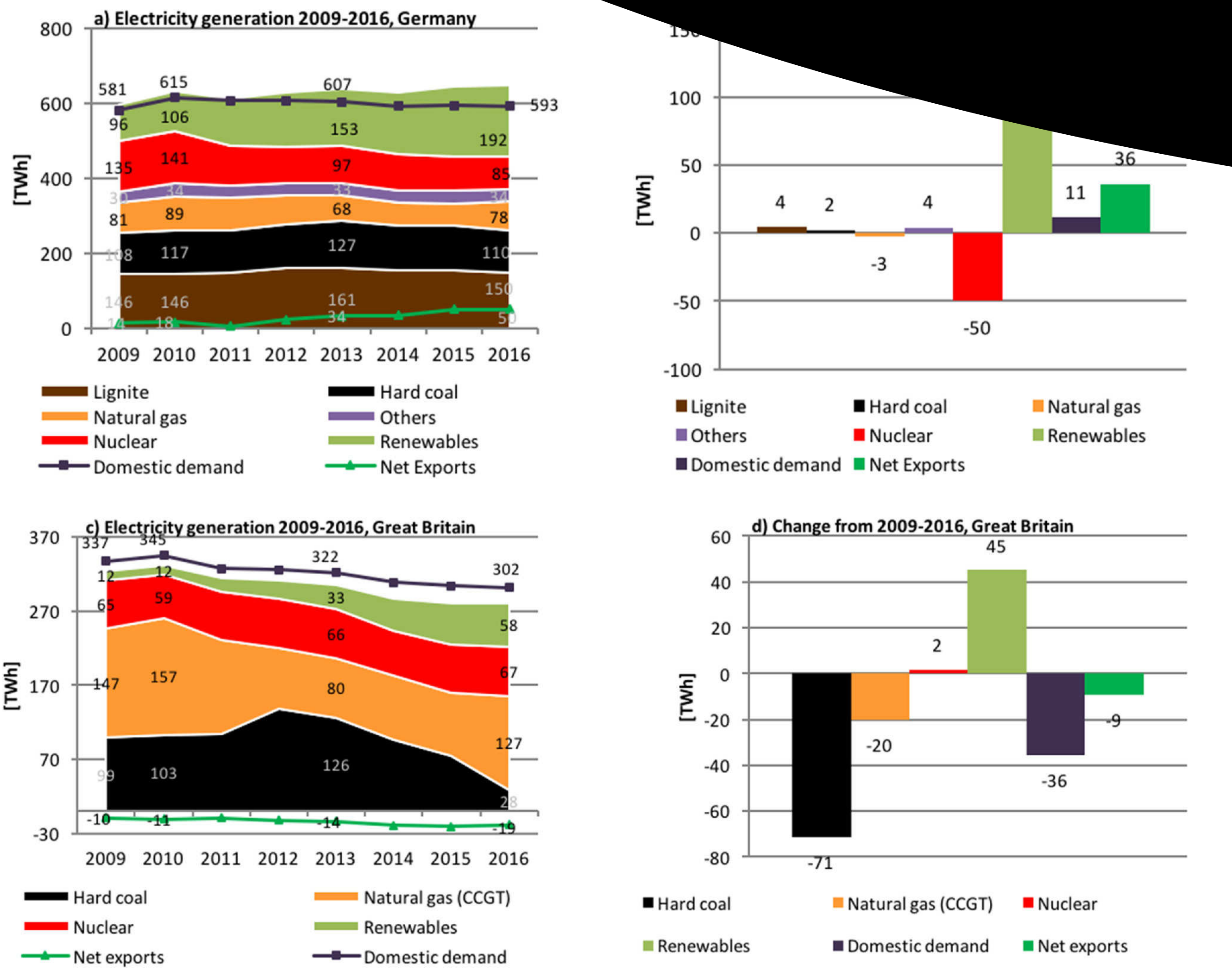

Fig. 1. a–d) Electrical energy transition in Germany and Britain from 2009 to 2016, data sourced from [24], energy-charts.de, elexonportal.co.uk, bmreports.com.

[7] used data from January 2006 to January 2012 and found that a 1% increase in wind generation decreased the Phelix Day Base by 0.1%. In addition, she found that the volatility of the day-ahead prices increased with greater amounts of wind generation. These conclusions were corroborated by Benhmad et al. [8] who also used the Phelix Day Base prices, but found a slightly greater level of price decrease from forecast wind generation, using different years (2009–2013) for the underlying data. In contrast, a dampening effect was seen for the intraday price volatility in the article by Tveten et al. [9], which focussed on the merit order effect of solar generation in Germany over the years 2009–2011. The contrasting findings by Tveten et al. might be explained by the difference in the resolution of the data, where they used hourly rather than daily prices, and also by a point mentioned by Ketterer where the regulatory changes in Germany in 2010 (to modify the market mechanisms for renewable power) were felt to have had a significant dampening impact on the volatility of the day-ahead prices. Ketterer and Benhmad [7,8] also considered interconnection between countries and suggested that market coupling also supressed the day-ahead daily prices. Clò et al. [10] analysed the Italian market from 2005 to 2013 with calculated day-ahead daily data and found decreasing prices and increasing volatility, which they attributed to increasing wind and solar generation. In addition to the absolute value of renewable generation on the system, Jónsson et al. [11] also focussed on the *ratio* of the forecast wind generation level to demand, and found it to be an important determinant in price formation. Rintamäki et al. [12] explored a more nuanced approach that considered the time of day as well as the ratio of wind generation to load, and found that wind power increased the daily volatility of day-ahead prices. Green and Vasilakos [13] modelled wholesale electrical prices to evaluate the impact of price volatility from increased wind generation and also the presence of market power. They found that electrical price volatility increased with greater levels of wind generation, which was exacerbated by an increase in market power of thermal plants as well as wind generation. In looking at other factors that impact day-ahead prices, Bublitz et al. [14] analysed the German day-ahead prices from 2011 to 2015 and found that lower coal and carbon prices supressed prices more than increasing renewable generation.

The literature therefore provides a range of results on the levels of price volatility which could be explained by differing markets, the different generation sources of solar, onshore and offshore wind, the different timeframes considered, and the different resolution of underlying data used. In general there appears to be agreement in these and other studies of the merit order effect that pushes generation with higher short-run marginal costs off the system (such as natural gas or coal) and replaces it with lower short-run marginal cost sources (wind and solar generation), thus decreasing wholesale electrical prices [15–20]. A comprehensive description of the merit order effect is presented in the 2010 EWEA report [21].

The literature surrounding the impact of renewable generation on pricing can therefore be viewed as a growing body of scholarship, but there is a gap in understanding how this pricing has affected the time-shifting revenues available to storage operators. In this work, we use 7 years of historical electricity prices from the German and Great British day-ahead electrical markets over the 2010–2016 time-period, with an algorithm adapted from previous work, to establish the maximum revenue available to storage via time-shifting. We analyse how the revenues available through the time-shifting of electrical energy have changed. The key contributions of our work are summarised as follows:

- The paper highlights how the revenues available to storage operators from time-shifting electrical energy have evolved over this period of significant change in the energy sectors of both Germany and the Great Britain, relating these changes to trends in the price profiles in both countries.
- The paper provides an up-to-date analysis which highlights why the conditions for storage deployment may have been less favourable during this recent period than had previously been anticipated.
- The paper confirms that time-shifting revenues are highly variable and subject to disproportionate influence by factors that are highly challenging to predict.

The determined trends and characteristics of these time-shifting revenues should be interesting for potential investors in (and regulators of) bulk storage, as well as the general energy storage community. The rest of the paper is divided as follows: Section 2 provides context to the changing electricity generation mixes in Germany and GB and introduces the price data. Section 3 describes the algorithm and methodology used in this study. Section 4 presents results analysing the underlying prices and the revenue available to storage. Section 5 includes a discussion of the results and their impact and then Section 6 presents the major conclusions.

2. Generation mix changes and price data

2.1. The electrical generation mix in Germany and GB

Fig. 1a–d shows the changes of electrical generation fuel types from 2009 to 2016 for Germany and GB. They show that Germany increased its renewable energy generation by 96 TWh over this period, with GB experiencing about half of this increase. Interestingly, the amount of coal and lignite generation in Germany is still considerable (> 40%), whereas the contribution from coal in GB has dramatically fallen, in part due to environmental factors and in part due to relative changes to coal and natural gas prices, but mainly by the introduction of a carbon price floor in April 2013 [22,23]. The domestic demand in Germany has also increased by 10 TWh over this timeframe as well as an increase in net exports (36 TWh), whereas in GB domestic demand decreased by 36 TWh (-10%), including a fall in net exports of 9 TWh.

2.2. Historical price data in Germany and GB

To understand how the price of electricity has changed, time-series price data from the day-ahead wholesale markets in Germany and Britain were chosen. Both of these markets represent actual physical delivery of electricity, rather than an option or derivative and have a resolution of one hour. This allowed a simple and robust comparison between the two markets. The data for the PHELIX day-ahead market in Germany is from the power exchanges operated by the EEX Group [25], and a description of its operation can be found in Pesch and Stenzel's 2013 article [26]. The equivalent markets for GB are termed the 'N2EX' market, which is operated by the Nord Pool group [27], and the EPEX SPOT Auction market [25] (formerly APX power UK) which both provide day-ahead auctions. The prices in both GB markets have been linked since the 5th of February 2014, and prior to this, the overwhelming volume was traded through the N2EX market. Therefore, for this analysis we have chosen the N2EX prices to represent the GB market.

The timeframe analysed was from the 13th of January 2010 until the 31[redacted] was unavailab[redacted] series with 61088 distinct [redacted] is robust and did not require cleanin[redacted] other markets through which a storage operat[redacted] buying and selling, such as the *within* day SPOT markets, howe[redacted] data for these was more challenging to compare between Germany and Britain due the time resolution differences with the German market using a 60-min window and Britain using a 30-min window. Furthermore, the within-day markets are considerably smaller and much greater volumes of energy are traded on the day-ahead markets in both countries.

3. Methodology to calculate storage revenue

3.1. Algorithm description

To calculate the revenue available to storage operators from the time-shifting of electrical energy, an algorithm developed in previous work [28] was adapted, using new data over an extended timeframe to compare the markets in Germany and Britain. The algorithm provides an upper limit of the revenue a storage operator could achieve given a set of prices over a fixed length time window. The algorithm is provided with a time-series of prices with a length matching the window, and it returns an optimised buying and selling schedule that provides a maximum revenue. The method uses an iterative Monte Carlo style approach, randomly selecting (sampling) time periods for operation and updating the storage device's operational schedule if an operation is found profitable. The algorithm is highly flexible and can represent many different storage devices, including parameters for charging/discharging efficiency, maximum/minimum state of charge, charging/discharging limits and notably including an exponential decay parameter for self-discharge (the reduction in stored energy in the storage device over time *e.g.* a specified percentage reduction in the stored energy in a specified time horizon). Once the algorithm converges to an optimised buying and selling schedule for the price time-series under consideration, the revenue corresponding to this optimised schedule represents the upper limit of the available revenue. In essence, the optimising algorithm using historical price data acts as storage operator having perfect foresight and seeking to maximise profit via time-shifting. In reality, a storage operator would have less than perfect foresight, and their time-shifting revenue would therefore be less than the upper limit calculated by the algorithm. Nonetheless, understanding the value of the upper limit is useful for storage operators. Previous work has shown that storage devices at this scale typically operate on a daily cycle [28,29]. It is clear from the operation of actual pumped storage schemes that there are multiple revenue streams that are stacked to provide greater levels of revenue than time-shifting arbitrage for day-ahead markets alone can provide, such as differing types of frequency response, balancing markets and providing black-start capacity. However, these additional forms of revenue are not the focus of this paper.

The operation of the algorithm is described as follows with a detailed description provided in the Supplementary material, and readers may also wish to refer to the paper in which the original version was developed [28]. The operation of the algorithm is summarised as follows:

1. The number of iterations is specified (with each iteration representing a random sampling of two time periods) with the price file data and storage device characteristics input.
2. At each iteration, two time-periods, t_1 and t_2 are randomly selected, with t_2 being within a specified window of t_1, in this analysis 24 time-periods.
3. An amount of energy ΔE is selected that can either be $+1$ unit or -1 unit. These values are sampled with equal probability so that 50% of

the time a value of $+1$ unit will be selected. A positive unit implies that the power transferred to the storage device at t_1 will be increased and the power transferred to the storage device at t_2 will be decreased, while negative implies the opposite case. The negative option is included to allow the algorithm to correct for previously suboptimal operations.

4. The storage operation at each period is considered, and the energy ΔE is scaled (*i.e.* the magnitude of ΔE is changed but the sign is unchanged) to the maximum amount that doesn't violate any of the storage device's physical constraints, including the charging and discharging power limits at each of the time periods and the maximum and minimum allowable energy stored between the two-time periods. Importantly, ΔE is also restricted so that the operation of the storage device at either time-period doesn't switch from charging to discharging, or vice versa. This is due to the switch of the efficiency factor when the storage device changes from charging to discharging – i.e. when the storage device charges 1 unit, the actual energy absorbed is $1/\eta_{charge}$ whereas when the device discharges 1 unit, the actual energy returned is $\eta_{discharge}$.
5. The price at each period is compared, and if there is an economic benefit from the storage action then the action is added to the devices operational schedule. Specifically, this will be the case with a positive ΔE if $\pi_2 > \pi_1/\eta_{RT}$ where π_1 is the price at period t_1 and π_2 is the price at period t_2 and η_{RT} is the round-trip efficiency given by $\eta_{charge} \times \eta_{discharge}$.
6. Once the final number of iterations has been reached then the schedule is considered to be sufficiently close to the optimal.

As the algorithm uses a non-deterministic method, each path towards the global maximum will be different, however with sufficient iterations it converges to the optimal solution. Once the iterations are complete, the result returns the storage operational schedule corresponding to the maximum yearly revenue, hence by multiplying the power exchanged at each period with the price at that period it is possible to obtain a time series of the revenue generated at each hour in the year.

3.2. Modelling assumptions and storage device characteristics

For this paper, the storage characteristics chosen were for a pumped-storage hydropower device with 1000 MWh energy capacity and a power limit in and power limit out of 125 MW. The efficiencies in and out were both set at a value of 86.6%, giving an overall round-trip efficiency of 75%. This gives a power-to-energy ratio of 12.5%, a full charge time of 9 h 14.5 min and a full discharge time of 8 h. This is felt to be broadly typical of a pumped-storage hydropower scheme in either market. In GB the range of power-to-energy ratios for pumped-storage hydropower ranges from 4%-28% [30]. The self-discharge variable in the model (how quickly the stored energy deteriorates over time) was set with an exponential decay constant of 1×10^{30} h. In effect this meant that all the energy charged in the storage device was available for discharge regardless of the time it had actually been stored. A further assumption that must be noted, is that the operation of the algorithm considers the storage device as a price taker. In reality, it is expected that at some point, increased levels of storage would have a significant impact on prices, but this is not an area explored in this paper. If an increase in storage did impact pricing, it would most likely tend to decrease the overall revenue by increasing the price at times of charging and decreasing the price at times of discharging; thus decreasing the overall price spread that the storage was seeking to capture. The assumption of a price taker therefore reinforces that the calculated value represents an upper boundary of revenue. This holds in the absence of market power.

3.3. P[illegible]

The algorithm was o[illegible] speed it was converted to Fortran90 [illegible] Computing resource at The University of Sheffie[illegible] verified using a range of price files with known profiles, inclu[illegible] stepped profile, a saw tooth profile and a sine wave profile, where the global maximum of revenue could be pre-calculated. In these cases, the algorithm converged to the global maximum within 10 million iterations. The number of iterations for the wholesale price files were set two orders of magnitude greater than this to cover the additional complexity of the variation in the actual price files and three runs for each market with different random starting points were compared, to understand the convergence to a global maximum. The value for the total upper boundary revenue over the 61088 distinct points over the 7 years was calculated to be within 0.06% of each other for the three separate runs, which was felt to be sufficiently accurate for this paper.

It is worth noting that other methods also exist to solve the revenue available from storage problem [29] and many authors opt to solve this as a constrained (typically linear) optimisation problem, using various commercial optimisation packages or toolboxes. A final development MATLAB version of the scheduling algorithm is available at https://github.com/EdwardBarbour/ArbitrageOptimisation along with a comparative linear programming formulation to solve a time-shifting scheduling problem with a time-series of prices as an input. Although we believe there is a computational speed benefit of our non-deterministic approach in comparison to linear optimisation when both solving approaches are run in MATLAB, this would require a detailed analysis to compare the different approaches, which is out with the scope of this paper.

4. Results

4.1. Day-ahead electrical wholesale price analysis

In the following three sections the underlying price data from 2010 to 2016 are analysed.

4.1.1. Day-ahead prices in Germany and Great Britain

The price profiles of the day-ahead hourly prices can be seen in Fig. 2 for Germany (€) and Fig. 3 (£) for Great Britain where the 2010 (blue) and 2016 (orange) prices are shown together. There are a number of noticeable differences between the two markets such as Germany recording negative prices whilst Britain has not. In addition, the spread of prices in the German market associated with a particular period for each day in each month in 2010 is significantly greater than in Britain, especially during the early hours of the day. Interestingly, this spread happens during hours of darkness and therefore cannot solely be attributed to solar generation.

Focussing on the summer months from April to September where solar contributes a greater share of electrical generation, in 2010, the German and the British prices are higher in late morning, with a general reduction until the evening, typified by the price profiles in June and July. In 2016, there is still a peak in the morning, but it is clear that there has been a significant drop in prices from 2010 to 2016 that straddle the midday period; this pattern is more pronounced in the German day-ahead market than in Great Britain. This midday drop in price also has a more marked impact in the summer months, so a rational explanation is that a higher amount of forecast solar generation in both markets puts downward pressure on day-ahead prices around midday. It is expected that wind would have an additional downward price impact if also forecast to generate over the solar period. In contrast, a price drop overnight associated with forecast renewable generation would have to be due to wind alone.

Fig. 3 clearly shows the early evening peak prices, with September, October and November in 2016 being well above £100/MWh in Britain

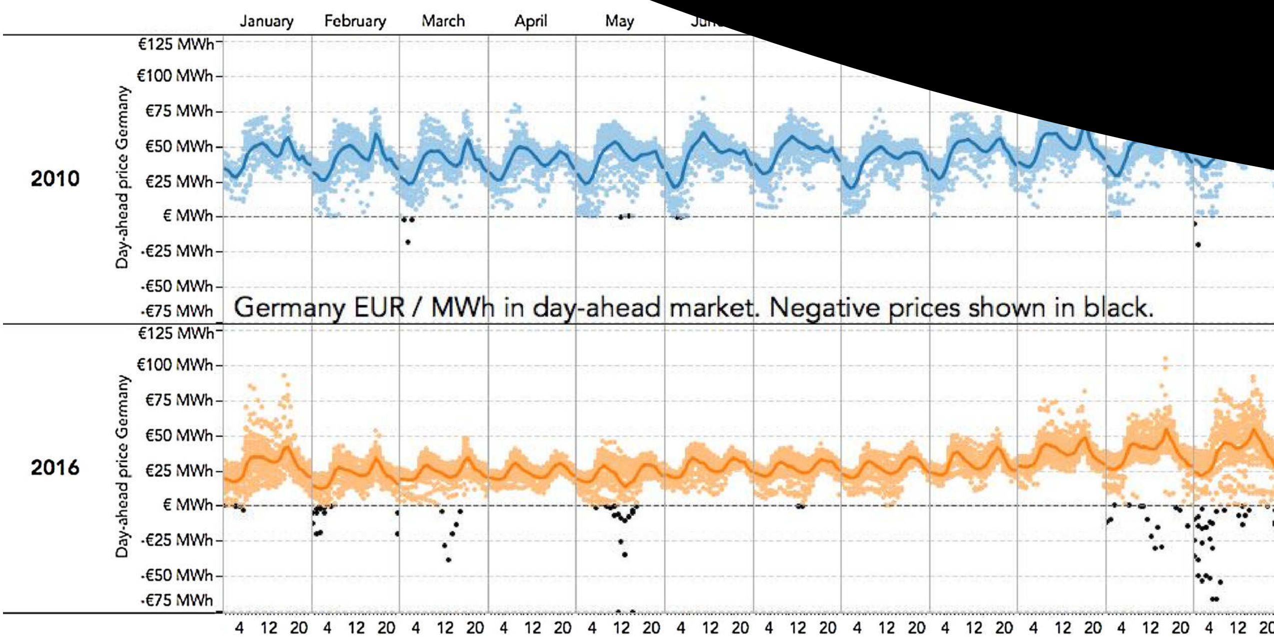

Fig. 2. The numbers on the bottom axis 4,12 and 20 refer to the hours of the day (from 1 to 24). Each cell in the Figure shows the data points for the day-ahead price per MWh, with a line showing the mean prices, for each hour and each month for 2010 (blue) and 2016 (orange). Source [25] for German prices. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(reasons for these extraordinary values are explored in the following Section 4.1.2). Tables 1 and 2 also give some statistics about the German and Great British day-ahead prices. The mean annual German day-ahead market prices fell by more than 43% between their peak value of €51.12/MWh in 2011, with a continual drop to the 2016 value of €28.98/MWh. In Great Britain, the mean price increases and decreases between one year and the next. Only from 2013 to 2015 does the mean decline continuously, with a similar average price in 2015 and 2016 (£40.44/MWh in 2016). The mean of the British data in 2016 is only 19% less than its peak value in 2013. The highest hourly German day-ahead electricity price occurred in February 2012 at €210/MWh whereas in Britain, the highest hourly price was in September 2016 at £999/MWh (the maximum value capped under regulation). The lowest electricity price in Germany was a negative price of −€221.99/MWh in December 2012 and in Britain was £3.99/MWh in December 2015.

4.1.2. Day-ahead price volatility

The absolute standard deviation for each month in each market is given by Eq. (1)

$$\sigma = \sqrt{\sum_{i=1}^{N} (\pi_i - \mu_m)^2 \Big/ N} \tag{1}$$

where N is the number of time periods under consideration in a month (which are indexed by i), π_i is the price during period i and μ_m is the

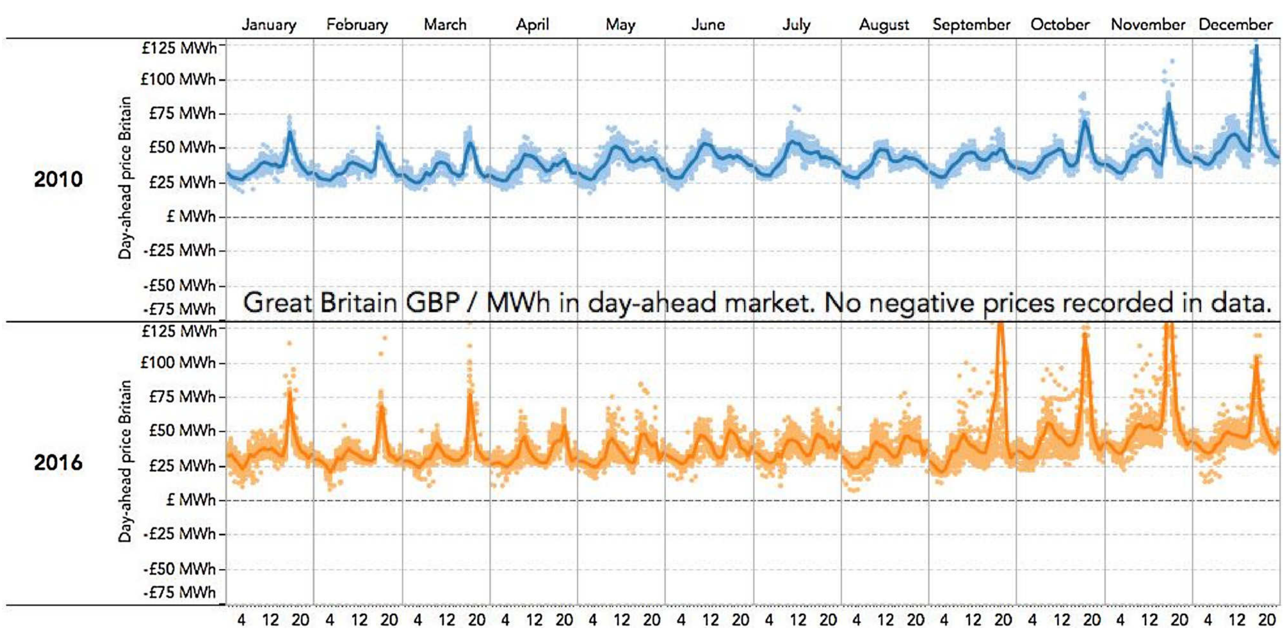

Fig. 3. The numbers on the bottom axis 4,12 and 20 refer to the hours of the day (from 1 to 24). Each cell in the Figure shows the data points for the day-ahead price per MWh, with a line showing the mean prices, for each hour and each month for 2010 (blue) and 2016 (orange). Source [27] prices for Britain. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Price statistics per MWh for Germany, own calculations based on price data from EEX [22].

	Median [€]	Mean [€]	Maximum [€]	Month Maximum	Minimum [€]	Month Minimu[redacted]	[redacted]
2010	45.25	44.62	131.79	December	−20.45	December	31.2
2011	51.85	51.12	117.49	October	−36.82	February	26.6
2012	42.08	42.59	210.00	February	−221.99	December	43.9
2013	36.07	37.78	130.27	August	−100.03	June	43.6
2014	31.64	32.76	87.97	December	−65.03	May	39.0
2015	30.54	31.63	99.77	November	−79.94	April	40.1
2016	28.24	28.98	104.96	November	−130.09	May	43.1

Table 2
Price statistics per MWh for Great Britain, own calculations based on price data from N2EX [27].

	Median [£]	Mean [£]	Maximum [£]	Month Maximum	Minimum [£]	Month Minimum	Relative Standard Deviation [%] (Volatility)
2010	39.70	40.79	299.98	December	16.96	May	29.9
2011	47.23	47.80	95.29	November	16.54	October	20.0
2012	43.50	44.70	175.04	October	19.94	January	28.6
2013	49.93	50.15	155.04	March	15.01	August	26.6
2014	40.00	42.10	195.73	November	9.98	December	27.9
2015	38.96	40.43	167.91	November	3.99	December	25.6
2016	35.69	40.44	999.00	September	7.05	August	78.2

monthly mean price. However, to express the price volatility between the two markets, throughout this paper we use the *relative standard deviation* of the prices over a particular number of time periods, *N*, as shown by Eq. (2). For a monthly time period this divides Eq. (1) by the mean of the month and multiplies this by 100 to express the value as a percentage.

$$v = \left(\frac{\sigma}{\mu}\right) \times 100 \tag{2}$$

Looking at the Relative Standard Deviation [%] (Volatility) column in Table 1 for years 2010–2016, we see that the price volatility jumped in Germany in 2012 and then remained significantly higher than in 2010 and 2011. Detail for each month is shown in Tables S6 and S7 in the Supplementary material. In Great Britain the price volatility was similar to Germany in 2010 but has since remained consistently less than in Germany from 2012 to 2015 (from 25% to 40% less), with a significant increase in 2016. The set of price spikes from September through December 2016 in Britain was exceptional, and explained by a combination of tight capacity margins, exacerbated at times by short-term interconnector capacity reductions, and the loss of capacity in the French nuclear fleet that was subject to emergency inspections. This led to France becoming a net electrical importer from Britain rather than a net exporter of electricity over several months, which further increased the day-ahead wholesale price in Britain to accommodate this additional demand. This resulted in 50 occurrences over 33 separate days where the price was above £150 per MWh. To put this in perspective, over the previous 6 years, there were only 23 occurrences exceeding £150 per MWh over 19 separate days in total.

4.1.3. Day-ahead negative pricing

An area that has had an impact on price volatility has been the increasing presence of negative prices in the German day-ahead market. The count of the occurrences and average negative prices are shown in Tables S3–S5 in the Supplementary material. While the lowest negative prices occurred in 2012, there has been a steady increase in the occurrence of negative prices from 2010 to 2014, a near doubling in 2015 to 126 occurrences (1.4% of all hourly periods) followed by a drop in 2016 to 97 occurrences (1.1% of all hourly periods).

There seems little pattern to negative prices other than the occurrence of a greater number in the winter period rather than the summer (a period of higher seasonal electrical demand), but also during off-peak times (a period of lower within day electrical demand). However, the absolute value of the average negative price is greater during periods when solar generation is possible than at other times. Negative prices generally represent a lack of system flexibility during the period during which the negative price persists. A contributory factor for negative prices in Germany, are the commitments of some combined heat and power (CHP) plants to provide heat for district heating systems; even if there are significant levels of electricity provided by wind and/or solar generating plants. Another factor is that thermal plants might produce electricity even if it is not economically viable over certain periods in order to be available for higher price periods in the near future, as a shut-down and new ramp up of power might lead to higher overall costs. These factors help to explain why negative prices happen on more occasions in the winter when greater heat and power is needed, than in the summer. In 2014, the cap on negative prices was reduced by changing the limit for negative prices from €-3000/MWh to €-500/MWh in the German/Austrian day-ahead market area.

As yet, there have been no occurrences of negative prices in Great Britain's *day-ahead* electrical wholesale market (although there have been a number of occasions of negative prices in the *within day* SPOT market). There are several reasons why this may be the case, but it is thought to reflect the lower amount of weather dependent generation on the British system, and the lower amount of CHP systems that need to be run for heating provision, both in absolute and in percentage terms in comparison to dispatchable 'non-must-run' generation.

4.2. Time-shifting revenues

The output of the algorithm for calculating the optimal storage operational schedule is multiplied by the electricity price to find the operational revenue at each hourly period. This is then summed over different periods of interest to provide results which can be related to back to trends in the underlying price data. While the results for the two countries could be matched using an exchange rate, this was not felt appropriate given the range of external factors which influence exchange rates. This is especially true given that the focus of this paper is to look at the effect of local market conditions. For example, the exchange rate change from the decision for the UK to leave the European Union would have had a significant effect on the revenues if the analysis had used a single currency comparison for both markets. Therefore, we keep the analysis in each market's currency so the German revenues are in Euros [€] while the Great British revenues are given in Great British Pounds [£]. We assume that pumped storage in

Germany and Great Britain serve markets using similar currencies, and therefore comparing them in their own currencies is valid.

4.2.1. Annual revenues

Fig. 4 shows the total *annual* revenues available in Germany and Britain over the years 2010–2016. At an annual level, the revenue of the two markets appears to move in parallel from 2010 to 2015. Having a similar movement in total revenue in the two markets is itself an interesting finding, given the large differences in generation mix, difference in demands, levels of interconnection and different regulatory regimes and market designs. One possible interpretation of this is that while the generation mixes are different, the marginal generator types have similar impacts on storage revenue over the year. This similarity diverged in 2016, with a series of historically high peak prices in the British day-ahead market, leading to far higher revenues.

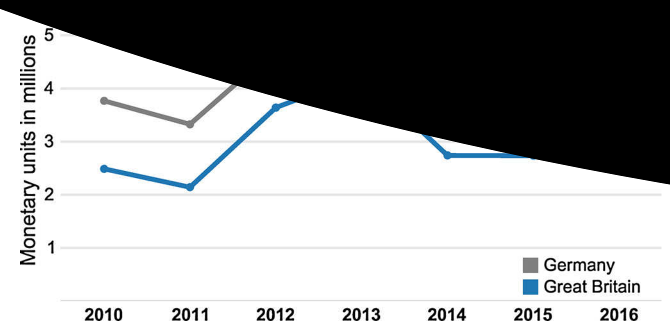

Fig. 4. Annual revenues for time-shifting energy with a 1000 MWh, 125 MW storage device with 75% round-trip efficiency. Monetary unit scale is millions of EUR for Germany or GBP for Britain: results from algorithm.

4.2.2. Monthly revenues

Fig. 5 shows the monthly revenues of the storage operator by weekday (orange) and weekend (grey). In both countries, a general pattern can be detected, with greater level of revenues available at the beginning and at the end of a year[1] rather than over the summer. In Germany, the year 2012 has high revenues in February and December whereas in Britain the year 2016 has high revenues in September, October and November. In Germany, 2012 was the year with the highest maximum price (€210 in February), lowest negative price (−€221.99 in December) and the highest price volatility (relative standard deviation of 43.9) of the 2010–2016 period (Table 1).

The results from the algorithm shown in Fig. 5 suggest that the majority of revenue is generated during weekdays rather than at the weekends, and that this has persisted throughout the 2010–2016 period. In Great Britain, there are fewer months with negative monthly total revenues over weekends than in Germany (the grey areas below the horizontal zero line), while in Germany the number of months with negative total revenues on weekends has decreased from 2010 to 2016. Negative weekend revenues typically happen if the storage is charged on Sunday and not discharged until Monday. Therefore, the cost shows in the weekend, and the revenue during the weekday, thus showing a negative value for revenue over the weekend.

4.2.3. Daily revenue maxima time of day changes

Fig. 6a–d provides a closer view of the changes of the timing of the hour with the highest revenue. Again, these peak hour graphs are divided into working days and weekends. Fig. 6a) shows the changes of revenue peaks on weekdays for April to September in Germany. There is a shift of the peak in the morning from hour 9 to the earlier time of hour 6 and the later hours 17 and 18. In the afternoon/evening (after h 17 inclusive) the number of peak hours increases from 12 (9% of possible days) in 2010 to 46 (35% of possible days) in 2016. In Fig. 6b–d only the years 2010 and 2016 are displayed for clarity. In Britain on weekdays, the change from peak hours in the morning centred at hour 10 to the afternoon/evening is equally distinct, with the majority of peak hours taking place at or later than hour 17 in 2016. In numbers − at hour 12 and before − there were 84% of peak hours in 2010 and 30% in 2016. For hours 17 and later, the share grows from 15% in 2010 to 70% in 2016. On weekends, there is also a shift of peak hours from the morning (hour 12 and before) to the afternoon/evening (after h 17 inclusive). All these observations are plausible taking into account the higher share of electricity produced by solar generation. The changes in timing of the highest revenues calculate by the algorithm imply that the operational timing of electricity storage charging and discharging has moved to take advantage of shifting market conditions in both the German and Great British markets over the last seven years.

[1] January 2010 is only half a month – as the values started on January the 13th.

4.2.4. Storage revenue against price volatility and mean price

To understand the effect of price volatility and mean price on the revenue available to storage operators, we study the correlations between monthly revenue available and average electricity price and volatility. The monthly price volatility is calculated as the relative standard deviation of the monthly prices, as described by Eq. (2) for the N time periods in the month (*i.e.* January has 744 hourly periods).

In Germany, we observe that volatility has a significant correlation with available revenue (R-squared value = 0.75), with a unit percentage increase implying an average increase of €300 in daily revenue. However, the average price has a smaller effect on the available revenue and the correlation is much less strong – we find that a price increase of €1/MWh leads to an average daily revenue increase of €100 and the R-squared value is 0.16. Fig. 7a shows the average daily revenue for the 1000 MWh, 125 MW, 75 % round-trip efficient storage device for each month plotted against that month's volatility and Fig. 7b shows the average daily revenue for each month plotted against the month's average price.

Fig. 8a shows the mean daily storage revenue for each month plotted against the volatility for Great Britain, while Fig. 8b shows the average daily revenue for each month plotted against the month's average price. We find that in GB there is again a very significant correlation between revenue and volatility (R-squared value = 0.87), with a percentage increase in volatility implying an increase of £550 in daily revenue. In terms of average electricity prices, we find that a £1/MWh increase in the average price implies an increase in daily revenue of approximately £380 (with R-squared value = 0.49). The outlying points for the months September, October and November in 2016 are highlighted and have not been used in determining the trend line.

5. Discussion

The analysis of the price files of the German and British Day-Ahead markets from 2010 to 2016 revealed several similarities and differences. The mean prices in Germany have fallen since 2011, however the price volatility has persisted at around 40%. In GB, the average prices in 2016 are similar to 2010 having experienced some fluctuations in the years between. The British price volatility remained at similar levels between 25% and 30%, again showing inter-yearly fluctuations which have little correlation with the average yearly price. However, late 2016 shows an extraordinary increase of within day price volatility in Britain due to special effects concerning the demand in France and interconnection disruption between France and GB. In Germany and GB, the price files show a shift of daily minima (between 7am and 7pm) from the morning and evening hours to the middle of the day, with a rational explanation being the greater amounts of electricity forecast from low short-run marginal cost photovoltaics reducing wholesale day-ahead prices.

Based on the actual electricity prices from 2010 to 2016, the potential storage revenues in Germany and Britain were analysed. The

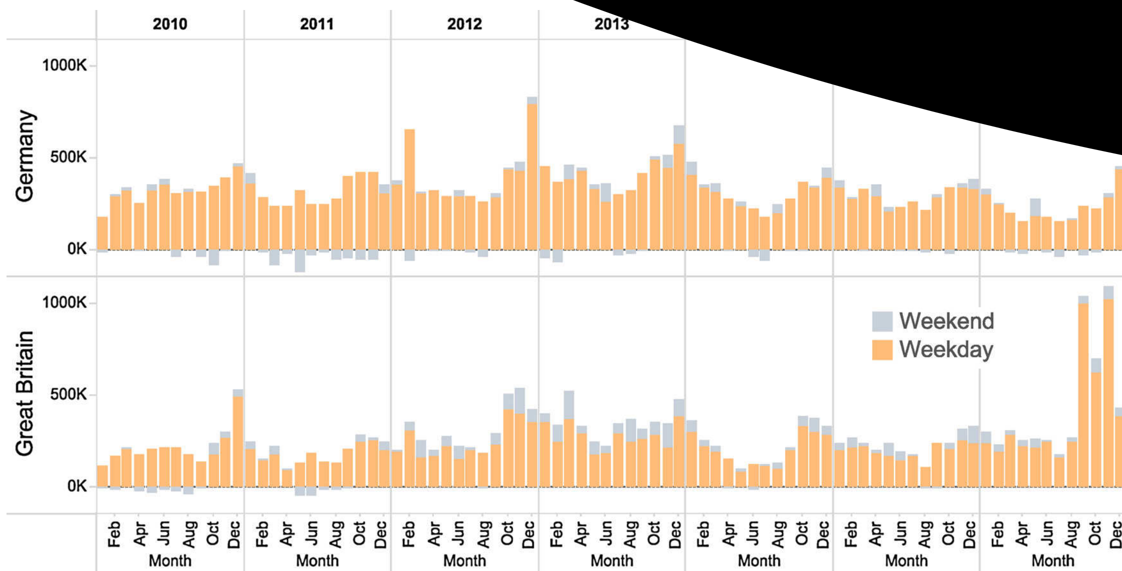

Fig. 5. Revenue by month grouped by weekday (orange) and weekend (grey): results from algorithm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

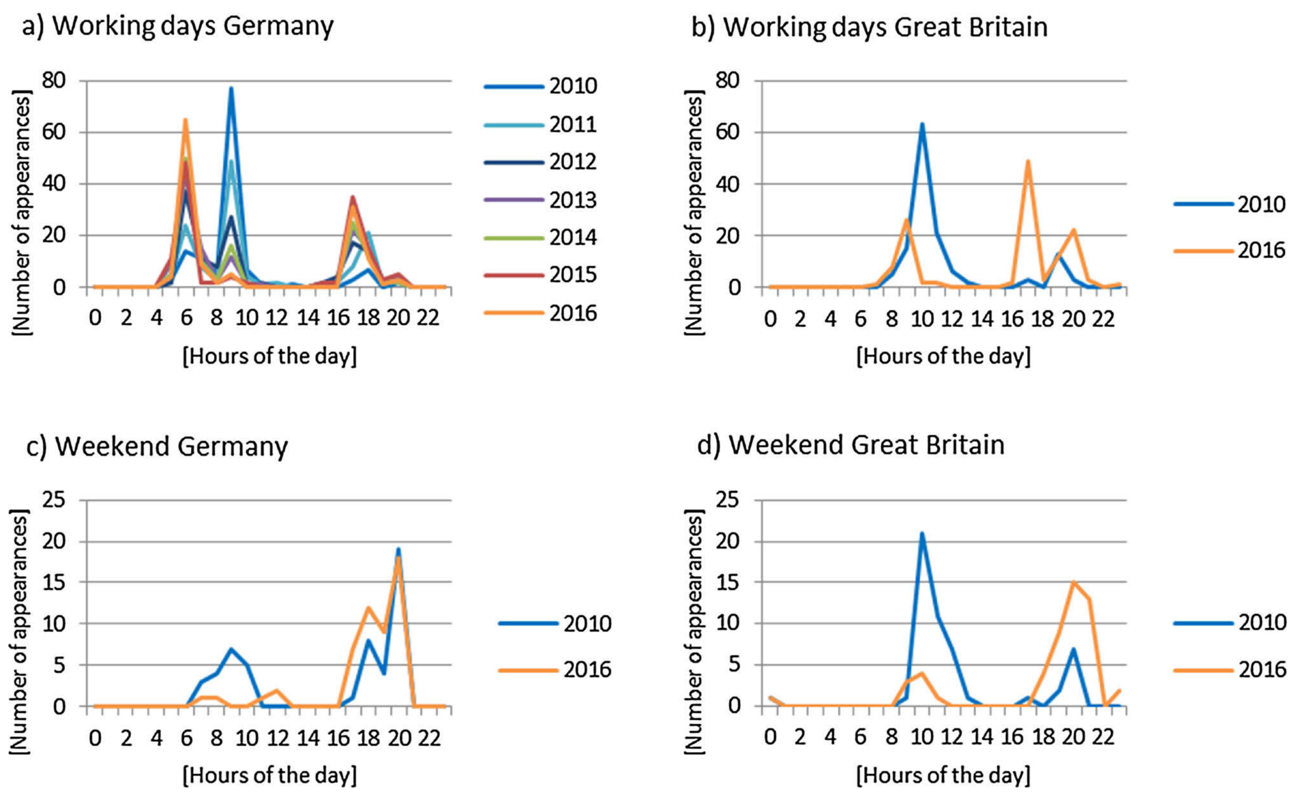

Fig. 6. a–d) Comparison timing of maximal revenue hour between the years, working days and weekends and Germany and Britain from April to September: results from algorithm.

potential level of revenue available from the day-ahead market in Germany has fallen since 2013. In particular, there has been a fall and shift of revenues away from the middle of the day, especially in the summer months, driven by the reduction in prices. This is also thought to be behind the shift in revenues away from the summer to the spring, autumn and winter in Germany. While it had been postulated that trends in British storage revenue might lag those observed in the German market due to the lag in renewable generation investment, our results imply this is not the case. Our results demonstrate that both markets experienced similar trends in the level of potential storage revenues from one year to the next, which suggests that the price setting of the marginal plant in both markets might be closer than the rest of the market dynamics, such as the generation mix, demand profiles, levels of interconnection and market frameworks. However, this similarity broke down spectacularly, when the revenues in both markets diverged in the latter part of 2016. A sudden reduction in available generation from France in the latter part of 2016 provided a significant increase in the potential revenues for storage operators in Britain by increasing both the volatility and the average price electricity in the of day-ahead market. The price data suggests that the tightness in French

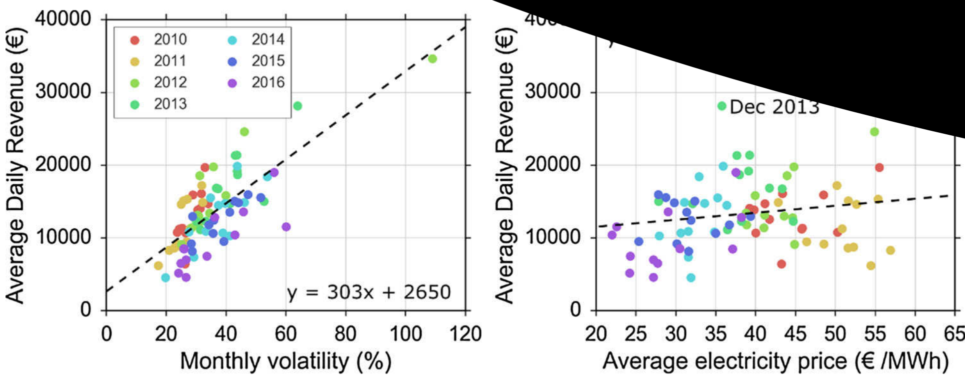

Fig. 7. a) Germany average daily revenue for each month for each month against volatility. b) Germany average daily revenue for each month against average electricity price. The months with the highest revenue (December 2012 and December 2013) have been highlighted.

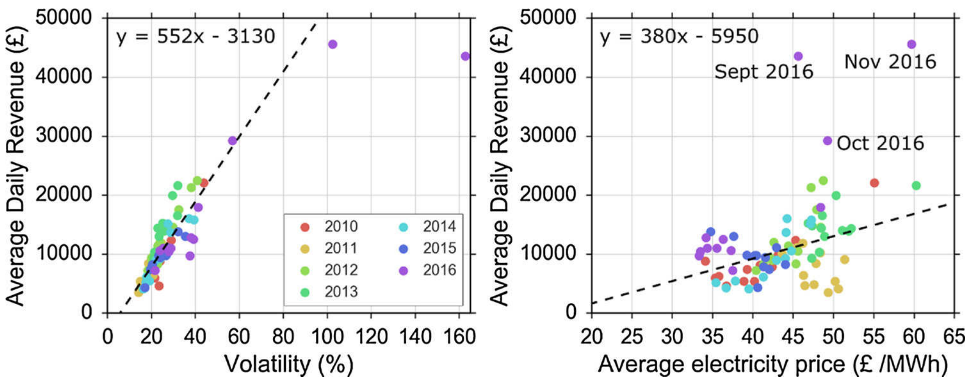

Fig. 8. a) British average daily revenue for each month for each month against volatility. The best fit line neglects the outliers above £40000 daily revenue. b) British average daily revenue for each month against average electricity price. The month with the highest revenue in September, October and November of 2016 have been highlighted.

generation did not impact the German day-ahead market to a similar level than that experiences in the GB market.

This finding is a reminder of the challenges of forecasting prices and therefore storage revenues well into the future, and underlies some major differences between the two physical electrical markets. With an interconnector capacity of at least 21 GW, Germany [31] has much greater levels than that of Britain at 4 GW [32]. Therefore, problems with tight generation margins in the home market, exacerbated by interconnection interruption and then compounded with further tight generation margins at the other end of interconnectors would have to be far more widespread and of a much greater level to cause such price deviations in Germany. In short, Germany's interconnectedness reduces the likelihood of price swings such as those seen in Britain in late 2016, but this of course is still in the age of access to significant levels of dispatchable generation throughout the interconnected central European market. As these reduce, and capacity margins become tighter, then one might expect the potential revenues of time-shifting electrical energy via storage to increase again and therefore to help incentivise investment. In Germany, the day-ahead market has also seen the growth of a non-trivial amount of negative day-ahead prices (97 occurrences in 2016), whereas in the British market, there were no occurrences in the day-ahead market up until the end of 2016. Negative prices should benefit storage operators by increasing the price spread that could potentially be captured, where storage operators would get paid to take electricity. Barbour, Wilson et al. [33] looked at the influence of negative day-ahead pricing on the consideration of round-trip efficiency, and found that these negative prices did not typically encourage the use of storage devices with lower round-trip efficiencies.

Although the change in revenues from time-shifting electrical energy will have a material impact on the appetite for investment in bulk electrical energy storage, it is acknowledged that there are several other factors that can explain the paucity of investment in Germany and Britain from 2010–2016. These include challenges in planning that leads to project delays, more profitable areas of investment for developers, and uncertainties around the changes to regulatory regimes over the short to medium term which further increase the risk of investment.

The findings confirm challenges for investment cases for pumped storage due to the variability of year-to-year revenues. The variability in underlying prices is due to many factors, most of which are outside the ability of pumped storage developers to influence. If we take an investment cost of pumped storage in Germany as €0.7 million per MW [4,34], then the cost of the 125 MW pumped storage scheme used for analysis in this paper would be €87.5 million. Using the most basic payback analysis without consideration of the time value of money, the cost of borrowing, operation and maintenance costs, or desired profit, it would take between 18 years (using 2013 revenue) and 32 years (using 2016 revenue) to pay back the original capital. This variation in revenue coupled to long payback periods points to the reasons why pumped storage operators seek to stack revenues from other sources such as grid balancing, and also helps to explain why the levels of storage investment have not passed final investment decisions to be built.

This analysis has focussed on bulk electrical energy storage on a merchant basis and the revenues from time-shifting electrical energy with pumped storage considered as a large centralised technology. Energy storage, with its inherent flexibility, is felt to be an important component of a future smart grid and can be realised on both a large-scale and more distributed-scales. While the time-shifting discussed previously could take place in either centralised or distributed storage, there is a challenge at highly distributed levels (*e.g.* household level storage) in terms of accessing the full range of pricing in the day-ahead market. Due to the cost of having a trading account with one of the day-ahead markets, it is not feasible that households would have direct access. Typically, households would only have access to the price differentials that their suppliers were willing to pass on, for example through time-of-use tariffs. Additionally, smaller scale storage devices suffer from higher costs and lower efficiency for most storage technologies. However, due to the increase in storage aggregators in both markets bringing forward a range of novel business models, it seems possible in future that household storage may be able to share in more of the potential revenue streams from the time-shifting of electrical energy than has historically been the case. Dispatchable demand from transport batteries may also be able to compete with bulk centralised storage for low day-ahead prices.

6. Conclusions

The results confirm the challenge of the investment case in pumped-storage hydropower scheme using a single revenue stream from the time-shifting of electrical energy. This challenge is not only from the absolute level of revenue that might be on offer, but also crucially the variability in this level of revenue from year to year. This makes it particularly challenging to forecast the revenues, and therefore increases the risk of a project.

In terms of the interplay between volatility (relative standard deviation) and mean price, in general we find that volatility rather than price is the dominant factor affecting storage revenues. A unit percentage increase in volatility leads to an average daily increase in storage revenues of €300 for Germany and £550 for Great Britain for the typical pumped storage scheme of 1000 MWh, 125 MW charging and discharging capacity with a 75% round-trip efficiency analysed. Conversely, an increase in average price in Euros or Great Britain Pounds per MWh in respective markets leads to an average daily increase in storage revenues of nearly €100 for Germany and £380 for Great Britain.

We also find a change in timing of when the highest revenues are derived, away from late morning to early evening during the period 2010–2016 which we attribute to increases in low short-run marginal cost solar PV electricity in both markets suppressing prices on the day-ahead wholesale electrical market.

In addition, we find a large increase in storage operator revenues in Britain in the last quarter of 2016, due to a number of events that impacted the price of electricity that would have been difficult if not impossible to predict with any degree of certainty. The paper highlights the perennial problem of forecasting time-shifting revenues for electrical energy, with their high degree of variation from one year to the next.

The supranormal peak prices in Britain that drove storage revenues, are thought to be moderated in Germany by its greater levels of interconnectivity and perhaps greater levels of mothballed plant in either its indigenous market, or in interconnected markets. Greater levels of interconnectivity in Britain are expected to have a dampening effect on very high peak prices and therefore the level of potential revenue that storage operators can derive through time-shifting energy via the day-ahead electrical wholesale markets. As greater levels of interconnectivity are a stated aim of policy throughout Europe and Britain, it is expected that bulk storage operators will continue to seek rents from other services to the market – as in the German Control Power Market for German operators – and not just the time-shifting market that is highly variable in terms of its annual revenue.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.est.2018.04.005.

Refere[redacted]

[1] B. Steffen, Prospects for pu[redacted] (2012) 420–429, http://dx.doi.org/1[redacted]
[2] M. Zuber, Renaissance for Pumped Storage in Eu[redacted] (2011), pp. 1–3 http://www.hydroworld.com/articles/print/[redacted] articles/new-development/renaissance-for-pumped-storage-in-europe.htm[redacted]
[3] SETIS Magazine, Power Storage, (2013). https://setis.ec.europa.eu/publications/setis-magazine/power-storage/europe-experience-pumped-storage-boom.
[4] J.P. Deane, B.P. Ó Gallachóir, E.J. McKeogh, Techno-economic review of existing and new pumped hydro energy storage plant, Renew. Sustain. Energy Rev. 14 (2010) 1293–1302, http://dx.doi.org/10.1016/j.rser.2009.11.015.
[5] E. Barbour, I.A.G. Wilson, J. Radcliffe, Y. Ding, Y. Li, A review of pumped hydro energy storage development in significant international electricity markets, Renew. Sustain. Energy Rev. 61 (2016) 421–432, http://dx.doi.org/10.1016/j.rser.2016.04.019.
[6] SSE, Coire Glass Hydro-Pumped Storage Project, (n.d.). http://sse.com/whatwedo/ourprojectsandassets/renewables/CoireGlas/.
[7] J.C. Ketterer, The impact of wind power generation on the electricity price in Germany, Energy Econ. 44 (2014) 270–280, http://dx.doi.org/10.1016/j.eneco.2014.04.003.
[8] F. Benhmad, J. Percebois, Wind power feed-in impact on electricity prices in Germany 2009–2013, Eur. J. Comp. Econ. 13 (2009) 81–96 http://eaces.liuc.it/18242979201601/182429792016130105.pdf.
[9] Å.G. Tveten, T.F. Bolkesjø, T. Martinsen, H. Hvarnes, Solar feed-in tariffs and the merit order effect: a study of the German electricity market, Energy Policy 61 (2013) 761–770, http://dx.doi.org/10.1016/j.enpol.2013.05.060.
[10] S. Clò, A. Cataldi, P. Zoppoli, The merit-order effect in the Italian power market: the impact of solar and wind generation on national wholesale electricity prices, Energy Policy 77 (2015) 79–88, http://dx.doi.org/10.1016/j.enpol.2014.11.038.
[11] T. Jónsson, P. Pinson, H. Madsen, On the market impact of wind energy forecasts, Energy Econ. 32 (2010) 313–320, http://dx.doi.org/10.1016/j.eneco.2009.10.018.
[12] T. Rintamäki, A.S. Siddiqui, A. Salo, Does renewable energy generation decrease the volatility of electricity prices? An analysis of Denmark and Germany, Energy Econ. 62 (2017) 270–282, http://dx.doi.org/10.1016/j.eneco.2016.12.019.
[13] R. Green, N. Vasilakos, Market behaviour with large amounts of intermittent generation, Energy Policy 38 (2010) 3211–3220, http://dx.doi.org/10.1016/j.enpol.2009.07.038.
[14] A. Bublitz, D. Keles, W. Fichtner, An analysis of the decline of electricity spot prices in Europe: who is to blame? Energy Policy 107 (2017) 323–336, http://dx.doi.org/10.1016/j.enpol.2017.04.034.
[15] M. Dillig, M. Jung, J. Karl, The impact of renewables on electricity prices in Germany – an estimation based on historic spot prices in the years 2011–2013, Renew. Sustain. Energy Rev. 57 (2016) 7–15, http://dx.doi.org/10.1016/j.rser.2015.12.003.
[16] F. Nieuwenhout, A. Brand, The impact of wind power on day-ahead electricity prices in the Netherlands, 8th Int. Conf. Eur. Energy Mark, EEM 11. 2011, 2011, pp. 226–230, , http://dx.doi.org/10.1109/EEM.2011.5953013.
[17] C. Brancucci Martinez-Anido, G. Brinkman, B.-M. Hodge, The impact of wind power on electricity prices, Renew. Energy 94 (2016) 474–487, http://dx.doi.org/10.1016/j.renene.2016.03.053.
[18] S. Forrest, I. MacGill, Assessing the impact of wind generation on wholesale prices and generator dispatch in the Australian National Electricity Market, Energy Policy 59 (2013) 120–132, http://dx.doi.org/10.1016/j.enpol.2013.02.026.
[19] C.K. Woo, J. Moore, B. Schneiderman, T. Ho, A. Olson, L. Alagappan, K. Chawla, N. Toyama, J. Zarnikau, Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets, Energy Policy 92 (2016) 299–312, http://dx.doi.org/10.1016/j.enpol.2016.02.023.
[20] C.K. Woo, I. Horowitz, J. Moore, A. Pacheco, The impact of wind generation on the electricity spot-market price level and variance: the Texas experience, Energy Policy 39 (2011) 3939–3944, http://dx.doi.org/10.1016/j.enpol.2011.03.084.
[21] P.E. Morthorst, S. Ray, J. Munksgaard, A.-F. Sinner, Wind Energy and Electricity Prices Exploring the Merit Order Effect, Wind Energy Assoc., 2010, p. 24 http://www.ewea.org/fileadmin/files/library/publications/reports/MeritOrder.pdf.
[22] J. Delebarre, The Carbon Price Floor, House of Commons Library, 2016, http://researchbriefings.files.parliament.uk/documents/SN05927/SN05927.pdf.
[23] I.A.G. Wilson, I. Staffell, Rapid fuel switching from coal to natural gas through effective carbon pricing, Nat. Energy (2018), http://dx.doi.org/10.1038/s41560-018-0109-0.
[24] BMWi (Bundesminiterium für Wirtschaft und Technologie), Energiedaten –Zahlen und Fakten – nationale und internationale Entwicklung, Bundesministerium Für Wirtschaft Und Energ (2012) 1–58.
[25] EPEX Spot Auction, Epex Spot Se 2016, (2018). https://www.apxgroup.com/trading-clearing/auction/.
[26] T. Pesch, P. Stenzel, Analysis of the market conditions for storage in the German day-ahead and secondary control market, Int. Conf. Eur. Energy Mark. EEM, 2013, pp. 1–8, , http://dx.doi.org/10.1109/EEM.2013.6607384.
[27] NORDPOOL, N2EX, (2017). http://www.nordpoolspot.com/Market-data1/N2EX/Auction-prices/UK/Hourly/?view=table.
[28] E. Barbour, I.A.G. Wilson, I.G. Bryden, P.G. McGregor, P.A. Mulheran, P.J. Hall, Towards an objective method to compare energy storage technologies: development and validation of a model to determine the upper boundary of revenue available from electrical price arbitrage, Energy Environ. Sci. 5 (2012) 5425–5436, http://dx.doi.org/10.1039/C2EE02419E.
[29] D. Connolly, H. Lund, P. Finn, B.V. Mathiesen, M. Leahy, Practical operation

strategies for pumped hydroelectric energy storage (PHES) utilising electricity price arbitrage, Energy Policy 39 (2011) 4189–4196, http://dx.doi.org/10.1016/j.enpol.2011.04.032.

[30] I.A.G. Wilson, P.G. McGregor, P.J. Hall, Energy storage in the UK electrical network: estimation of the scale and review of technology options, Energy Policy 38 (2010) 4099–4106, http://dx.doi.org/10.1016/j.enpol.2010.03.036.

[31] E. Agora E. Bayer, Report on the German Power System, Boletín Of. Del Estado. (2014) 103. http://www.agora-energiewende.org/fileadmin/downloads/publikationen/CountryProfiles/Agora_CP_Germany_web.pdf%5Cnhttps://www.epexspot.com/document/26145/EPEX SPOT_Trading Brochure.pdf.

[32] Org [redacted] electricity/ [redacted] November 2017).

[33] E. Barbour, G. Wilson, P. Hall, [redacted] courage inefficient electrical energy stora [redacted] (2014) 862–876, http://dx.doi.org/10.1080/0020 [redacted]

[34] E. Fertig, A.M. Heggedal, G. Doorman, J. Apt, Optimal investment [redacted] pacity choice for pumped hydropower storage, Energy Syst. 5 (2014) 285–300, [redacted] http://dx.doi.org/10.1007/s12667-013-0109-x.