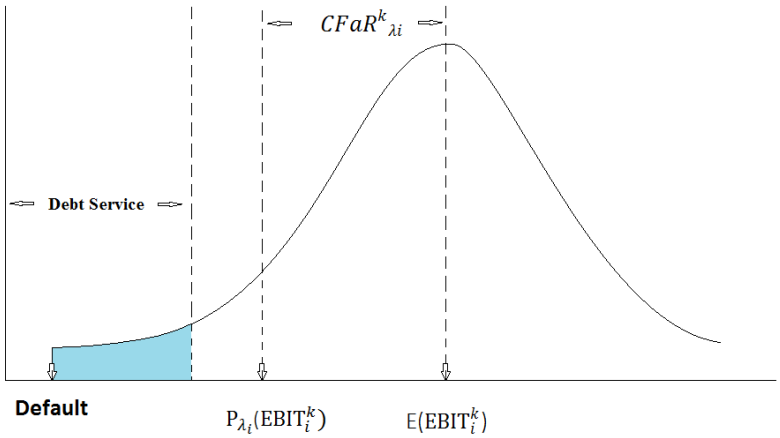

Figure 47: Debt Service and CFaR

Source: The author

Given the typical required numbers for $\lambda_i = 0.1$ and $\gamma_{\mathrm{E}(\mathrm{EBIT}_i^k)}$=1.4, $\gamma_{P_{\lambda_i}(\mathrm{EBIT}_i^k)} = 1.2$ and that maximum debt is exercised,, the above equation leads to:

$$D_i^{(\max)k} = \frac{CFaR^k{}_{\lambda i}}{0.2 r_{D_i} \dfrac{(1+r_{D_i})^{\eta}}{(1+r_{D_i})^{\eta}-1}}$$

Appendix 4: Additional Data on Chapter 5

Technology	Sub-category	Capacity (GW)	Min power (prop.)	No-load carbon (kg/MW/hour)	Incremental carbon (kg/MWh)	Start-up carbon (kg/MW)
Nuclear	1	2.56	0.8	0.00	0.00	0.00
	2	2.56	0.8	0.00	0.00	0.00
	3	2.56	0.8	0.00	0.00	0.00
Coal	1	1.28	0.5	6.09	95.38	1800.00
	2	1.28	0.5	6.68	104.61	1974.19
	3	1.28	0.5	7.39	115.82	2185.71
CCGT	1	1.91	0.3	67.86	356.26	530.15
	2	1.91	0.3	68.00	357.00	531.25
	3	1.91	0.3	68.14	357.75	532.36
	4	1.91	0.3	68.28	358.49	533.47
	5	1.91	0.3	68.43	359.25	534.59
	6	1.91	0.3	68.57	360.00	535.71
	7	1.91	0.3	68.72	360.76	536.84
	8	1.91	0.3	68.86	361.52	537.97
	9	1.91	0.3	69.01	362.28	539.11
	10	1.91	0.3	69.15	363.05	540.25
	11	1.91	0.3	69.30	363.82	541.40
	12	1.91	0.3	69.45	364.60	542.55
	13	1.91	0.3	69.59	365.37	543.71
	14	1.91	0.3	69.74	366.15	544.87
	15	1.91	0.3	69.89	366.94	546.04
Biomass	1	2.70	0.5	45.71	240.00	857.14
	2	2.70	0.5	49.23	258.46	923.08
	3	2.70	0.5	53.33	280.00	1000.00
OCGT	1	1.56	0.3	79.61	417.95	49.76
	2	1.56	0.3	81.60	428.40	51.00
	3	1.56	0.3	83.69	439.38	52.31

Table 29: General input data

Technology	Sub-category	No-load cost (£/MW/h)	Incremental cost £/MWh	Start cost (£/MW)	Incremental efficiency (prop.)	Average efficiency (prop.)	No-load fraction	Variable O&M
Nuclear	1	1.26	7.64	1000.0	0.47	0.39	0.16	1.01
	2	1.27	7.66	1000.0	0.47	0.39	0.16	1.01
	3	1.27	7.68	1000.0	0.47	0.39	0.16	1.01
Coal	1	1.83	30.75	131.91	0.36	0.34	0.06	2.13
	2	2.00	33.52	144.68	0.33	0.31	0.06	2.13
	3	2.22	36.88	160.18	0.30	0.28	0.06	2.13
CCGT	1	4.97	27.49	38.85	0.57	0.48	0.16	1.39
	2	4.98	27.55	38.93	0.57	0.48	0.16	1.39
	3	4.99	27.60	39.01	0.57	0.48	0.16	1.39
	4	5.00	27.66	39.10	0.57	0.48	0.16	1.39
	5	5.01	27.71	39.18	0.57	0.48	0.16	1.39
	6	5.03	27.77	39.26	0.57	0.48	0.16	1.39
	7	5.04	27.82	39.34	0.57	0.48	0.16	1.39
	8	5.05	27.88	39.43	0.56	0.47	0.16	1.39
	9	5.06	27.94	39.51	0.56	0.47	0.16	1.39
	10	5.07	27.99	39.59	0.56	0.47	0.16	1.39
	11	5.08	28.05	39.68	0.56	0.47	0.16	1.39
	12	5.09	28.10	39.76	0.56	0.47	0.16	1.39
	13	5.10	28.16	39.85	0.56	0.47	0.16	1.39
	14	5.11	28.22	39.93	0.56	0.47	0.16	1.39
	15	5.12	28.28	40.02	0.56	0.47	0.16	1.39
Biomass	1	13.71	76.74	257.14	0.42	0.35	0.16	4.74
	2	14.77	82.28	276.92	0.39	0.33	0.16	4.74
	3	16.00	88.74	300.00	0.36	0.30	0.16	4.74
OCGT	1	5.83	32.01	3.65	0.49	0.41	0.16	1.39
	2	5.98	32.78	3.74	0.48	0.40	0.16	1.39
	3	6.13	33.59	3.83	0.46	0.39	0.16	1.39

Table 30: Data used for adjusting start-up, no-load and incremental costs

Yearly from 1997-2015	Bre	Crude OECD	Gas UK	Gas EU	LNG Japan	LNG Germany	Gas Canada	Gas US	Co al	Coal NW EU	Coal US	Coke Coal Japan	Steam Coal Japan	Coal Asia
Brent	1.0 0													
Crude OECD	1.0 0	1.00												
Gas UK	0.9 4	0.94	1.00											
Gas EU	0.9 6	0.96	0.96	1.00										
LNG Japan	0.9 6	0.96	0.88	0.91	1.00									
LNG Germany	0.9 7	0.97	0.95	0.99	0.92	1.00								
Gas Canada	0.2 8	0.28	0.44	0.39	0.07	0.36	1.00							
Gas US	0.2 6	0.25	0.43	0.36	0.04	0.33	0.99	1.00						
Coal	0.9 0	0.91	0.85	0.90	0.84	0.91	0.30	0.28	1. 0					
Coal NW EU	0.8 5	0.86	0.84	0.88	0.74	0.89	0.51	0.48	0. 96	1.00				
Coal US	0.8 1	0.82	0.87	0.87	0.72	0.87	0.57	0.55	0. 90	0.93	1.00			
Coke Coal Japan	0.8 9	0.89	0.80	0.87	0.84	0.90	0.16	0.13	0. 95	0.86	0.82	1.00		
Steam Coal Japan	0.9 3	0.94	0.85	0.92	0.92	0.94	0.13	0.11	0. 95	0.86	0.83	0.98	1.00	
Coal Asia	0.8 8	0.88	0.85	0.90	0.79	0.90	0.37	0.36	0. 99	0.99	0.93	0.90	0.91	1.00

Table 31: Fuel price correlation matrix for different index