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The impact of wind power on arbitrage revenue for electricity storage

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Abstract: Electrical energy storage provides a potential solution to the challenge of integrating large amounts of intermittent renewable energy into the electricity system. To make storage commercially viable its operators will have to aggregate multiple revenue streams across the electricity industry. Arbitrage is recognised as one potential revenue stream. To date, wind power has provided a small contribution towards electricity generation in Great Britain. Gas generators have delivered a significant proportion of total demand. Historic electricity prices reflect this, being driven principally by variations in gas price and daily demand cycles. The work reported here investigates the potential impact of wind power on electricity prices and arbitrage opportunities for energy storage in Great Britain. Results indicate that increased wind power leads to higher price volatility for low electricity prices, but reduced frequency of higher prices which may be detrimental to storage revenue.

1. Introduction

Electrical energy storage is a potential solution to the challenge of the Energy Trilemma, facilitating the integration of intermittent renewable energy into the electricity grid. Many potential benefits have been identified throughout the electricity system [1] including:

1. improved system control, power quality and reliability;
2. provision of emergency power and black start services;
3. reduced network congestion and deferral of investment in distribution and transmission infrastructure;
4. system balancing;
5. peak shaving and load levelling;
6. more efficient use of generation plant;
7. avoided curtailment of renewables; and
8. firming up intermittent generation and shaping inflexible plant.

Storage has the potential to benefit a range of users in different subsectors of the electricity industry including the System Operator, distribution network operators, renewable energy generators, conventional generators, industrial users and consumers. However, each would traditionally be more likely to invest in established technologies which would be more cost effective to them in the short term, overlooking the system-wide, longer-term benefits of storage [2]. It has been estimated that by 2050 deployment of energy storage could lead to savings of £10bn/year within the British electricity system [3]. Despite this, accessing commercial rewards remains challenging.

It is increasingly understood that operators will have to aggregate multiple revenue streams for storage to be commercially viable [4]. Arbitrage, purchasing cheap off-peak electricity and selling it on-peak when the price is high, is recognised as one revenue stream which will contribute to a business model. Many studies have investigated revenue available to a storage operator based on historic electricity prices and generally highlight a lack of commercial opportunities for storage despite the wide range of benefits which are provided.

Walawalkar et al [5] investigated the potential for storage in the New York spot market and found a high sensitivity of arbitrage revenue to the round trip efficiency of the storage technology. The paper highlighted that there may be opportunities for storage in arbitrage and reserve services markets, but that there remained barriers to large scale integration for wholesale market applications. Connolly et al [6] compared arbitrage value of a pumped storage plant in 13 different global markets highlighting the range of values which could be achieved. This demonstrated the dependence of value on regulatory frameworks and generation portfolios which other studies also point to. Sioshansi et al [7] attributed variations in arbitrage value of storage in the PJM market to the specific generation mix and cost of fuel. This highlighted the high level of risk associated with an investment in energy storage. Even with perfect foresight of electricity prices, profits vary from year to year with variations of 50% and 75% identified in [6] and [8] respectively. Other studies including [9] [10] and [11] assessed different optimisation methods and the importance of forecast accuracy, but similarly, were based on historic market prices.

Projecting the future scope for arbitrage is more challenging and this is particularly so for markets such as Great Britain (GB) where substantial structural changes will occur. Historically, peak electricity prices in GB tend to have been driven by gas prices as Figure 1a shows. This occurs as mid-merit and peaking generators include a large proportion of combined and open cycle gas turbines [12]. Furthermore, as wind power has made only a small contribution and has had little impact on wholesale electricity prices, daily fluctuations in price have been driven principally by variations in demand as shown in Figure 1b. Over the next decade the contribution from wind generation is expected to increase dramatically. It is often speculated that commercial opportunities for storage will emerge as the penetration of intermittent renewables grows as it has the potential to increase price volatility [13]. More frequent and more acute price differentials would provide additional opportunities for arbitrage which could become a more profitable revenue stream in the future.

A notable analysis of this phenomenon for future GB systems is presented by Grünewald et al [14], finding that 32GW of wind capacity would enable the gross value of storage to cover its capital costs and investment could be commercially viable through price arbitrage alone. The framework applied is credible, but there are a number of areas within the model that may have limitations. The simulation of future energy prices using a simple marginal generation cost model did not consider the impact of varying fuel and carbon prices, which are both significant sources of uncertainty. Additionally, wind is attributed a marginal value equivalent to the opportunity cost of a Renewable Obligation Certificate (ROC) which has the effect of driving costs negative. An exponential mark-down was also applied to electricity prices when demand was lowest to represent generators' preferences not to curtail output. This subsidy was available for renewable generators although this will not be the case in the future as the UK Government has announced an end to ROCs for all new onshore wind farms as early as 2016 [15]. While adopting a broadly similar framework, this paper specifically addresses these aspects by incorporating changing fuel and carbon prices in future energy scenarios and making the assumption that no subsidy is paid for wind generation meaning that the minimum price of electricity never falls below zero. Subsequently, an alternative price function is applied for periods of low demand. While the magnitude of electricity prices will depend on the specific subsidy regime in place, the shape of the supply curve used here is expected to be more realistic as prices would ultimately be limited by the value which could be recovered by a subsidy payment for a renewable generator, and would not be infinitely negative, as an exponential mark-down implies. These changes lead to distinct results, observing that increased wind capacity leads to more frequently supressed electricity prices which may be detrimental to arbitrage revenue, which contradict previous findings. Given the rapidly changing portfolio of generation technologies, this paper makes a valid contribution by enabling understanding of the implications of wind power on energy storage and the business case for developing storage in the future.

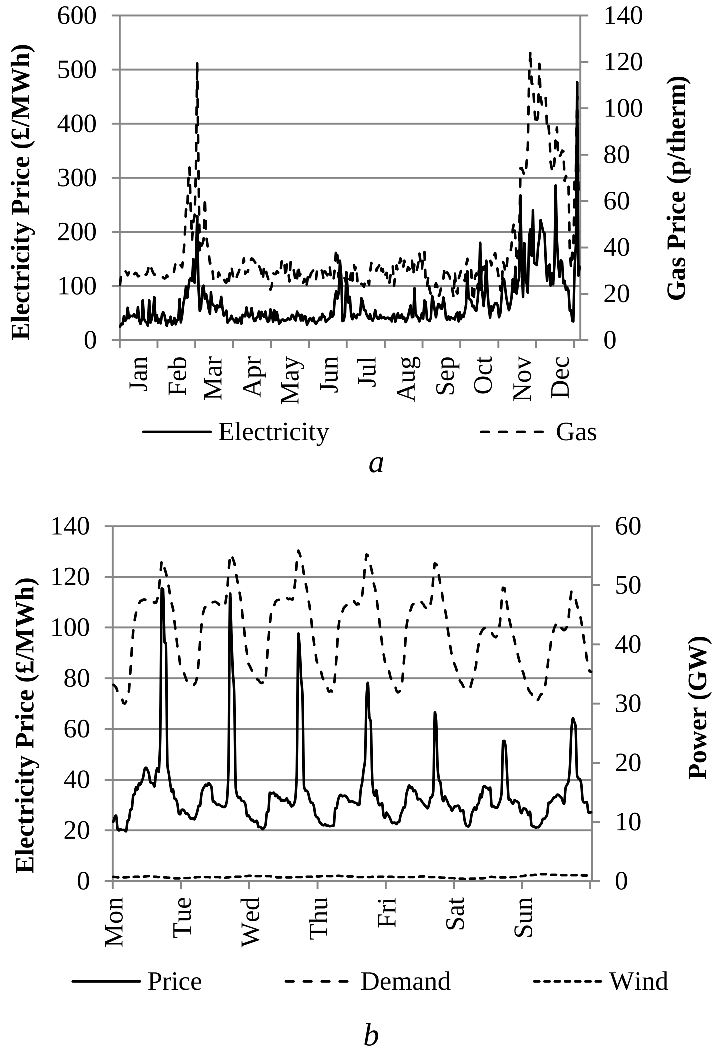


Figure 1. *Historic electricity price variation*
a Daily peak electricity price ***[16]*** *and National Balancing Point gas price* ***[17]****, 2005*
b Half hourly electricity price ***[16]****, demand* ***[18]*** *and wind power output* ***[19]****, first week of November 2005*

2. Model

2.1. *Overview*

A model was created to simulate time series of electricity prices under different generating capacity and fuel price assumptions. The electricity prices were used to define the optimum operating schedule for an energy storage device and determine how much revenue could be expected from arbitrage.

The majority of electricity in GB is traded through private bilateral exchanges in forward markets. It is not possible to model these contracts directly as electricity prices are not published. Around 3% of electricity is traded on the power exchange, a spot market operating up to one hour ahead of real time [20]. Although only a small volume of electricity is traded, prices are published and so the market index price is expected to strongly influence pricing in forward markets. Fundamental price-based market models, established on the assumption of perfect competition, have been shown to be representative of the power exchange and are commonly used for modelling scenarios of future energy prices [21].

To model market prices the dispatchable power which must be delivered by thermal generators in the system was calculated. For each half hour period, renewable power output was deducted from electricity demand to produce a 'net demand' curve. The generator supply function was formed by stacking thermal plant in merit order of increasing marginal cost. The price of electricity for each time period was determined by the market clearing price.

The electricity price time series and storage system characteristics were used to determine the optimum operating schedule to maximise arbitrage revenue. A summary of the model is shown in Figure 2, which is based on a fundamental price model coupled with an arbitrage optimisation. This is broadly similar to that proposed by Grünewald [14] but critical aspects differ including:

1. the approaches used for modelling the meteorological data for renewable energy output;
2. the generator supply function;
3. the calculation of marginal generation costs;
4. the optimisation of the storage operating schedule.

The details of the model are described below. Section 2.2 describes how the thermal generator supply function was formed. Section 2.3 explains how wind power output was calculated. Section 2.4 outlines the approach used to represent demand data and Section 2.5 describes how the storage operating schedule was determined and the technical characteristics of the device that were used.

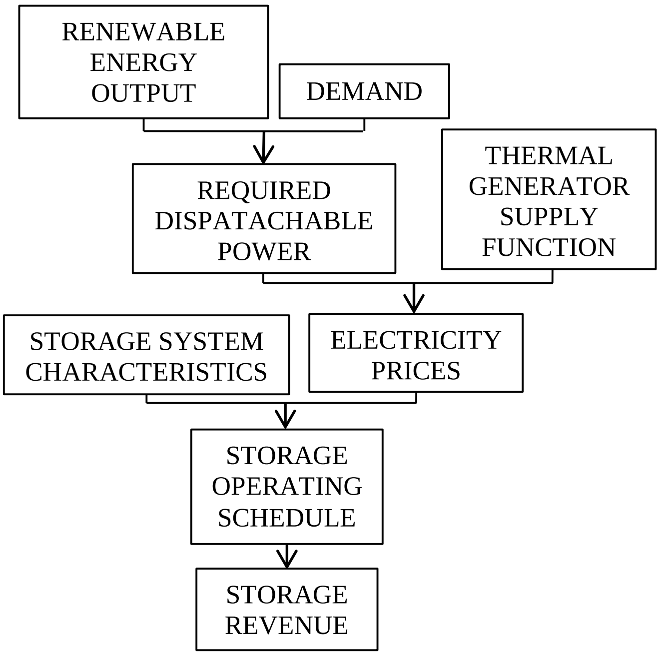


Figure 2. *Model overview*

2.2. Generator Supply Function

Thermal generators were grouped into four classes of plant; nuclear, coal, combined cycle gas turbine (CCGT) and open cycle gas turbine (OCGT). Each class was bound by a lower limit of its own marginal cost and an upper limit of the marginal cost of the next class in the merit order stack [4]. Between these two values the hyperbolic function shown in equation (1) was assumed. This smoothed the discontinuities in the step function and better represented the complexities of the supply curve, such as differing ages and efficiencies of plant within each class of generation.

$$CE = \Pi_x \left[1 + \frac{\Pi_{x+1} - \Pi_x}{\Pi_x} \frac{\cosh\left(\frac{P_x}{C_x}\right) - 1}{\cosh(1) - 1} \right] \quad (1)$$

where CE is the cost of electricity, Π_x is the short run marginal generation cost, x denotes the merit order of the marginal class (i.e. for base load $x=1$ and for peaking plant $x=4$), P_x and C_x are power output and installed capacity of the marginal class respectively.

All generators were assumed to be paid the market clearing price which was set by the highest merit order generator that was scheduled to run. The difference between the market clearing price and a generator's short run marginal cost is known as a scarcity rent and covers long run fixed costs [22].

Peaking plant was the last class of generator to be dispatched. Its maximum price was not limited by a more expensive generator and so it bid to produce electricity at a premium price to reflect scarcity of supply. This enabled peaking generators to recover their fixed costs. Following a similar approach to Eager [23], the exponential function in equation (2) was used:

$$CE = \Pi_x \left[\beta e^{\alpha\left(\frac{P_x}{C_x}\right)}\right] \tag{2}$$

where α and β are constants which were determined empirically and used to define the extent of the uplift applied when capacity was scarce. Figure 3 shows an example aggregate supply curve.

Historic generator capacity was sourced from the Digest of United Kingdom Energy Statistics [12]. Smaller peaking plant including oil, as well as pumped storage, was grouped with OCGTs. Other small generators, such as run-of-river hydro, were grouped with coal. Plant capacity was assumed to be fixed throughout the year with a constant availability applied to each class of generator reducing its total capacity. The British system was considered an islanded network with no interconnector capacity.

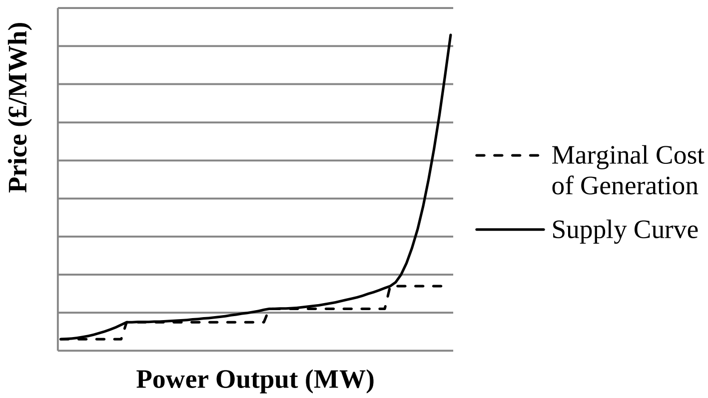


Figure 3. *Electricity supply curve*

Marginal generation costs were calculated for each class using equation (3):

$$\Pi_x = \frac{1}{\eta_x}(\mathrm{a}_x F_x + \nu_x F_{car}) + V_x + e_x \tag{3}$$

where η_x is the thermal efficiency (x denoting the generator class), a_xF_x is price of fuel, with a_x a conversion coefficient and F_x the fuel price in units relating to the fuel for each class of generator. Specifically, nuclear and coal fuel prices were in £/kg while gas prices were in £/therm. v_x is the amount of carbon produced from burning fuel at 100% efficiency, F_{car} is the price of carbon, V_x is the variable operation and maintenance cost and e_x is the cost of enriching fuel which only applies to nuclear generators. The data used for each class is listed in Table 1.

__Table 1__ Thermal generator data __[24] [25] [26]__

Generator Type	Thermal Efficiency η (%)	Carbon Emissions ν (kg/MWh)	Variable Operating Costs V (£/MWh)	Enrichment Cost e (£/MWh)	Availability (%)	Conversion Coefficient a
Nuclear	36	0	1.8	2.5	78	8.24x10-3
Coal	36	285	2.0	0	86	150
CCGT	60	185	2.2	0	87	34.128
OCGT	46	185	2.7	0	95	34.128

Time series of historic fuel, F_x, and carbon prices, F_{car}, were sourced from the NUEXCO Exchange [27], the Department of Energy and Climate Change [28], the ICE ENDEX [17] and the European Environment Agency [29].

2.3. Wind Power Output

Wind power was the only form of renewable energy considered in the model. It was assumed to have zero marginal cost and was always dispatched when available. GB was conceptually modelled as a single bus transmission system and network constraints were neglected. It was assumed that wind output was not curtailed unless demand was fully satisfied.

Hourly wind speed data for the United Kingdom and surrounding waters was produced by Hawkins [19] using the Weather Research and Forecasting model for the years 2001-2010. Wind speeds were available at a spatial resolution of 3km by 3km and were extracted at 80m above ground or sea level.

The DECC RESTATS planning database [30] was used to identify the location and capacity of wind farms in GB. Each farm was considered to be producing power from the start of the year in which the database stated it was fully commissioned and operational. The time series of wind speed data corresponding to each farm location was extracted from the wind model.

Power output from each wind farm was calculated using the equivalent aggregate power curve described by equation (4) [19], where P is the power output and U is the wind speed. Although this was not representative of all wind farms, it was expected to be typical and accounted for effects due to interactions between turbines that tend to smooth power production, which manufacturers' power curves do not [19].

$$P = \frac{1}{1+e^{-\frac{U-9.7}{1.8}}} \tag{4}$$

Power output from all wind farms was summed to give the aggregate output for both onshore and offshore wind and reduced by 10% to account for availability. This was a conservative estimate for onshore but early offshore availability may be less than 90% [31]. The data was interpolated linearly to obtain a time series of power output at half-hourly intervals.

2.4. Demand

Historic demand data is available from National Grid [18]. Demand was assumed to have zero price elasticity, a reasonable assumption for historic electricity prices. This may change in the future with the introduction of smart grids and demand side response. These effects were not considered in this paper.

2.5. Storage Operating Schedule

The optimum operating schedule for a storage device was established assuming perfect foresight of electricity prices and subject to the technical constraints of the device. Revenue was optimised on a weekly basis with the additional constraint that the state of charge must be zero at the start and end of each week. This had minimal impact on total revenue compared to optimisation on a daily, monthly or annual basis, but reduced the computational time. The following assumptions were applied:

- The storage device had 100% availability.
- The storage capacity was small compared to total electricity demand. It was a price taker and did not affect the market price of electricity.
- GB was a single bus system and storage was not subject to network constraints.
- The device characteristics were constant over its life time.
- The conversion efficiency was modelled during charging only. The discharge cycle was 100% efficient.
- The ramp rate was negligible compared to the time period.
- The cost of charging and discharging (in addition to the cost of electricity) was negligible.
- The discount rate was negligible over the time period considered.

The decision variables for the storage operator were how much electricity to buy, q_t^C (MWh), and sell, q_t^D (MWh), during each time period, *t*. The state of charge of the storage device, S_t (MWh), was defined by equation (5) and subject to the constraints given in equations (6), (7) and (8):

$$S_t = \eta_s S_{t-1} + \eta_c q_t^C - q_t^D \tag{5}$$

$$0 \leq S_t \leq S_{max} \tag{6}$$

$$0 \leq q_t^C \leq q_{max}^C \tag{7}$$

$$0 \leq q_t^D \leq q_{max}^D \tag{8}$$

where η_s is the storage efficiency (%), η_c is conversion efficiency (%), S_{max} is maximum storage capacity (MWh), q_{max}^C and q_{max}^D (MWh) are maximum quantities of energy which can be charged or discharged in a single time period. These are a function of the maximum charging and discharging rates, Q_C and Q_D (MW).

The objective was to maximise annual revenue, R, which is the sum of the price, P_t, multiplied by the net quantity sold during each settlement period. This is defined in equation (9).

$$R = \sum P_t(q_t^D - q_t^C) \tag{9}$$

The linear optimisation described by Byrne and Silva-Monroy [32] was applied to calculate the optimum operating schedule and determine the maximum revenue available to the storage operator.

There is a range of storage technologies with different technical and cost characteristics. The applications, benefits and disadvantages are discussed by a number of authors [33]. The characteristics presented in Table 2 were used as the storage constraints in this study. These are representative of a grid scale device which would likely participate in arbitrage markets. This paper does not seek to investigate the impact of varying storage characteristics on arbitrage or to compare the performance of different technologies.

Table 2 *Storage characteristics*

Storage Capacity S_{max} (MWh)	Maximum Charging Rate Q^C (MW)	Maximum Discharging Rate Q^D (MW)	Conversion Efficiency η_c (%)	Storage Efficiency η_s (%)
200	20	20	75	100

3. Model Validation

The simulation was initially run for three historic years to validate the price model and investigate the revenue available to a storage operator under market conditions with a small penetration of wind power. The years 2005-2007 were selected as robust data sets for coal, gas and nuclear fuel prices were all available, in addition to wind resource data. For other years, this information was not available at as high a temporal resolution.

A number of characteristics of the price time series affected the storage operating schedule including the frequency and magnitude of peaks and troughs as well as the mean price. The uplift coefficients, α and β, were calibrated using the revenue available from historic and simulated electricity prices. Using revenue, rather than a statistical measure from the time series, allowed multiple characteristics, which may have impacted the storage operating schedule, to be accounted for. Alternative approaches used to calibrate uplift functions include assigning a value of lost load (VOLL) to the price when the capacity margin is zero [24] or pricing to ensure that the investment case for peaking plant remains viable [14]. These methods introduce challenges of accurately defining VOLL and peaking plant costs respectively. Furthermore, in this model, installed generation capacities were defined exogenously and were not dependent on simulated electricity prices. They were expected to be reflective of future scenarios, but would not necessarily represent the system margin accurately enough to employ these methods.

3.1. Generation Capacity

The classifications of installed generation capacity for 2005-2007 are shown in Figure 4. Over these years the installed wind capacity increased from 1.65GW to 2.82GW. In 2007, it represented 3.7% of the total installed capacity.

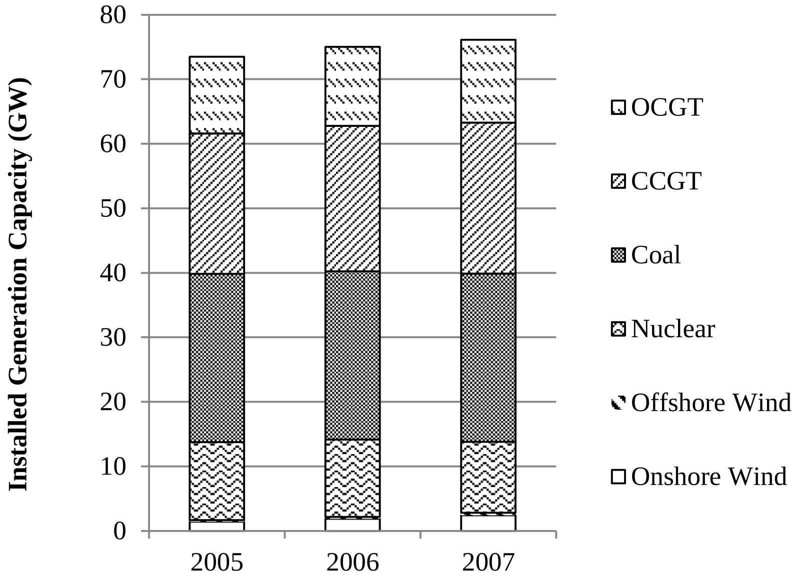
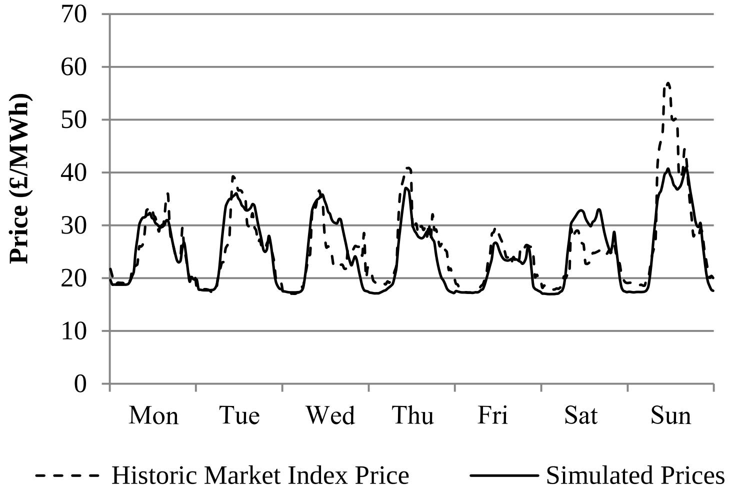


Figure 4. *Installed generation capacity 2005-2007* ***[12]***

3.2. Electricity Price

Historic electricity prices from the UK power exchange [16] were used to validate the price model. For reasons discussed in Section 2.1 the power exchange can be used as a reference for forward and ancillary electricity prices. Additionally, as a market of last resort, price volatility is high and so it is likely to be the market where energy storage would participate for arbitrage sales.

Figure 5 shows a comparison between historic spot market index prices and electricity prices simulated using the model.



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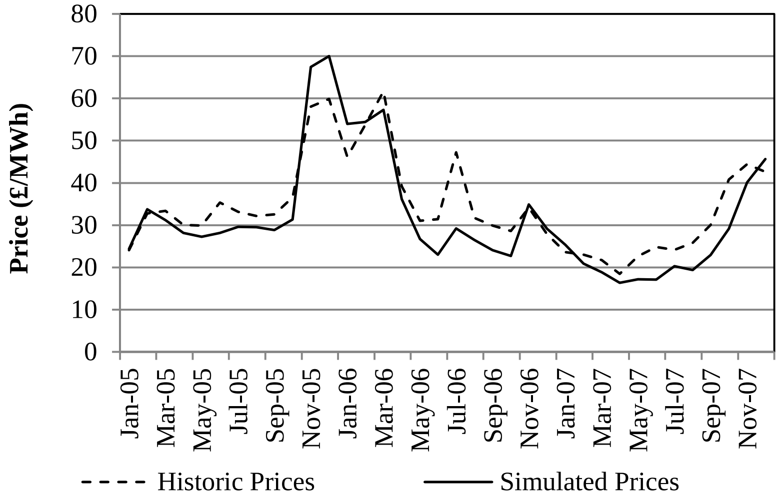

b

Figure 5. *Historic market index prices and simulated electricity prices*
a First week in August 2007
b Average monthly electricity prices

The model adequately captured the basic characteristics of the market. Critically, the good fit of the half hourly prices in Figure 5 shows that the diurnal variations, to which arbitrage is particularly sensitive [14], were well represented.

Figure 6 shows demand net wind output and corresponding historic electricity price for November and December 2007. This shows that price troughs of a similar magnitude occurred on a daily basis when the net demand was lowest. Price peaks corresponded with the daily peaks in net demand; however, the magnitude varied. The maximum peak, in mid-November, did not coincide with maximum net demand, indicating that other factors were influencing the magnitude of price spikes.

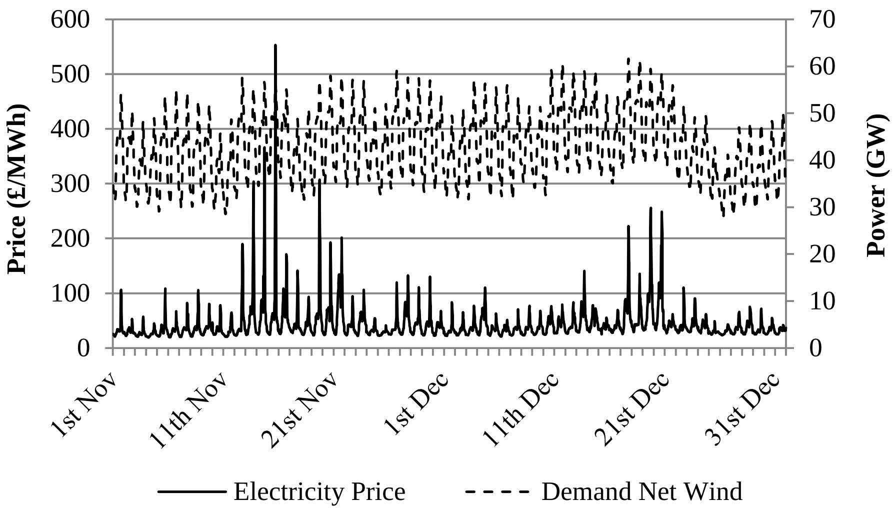

Figure 6. *Demand net wind and electricity price (2007)*

Table 3 presents the annual minimum and maximum electricity prices using historic data from 2005-2007. The mean and standard deviation of the daily troughs and daily peaks for each year are also presented. This shows that there was significant variation in maximum daily price but little variation in the minimum daily price. The same data for the simulated electricity prices is presented in Table 4.

Table 3 *Annual peak and trough electricity price statistics from historic data*

Year	Minimum Price (£/MWh)	Daily Trough Mean (£/MWh)	Daily Trough Standard Deviation (£/MWh)	Maximum Price (£/MWh)	Daily Peak Mean (£/MWh)	Daily Peak Standard Deviation (£/MWh)
2005	11.86	23.18	4.41	476.91	67.49	47.86
2006	1.09	4.38	6.70	414.71	69.93	47.92
2007	5.92	17.06	4.47	553.30	60.50	52.94

Table 4 *Annual peak and trough electricity price statistics from simulated data*

Year	Minimum Price (£/MWh)	Daily Trough Mean (£/MWh)	Daily Trough Standard Deviation (£/MWh)	Maximum Price (£/MWh)	Daily Peak Mean (£/MWh)	Daily Peak Standard Deviation (£/MWh)
2005	17.38	28.41	6.44	617.18	72.26	64.26
2006	8.62	18.67	5.95	513.60	70.27	53.53
2007	9.02	13.23	4.11	451.06	63.32	53.22

The simulations adequately represented the key characteristics of the historic electricity price time series that were significant to arbitrage. As one-off, extreme measurements the absolute maximum and minimum values were less critical than the mean and standard deviation data which was in better agreement. The peak statistics showed better agreement than the trough statistics. The maximum difference between historic and simulated mean peak values in any year was 7%. The maximum difference between the mean trough values for 2006 was 326%; however, the absolute error for this year was still only £14.29/MWh. The better representation of peak values was possible through calibration of the uplift coefficients α and β whose values did not affect the trough characteristics. The simulated results showed slightly higher standard deviation of peak prices compared to historic data which may have provided additional price volatility to compensate for the minor overestimation in minimum prices. The error in the peak standard deviation was negligible in 2007 where the difference between the mean trough values was also smallest.

3.3. Electricity Price Forecast Error

The price time series in this model is the out turned price and represents a projection of future prices rather than a forecast. In reality, a storage operator will not have perfect foresight of electricity prices and will have to devise an operating schedule using a price forecast. Errors in the price forecast will lead to sub-optimal decisions being made and storage revenue being reduced. The price forecast error is dependent on the wind forecast error, the demand forecast error and other associated errors. Demand has historically been forecast relatively accurately and wind forecasts are becoming more precise as more capacity is deployed. Hu and Taylor [34] suggest that electricity price forecasts with errors of less than 10% could be readily achieved in the short term British electricity market. The implications of price forecast accuracy on the optimality of storage revenue are analysed by Dunbar et al [11]; relative to perfect foresight, an error of 10% would typically equate to a few percent reduction and, in the extreme, a loss of 10% revenue. These errors would be expected to be consistent across a range of scenarios and are small compared to uncertainties associated with other inputs such as future gas prices and carbon prices and the variation in wind power output from one year to the next. Due to the high level of uncertainty associated with future energy scenario inputs, the results are used to identify trends in revenue over several years, rather than to compare the absolute value with storage costs and assess the return on investment for a storage device. It is believed that a lack of explicit treatment of forecast error within the modelling will therefore not have a substantial impact on the results and conclusions.

3.4. Arbitrage Revenue

The storage operation algorithm was applied to both historic market index price and simulated price time series for 2005-2007 to compare the revenue. The results are shown in Table 5.

Table 5 *Annual arbitrage revenue 2005-2007*

Year	Revenue from historic market index prices (£m)	Revenue from simulated electricity prices (£m)
2005	0.892	0.839
2006	0.831	0.914
2007	0.875	0.845

Using simulated prices, the revenue was not consistently over or under estimated compared to historic prices. The simulated price results were within 10% of those obtained using historic prices. This gives further confidence that the characteristics critical to arbitrage revenue were captured well in the electricity price model. The revenue varied by less than 10% between years with the same three year average of £0.87m from both historic and simulated price data.

Figure 7 shows the optimum operating schedule for November 2007 using simulated prices. This shows that the device was charging and discharging on at least a daily basis in line with the daily cycle of electricity prices. This pattern was typical of the operating schedule over the three years investigated.

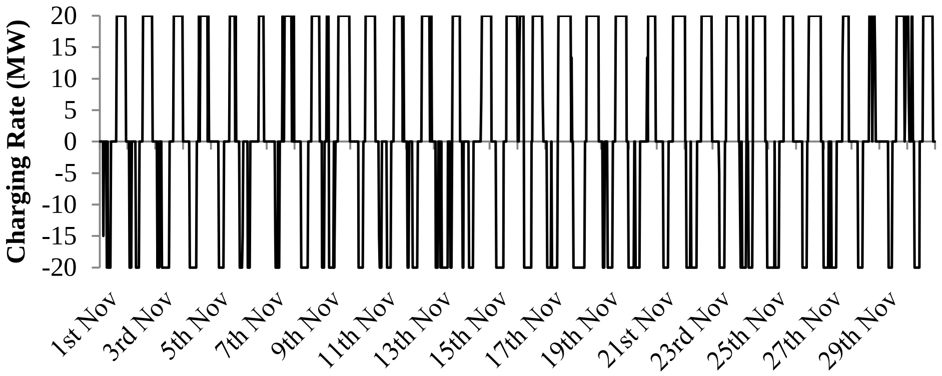

Figure 7. *Storage operating schedule November 2007*

4. Future Energy Scenario Case Study

A wide range of scenarios have been developed for future energy systems in GB including scenarios based on system optimisation [35] and capacity investment decisions [23]. Any future scenario or forecast could be applied to the model. In this paper, the National Grid Gone Green Future Energy Scenario 2014 [36] was used as a case study for analysis of future years with a high penetration of wind power. The Future Energy Scenarios are published annually by National Grid and are defined through discussion with stakeholders and operational experience. The input data are clearly defined and publicly available. The scenarios take into account a range of socio- and techno-economic factors to describe plausible future energy systems. For each scenario, there is a range of changing inputs such as fuel costs, generation mix and demand. In the Gone Green scenario sustainable energy policies are aligned and renewable energy and carbon targets are met. There is strong economic growth and investment in new technologies; particularly wind.

Figure 8 shows the classification of installed generation capacity from 2020-2025 for the Gone Green scenario. The extent to which coal capacity was reduced is not explicit from Figure 8 as carbon capture and storage and biomass, whose capacity increased, were grouped in the same classification as coal for the purpose of the model. From 2020 to 2025, the total installed wind capacity increased from 22GW to 42GW which represented an increase from 26% to 39% of the total installed generation capacity.

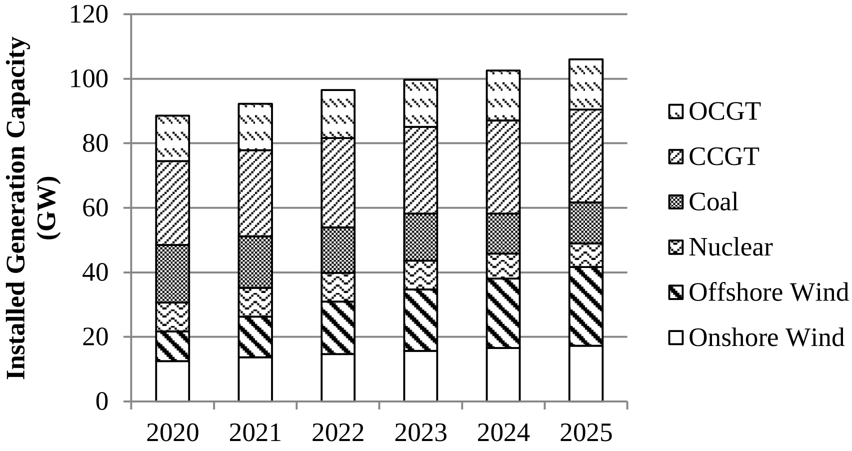

Figure 8. *National Grid Gone Green future installed generation capacity 2020-2025* ***[36]***

Several approaches can be taken to determine the future spatial distribution of wind farms. Grunewald [14] used an optimisation algorithm to place wind capacity in geographically diverse areas. This did not consider planning restrictions or network constraints, both of which are critical factors in the development of wind farms. Green and Vasilakos [37] assumed that offshore installations would be focussed in areas where National Grid was intending to upgrade transmission lines and placed additional capacity in regions which aligned with these locations. Here, wind capacity was scaled at existing sites. This assumed that the spatial distribution in the future would be the same as it is currently. Onshore and offshore capacities were scaled as separate regions to ensure that variations between onshore and offshore resource were captured. The power output was calculated as described in Section 2.3 using spatially distributed wind speed time series from a historic year – this year is termed the 'wind year'.

Future average annual fuel and carbon prices are detailed in the Gone Green scenario data and summarised for the years 2020 to 2025 in Table 6. Time series of fuel price data from the wind year was scaled to match the average value to ensure that some intra-annual volatility was maintained. Similarly, a time series of historic demand data from the wind year was transformed to match the average and peak demand for future years. Taking historic time series from the same wind year ensured that the relationship between weather, demand patterns and fuel costs was maintained.

Table 6 National Grid Gone Green future fuel and carbon prices ***[36]***

Year	Wholesale Gas Price (pence/therm)	Wholesale Coal Price ($/Tonne)	Wholesale UK Carbon Price (£/Tonne)
2020	75.9	96.5	32.7
2021	78.5	96.5	37.0
2022	80.6	96.6	41.4
2023	81.9	96.4	45.7
2024	83.2	108.9	50.1
2025	84.9	109.1	54.5

5. Results and Discussion

5.1. Electricity Price

Figure 9a shows the time series of demand and wind power output predicted for November and December 2025 using a 2007 wind year. In 2025, the average demand was similar to that from 2005 shown in Figure 1b; however, the average wind power output was significantly increased. Figure 9b shows the demand net wind power output and the resulting electricity price for the same period. This can be compared to Figure 6 which shows the same time series for 2007.

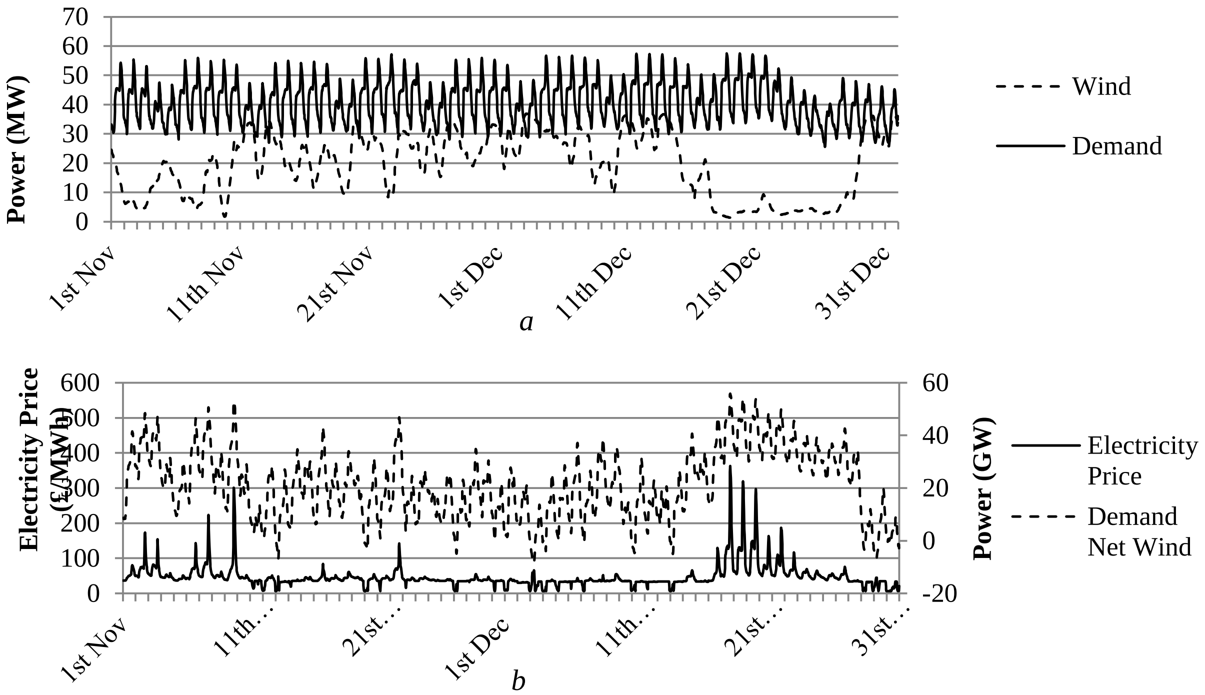

Figure 9. *Outputs for 2025 using 2007 wind year*
a Demand and wind power
b Demand net wind and electricity price

The demand net wind time series represents the output which thermal generators would be required to supply. In 2025, this was less regular than in 2007 due to the increased output from wind power, a similar result to that presented by Cox [13]. As a result, the daily electricity price troughs were more volatile. This is evident from the dips in price seen in Figure 9b which are absent in Figure 6. These occurred during periods of low demand and high wind output where base load generation, rather than mid-merit plant, acted as the marginal generator and set the price of electricity. The standard deviation of the daily minimum electricity price in 2025 was £10.76/MWh, double that from 2007. There was also reduced frequency of high electricity prices due to periods of high wind output reducing the peaks in net demand. Peaking generators were no longer needed during these periods and mid-merit plant set the electricity price. These results were largely in agreement with other studies [21], [13], which additionally concluded that these less frequent price spikes were likely to be of a larger magnitude to enable peaking plant to cover its fixed cost over fewer operational hours. Modelling this phenomenon would have required the uplift coeffients α and β to be recalibrated each year depending on the capacity margin and peaking plant investment case. This was not carried out here.

The effect of increased wind power was to increase the volatility of the output which thermal generators were required to supply, but to reduce the overall volatility of electricity prices. This was due to the shape of the supply curve, shown in Figure 3, which was steep during periods of high demand, but shallow during periods of low demand; indicating higher supply-side price elasticity when electricity was scarce. Increased wind power output reduced scarcity of supply and shifted thermal demand down the supply curve to where supply-side price elasticity was at its lowest. This result contradicts previous studies and suggests that the available revenue through price arbitrage is *reduced*. There would be increased opportunities for storage to charge when prices were low, but reduced opportunities for storage to discharge and sell electricity at an inflated price.

5.2. Arbitrage Revenue

Figure 10 shows the storage operating schedule for November 2025 using a 2007 wind year. The device generally cycled on a daily basis, however, unlike Figure 7, which shows the operating schedule for the same month in 2007, there were some days that the device did not charge or discharge at all. These days coincided with periods of high wind power output where previously inflated prices were diminished.

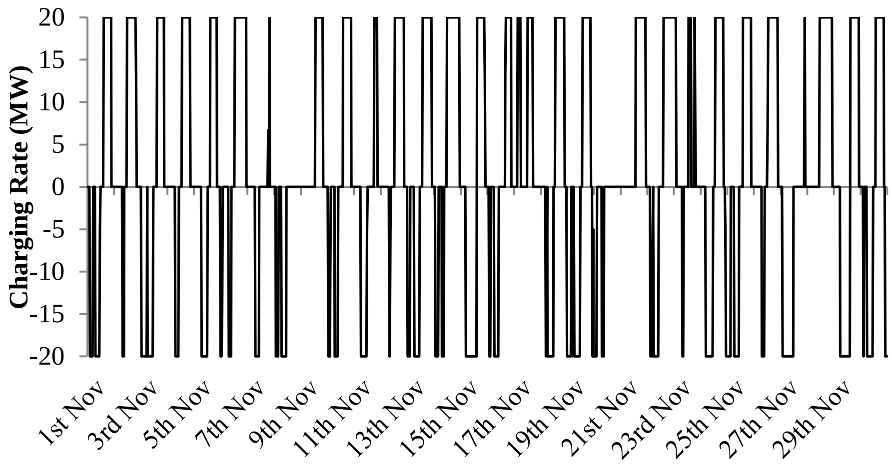

Figure 10. *Storage operating schedule November 2025 using 2007 wind year*

Table 7 presents the maximum expected annual revenue from 2020 to 2025 using both 2006 and 2007 wind years. The results showed a modest increase in revenue over the years investigated compared to the 90% increase in installed wind capacity over the same period. Furthermore, the increase in revenue from 2006 to 2020 with a 2006 wind year was less than 5%. Over this period wind capacity increased from just over 2GW to 22GW. This suggests that there were other factors influencing the storage revenue and, in accordance with the observation from Section 5.1, the increase in wind capacity was unlikely to be the cause of the rise in revenue.

Table 7 *Maximum annual arbitrage revenue 2020-2025*

Year	Revenue 2006 wind year (£m)	Revenue 2007 wind year (£m)
2020	0.943	0.447
2021	0.991	0.470
2022	0.989	0.472
2023	1.010	0.482
2024	1.076	0.556
2025	1.086	0.584

Increasing gas and carbon prices over the period are likely to have led to the increased revenue. Increases in both gas and carbon prices would increase the marginal cost of generation for peaking plant, but have no impact on the marginal cost of the baseload generator, nuclear, which has zero emissions. As a result, the daily price spread would be larger and the opportunity for revenue from arbitrage increased. In the National Grid Gone Green Scenario, carbon prices increased steadily up to 2025. The expected increase in revenue from this may have been counteracted by the increase in wind power over the same period. Gas prices, however, decreased from 2015 to 2020 followed by a small but steady increase from 2020 to 2025. This trend is consistent with the changes is arbitrage revenue over the period.

A second observation evident from the results in Table 7 is the reduction in expected revenue when the wind year changed from 2006 to 2007 and a different wind pattern was assumed. This highlights the additional risk to a storage operator when there is a large amount of intermittent generation in the system. Revenue could reduce by up to 50% from one year to the next.

The results support Grünewald's conclusions that commercialisation of storage, as a facilitating technology, is dependent on a number of uncertainties including the future energy mix, the regulatory environment in the energy sector and the stochastic uncertainty from one year to the next [14]. Arbitrage revenue is dependent on the individual behaviour of each of these characteristics, but also on the complex interactions between them. These uncertainties increase the cost of finance for storage technologies and reduce the chance of successful market uptake.

5.3. Wind as a price setter

The analysis above models wind as negative load, however, in the UK, it is only embedded generation below 50MW capacity which truly behaves in this way. Larger wind farms forecast their output in advance and trade in forward markets. Instead of contributing to negative demand, wind farm output would adjust the supply function for each half hour period. Thermal generation would be required to respond not only to changes in demand, but also to forecast errors. Moreover, the assumption that thermal plant is dispatched in merit order is a simplification. In reality, the network responds in different ways to variation in wind and demand and, consequently, there are different cost implications. Additionally, if there was a significant market share of wind, wind generators would not bid to produce electricity at their marginal cost of zero. These effects would change the electricity price at the lower end of the supply curve and some cases may drive it negative. In the UK, this would be expected only at high levels of installed capacity and would be infrequent [38]. While this would have some impact on the results, trends in arbitrage revenue would be unlikely to be affected as the magnitude and frequency of price spikes would remain largely unchanged.

6. Conclusions

Grid scale electrical energy storage could be a facilitating technology enabling intermittent renewable generation to be connected to the electricity grid. However, the commercial arrangements for storage are complex and it can be challenging to access financial rewards for the benefits which are provided. Electricity price arbitrage is one revenue stream which is available to a storage operator. Electricity prices, currently driven by gas prices and daily demand cycles, are expected to vary in the future as more intermittent wind power is connected to the grid. This will change the potential revenue available from arbitrage.

This paper presents a model developed and used to investigate the revenue available to a storage operator through price arbitrage in future years. The National Grid Gone Green Future Energy Scenario, which has significantly increased wind capacity, was investigated. The results showed a modest increase in arbitrage revenue from 2020 to 2025 which was not expected to be a direct result of the increase in wind capacity, but due to contributions from a number of changing factors including increased fuel and carbon prices. The investigation into electricity prices suggested that, contrary to previous findings, increased wind power may, in fact, be detrimental to storage revenue. With increased wind capacity there were numerous occasions of supressed electricity prices and a reduced frequency of price spikes. This may create fewer opportunities for storage to discharge and sell electricity at a high price. Furthermore, increased wind capacity is likely to lead to large variations in revenue from one year to the next which will increase the risk of investment in energy storage technology.

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