Intermittency and the social benefits of storage

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– Preliminary version, please do not quote –

1. Introduction

Energy storage is arguably a vital element in maintaining a healthy reliable balance between supply and demand in the presence of intermittent green technologies such as wind power. When trying to understand the current and future role of energy storage, the first consideration is on the potential social benefits which storage might generate in the context of intermittent technologies. In principle, we have:

- Saving capital expenditure on new peaking plant (versus storage construction costs)
- Reduced expenditure on grid reinforcement
- Avoiding some curtailment of renewable energy
- Fuel saved through reduced ramp rates
- Reduced need for low efficiency plant to operate

Private benefits have often been investigated by assessing arbitrage possibilities. However, not all these factors can be captured through arbitrage, so essentially, there is a missing market problem due to uncaptured positive externalities. The problem is then to identify the potential social benefits from storage which can be evaluated using market information, i.e. how can we use market information to quantify the social benefits of storage? To achieve this it is necessary initially to put capital expenditure and grid reinforcement to one side because these are not observable. We focus therefore on the potential social benefits of storage arising from reduced ramp rates and on the increased efficiency.

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We approach the issue by considering grid-scale store capacity being used to flatten wind generation -as a measure to tackle the variability- and also capable of absorbing the wind forecast errors, therefore, mitigating the wind impact on the level and volatility of market prices. In the absence of storage, the impact of wind generation on price level and volatility comes from wind intermittency, which encompasses variability and imperfect prediction. The variability of output impacts on both the level and volatility of prices, given the underlying need to use generation with higher cost sources to a greater or lesser extent depending on the size of the deviation. The imperfect wind prediction results in forecast errors which are passed through the market price as additional price volatility.

With these effects in mind, we set out to evaluate the market price effects of introducing grid-scale store capacity sufficient to absorb the wind generation impact on prices. To do so, it is first necessary to explore the possible alternatives to storage, namely:

- Interconnectors – but these depend on what happens in other geographical locations, so it would bias any result
- OCGT - runs on very few occasions (2% in 2015), and is not a good case to consider as new investment is unlikely
- CCGT – runs much more often, but ramp-up and down exceed 1GW within 5 minutes. This is a performance that grid-scales storage cannot emulate
- which leads us to the fourth, and most attractive alternative, which is for storage to smooth wind to the extent that it emulates the output of a baseload plant. This is probably the most straightforward case to evaluate.

Specifically we examine what happens if we transform the hourly wind generation into a smoother baseload plant generating the daily average of wind which, by combining wind and grid-scale storage, can also absorb the forecast error.

2. Data

Given that the power flexibility required for the integration of intermittent generation is provided through the balancing market, to answer the above question, our first data source is UK balancing market prices (APX mid- prices obtained from Elexon[1]) information for the period between December 2014 and June 2016. We split the data into peak and off-peak periods to control for different system conditions. Figure 1 shows the balancing market index prices for peak (a) and off-peak (b) hours and Figure 2 shows the same data zooming on the prices below 120 £/MWh. These figures help to picture

[1] Elexon is the balancing and settlement code company which manages electricity trading arrangements in England and Wales (https://www.elexon.co.uk/)

both, the existence of price spikes (up to 296 £/MWh in peak hours and 117 £/MWh in off-peak hours) and the clearly higher price levels on peak hours (with average of 42.13 £/MWh and 34.46 £/MWh, respectively).

Figure 1. Peak and off-peak prices (£/MWh)

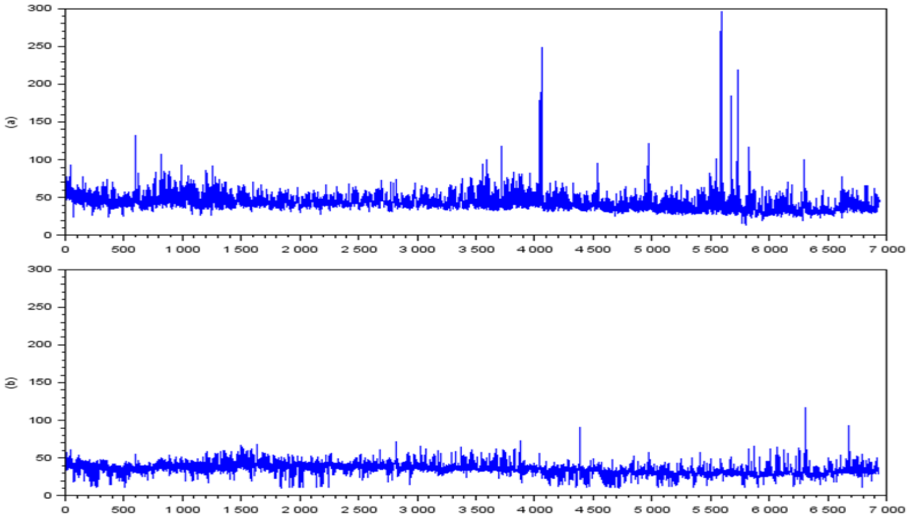
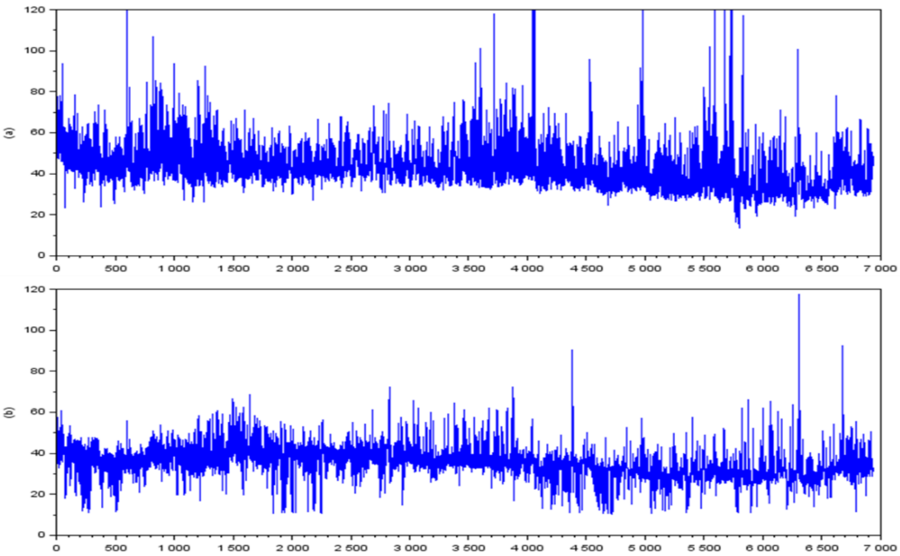


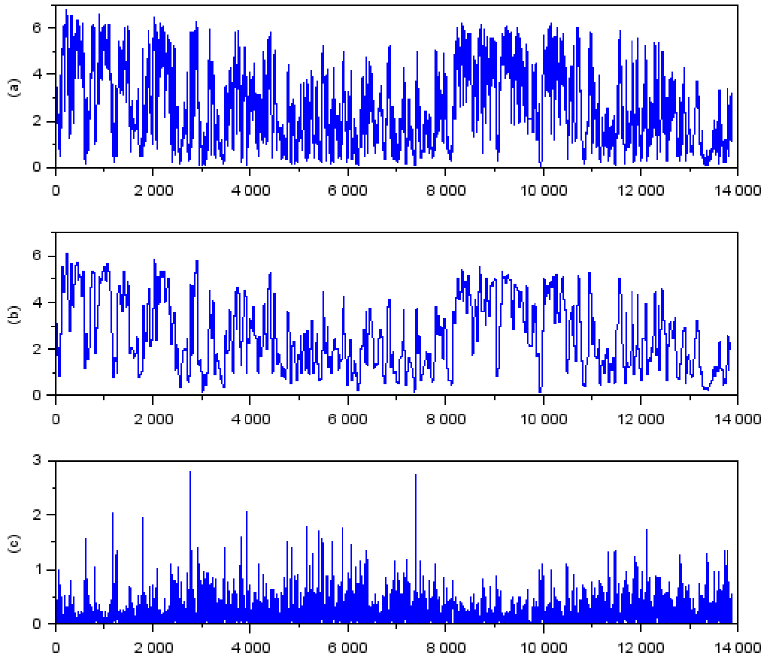
Figure 2. Peak and off-peak prices (£/MWh)



To analyse the extent of wind intermittency in terms of the wind generation variability we use a relativized indicator based on British actual wind generation information from National Grid. θ_t is the relative deviation of the hourly wind generation (W_t) from its daily average (μ_w) measured as shown in Eq (1). Figure 3 shows the hourly wind generation (a) -with a maximum of 6.7 GWh, the daily average (b) -with a mean of 2.9GWh, and the wind relative deviation (c) -with a maximum of 2.8 %.

$$\theta_t = | (W_t / \mu_w) -1| \qquad (1)$$

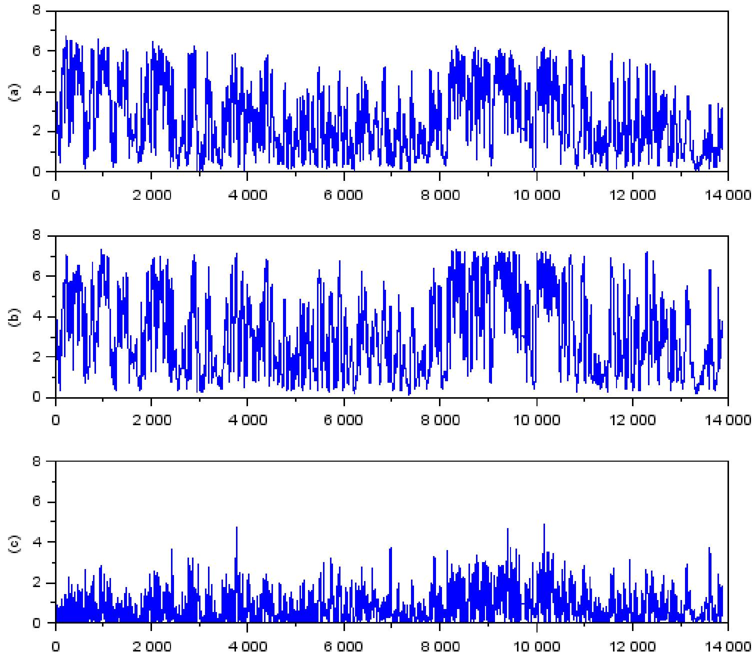
Figure 3. Wind generation, daily average and relative deviation (GWh & %)



To evaluate the extent of intermittency in term of imperfect wind prediction we use the wind forecast error (K_t) measured as the absolute difference between the actual (W_t) and the forecast (FW_t) generation -see (Eq. 2). We use wind generation forecasts published for the next day by National Grid (day-ahead forecast), extracted from the archive of the "Gridwatch" website. Figure 4 shows the actual wind generation (a), the forecasted wind (b) and the wind forecast error (c) --with a maximum of 4.9 GWh.

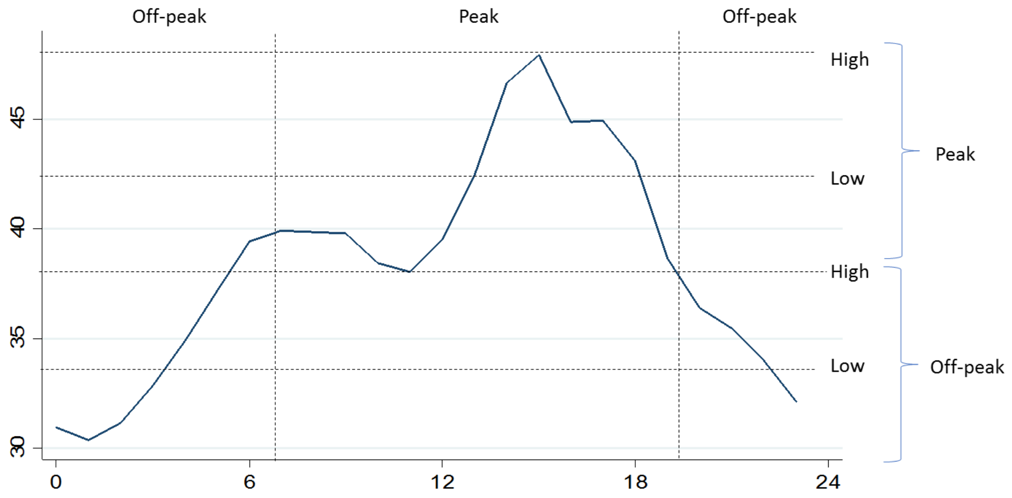
$$K_t = | W_t - FW_t | \qquad (2)$$

Figure 4. Wind generation, forecasted and forecast error (GWh)



Given that we analyse the inclusion of a store facility operating as baseload, it is useful to have information on the hourly price pattern during the day. Figure 5 shows the hourly average price in our sample[2]. Here it is observable that within both peak and off-peak periods prices might be higher or lower, hence, it is possible to identify four different states of prices, in order of magnitude: off-peak low, off-peak high, peak low and peak high. We follow a parsimonious modelling approach to capture these different states of prices. In the next section the models are detailed described.

Figure 5. Average prices (£/MWh)



3. Methodology

Although different methodological approaches can be followed to capture price fluctuations and answer our research question, two features of the prices we are analysing have driven our modelling choice of using Markov regime-switching models (RSM); first, the existence of price spikes (see Figure 1), and second, the four price states -roughly- identified within the day (see Figure 5). This type of pricing model, developed by Hamilton (1989), was highly used for analysing spikes in stock market prices (for instance in Pagan and Schwert [1990]; Sola and Timmermann [1994]), but since nowadays wholesale electricity markets work in a similar way, these models have been increasingly used to analyse the price of electricity in different contexts (Huisman and Mahieu [2003]; Weron et al. [2004]; Mount et al. [2006]; Huisman and Kilic [2013]; Kilic and Trujillo-Baute [2016]), with a very good fit (Huisman [2009]). Basically, in these models the price time series is divided into regimes, with each regime having different underlying price processes, so it is possible to identify different means, rates of mean reversion and volatilities depending on the state. More precisely, with this type of model

[2] For comparison purposes, Appendix 2 provides an analogous figure with price during a day of sample.

we obtain different parameters of electricity price dynamics for the electricity market price in a normal and a non-normal regime. The non-normal regime takes place at times when the price spikes occur, these spikes being positive or negative depending on the direction of the frictions in the market. So, in the first regime the parameters will characterise the dynamics of market price in its normal state and in the second regime the presence of spikes.

This empirical exercise involves a two-part model. In the first part, we model the impact of wind generation intermittency (variability and forecast errors) on the level and volatility of the market price. In the second part, we evaluate what happens when we introduce a change in the system -i.e. a facility (or a groups of facilities), through which the generation from wind is flattened -to its daily average- and the forecast errors are absorbed. This may be seen as a first step towards examining the trade-offs over a range of storage levels covering different degrees of smoothing of wind output.

3.1 The impact of wind

The price of electricity using electricity generated from wind inherited the wind intermittency, involving both variability and imperfect prediction. The former affects the price level -to a higher or lower extent depending on the intensity of the deviation, and both are passed through the additional price volatility resultant from the variability and wind forecast error.

In the RSM model (Hamilton, 1994) the price in logs (S_t) is assumed to be the sum of a deterministic component d_t and a stochastic component X_t (see Eq. 3). The first component - see Eq (4)- consists of a constant mean price level μ_1, and the wind deviation -as described above- θ_t. This component might also include some seasonality control, usually a peak/off-peak dummy. Instead, we are performing separate estimates for peak and off-peak hour to better capture the differences in all the parameters of price dynamics between the two periods.

$$S_t = d_t + X_t \qquad (3)$$

$$d(t) = \mu_1 + \beta\theta_t \qquad (4)$$

The stochastic component in the normal regime consists of a mean reversion component α with Speed of mean reversion and the error term in regime 1 $\varepsilon_{1,t}$ is assumed to be standard normally distributed multiplied with σ_1 that represents the standard deviation of the error term. The mean reverting stochastic component then is represented in Eq (5):

$$X(t) = (1-\alpha)x_{t-1} + \sigma_1\, \epsilon_{1,t} \qquad (5)$$

The stochastic component in the abnormal regime (see Eq (6)) consists of a constant mean price μ_2, which is the increase in the price level in the abnormal regime. $\epsilon_{2,t}$ is a normally distributed error term with standard deviation σ_2.

$$x(t) = \mu_2 + \sigma_2\, \epsilon_{2,t} \qquad (6)$$

Note that when we condition on the regimes, the parameters of the model can easily be estimated by maximum likelihood. The transition probability is determined by a random variable that follows a Markov chain with different possible states (see Eq (7)). The transition probability for switching from one regime to the other regime as logistic functions ensures that predicted probabilities are between 0 and 1. The element $P_{i,t}$ denotes the conditional probability that the process is in regime *i* at time *t* given that the process was in regime *i* at time *t*−1: $Pi_{,t} = Pr\ S_t = i | S_{t-1} = i$. The transition probability 1-$P_{i,t}$ equals the probability from being in regime *i* at time *t*−1 and moving to the other regime in the next hour. The transition probabilities for the regime-switching model are assumed to be depending on the wind deviation θ_t and forecast error κ_t. Higher wind deviation or forecast error will increase the need for system flexibility and effect the price volatility.

$$P_{i,t} = \lambda_i + \gamma_i \theta_t + f_i\, \kappa_t \qquad (7)$$

3.2. Introducing storage

In this part of the model we evaluate what happen when we introduce a change in the system -i.e. the inclusion of a facility (or a groups of facilities), through which the generation from wind is flatten -to its daily the average minus the efficiency loss - and the forecast errors are absorbed. These will imply only two changes in the previous model, more precisely in Eq. (4) and Eq. (7), which are now as follow:

$$d(t) = \mu_1 + \beta \tau_t \qquad (4.1)$$

$$P_{i,t} = \lambda_i + \gamma_i\, \tau_t \qquad (7.1)$$

where τ_t is the generation from the store facility with a 70% efficiency round used system wide during the day. It is assumed that the 30% efficiency loss takes place when the wind generation is input into the store[3]. Summary statistic of the variables described in the models are presented in Table 1.

Table 1. Summary statistics

	Peak				Off-peak			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
$Price_t$	42.13	12.15	13.50	296.07	34.46	8.32	10.18	117.68
W_t	2675.96	1692.07	72.00	6779.00	2557.61	1589.40	53.00	6708.00
FW_t	3206.79	1987.58	174.00	7233.00	3116.40	1994.34	114.00	7377.00
K_t	786.61	681.88	0.00	4719.00	793.17	714.34	0.00	4940.00
θ_t	0.19	0.17	0.00	1.31	0.28	0.27	0.00	2.80
τ_t	2542.59	1490.29	133.08	6098.65	2542.38	1490.29	133.08	6098.65

Note: Peak 6,936 obs. and Off-peak 6,935 obs.

In sum, to evaluate the impact of wind on prices we estimate the first model including equation (3) to (7) and to analyse the effect of introducing storage we estimate the second model including equations (3), (4.1), (5), (6), and (7.1). The parameters of the two regimes switching models are estimated using maximum likelihood (see for instance Harvey, 1989). Results for peak and off-peak hours are presented below.

4. Results

Regression results from the first model -without storage- are presented in Table 2. Results on this model indicate as expected that the normal regime is characterized by lower price and volatility than in the non-normal regime ($\mu_2 > 0$ and $\sigma_1 < \sigma_2$). Deviations of the hourly wind generation from the daily average increase the price level ($\beta_1 > 0$) and decrease the probability of remaining in the normal volatility regime ($\gamma_1 < 0$). In other words, the intermittency increases the probability of passing from the normal to the high volatility regime (from one hour to the next having started in the normal regime). Regarding the impact of wind forecast errors we observe different effects on off-peak

[3] To calculate the hourly based-load of the store facility with an input loss the following reasoning was use:

First, during the hours when the wind generation is above the average the power is stored (ST_d).

$$ST_d = \sum_1^{24}(W_t - \mu_w) \quad if \quad W_t \geq \mu_w \qquad (8)$$

Second, the generation (WS_t) could be equal to the average without storage when the wind generation is above the average and equal to the actual wind generation when is below the average.

$$WS_t = \begin{cases} \mu_w & if \quad W_t \geq \mu_w \\ W_t & if \quad W_t < \mu_w \end{cases} \qquad (9)$$

Therefore, the hourly -daily average- generation of the store facility considering in addition the efficiency losses will be:

$$\tau_t = [\sum_1^{24} WS_t + (0.7 * ST_d)\,]/24 \qquad (10)$$

and peak hours, but both acting to make price spikes more likely. During off-peak hours, the wind forecast error decreases the probability of remaining in the normal volatility regime ($f_1 < 0$), in other words, the forecast error increases the probability of passing from normal to the high volatility regime (from one hour to the next starting in the normal regime). During peak hours, the wind forecast error increases the probability of remaining in the non-normal volatility regime ($f_2 > 0$), in other words, the forecast error decreases the probability of passing from the non-normal to the low volatility regime (from one hour to the next starting in the non-normal regime).

Table 2. Wind generation effect on market prices

	Peak		**Off-peak**	
μ_1	**3.666**	(0.0125)	**3.331**	(0.0196)
μ_2	**0.132**	(0.0165)	**0.187**	(0.0240)
β	**0.036**	(0.0120)	0.004	(0.0066)
α	**0.115**	(0.0066)	**0.099**	(0.0063)
λ_1	**2.024**	(0.1257)	**1.725**	(0.1107)
λ_2	**-0.452**	(0.1929)	-0.203	(0.1783)
γ_1	**-1.370**	(0.3318)	**-1.153**	(0.2503)
γ_2	0.477	(0.5303)	0.831	(0.4518)
f_1	-0.011	(0.0879)	**-0.335**	(0.0721)
f_2	**0.204**	(0.0137)	-0.048	(0.1151)
σ_1	**0.082**	(0.0017)	**0.074**	(0.0014)
σ_2	**0.773**	(0.0516)	**0.989**	(0.0931)

Our conception of storage is of bulk storage that is less than perfectly efficient. The running costs of the store are incorporated into the assumption that the store is 70% efficient[4] in transforming input into output; that is for every 10MWh input, useful output corresponds to 7MWh. Once storage is introduced in the system generation from wind is assumed flattened to its daily average (with a 70% efficiency) and the forecast errors are absorbed. Results (in Table 3) are consistent with those of the first model. Again we have two regimes -the first one with low price and volatility, and the second one with high price and volatility. The inclusion of the new storage facility has a price suppressing effect ($\beta_1 < 0$). Regarding the storage effect on the transition probabilities, during peak hours the storage deceases the probability of remaining in the non-normal regime ($\gamma_2 < 0$), and during the off-peak hours it increases the probability of remaining in the normal volatility regime ($\gamma_1 > 0$).

[4] Results with 100% and 60% are in Appendix 1.

Table 3. Storage effect on market prices

	Peak		Off-peak	
μ_1	**3.629**	(0.015)	**3.374**	(0.020)
μ_2	**0.176**	(0.016)	0.191	(0.022)
β	**-0.017**	(0.003)	**-0.019**	(0.003)
α	**0.117**	(0.007)	**0.113**	(0.006)
λ_1	**1.858**	(0.115)	**2.963**	(0.116)
λ_2	**0.446**	(0.149)	**-1.087**	(0.184)
γ_1	-0.025	(0.039)	**0.316**	(0.034)
γ_2	**-0.112**	(0.052)	0.309	(0.523)
σ_1	**0.080**	(0.002)	**0.073**	(0.001)
σ_2	**0.267**	(0.007)	**0.375**	(0.009)

Main implications

Implications of these results on the effects of combining storage and wind generation can be classified in terms of price level, price volatility and transition probability. Results show that during peak hours there is a significant decrease in the price level of the normal and non-normal regime (see Table 4), implying a saving for consumers. The significant decrease in the price volatility (see Table 5) of the non-normal regime implies that spikes are softer and more predictable. The lower volatility of the non-normal regime combined with the lower mean price implies that the market will become more stable. Our results also show that when the storage is in the system there is a decrease the probability of observing spikes both in peak and off-peak hours, and that once we have a spike the probability of returning to the normal price increases (see Table 6).

Table 4. Price levels

	Wind	Storage	Diff.
Peak			
Norma	40.556	37.057	-3.498
Non-normal	46.291	44.212	-2.079
Off-peak			
Norma	28.097	29.021	0.924
Non-normal	33.865	34.910	1.045

Table 5. Price volatility

	Wind	Storage	Diff.
Peak			
Norma	0.082	0.080	-0.003
Non-normal	0.773	0.267	-0.506
Off-peak			
Norma	0.074	0.073	-0.001
Non-normal	0.989	0.375	-0.614

Table 6. Transition probabilities

		Wind	Storage
Peak			
	P (1,1)	0.66	0.86
	P (2,2)	0.56	0.58
Off-peak			
	P (1,1)	0.56	0.96
	P (2,2)	0.64	0.31

Beyond the probability of transition from one state to the other, to better assess the differences in the prices obtained for two models, it is relevant to know the probability of each state occurring. Following Hamilton (1989) it is possible to compute the probability of each state from the transition probabilities, with Eq. (11):

$$\pi(i) \equiv (1-q)/(1-p+1-q) \qquad (11)$$

where $p = P(1,1)$ and $q = P(2,2)$.

Results, presented in Table 7, indicates that storage meaningfully decreases the probability of a high price and volatility regime in both peak and off-peak periods, or the same in another way, increases the probability of having lower and less volatile prices. More precisely, in the peak period the probability of having lower prices increases from 0.56 in the model with only wind to 0.75 when including storage, and in the off-peak period this increase is from 0.45 to 0.95.

Table 7. Probability of states

		Wind	Storage
Peak			
	π (1)	0.56	0.75
	π (2)	0.44	0.25
Off-peak			
	π (1)	0.45	0.95
	π (2)	0.55	0.05

Results from the two models are graphically illustrated in Figure 6 (wind) and Figure 7 (storage), with the four different states of prices -average and probability- identified in each model. From these figures is possible to observe, first, a considerable similarity between Figure 6 and Figure 5 with the hourly average price in our sample, and second, the price level and volatility decreasing effects from the inclusion of storage in the system.

Figure 6. Wind model results illustration

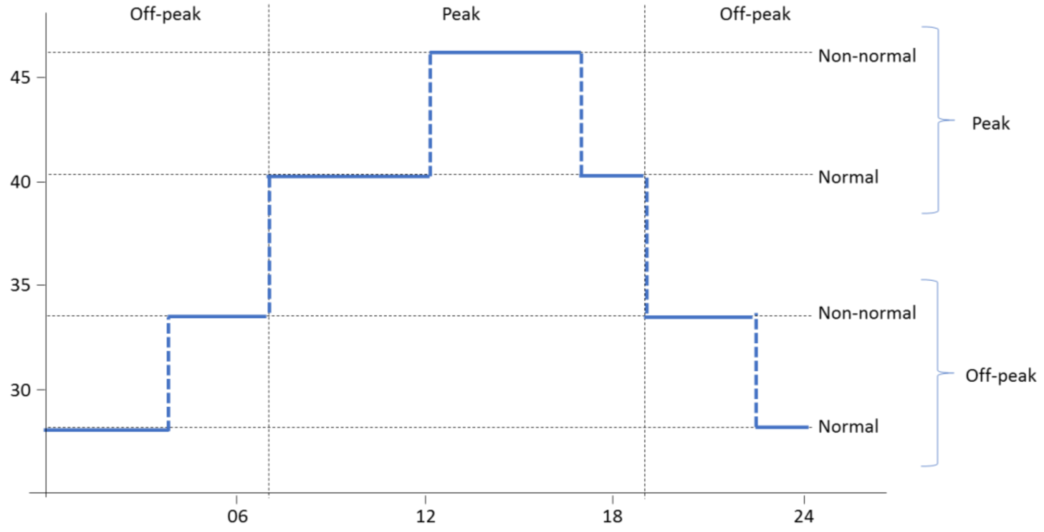
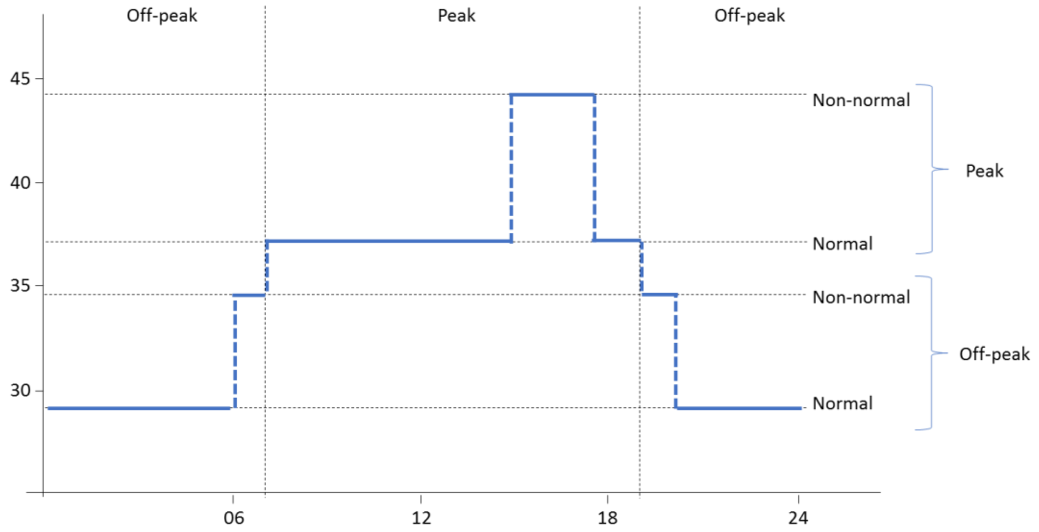


Figure 7. Storage model results illustration



Finally, combining prices and probabilities obtained from the models we have the simulated weighted average prices in the different electricity system conditions. Results, shown in Table 8, highlights the price suppressing effects from storage and the consequent savings in terms of costs per MWh. Average price decreases during the peak period in 4.24 £/MWh (from 43.063 £/MWh to 38.827 £/MWh) and in 2.33 £/MWh (from 31.275 £/MWh to 28.944 £/MWh) during the off-peak period. With the calculated cost savings from transforming the hourly wind generation into a smoother baseload plant with storage, the case from a system perspective is apparent, as mitigating intermittency effects through storage captures the value of flexibility.

Table 8. Simulated weighted average prices (£/MWh)

	Wind	Storage
Peak	43.065	38.827
Off-peak	31.275	28.944

5. Conclusions

Overall our results imply that introducing storage to render wind hourly generation into the activity of a smoother baseload plant and to absorb the forecast error, makes it more likely that lower and more stable market prices will be observed. Finally, under the assumption that the effects on market prices are passed-through to final consumers and ignoring the facility construction costs, these results strongly suggest that there are clear potential social advantages resulting from storage in the presence of intermittent wind generation.

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Appendix 1 - Summary to compare results with different levels of efficiency

Price

	Wind	Store 100	Store 70	Store 60	Diff (S-W)	Diff (S7-W)	Diff (S6-W)
Peak							
Norma	40.556	37.048	37.057	37.076	-3.507	-3.498	-3.480
Non-normal	46.291	44.195	44.212	44.236	-2.096	-2.079	-2.055
Off-peak							
Norma	28.097	28.642	29.021	29.081	0.545	0.924	0.984
Non-normal	33.865	34.660	34.910	34.888	0.795	1.045	1.023

Volatility

	Wind	Store 100	Store 70	Store 60	Diff (S-W)	Diff (S7-W)	Diff (S6-W)
Peak							
Norma	0.082	0.080	0.080	0.080	-0.003	-0.003	-0.003
Non-normal	0.773	0.267	0.267	0.267	-0.506	-0.506	-0.506
Off-peak							
Norma	0.074	0.073	0.073	0.073	-0.001	-0.001	-0.001
Non-normal	0.989	0.375	0.375	0.375	-0.614	-0.614	-0.614

T. Probabilities

	Wind	Store 100	Store 70	Store 60
Peak				
P(1,1)	0.66	0.86	0.86	0.86
P(2,2)	0.56	0.58	0.58	0.58
Off-peak				
P(1,1)	0.56	0.96	0.96	0.96
P(2,2)	0.64	0.31	0.31	0.31

Appendix 2 – Price during a day of sample (£/MWh) – First day