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A novel method for forecasting electricity prices in a system with variable renewables and grid storage

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ABSTRACT

In future UK energy scenarios with a high level of electrification, a large share of electricity is expected to be generated from renewable sources. To accommodate the variability of renewable generation, flexibility in the network is vital. An important flexibility option is grid scale electricity storage. The aim of this paper is to develop a methodology to study the effect of storage on electricity prices and then to demonstrate its application.

A simulation is made of the electricity system with variable renewable generation, electricity storage and flexible high carbon generators, assumed to be gas CCGT, for various UK scenarios. The simulation uses historical hourly meteorology to drive models of demand and renewable variation, and the consequent input/output operation of storage and dispatchable generation to balance differences between demand and renewables. A marginal cost method is devised to calculate the storage, renewable and dispatching capacity and operational costs incurred in each hour. These cost structures can form a transparent economic base for informing market design and setting prices for use in energy system models.

Results show that while marginal costs for renewable generation are relatively low, reliance on battery storage for backup particularly during peak periods can result in high electricity prices and without a significant increase in projected fossil fuel or carbon prices, traditional high carbon electricity generators will still be cheaper to operate. This work will be used to analyse the interaction between district heating with thermal energy storage and heat pumps, and the electricity system.

Keywords:

Electricity prices;
Variable Renewable Energy;
Storage;
Economic model;

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1. Introduction

To meet its decarbonisation goals, the UK targets a near zero emissions electricity grid and consequently, an expansion of renewable generation capacity [1]. The UK already has a large amount of variable renewable energy (VRE) on the electricity grid and with predicted mass electrification of other sectors such as heating and transport, the demand on the grid is also likely to grow. Managing this demand with VRE will require a change in the way in which the grid is operated, possibly requiring significant amounts of electricity and other storage operated in a smart energy system.

The increase in VRE on the grid is creating challenges with grid balancing and meeting peak electricity demand, a problem that is currently solved largely through the use of dispatchable, fossil fuel operated plants such as gas-fired turbines. Battery electricity storage is an option to provide flexibility and reduce curtailment of renewable resources but their economic viability and impact on prices requires analysis, which is a major objective of this work.

Historically, electricity prices have followed a predictable pattern of daily cycles of peak and off-peak prices with seasonal variability and a strong link with

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fluctuations in fuel prices [2]. This predictability enables planning of smart grid infrastructure requirements as well as the electrification of other sectors by making informed investment decisions. However, with VRE composing a larger share of the electricity system's generating capacity, electricity prices are becoming less predictable as exemplified by a recent record run of negative prices following by a sharp spike in balancing costs on the grid [3,4].

As VRE increases, imbalances between supply and demand at daily, seasonal and annual timescales are expected to increase [5]. To avoid curtailment of VRE and to ensure that low carbon electricity is supplied during periods of VRE, some forms of electricity storage will be required on the grid. With capital costs declining, lithium-ion batteries are experiencing a rapid uptake at the utility scale with it suggested that upwards of 15GWh of battery storage could be deployed on the grid by 2030 [6].

At present, in a system with low penetration of VRE and fossil fuel plants composing the largest share of electricity generation, flexibility is largely achieved by dispatchable plant using stored fossil, nuclear and biomass fuels, that provide a large amount of the balancing requirements in the current Great Britain power system, with this being complemented by storage such as pumped storage and off peak storage heaters. VRE generators have been rapidly reducing in capital costs and have very low operational costs [7], but they are inflexible, and the costs of integrating VRE must then be considered. As the penetration of VRE on the system increases, the flexibility costs associated with them are envisioned to rise [8]. What effects a larger battery storage capacity will have on the electricity generation cost patterns is uncertain, particularly when future demand and supply profiles are uncertain. However, while many studies show that VRE reduce electricity prices, there has been little analysis into what effect factoring the cost of energy storage has on system electricity generation prices.

This paper outlays a methodology used to derive a series of electricity supply prices for high renewables scenarios with large capacities of grid connected energy storage. This methodology and results will be used to assess the economic viability of thermal storage in district heating in managing the electricity system.

2. Literature review of VRE price variance

Forecasting of electricity prices has been well explored with various approaches such as econometric, statistical or multi-agent models used to assist in estimating electricity spot prices over various time horizons. Weron has provided a detailed review on the state of the art in electricity price forecasting techniques [9].

There have been numerous studies analysing the effects of increased VRE in electricity systems on spot prices, many of these show a rise in volatility of prices. Much of this analysis has been performed on historical data of northern European electricity markets.

Dong et al. showed using historic data on the Nordpool market that electricity price volatility increases with a higher penetration of renewables and that this increase in volatility is more pronounced in regions where wind generation dominated [10]. Wozabal et al. performed a statistical analysis of spot price variance in Germany [11], challenging the assumption that higher VRE always increases price variance. They found that small fractions of VRE actually decreased price volatility but higher fraction penetrations of VRE resulted in larger increases in price variance. They highlight the importance of price variance as a revenue stream for smart grid infrastructure such as storage. Dillig et al. use historic spot prices in Germany to create counterfactual prices in the absence of VRE [12]. They found increased hourly volatility in prices and show that prices in a higher VRE system are lower on average than a system without VRE. They also find that increasing VRE in the system results in a higher cost of dispatchable generation, potentially due to lower capacity factors. Comparing the German system with high solar capacity and the Danish system with high wind over various timescales, Rintamaki et al. studied volatility of prices during high VRE periods [13]. They observe that daily volatility in the wind dominated system is reduced in high wind areas, owing to stable wind speeds over daily timescales but increased in a high solar system due to the daily fluctuation in solar power. Price volatility on a weekly scale was shown to increases in both cases. This is supported by Wozabal et al. which found that small fractions of wind power leads to a reduction in price volatility as wind power penetration in Australia currently accounts for below 5% of all electricity generation [14].

There have recently been some attempts to quantify the effects of largescale VRE in future scenarios in various markets. Pikk and Viiding use a Nordpool market spot price analysis and predict a higher volatility of prices in a high VRE scenario and similarly in Germany, Ketterer found that an increase in wind generation capacity will lead to a more volatile electricity spot price but with reduced average prices [15,16]. Sorknæs et al.

Investigated the effect of VRE on wholesale prices using a market economic simulation in EnergyPLAN [17]. They calibrated their economic model with 2015 Nordpool spot prices then simulated future VRE capacity effects on prices. The authors determined that any increase in VRE generation reduces wholesale prices.

Badyda and Dylik studied historical market and renewable generation data for several European countries [18]. Extrapolating their observations, they predict a pronounced seasonality in the price variance with up to three times higher average prices in high demand periods. Maxwell et al. used a similar method to investigate the role of renewable subsidies in Denmark and state that future work would benefit from a better understanding of how VRE effects electricity prices [19].

2.1. Marginal cost methods

The previous authors have studied price variance using statistical or econometric analysis to model and describe prices in high VRE scenarios. Another class of pricing models described by Weron falls into the "fundamental model" category [9], so called as it attempts to describe the important physical and economic factors that give rise to electricity prices. The use of marginal generating costs falls into this latter class. These models typically use defined marginal cost curves for generators and locations and determine prices by the point at which it intersects with demand curves.

The use of marginal costs in predicting electricity prices is a standard method to predict system electricity prices and is a useful price estimator [20]. Electricity markets consist of many generators bidding to supply electricity, each with differing costs. Economic theory predicts that in a market with perfect competition and sufficient capacity, the market auction price should clear at the cost of supplying a marginal increase of demand in the system. Further, the price of electricity should be equal to the marginal cost of the most expensive generator active on the system. This is as even though cheaper generators may be active on the system, market price is set at the highest auction clearing price and all electricity generators obtain the same remuneration.

However, the actual wholesale price of electricity is rarely at the marginal cost due to market imperfections and secondary costs, but marginal costs provide a reference point about which wholesale prices have been shown to deviate. Marginal costs have been shown to be the largest component of day-ahead wholesale electricity prices in the UK which includes the added costs of transmission, distribution and mark-ups from utility companies, composing about 40% of end electricity prices [21].

Haas et al. study the impact of solar power in European electricity markets using a marginal cost method [22]. Similar to other studies, they predict higher volatility at both hourly and daily timescales which will in turn result in higher prices for dispatchable generators in the long term. They highlight the growing importance of balancing markets going forward in Europe. Morales et al. used locational marginal costs to study the impact of regional wind power generation on a simulated electricity market to obtain statistical characterisation of wind prices with wind power and Musgens has used marginal costs with a dispatch model to study market power in Germany and the effect of integration with other markets [20,23]. A study of the merit order effect due to the price of wind generation found depressed electricity prices and lower returns to other generators in the Spanish market [24]. The authors used this to highlight the inadequacy of the Iberian power market to incentivise further investment.

Marginal costs have been used by Lamont to assess the system value of VRE and to optimise generator capacity on the GB system [25]. They use a simplified dispatch model of 'always-on' baseload, then a selection of VRE or dispatchable plant based on marginal costs assuming that the cost of constraining wind power is at the price set by the renewable obligation certificate rather than marginal run costs. Green and Vasilakos used a market equilibrium model with marginal generator costs to study market behaviour and the impact of wind power on longterm electricity prices using data on expected wind generation capacity and demand for 2020 [26,27]. Hourly wind data for the period 1993–2005 are used to obtain wind output generation profiles for thirty regions (onshore and offshore. They find that yearly variations of wind output can affect intra-year revenue for wind generators by up to 20%, but this is lower than the effect of fluctuating fuel prices at present. In addition, they find that that the prices wind generators receive for constraining output has significant consequences on the resulting capacity mix. The impact of including storage is left for future work. Seel et al. have used marginal costs to analyse wholesale electricity price patterns in four grid regions in the USA [28]. First using a capacity expansion model to derive high VRE scenarios, they found a reduction in average annual prices throughout but differing average price patterns based on VRE type mix and region.

Notably, in the literature presented, there has been a lack of analysis on the effect of large-scale grid battery storage on electricity prices and how this alters marginal electricity prices. The method presented in the following sections attempts to address this.

3. Modelling methodology

Nomenclature

D	Demand, MWh
G	Generation, MWh
C	Capacity, MW
A	Capacity Factor/Availability, %
P	Price, £/MWh
V	Variable Costs, £/MWh
M	Constrained-down loss, £/MWh
F	Fixed Costs, £/MW/annum
R	Forced outage rate, %
N	Number of hours count
Q	Charge/Discharge quantity, MWh
L	Storage loss factor, %
E	Efficiency, %

Subscripts

i	Hour i
LCB	Low Carbon Generation
BSL	Baseload
ONS	Onshore wind
OFS	Offshore wind
SOL	Solar PV
SRP	Surplus hours
CHR	Charge hours All
CHRc	Charge hours in cycle
DCH	Discharge hours,
DCHf	Discharge hours, full cycle
DCHp	Discharge hours, part cycle
DSP	Dispatch hours
DSPp	Dispatch hours, peak
DSPo	Dispatch hours, off peak
CDD	All Charge, Discharge and Dispatch hours
m	Marginal renewable generator
n	Incremental renewable generator
c	Dispatchable generator
s	Storage
d	discharge

The methodology presented here first describes how the dispatch model is designed and then in detail how marginal costs are used with the dispatch model to derive marginal electricity supply prices.

3.1. Dispatch model

A simplified representation of the electricity system for possible future low carbon energy system scenarios with large fractions of variable renewable energy (VRE) and grid connected electricity storage is developed. The main simplifications are each generator type is treated as an aggregate and while spatial and transmission constraints are not explicitly modelled. Generation capacity is split into flexible and inflexible generation. Flexible generators are assumed to be CCGTs that are able to adjust output instantly to follow demand. VRE output varies uncontrollably with the wind resource but can be spilled. Baseload is assumed to be nuclear generation with constant output. The modelling work conducted here is focused on scenarios where flexibility is first achieved with grid battery storage, and secondly with dispatchable CCGT. The methodology will later be applied to include heat demands, thermal storage and heat pumps in district heating. Note that the prices calculated are at the point where generator and storage supply electricity to the high voltage grid, and do not include transmission and distribution losses and costs. These costs might be simple constant additional costs per kWh, or more complex such as also reflecting peak flows which drive capacity and maximum losses. These additional costs will be smaller for high voltage supply, such as to industrial heat pumps for example, than lower voltage to the majority of consumers.

Renewable generation is defined via hourly capacity factors (percentage of installed capacity generating), from historical meteorological data and projected installed capacity, while dispatchable generation capacity is assumed to be sufficient to meet any residual demand. The maximum required dispatchable generation occurring in a year is then one input to the capital cost of the system used in the calculation of marginal costs.

Demand data is an exogenous input to the model and assumed inelastic i.e. demand is always met regardless of the cost of electricity. Hourly demand has been scaled for each scenario from a historical demand timeseries such that it corresponds to the hourly renewable generation capacity factors from the same location and time period to maintain the weather effects that fundamentally link them. The scaling assumes that historical demand load profiles are preserved in future demand profiles.

The capacity factor for each renewable generator is multiplied by the installed capacity to obtain hourly renewable generation which is added onto a baseline generation capacity assumed in the scenario. Baseload generation is assumed constant throughout the simulated period and always less than demand and consequently never sets the marginal price in this model.

Total low carbon electricity generation for each hour, i, is then the sum of baseload and all VRE generators:

$$G_{LCB,i} = C_{BSL} + C_{ONS}A_{ONS,i} + C_{OFS}A_{OFS,i} + C_{SOL}A_{SOL,i} \qquad (1)$$

If there is a surplus of electricity generation over demand Di, $G_{LCB,i} – D_i > 0$, then $G_{LCB,i} – D_i$ is allocated to the available storage if charge capacity is available otherwise the renewable power is constrained. If the demand exceeds the available generation $G_{LCB,i} – D_i < 0$, then the electricity storage is discharged by the amount $D_i – G_{LCB,i}$. If the discharge is insufficient, the dispatchable power generators, CCGT is then activated and the dispatchable generation is $G_{DSP} = D_i – G_{LCB,i} – G_{DCH,i}$.

Here it is assumed that storage operates in coordination with VRE to meet residual demand or absorb surplus generation and a modelling assumption is made that all stores charge and discharge simultaneously by the same fraction of their capacity. High carbon Dispatchable power generation is treated as a last resort in order to minimise the associated emissions from generating electricity i.e. rather than a conventional market where generators bid to supply electricity, the smart grid infrastructure prioritises limiting of carbon emissions. It is initially assumed that there are no constraints on the charging and discharging power of storage, an assumption that becomes reasonable as the number of individual stores increases.

3.2. Marginal pricing method

Upon completing a simulation of the electricity system, each hour is divided into four basic hour types some of which have further subdivisions. For each hour type there is a different algebraic expression used to calculate the marginal electricity generation price.

- Type 1 SRP: Hours with surplus renewable generation, “Surplus Generation hours”. These are hours where supply exceeds demand and remaining storage capacity.
- Type 2 CHR: Hours in which electricity storage is charged “Charge hours”
- Type 3 DCH: Hours in which electricity storage is discharged “Discharge hours” subdivided into:
  - Full cycle discharge (DCHf) hours where storage capacity is full prior to discharging
  - Part cycle discharge (DCHp) hours in which storage is partly charged prior to discharging
- Type 4 DSP: Hours in which backup dispatchable generation is required “Dispatch hours” subdivided into:
  - Peak dispatchable hours DSPp where the difference between electricity demand and low carbon generation is at its highest which determines its capacity
  - Off-peak dispatchable hour DSPo which are all other dispatchable hours

The procedure must be carried out in a particular order. After simulating the electricity system for a period of a year (or number of years), P_{SRP}, Surplus generation hours are calculated followed by the generation price for Dispatch hours, P_{DSP}, both peak and off-peak. Charge hours P_{CHR}, are then calculated which are then required for the calculation of P_{DCH}, Discharge hours.

3.2.1. Surplus generation hours

When baseline and renewable generation exceeds demand and electricity storage charging capacity, curtailment of renewable generation will be required. It would be economic to curtail the renewable technology with the highest variable cost (however small these are for renewable generators). This is analogous to creating a merit order of net variable cost and identifying where Demand intersects the resulting merit-order stack. This indicates the particular renewable technology that sets the price during that hour and may vary hour by hour. This technology is the “marginal technology”, denoted by the subscript m.

Figure 1: Order of operation to calculate prices per hour type

The price for Surplus Generation hours is then given by the variable minus the cost of constraining output:

$$P_{SRP,i} = V_{m,i} - M_{m,i} \tag{2}$$

3.2.2. Off-peak dispatch hours

When electricity demand exceeds the available low-carbon power including stored electricity, demand must be met by dispatchable plant, this is assumed to be CCGT but could be one of several plant types. To minimise carbon emissions, it is assumed that this plant only operates during the hours required to make up the generation shortfall. Therefore, all of the year-on-year costs of the dispatchable plant must be met by this operation; but it is assumed these are legacy plant with sunk costs so they do not incur capital costs. Hence, for off-peak dispatchable hours, the electricity generation price is given by the variable operating costs of the dispatchable plant:

$$P_{DSPo,i} = V_c \tag{3}$$

The variable operating costs include fuel and carbon costs, and variable O&M costs. The O&M costs in this case will need to be a conservative estimate due to the impact on efficiency and O&M of frequent ramping, part load and cold start.

3.2.3. Peak dispatch hours

The annual fixed operating costs of the dispatchable plant are recovered during the peak dispatch hours. These costs are often called Fixed Other-Works Costs (FOWC) which are a close approximation of the Net Avoidable Cost (NAC), the net cost of keeping the plant open for another year.

In a system with VRE, there is uncertainty as the operation of dispatchable capacity and therefore of the revenue it will obtain from the hourly market. Therefore, the UK has had a Capacity Market auction whereby the generator or store receives a guaranteed annual payment regardless of the amount generated. This market is currently under investigation but is assumed to apply in the pricing methodology [29]. Battery storage was permitted to participate in the capacity market; however, the marginal cost of providing peak demand from storage remains high. The National Grid recovers the cost of the capacity market auctions during peak weekday demand periods, November-February 4–7pm or around 240 hours or 2.7% of hours in the year (though this means of allocation is somewhat arbitrary) [30].

Following this means of recouping marginal capacity costs, 2.7% of the Dispatch hours with the highest difference between Demand and Low Carbon Generation, $D_i - G_{LCB,i}$, are allocated as Peak Dispatch hours.

$$P_{DSPp,i} = \frac{F_c \max\limits_{DSP}\left(G_{c,i}\right)}{\left(1 - \frac{R_c}{100}\right)\sum_{\mathrm{DSPp}}\left(G_{c,i}\right)} + V_c \tag{4}$$

3.2.4. Charge hours

A projection of the incremental renewable generator is made which is the renewable generator that sets the charge price. The incremental technology in the UK would likely be offshore wind, given the constraints on the building of further onshore wind, its higher output in winter when demand is high and the higher cost of solar generators. The incremental technology is distinct from the marginal generator which can be any VRE (including incremental), storage or dispatchable, during an hour.

The generation cost during charge hours is set by the incremental technology for a given scenario. The variable cost of the incremental technology during surplus hours in which it is less than that of the marginal technology must also be recovered. The 'energy credits' can be calculated by:

$$\sum_{SRP} G_{n,i}\left[\left(V_{m,i} - M_{m,i}\right) - \left(V_n - M_n\right)\right] \tag{5}$$

The fixed costs of the incremental renewable generator during across the year (or the chosen time period for calculation) must be recovered. This fixed cost is given by:

$$\begin{aligned} F_n = {} & \sum_{CHR}\left(A_{n,i}P_{CHR,i}\right) + \sum_{DCH}\left(A_{n,i}P_{DCH,i}\right) + \sum_{DSP}\left(A_{n,i}P_{DSP,i}\right) \\ & - \sum_{CDD} A_{n,i}\left(V_n - M_n\right) \\ & + \frac{1}{C_{n,i}}\sum_{SRP} G_{n,i}\left[\left(V_{m,i} - M_{m,i}\right) - \left(V_n - M_n\right)\right] \end{aligned} \tag{6}$$

Substituting for P_{DCH} and using the following approximation gives:

$$\begin{aligned} & \sum_{DCH}\left(A_{n,i}\left[\sum_{CHRc}\left(A_{n,i}P_i\right) \Big/ \sum_{CHRc}\left(A_{n,i}\right)\right]\right) \\ & \approx \left(\sum_{DCH} A_{n,i}\right)\left(\sum_{CHR}\left(A_{n,i}P_i\right) \Big/ \sum_{CHR}\left(A_{n,i}\right)\right) \end{aligned} \tag{7}$$

The Charge Price is given, from (6) and (7), and from (12) below, by:

$$P_{CHR,i} = \frac{F_n - \frac{1}{E_s}\sum_{DCH} K_{DCH,i} A_{n,i} - \sum_{DSP}\left(A_{n,i} P_{DSP,i}\right) - \frac{1}{C_n}\sum_{SRP} G_{n,i}\left(V_m - M_m\right)}{N_{CHR} A_{n,i}\left(1 + \frac{1}{E_s}\frac{\sum_{DCH} A_{n,i}}{\sum_{CHR} A_{n,i}}\right)} + \frac{\left(\frac{1}{C_n}\sum_{SRP} G_{n,i} + \sum_{CDD} A_{n,i}\right)\left(V_n - M_n\right)}{\frac{1}{E_s}\sum_{DCH} A_{n,i} + \sum_{CHR} A_{n,i}} \tag{8}$$

3.2.5. Discharge hours
Assuming the battery has a constant loss factor of L (thus an efficiency E of 1-L) with no standing loss assumed then for every unit of power discharged, 1/E units of power must be charged. The cost of charging the storage must be recouped from discharging. The assumption is made that all the individual batteries are charged and discharged evenly across each individual unit in the capacity as if one single aggregate battery. The cost incurred from this charging is dependent on the cumulative charge hour generation costs preceding the discharge, back to when the store was last empty, denoted with CHRc. The average cost of charging during charge hours in the period preceding the discharge, weighted by the availability of the incremental renewable generator is given by:

$$\sum_{CHRc}\left(A_{n,i} P_i\right) \Big/ \sum_{CHRc}\left(A_{n,i}\right) \tag{9}$$

The fixed cost of storage capacity must also be recovered during discharging. Here it is assumed that the marginal electricity generation cost of supplying power from discharging storage is driven by the incremental storage cost to meet incremental demand and the cost of charging the storage from renewable generators.

This recovery of the fixed cost of storage during discharge hours in this method is recovered through full charge-discharge cycles. A full discharge cycle is defined as each time the storage capacity is full preceding the discharging cycle which can run for multiple hours. A part discharging cycle are other hours when storage is not full prior to the discharge cycle. The cost of storage capacity during a part and full discharge hour K is:

$$K_{DCHp,i} = R \tag{10}$$

$$K_{DCHf,i} = \left(\frac{E_s F_s C_s}{\sum_{DCHf} Q_{d,i}}\right) + R \tag{11}$$

The generation cost during a discharge hour is then given by:

$$P_{DCH,i} = \left(\frac{1}{E_s}\right) \times \left(K_{DCH,i} + \frac{\sum_{CHRc}\left(A_{n,i} P_i\right)}{\sum_{CHRc}\left(A_{n,i}\right)}\right) \tag{12}$$

3.3. Data sources
The capacity factor data to construct hourly renewable generation profiles have been obtained from the work of Pfenninger and Staffell published on the 'Renewables Ninja' website [31,32]. The capacity factors are derived from a combination of historical meteorological data and known or planned renewable generator locations.

Electricity demand data is obtained from the National Grid's historic demand data archive which contains the demand on the transmission network and a breakdown of output from each generator type per half hour [33]. Hourly demand is calculated from the sum of two half hourly periods. This data however is not representative of the true GB electricity demand as it does not include any power generation embedded in the distribution network.

4. Results and discussion

The model output is first compared to historic generation data for the year 2016 before the results from two high VRE scenarios are presented. These scenarios are adapted from the National Grid's Future Energy Scenarios [34], using the projected generation capacity mix from the two scenarios that conform to the 2050 decarbonisation targets.

4.1. Dispatch model validation
The model output using 2016 renewable capacities is compared to historic generation data for the year in Table 1 [35]. This method is designed for a renewable and storage dominated system thus an exact match for electricity generation and prices with a present-day system should not be expected. However, it is useful to

Table 1: Comparison of 2016 low carbon generation statistics with modelled generation

	Onshore Wind TWh	Offshore Wind TWh	Solar PV TWh	Nuclear TWh
2016 Data	21.1	16.4	10.3	65
Modelled	24.3	16.0	10.7	78

compare the low carbon generation output from the model with the data. In the model, all other generation is assumed to be dispatchable whereas this is not the case in the present-day system.

Baseload nuclear generation is overestimated as the model assumes a 100% availability. The data shows an 83% annual capacity factor for nuclear generators which would be due to maintenance and seasonal availability. Comparison for the output of the renewable generation data from Stafell and Pfenninger [31,32] shows that it has been calibrated accurately. Solar PV and offshore wind outputs are very close while onshore wind has been slightly overestimated.

4.2. Scenario Analysis

The scenarios “Two Degrees” and “Community Renewables” from the National Grid’s Future Energy Scenarios are designated here as ‘Scenario A’ and ‘Scenario B’. The details of these scenarios are presented in Table 2. The renewable generation and grid storage capacity from the two scenarios was used as input for the scenario analysis and 5% interest on all capital costs has been applied for initial analysis.

A comparison of the electricity generation prices for each scenario and 2016 in Table 3 shows that the average daily cost of electricity generation is lower than 2016 average in both high VRE scenarios modelled here. The input cost assumptions can be found in Appendix B. The maximum average daily cost increases however due to the fixed annual costs of dispatchable generation (assumed here as CCGT) being recouped over fewer hours of the year. Additionally, these would also be the days that have the highest difference (residual) between electricity demand and renewable generation, requiring dispatchable plant to fulfil the remaining demand.

The scenarios were modelled using demand and renewable data from 2006–2016. The results for individual years can be found in Appendix. A. detailed look at Scenario A in Figure 2 shows a winter month period in 2013 with the residual renewable generation (above) and storage levels and electricity prices (below), showing electricity prices frequently spike corresponding to cycling of electricity storage levels in the system. When storage levels are full, surplus generation hours result in low prices. However, as a result of renewable fluctuation the storage level rapidly varies requiring discharge then dispatch periods of higher prices. A peak dispatch hour occurs towards the end of November when residual generation is most negative. Figure 2 suggests that the storage capacity in Scenario A is insufficient for the renewable capacity in the absence of other flexibility options.

Explicit constraints on charging and discharging rates have not been applied. However, the peak power to energy ratio in the simulations of the scenarios was 0.66. This is within the limits of grid scale lithium-ion storage where typical power to energy ratios are 1.0 [36].

Off-peak dispatch hours are cheaper than discharge hours under the current cost projections used. This is the case with the current assumptions of short run variable costs of dispatchable hours being less than that of discharge prices (fuel £35/MWh, carbon £70/MWh, O&M £1.5/MWh). For the storage capacity defined in

Table 2: NationalGrid FES 2017 Scenarios (2050) comparison

Scenario Name	Demand (relative to 2017)	Offshore Wind GW	Onshore Wind GW	Solar PV GW	Nuclear GW	Total Capacity GW	Grid Storage GWh
A (Two Degrees)	+25%	43.4	22.3	43.7	20.0	224.3	17.3
B (Community Renewables)	+48%	32.5	50.7	66.2	18.6	267.6	29.0

Table 3: Price comparison with renewable capacity and storage

Scenario	Renewable Capacity GW	Share of total capacity Wind	Share of total capacity Solar	Ave price £/MWh
A (Two Degrees)	109.4	29%	19%	34.1
B (Community Renewables)	149.4	31%	25%	35.1
2016 actual	26.79	16%	11%	41.12

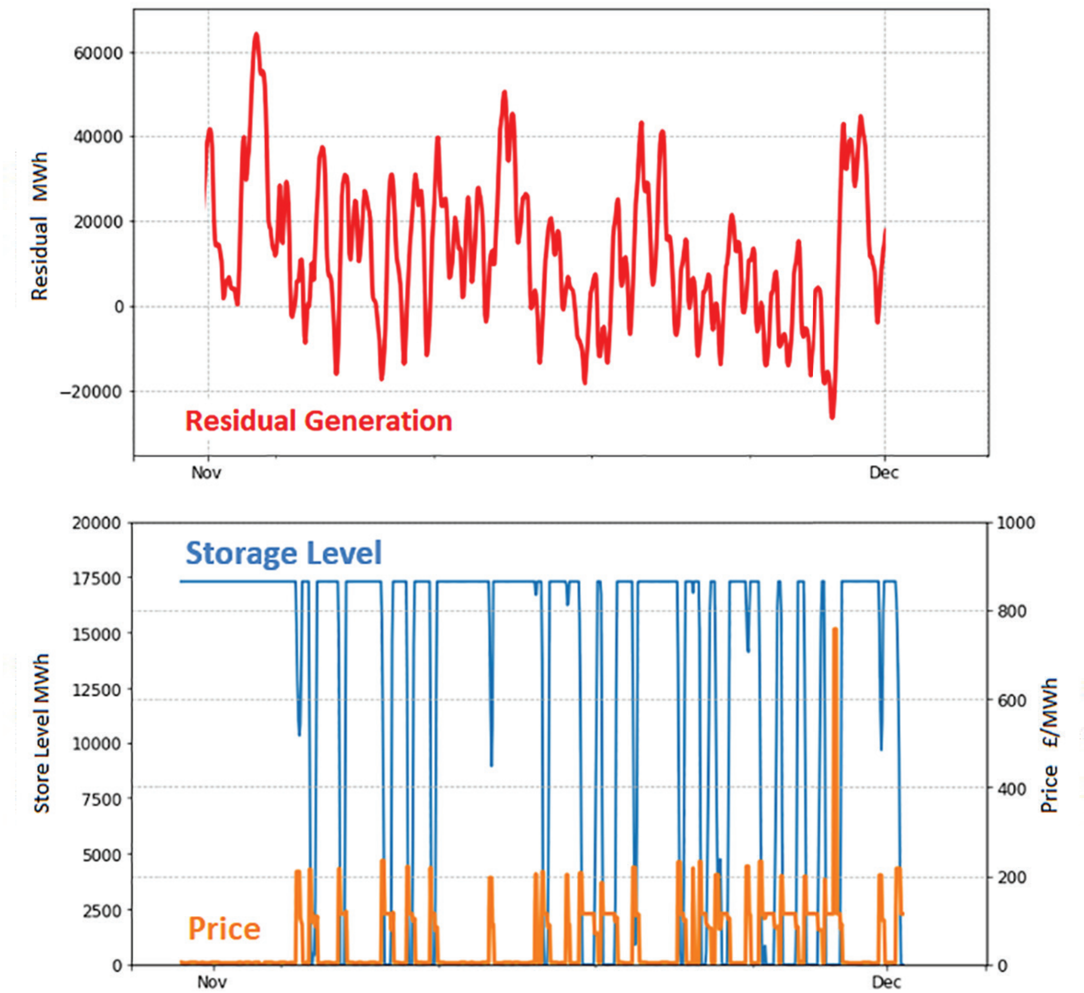

Figure 2: Residual renewable generation (above) and resulting cycling of storage and prices (below) for Scenario A 2016

Scenario A, a total short run variable cost for dispatchable generation would need to be at least that of the highest discharge prices, £251/MWh. From the perspective of limiting carbon emissions, it would be desirable to have dispatch hours cost higher than discharge hours. Adjusting dispatch hour prices to be higher than discharge hours meant that the average price in Scenario A 2013 increased from £36.34 to £49.83, almost a 40% increase in average annual prices.

Within the current market framework where bids are accepted based on price, unless fuel or carbon costs increase above projected values, dispatchable/thermal generation would be higher in the merit order than less carbon intensive electricity from discharging electrical storage, owing to their lower marginal costs, Figure 3. Figure 4 shows adjusted dispatch hour costs to reflect an ideal scenario where dispatch costs are higher than discharge costs.

For both scenarios, the positive residual generation from renewables is far higher than negative, Figure 5, which perhaps suggests an overcapacity of renewables in both scenarios. Analysis of the residual duration curves as well as the absolute maximum of negative residual generation can allow better estimates of storage requirements and the corresponding effect on prices, but an optimisation of scenario storage levels is beyond the scope of this paper.

Figure 6 shows a 24-hour rolling average of the mean generation prices for scenario A from the 2006–2016 data, scenario B exhibited a very similar distribution. A clear seasonality can be observed in the prices with higher prices periods being concentrated in the winter

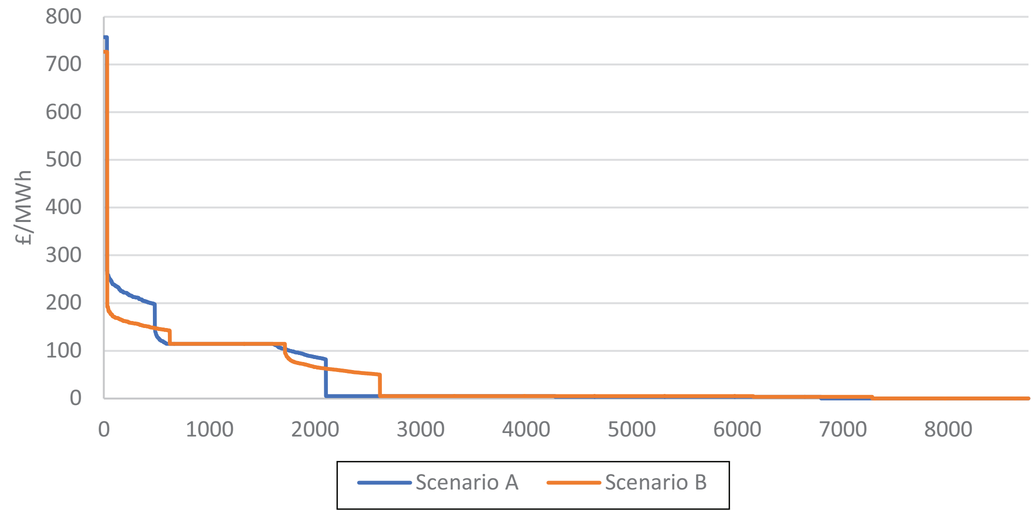

Figure 3: Scenario price duration curves 2013

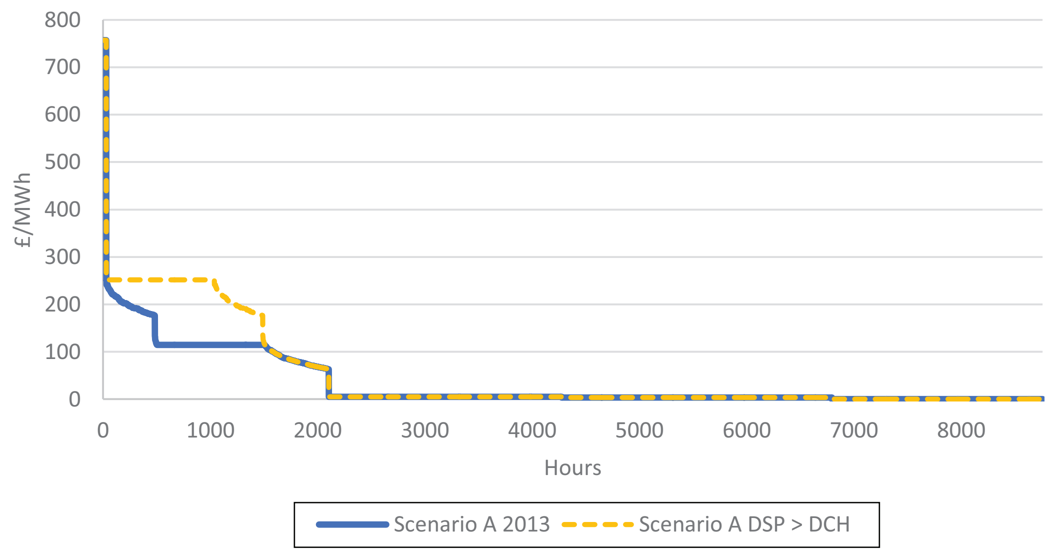

Figure 4: Scenario A 2013 price duration curve with adjusted DSP costs

periods where despite wind generation in these scenarios being higher during the winter, there are periods of low generation coinciding with high demand often leading to higher prices.

Also observable is that an increase in the share of renewables does not directly lead to lower average electricity generation prices. This can be seen in the average price difference between scenario A and B being very similar, despite B having a significantly higher renewable capacity to meet a significant difference in demand. Neither scenario has consistently higher average prices than the other across the modelled years, with some years resulting in Scenario A having higher average prices.

The fewer dispatch hours that occur within a year, the higher the maximum prices become as there are fewer hours where dispatchable plant operates. The fixed annual costs of the dispatchable plant per MWh of electricity grows as there are fewer peak dispatch hours against which to recover fixed costs of the capacity. The price of peak dispatch would decline if dispatchable plant capacity decreased, in other words, if the highest negative residual generation decreases.

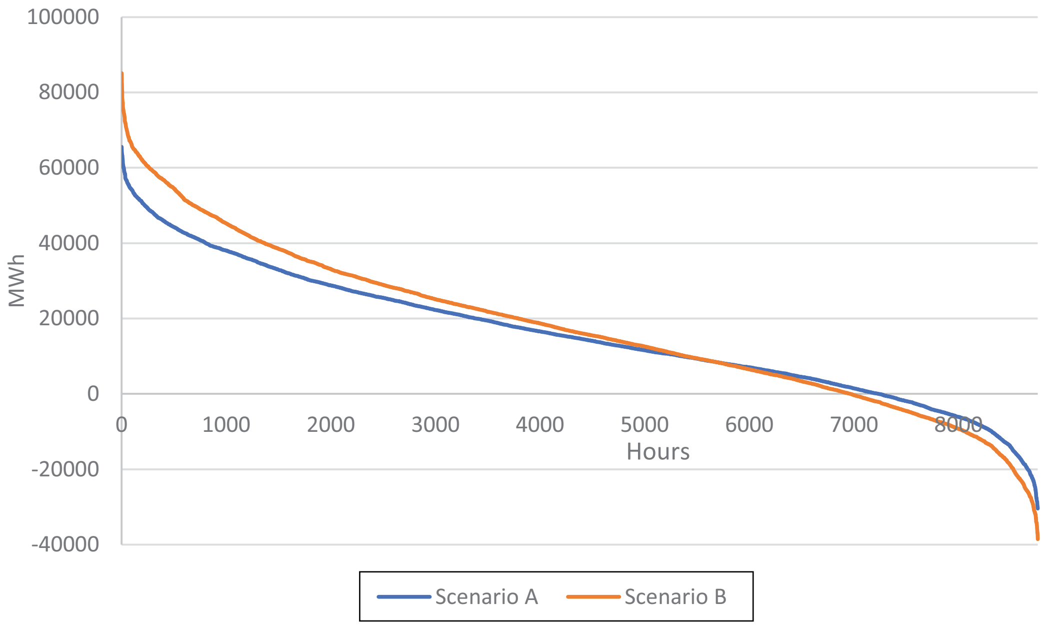

Figure 5: Residual renewable generation for both scenarios 2013

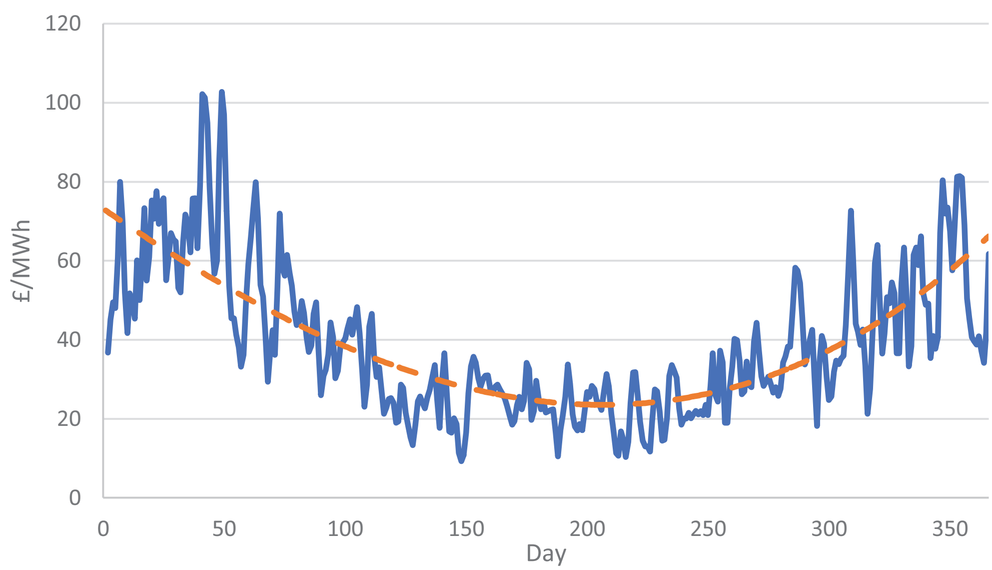

Figure 6: Scenario A 24-hour rolling average prices and trendline 2006–2016

This peaking function at high demand times is normally performed by open cycle gas turbines (OCGT) that are able to ramp output, consequently they have high O&M and variable costs but low fixed costs. Cost for dispatchable hours here are based on projections from closed cycle gas turbines (CCGT) due to their higher efficiency and predicted improvement in technology and ramping ability. Also, as renewable generation grows dispatchable generation will be gradually retired; by about 2050, the remaining dispatchable plant is likely to be already-existing residual CCGTs.

4.3. Sensitivity Analysis

Scenario B is presented alongside high and low cost projections to display the sensitivity of prices to capital cost projections. In this case, the interest rate on capital costs for renewables and storage has been adjusted from the base case of 5% to a low case of 2.5% and high case of 10%. The variable operational costs of dispatchable generation have been adjusted to ±20%.

It is observable in Figure 7 that surplus hours are the same for each case as these are only dependent on the variable operating costs of renewables. Peak dispatch hours (not shown here) are affected in the same way as off-peak dispatchable hours as it is assumed that no new dispatchable plant is built and thus no new capital is required. Discharge hours are affected as expected due to the changed annuitised capital costs of storage capacity. In this particular scenario, the prices for charge hours in the high costs case is below the base case (Table 4). This is due the increased revenue to the incremental renewable from higher prices in both dispatchable hours and discharge hours. If dispatchable generation costs were left unchanged, then it is expected that charge hour costs would be changed in line with the change in annuitised capital costs of the incremental renewable generator.

5. Conclusion

Higher VRE capacities in the future will increase the need for flexibility options. The GB system currently has a lot of flexible dispatchable generation using stored fossil fuels. To reduce carbon emissions from power generation, the reliance on fossil fuel dispatchable generation will need to be virtually eliminated. Flexibility can be provided with electricity storage of some form, but also by storage such as with heat or bioenergy or synthetic fuel such as hydrogen input to CHP or electricity only plant. Transmission links with other countries can help average out demands and VRE and thereby reduce storage needs.

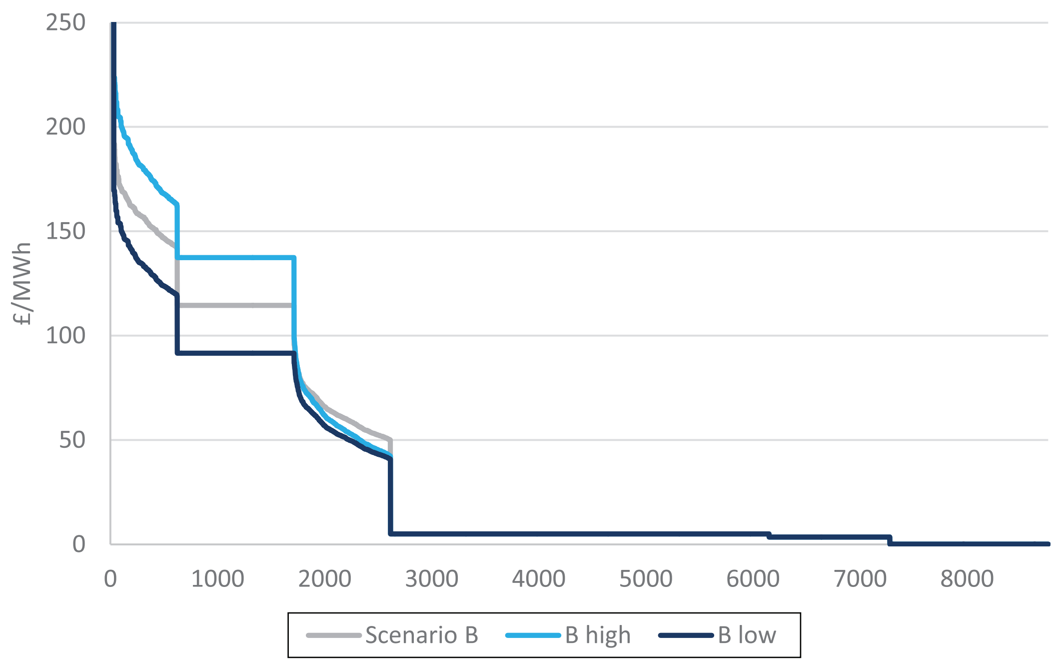

Figure 7: Scenario B with high and low cost projections (clipped for detail)

Table 4 Average price comparison for high and low cost cases

	£/MWh		
	Scenario B	**Scenario B High**	**Scenario B Low**
Average Annual Price	36.40	40.51	31.05
Average Discharge Price	156.97	181.65	134.95
Average Charge Price	62.88	58.02	53.79

VRE, particularly wind, has rapidly reducing total generation cost and low marginal short run avoidable costs but requires other technologies to balance demand and supply. The cost patterns of future electricity generation will become more uncertain and unpredictable, which translates to uncertainty in wholesale electricity spot prices. Better knowledge of these price patterns enables better decision making and encourages investment in smart grid infrastructure and electrification of other sectors as well as being important for electricity utility and industrial consumers.

A simplified electricity dispatch model has been described as well as the details of a marginal cost based pricing method to output potential price patterns corresponding to high VRE and storage scenarios. Forecasting precise electricity prices is infeasible and nor is it required. Rather, the method presented here allows an exploration of future price patterns and magnitudes that can provide some insight into how electricity purchasing decisions can be made. The output from the price time series can then be used in energy system models to assess options such as district heating storage, and to help define markets for investment and dynamic operation.

Previous studies that have quantified the distribution and variance of future electricity generation prices have been based on detailed simulations of the electricity market but have lacked detail on how to replicate these prices without access to custom tools or software. Most have also lacked an analysis of the effect of integrating electricity storage into a system with renewables.

Electricity prices arising from markets should reflect the costs of building and operating electricity assets, including storage, such that economic optimality arises to the degree possible given market imperfections. Markets should be sufficiently competitive regardless of who owns and controls storage operation: The operational market might be managed by, for example, National Grid, even if owning no storage. The costing method presented here can inform the design of efficient, cost reflective markets that also meet other criteria such as the avoidance of penalising the poorer consumers with extreme price spikes.

The modelling of marginal costs here assumes perfect foresight. In practice, in real-time indicative marginal costs could be estimated ex-ante, using modelling taken forward as the rolling year develops, and using past history and forecasts of demand and of generation availability. At the end of the accounting year, adjustments could be made to settlements so that they conform to accurate marginal costs calculated ex-post.

The method presented here has made several key assumptions, one of which is that the carbon intensity of electricity generation should take precedence in the merit order of supply. The analysis of two high VRE and storage scenarios shows that that the capacity cost of storage means that the cost of battery discharge is higher than the marginal costs of dispatchable plant. The merit order would be the same as a typical cost based order if the short run cost of dispatchable generation was more expensive than electricity discharged from storage but this will require carbon or fuel costs to be significantly higher than is assumed in Appendix B.

The high VRE scenarios modelled here show prolonged low marginal cost periods that last for several days followed by spikes usually occurring at high demand periods where peaking plants are normally required. This confirms the observation from previous work that short term variability is reduced in high wind scenarios but intra-day variance is increased, related to the frequency of wind front generating high VRE. These price spikes may be predictable in advance through projections of demand and advanced forecasts of VRE generation that is particular to these high wind scenarios. Another trend observed from these high wind scenarios is the seasonality in mean prices that are observed in both scenarios for each modelled year. That is, the frequency of prices from discharge and dispatch hours is higher in winter periods and suggests that there is a role for seasonal energy storage to reduce this seasonality effect.

6. Future Work

This method has been developed to provide a series of electricity generation prices for use in energy system models to analyse the effects of interventions in the grid. Previous studies have shown that electricity storage alone can be an expensive option and other forms of storage in a smart energy system can be a lower cost solution [37]. Future work will be to analyse the effect of integrating electrified heating and the potential use of large-scale thermal energy storage in the UK and contrast the reduction in battery storage requirements this facilitates.

A further step, outside this paper's scope, is to optimise renewables and storage capacities such as to find a least cost near zero emission system. Renewables and storage might include other technologies not considered here such as solar heat and thermal storage.

Acknowledgements

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Appendix A. Modelled Scenario Results

Table 5 Modelled scenario results and average prices all years

Modelled Year	Demand A TWh	Ren. Gen A TWh	Demand B TWh	Ren. Gen B TWh	Ave. Price A £/MWh	Ave. Price B £/MWh
2006	426.25	507.20	504.68	589.87	46.42	47.11
2007	417.19	510.49	493.95	594.53	43.55	43.02
2008	414.89	523.95	491.23	609.91	41.25	41.28
2009	393.29	502.12	465.66	587.15	39.84	40.38
2010	400.05	477.85	473.66	552.22	45.28	46.15
2011	384.82	511.35	455.63	596.13	36.76	37.13
2012	386.22	499.52	457.29	578.17	38.37	38.58
2013	381.88	510.53	452.14	596.28	36.34	36.41
2014	363.11	503.10	429.92	584.94	32.11	33.18
2015	352.73	523.59	417.63	612.54	29.47	30.25

Appendix B. Input Cost Assumption

Table 6 Input cost assumptions used in price modelling

	CAPEX £/kW	Fixed O&M £/MW/a	Var O&M £/MWh	Eff. %	Fuel cost £/MWh	Carbon Cost £/MWh	Lifetime years	Refs
CCGT Class H	526.8	15,520	1.5	0.6	35	19	25	[7,39]
OFF.Wind	1860	45,715	3.5	0	0	0	25	[7,40]
ONS.Wind	1395	22,100	5	0	0	0	23	[7,40]
Solar PV	652	4,792	0.1	0	0	0	25	[7,40]
Li-Ion (MWh)	337	2,120	2	0.9	0	0	15	[41,42]