Intermittency and the social role of storage

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Abstract

Our paper examines the social benefit of energy storage in terms of smoothing the intermittent output of wind in Britain in the context of a significant wind generation presence. The resultant price smoothing creates benefits as follows: grid scale storage has a price suppressing effect, decreasing the probability of remaining in the high price and high volatility regime during peak hours, and it increases the probability of remaining in the normal regime during off-peak hours. Under the assumption that the effects on market prices are passed through to final consumers, and ignoring the facility construction costs, our results strongly suggest that there are clear potential social advantages resulting from deploying grid-level storage in the presence of intermittent wind generation.

Keywords: Storage; Intermittency; Wind; Price; Volatility; Markov regime-switching

1. Introduction

Energy storage potentially has a vital role in maintaining a healthy reliable balance between supply and demand for electricity in the presence of intermittent green technologies such as wind power. When trying to understand the current and future role of energy storage, a major consideration concerns the potential social benefits which storage might generate in the context of intermittent technologies. In principle, they include:

- 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

The private benefits which can be obtained from storage facilities have often been investigated by assessing arbitrage possibilities. However, not all the factors listed above 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? Here we focus on the potential social benefits of storage in Britain arising from reduced ramp rates and increased efficiency, leaving capital expenditure and grid reinforcement to one side.

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 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 high-cost generation 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 to the market price as additional price volatility.

The choice of wind as a renewable source of electricity in our analysis is driven by its relevance in Great Britain's generation. Among renewable sources of electricity generation wind has the largest share if we combine onshore and offshore generation. In 2020 it accounted for 24% of generation as opposed to around 13% for bioenergy and waste and 4% for solar (BEIS, 2021).

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[1] – but these depend on what happens in other geographical locations, so cannot be counted on to operate according to domestic interests

[1] Interconnectors are high-voltage cables that connect the electricity systems of neighbouring countries. They enable excess power, such as that generated from wind and solar farms, to be traded and shared between countries.

- Open-Cycle Gas Turbines (OCGT)[2] - run on very few occasions during the year (generation from OCGTs represented about 0.3% of total generation in 2021) [3], and is not a good case to consider as new investment is unlikely
- Closed-Cycle Gas Turbines (CCGT)[4] – run much more often, but ramp-up and down exceed 1GW within 5 minutes. This is a performance that grid-scale storage cannot emulate

Relative to the alternatives listed above we consider storage as the most attractive option to smooth electricity generation from wind to the extent that it emulates the output of a baseload plant (see also Waterson [2017] for a discussion of the role of storage in comparison with other technologies in energy systems with high penetration of renewables). In the discussion which follows we therefore focus exclusively on the behaviour of a grid-scale storage unit, as this represents the most straightforward case to evaluate on the basis of publicly available market information.

As the benefits from an increased availability of storage facilities are associated with the costs of integrating higher proportions of intermittent generation into the energy system it is possible to broadly evaluate the potential benefits of storage in monetary terms by looking at the potential saving which can be generated by deploying storage at the national level. The UK's National Infrastructure Commission (2016) indicates that energy storage, together with interconnection and flexible demand innovation, could save consumers £8 billion per year by 2030, while research carried out at Imperial College London (2016) reveals that around £7 billion in cost savings could be achieved

[2] An open cycle gas turbine is a combustion turbine plant fired by liquid fuel to turn a generator/rotor, that produces electricity. The gases coming out from the turbine are exhausted in the atmosphere and the working fluid is replaced continuously.
[3] Source: Gridwatch website (https://gridwatch.co.uk/Ocgt)
[4] A closed cycle gas turbine is a combustion turbine in which the air and the working fluid are circulated continuously within the turbine.

by 2030 by adopting the least cost energy storage options under a market driven approach.

The UK energy research centre (Heptonstall et al., 2017) has recently produced a detailed report on the costs and impacts of integrating intermittent renewable sources into the UK electricity system. One of the key conclusions of the report is that the costs of integration can vary widely with the flexibility of the system to which the generation is being added and the extent to which the system is optimised for integration. The authors identify two sets of costs of integration which are likely to be non-negligible even for relatively modest levels of penetration: 1) the costs associated with short term reserves for balancing the system and 2) the cost of generating capacity which can reliably satisfy demand at peak times. Furthermore, they point out that an increased penetration of renewable sources creates additional costs in terms of curtailment, network reinforcement, the potential for reduced efficiency of thermal plant and the costs associated with guaranteeing sufficient mechanical inertia to maintain frequency stability. For example, when they evaluate capacity costs (which reflect the cost of conventional plants which need to be used to compensate for low capacity value of renewable generators) at a 30% level of renewable penetration, they produce cost estimates ranging between £4/MWh and £7/MWh, with only a few observations above £15/MWh. The authors come to the general conclusion that the key challenge for policy makers, regulators and markets is to deliver a flexible low carbon system, which obviously requires the contribution from storage, interconnection and some form of demand side response, as well as more structural changes to system operation, regulation and market design.

In our investigation of the impact on price and volatility of a bulk storage facility we do not assess the technical features of different storage technologies, as this area has been covered in several contributions from the science and engineering disciplines (see Mahlia et al. 2014 for a review and comparison of different technologies). However, our calculations are based on some of the technical features of compressed air storage (CAES), so that in our calculations we use a roundtrip efficiency (RTE) of 70%, which is line with the estimated RTE for CAES. The choice of this technology is justified by the information published by the US Department of Energy (2020) about the relative cost of different storage technologies, which identifies CAES as the technology with the lowest annualised costs[5]. Indeed, for a 100 MW 10-hour installed storage system, the annualised cost for CAES is about £22/kWh as opposed to about £27/kWh for pump hydro storage, about £49/kWh for hydrogen storage systems, about £70/kWh for (grid-level) lithium-ion phosphate batteries, and about £105/kWh for (grid-level) lithium-ion nickel-manganese-cobalt batteries.

In this paper we examine the effect of a grid-level storage facility in Britain which can transform the hourly wind generation into the smoother output of a baseload plant generating the daily average of wind and which can also absorb the forecast error. We discuss the related literature in Section 2. The data used for our empirical analysis is presented in Section 3, while Section 4 describes our methodological approach. Section

[5] Annualised cost measures the cost to be paid each year to cover all capital and operational expenditures across the usable life of the asset while also accounting for additional financial parameters such as taxes and insurance. The unit energy or power annualized cost metric is derived by dividing the total annualized cost paid each year by either the rated energy to yield $/rated kilowatt-hour (kWh)-year or by rated power to yield $/rated kilowatt (kW)-year, where the kWh and kW are rated energy and power of the energy storage system, respectively.

5 contains a discussion of the main results and their implication before providing conclusions in Section 6.

2. Literature Review

Previous studies have examined the impact of wind power on balancing cost in European electricity markets. Holttinen (2008) looks broadly at the cost impact of increased wind power penetration using case studies from European countries and US states. More recently Miettinen and Holttinen (2019) have investigated the impact of wind forecast errors on balancing needs, with an application to the Nordic market, while Hu et al. (2021) evaluate the impact of wind power on the intra-day market in Sweden.

Bueno-Lorenzo et al. (2016) use data from the Spanish electricity market to identify a pricing scheme which can minimise the need to rely on ancillary services as a result of wind intermittency, while Batalla-Bejerano and Trujillo-Baute (2016) provide empirical evidence of the positive impact of increased wind output in Spain on constraint payments, which include both balancing costs and capacity payments.

Swinand and O' Mahoney's (2015) study of the Single Electricity Market (SEM) in Ireland has also provided evidence about the impact of wind output on electricity prices, considering both the direct effect of wind intermittency and the indirect effect due to forecast errors. Vorushylo et al. (2016) use a techno-economic approach to investigate the Irish SEM in order to identify the form of flexible generation which maximises technical system benefits, economic benefits for consumers and investment viability. The authors conclude that advanced CCGT and storage technologies are most able to generate such benefits but acknowledge that they require Government support to be financially viable. Di Cosmo and Malaguzzi Valeri (2016) also investigate the Irish SEM confirming the positive impact of wind output on balancing payments, importantly highlighting that such a positive effect is reinforced in situations of outage of storage facilities.

Swinand and Godel (2012) find similar results in their analysis of the impact of wind generation on the Great Britain electricity market between 2008 and 2011. Based on an econometric cost function approach, they provide evidence of a significant effect of wind generation on balancing costs, so that when wind generation increases balancing costs also increase. However, they warn that due to the quadratic shape of the cost function at high levels of wind generation the effect on balancing costs is negligible. This situation applies to the energy system in Great Britain given its current generation portfolio. Joos and Staffel (2018) carry out a comparison of balancing and congestion costs associated with the integration of wind power in the energy system in Great Britain and Germany. They find that balancing costs are flat or falling in the two countries with about 5TWh of wind power being curtailed in 2016. The also record an increase in congestion management costs in both countries.

More generally Cambini et al. (2020) discuss the role of storage in meeting the demand for flexibility in smart energy systems. They identify and describe several large-scale projects at the European level where storage facilities are implemented as part of integrated energy systems to address the challenges associated with generation from renewable sources.

3. Data

Given that the power flexibility required for the integration of intermittent generation is provided through the balancing market, our first data source is information on the GB balancing market prices (APX mid- prices obtained from Elexon[6]) 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 both the existence of price spikes during this period (up to £296 /MWh in peak hours and £117 /MWh in off-peak hours) and the clearly higher price levels during peak hours (with average of £ 42.13 /MWh and £34.46 /MWh, respectively).

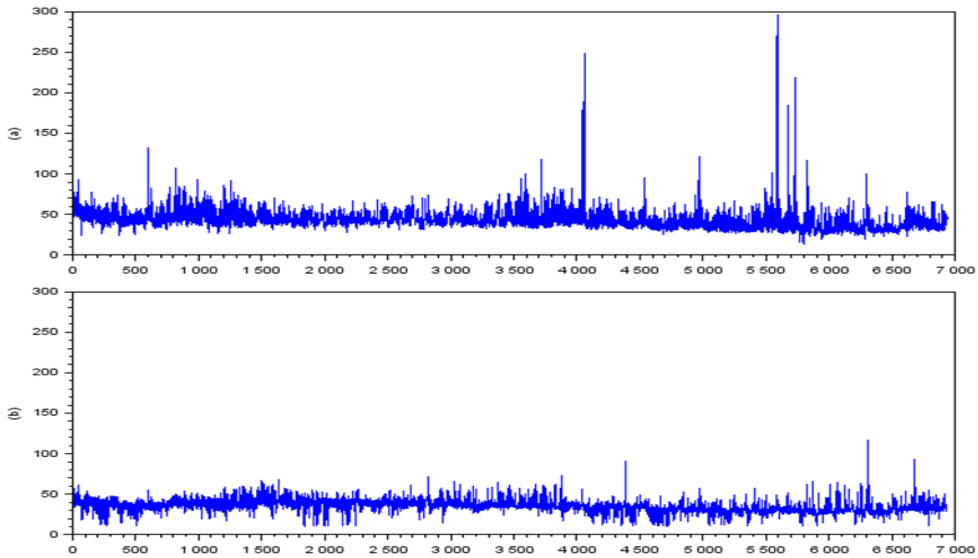

Figure 1. Peak and off-peak prices (£/MWh)

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

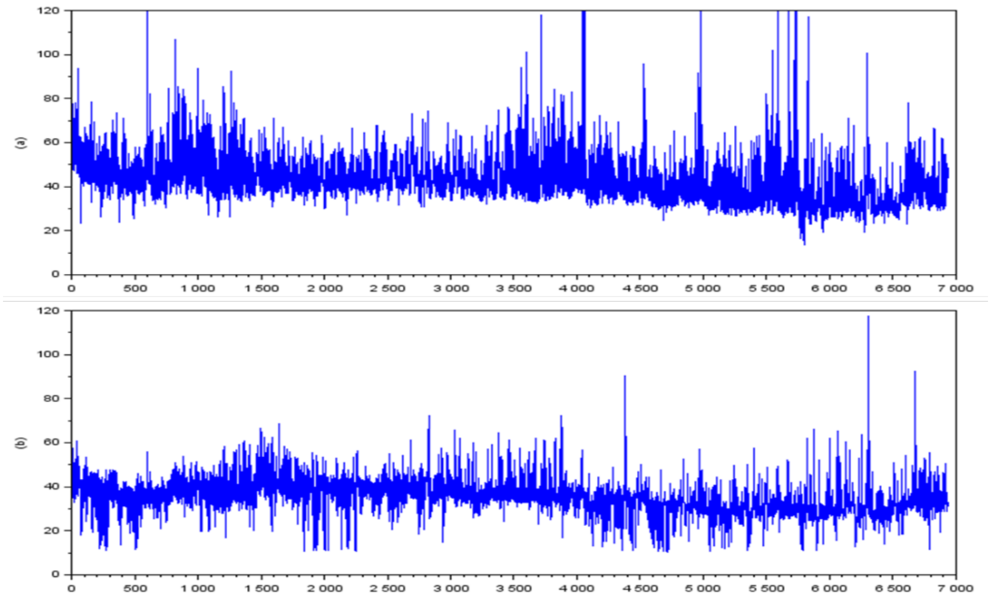

Figure 2. Peak and off-peak prices (£/MWh)

To analyse the extent of wind intermittency in terms of the wind generation variability we use a relativized indicator-based information from National Grid (NG) on actual wind generation in Britain. θ_t is the relative deviation of the hourly wind generation (W_t) from its daily average (μ_w) measured as shown in Equation (1) below. 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 %.

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

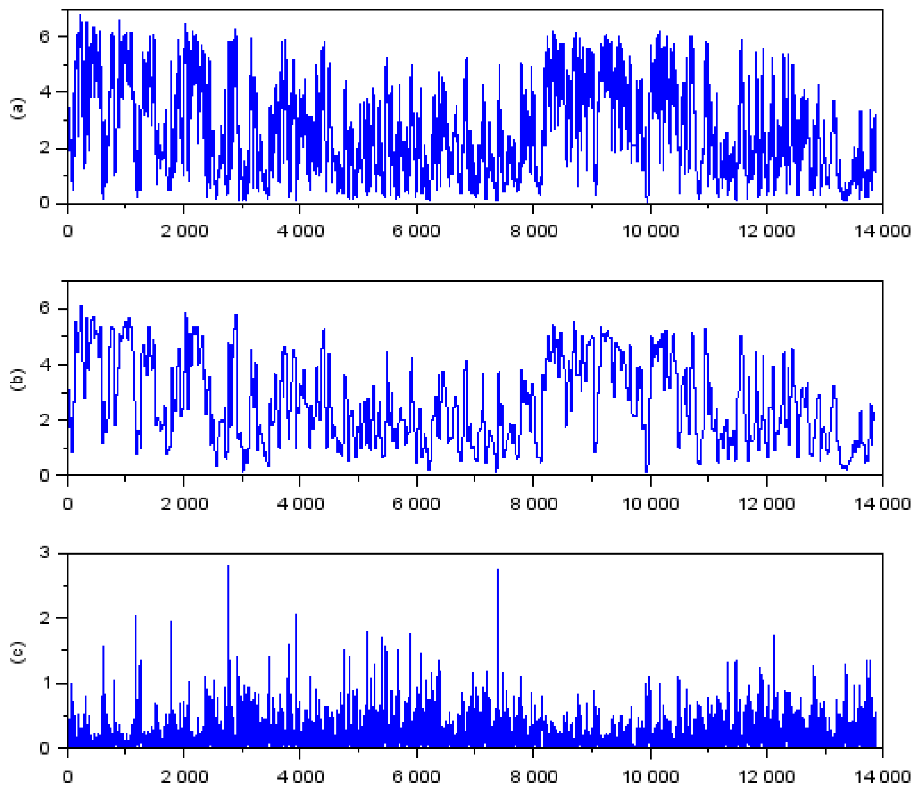

Figure 3. Wind generation, daily average and relative deviation (GWh & percentages)

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 equation 2 below. We use the wind generation forecasts published for the next day by NG (day-ahead forecast), extracted from the archive of the "Gridwatch" website[7]. 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.

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

[7] https://gridwatch.co.uk/

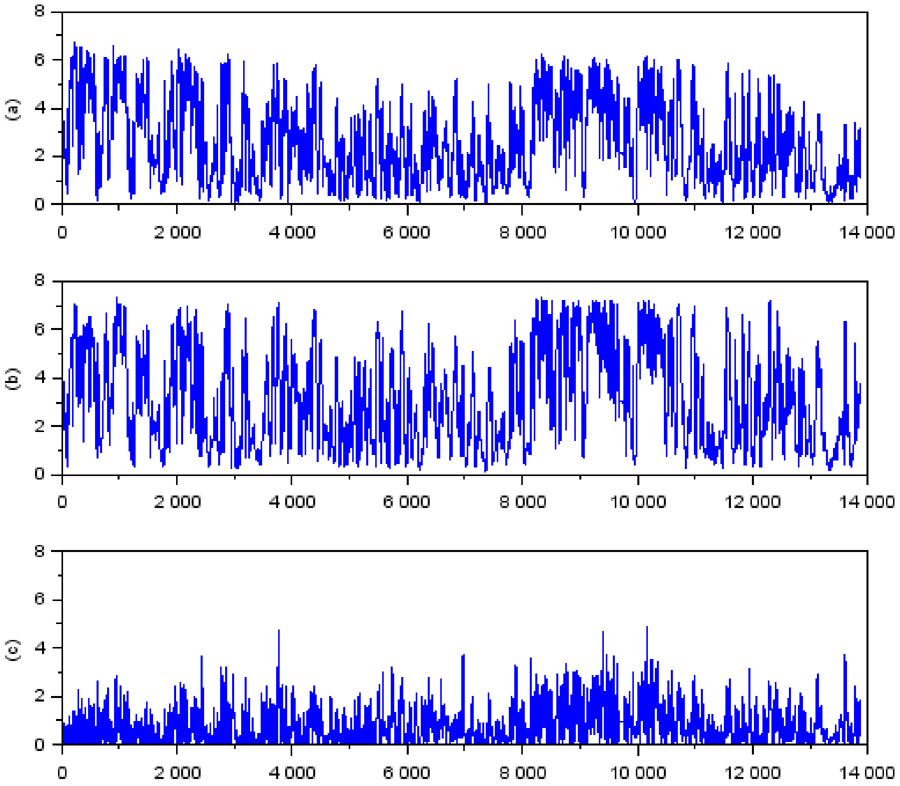

Figure 4. Wind generation, forecasted and forecast error (GWh)

Given that we analyse the effect of including a storage 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[8]. Here it is noticeable 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 described in detail.

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

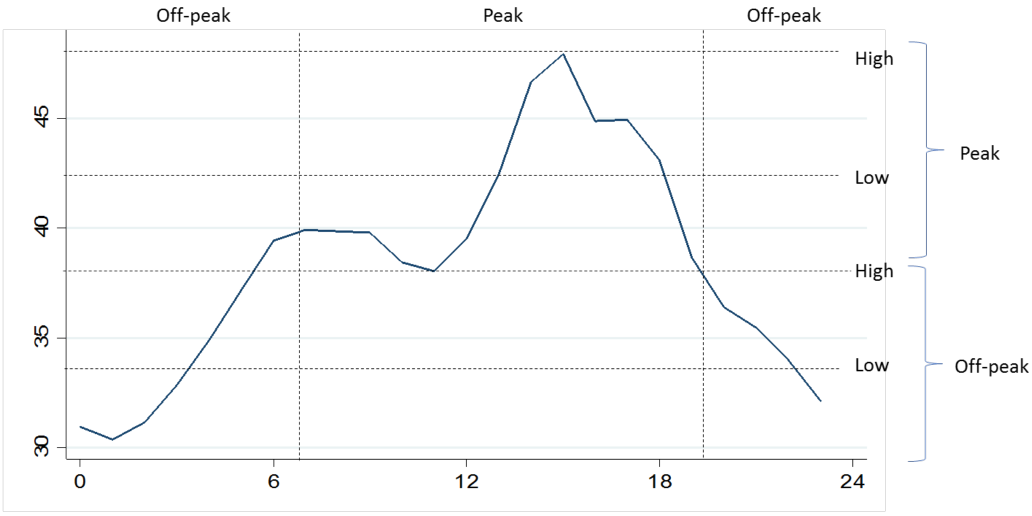

Figure 5. Average prices (£/MWh)

4. 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 used extensively 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 to stock markets, 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 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 price spikes.

This empirical exercise involves a two-part modelling process. 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 allowing different degrees of smoothing of wind output.

4.1 The impact of wind

The price of electricity produced using wind generation inherits the intermittency of wind output, 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 output 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 Equation 3). The first component - see Equation (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. However, rather than using a dummy variable we chose to perform separate estimations for peak and off-peak hours 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. The error term in regime 1 $\varepsilon_{1,t}$ is assumed to be standard normally distributed multiplied by σ_1 that represents the standard deviation of the error term. The mean reverting stochastic component then is represented in Equation (5):

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

The stochastic component in the abnormal regime (see Equation (6)) consists of a constant mean price μ_2, which represents 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 Equation (7)). The transition probability for switching from one regime to the other regime, modelled as logistic functions, ensure that predicted probabilities have values 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: $Pi_{,t} = Pr\ S_t{=}i|S_{t-1} = i$.

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

4.2. Introducing storage

In this part of the model we evaluate what happens to electricity pricing 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 flattened 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 Equation (4) and Equation (7), which are now as follows:

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

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

where τ_t is the generation from the storage facility with a 70% turnaround efficiency 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[9]. Summary statistics of the variables described in the models are presented in Table 1.

[9] To calculate the hourly baseload of the storage facility with an input loss the following reasoning was used:
First, during the hours when the wind generation is above the average power will be 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 wind generation 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 storage facility, considering the efficiency losses, will be:

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

	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.

Table 1. Summary statistics

In sum, to evaluate the impact of wind generation on prices we estimate the first model including Equations (3) to (7). 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 discussed below.

5. Results

Regression results from the first model -without storage- are presented in Table 2. Results from this model indicate as expected that the normal regime is characterized by lower prices 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, wind 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 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).

	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)

Table 2. Wind generation effect on market prices

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[10] 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.

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

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 decreases 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 ($\gamma_1 > 0$).

	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)

Table 3. Storage effect on market prices

5.1 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. Our 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).

	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 4. Price levels

	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 5. Price volatility

	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

Table 6. Transition probabilities

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

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

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

The results, presented in Table 7, indicate that storage significantly decreases the probability of a high price and high volatility regime in both peak and off-peak periods, or in other words, storage 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 we include storage, and in the off-peak period this increase is from 0.45 to 0.95.

		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

Table 7. Probability of states

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

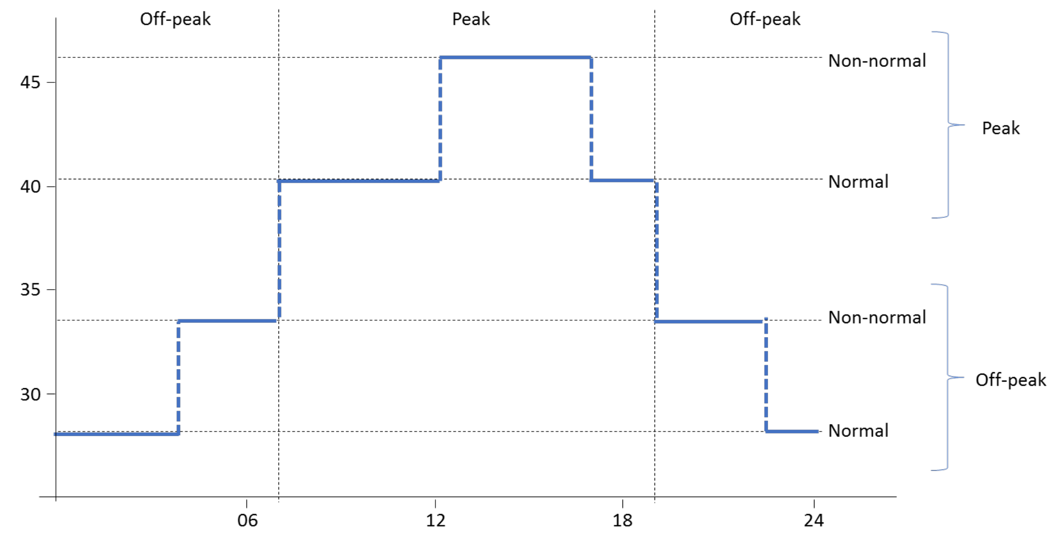

Figure 6. Wind model results illustration

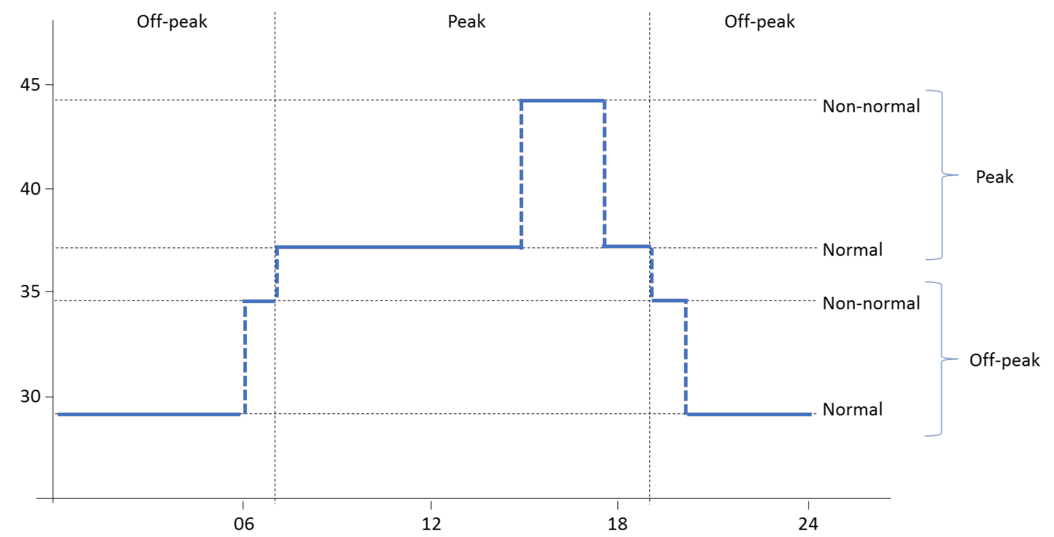

Figure 7. Storage model results illustration

Finally, combining prices and probabilities obtained from the models (in Table 4 and Table 7, respectively) we have the simulated weighted average prices in the different electricity system conditions. The results shown in Table 8 highlight the price suppressing effects from storage and the consequent savings in terms of costs per MWh. Average price decreases during the peak period by £4.24 /MWh (from £43.063 /MWh to £38.827/MWh) and by £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 at least some of the value of flexibility.

	Wind	Storage
Peak	43.065	38.827
Off-peak	31.275	28.944

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

6. Conclusions and policy implications

The analysis of the social role of storage is increasingly relevant in the current context characterized by an increasing use of intermittent generation in power systems. This relevance is magnified by the massive electrification expected in the coming decades in pursuit of net zero ambitions, which predictably will be covered mostly with renewables sources, including wind power generation. In this paper the social potential of storage is quantified using market information, capturing the benefits arising from reduced ramp rates and from the increased efficiency introduced when considering grid-scale store capacity being used to mitigate the wind impact on the level and volatility of market prices.

Results from a Markov regime switching model confirm that, in the absence of storage, wind intermittency increases the probability of passing from the normal to the high price and high volatility regime (from one hour to the next), and the impact of wind forecast errors makes price spikes more likely. The mechanism behind the observed effects comes from wind intermittency (variability and imperfect prediction). While the variability of output impacts on both the level and the volatility of prices (from the underlying need to use generation from higher cost sources), the imperfect wind prediction results in forecast errors which are passed through to the market price as additional price volatility.

The inclusion of grid scale storage has a price suppressing effect, decreasing the probability of remaining in the high price and high volatility regime during peak hours, and it increases the probability of remaining in the normal regime during off-peak hours. Implications from these effects are straightforward: the decrease in the price level leads to direct savings for consumers and the decrease in the price volatility implies that spikes are softer and more predictable. The combination of both effects ultimately leads to the prediction that the market will become more stable in the presence of wind generation combined with grid scale storage.

In addition, when considering the probability of occurrence for each state, the results imply that storage significantly increases the probability of having lower and less volatile prices. Moreover, the simulated weighted average prices in the different electricity system conditions highlight the price suppressing effects of storage and the consequent savings in terms of costs per MWh. With the calculated cost savings from combining wind generation and grid-scale storage, the supporting evidence from a social perspective is clear. While we expect that our results would be different if the generation from other sources was also included in the analysis, we believe that our results would likely be reinforced by the consideration of other renewable sources with variable output at different times of day and year, given the ability of our proposed storage facility to adjust to unexpected changes in output. Furthermore, given the leading role of wind in the GB electricity system we believe that we are accounting for the most significant source of intermittency.

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 deploying grid-level storage in the presence of intermittent wind generation.

It is important to stress that our analysis allows us to evaluate the value of storage based on market information, but we are not able to assess the cost implications of our proposed approach to mitigating wind power intermittency. Based on current estimates of annualised costs of storage technology presented above it would appear that the costs of storage technology are not yet sufficiently low compared to the potential benefits derived from the reduced volatility in the wholesale market, however other potential benefits of storage technology are not limited to the impact on wholesale price level and volatility.

Indeed, natural extensions of this first approximation to the social role of storage might come from alternative approaches. The valuation of consumers' willingness to pay for having a guaranteed energy supply in the presence of intermittency is one option, while keeping in mind that the social value of security of supply and reduced dependence from fossil fuel sources might be difficult to assess in monetary terms. Another approach could be to look at the different alternatives to storage, including grid reinforcement, interconnectors or demand side management, through a cost comparison. More generally, evaluating the relative costs and benefits of alternative ways to promote increased flexibility in the energy systems remains a critical area for future research in order to support an efficient transition to a low carbon economy. These considerations should be kept in mind when developing policy interventions aimed at supporting alternative sources of market flexibility, able to mitigate the impact of the intermittency of generation from renewable sources. While we have characterised storage, and CAES technology in particular, as the most appealing technology compared to alternative sources of flexibility, only a full comparison of the costs and benefits of the different technologies available can provide policy makers with informed guidance about the most economically efficient and most appropriate technologies. We would like to address this more extensive comparison across technologies in future research which would complement the current work.

References

Batalla-Bejerano, J. and E. Trujillio-Baute, 2016, Impacts of intermittent renewable generation on electricity system costs, *Energy Policy*, 85, 511 - 40.

BEIS, 2021, Energy Trends, Department for Business Energy and Industrial structure, London, December

Bueno-Lorenzo, M., Moreno, M.A., and J. Usaola, 2013, Analysis of the imbalance price scheme in the Spanish electricity markets: a wind power test case, Energy policy, 62, 1010 – 1019.

Cambini, C., Congiu, R. and Soroush, G., 2020. Regulation, innovation, and systems integration: evidence from the EU. *Energies*, *13*(7), p.1670.

Carbon Trust and Imperial College London, 2016. Can storage help to reduce to reduce the cost of a future UK electricity system. Report for the Carbon Trust, London.

Di Cosmo, V. and L. Malaguzzi Valeri, 2016, Wind, storage, interconnection and the cost of electricity, IEB working paper 2016/30.

Hamilton, J., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57, 357–384.

Hamilton J., 1994. Time Series Analysis. Princeton University Press.

Harvey, A.C., 1989. Forecasting, Structural Time Series and the Kalman Filter. Cambridge University Press.

Heptonstall, P., R. Gross and F. Steiner, 2016. The costs and impact of intermittency - 2016 update, UK Energy Research Centre, February, London.

Holttinen, H., 2008, Estimating the impact of wind power on power systems – Summary of IEA Wind collaboration, *Environmental Research Letters*, 3, 025001, doi:10.1088/1748-9326/3/2/025001.

Hu, X., Jaraitė, J. and Kažukauskas, A., 2021. The effects of wind power on electricity markets: A case study of the Swedish intraday market. *Energy Economics*, *96*, p.105159.

Huisman, R., and R. Mahieu, 2003. Regime jumps in electricity markets Energy Economics, 25, 425-434.

Huisman, R., 2009. An Introduction to Models for the Energy Market: the thinking behind econometric techniques and their application, RISK books, ISBN 978-1906348229.

Huisman, R., and M. Kilic, 2013. A History of European Electricity Prices. Applied Economics, 45, 2683-2693

Joos, M. and Staffell, I., 2018. Short-term integration costs of variable renewable energy: Wind curtailment and balancing in Britain and Germany. *Renewable and Sustainable Energy Reviews*, *86*, pp.45-65.

Kilic, M., and E. Trujillo-Baute, 2016. Flexibility in power generation enough to stabilize intraday power prices? Barcelona Institute of Economics, Document de Treball 24/2016.

T.M.I. Mahlia, T.M.I., Saktisahdan, T.J. Jannifar, A., Hasan, M.H. and H.S.C. Matseelar, 2014, A review of available methods and development on energy storage; technology update, Renewable and Sustainable Energy Reviews, 33, pp. 532-545, doi.org/10.1016/j.rser.2014.01.068.

Miettinen, J. and Holttinen, H., 2019. Impacts of wind power forecast errors on the real-time balancing need: a Nordic case study. *IET Renewable Power Generation*, *13*(2), pp. 227-233.

Mount, T.D., Ning, Y. and Cai, X., 2016. Predicting price spikes in electricity markets using a regime switching model with time-varying parameters. Energy Economics, 28, 62-80.

National Infrastructure Commission (2016). Smart Power.

Pagan, A.R. and G.W. Schwert, 1990, Alternative models for conditional stock volatility, Journal of Econometrics 45, 267-290.

Swinand, G. P. and M. Godel, 2012, Estimating the impact of wind generation on balancing costs in the GB electricity market. Proceedings from 9th International Conference on the European Energy Market 2012, Florence.

Swinand, G. P. and A. O'Mahoney, 2015, Estimating the impact of wind generation and wind forecast errors on energy prices and costs in Ireland, Renewable Energy, 75 (0), 468 – 473.

Timmermann, A., 1995, Cointegration tests of present value models with a time-varying discount factor, Journal of Applied Econometrics, 10.

US Department of Energy, 2020. 2020 Grid Energy Storage Technology Cost and Performance Assessment. Technical Report Publication No. DOE/PA-0204. Available at: https://www.energy.gov/energy-storage-grand-challenge/downloads/2020-grid-energy-storage-technology-cost-and-performance

Vorushylo, I, P Keatley, and N.J. Hewitt, 2016, Most promising flexible generator for the wind dominated market, *Energy policy*, 96, September, 564-575.

Waterson, M., 2017. The characteristics of electricity storage, renewables and markets. Energy Policy, Volume 104, Pages 466-473.

Weron, R., Bierbrauer, M. and Truck, S., 2014. Modelling electricity prices with regime switching models. LectNotes Comput Sci, 3039, 859-867.

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