Intermittency and the social benefits of storage

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Introduction - IMAGES project

- Funded by the Research Councils UK Energy Programme
- Consortium 3 Universities: Warwick, Nottingham & Loughborough
- Academics from Engineering, Business Studies, Maths, & Economic
- Energy storage is view as vital to maintaining a healthy balance between supply and demand in the presence of **intermittent** green technologies such as **wind power** in the UK
- Economics team, leaded by Prof. Michael Waterson, analysing the potential economic value of the energy storage at the grid-scale (2S)

First stage - private profit

- Evaluate the likely market for electricity storage, taking prices as given and determining the extent to which a strategy of arbitrage (day) generates profits in the British context (with L. Grossi)
- Explored out the potential problems as the market moves to absorb increasing amounts of wind
- Characterised the nature of prices. Model the ongoing costs of operation and compared them with revenues - profit optimisation model - results:
  Profits? Yes, but over a limited number of hours during the day
- Conclusion: Additional incentives may need to be put into place in order to render grid-scale storage more attractive

Second stage - social potential

The social benefits include in principle:

- Saving capital expenditure on new peaking plant (at the expense of increased 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

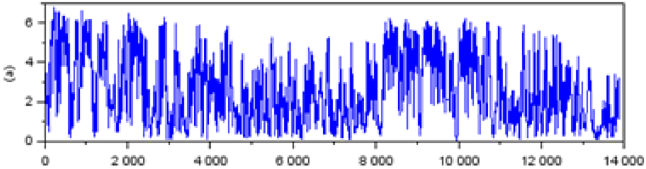
Essentially, there is a missing market problem due to uncaptured positive externalities

The problem

To identify the potential social benefits from storage - market information

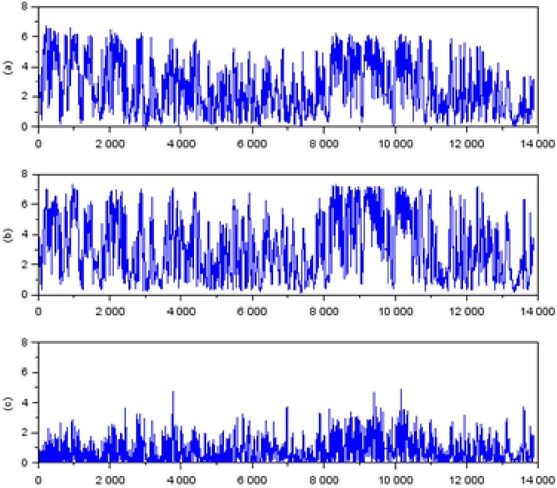
- Capital expenditure and grid reinforcement on a side, not observable -missing information - capacity market approach
- Focus then on ramp rates & efficiency
- Context - the grid-scale store is used to flatten wind generation and absorb forecast errors
- Therefore, mitigating the wind impact on market prices level & volatility

Wind output - variability (UK Dec. 2014 - June 2016)



The problem - Intermittency

Forecast Error (UK Dec. 2014 - June 2016)



Research question

What are the market price effects of introducing a grid-scale store capacity sufficient to absorb wind generation impact on prices?

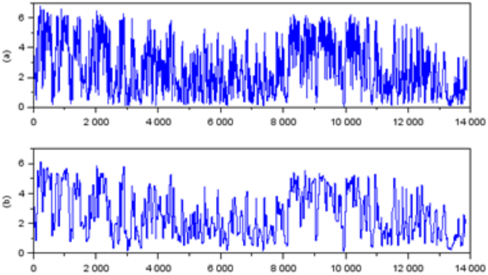
Options for counterfactual:

- Interconnector depend on what happened elsewhere
- OCGT - runs on few occasions (2% in 2015)
- CCGT ramp-up & down excess 1GW within 5 mins.
- Most attractive alternative - for storage to smooth wind to the extent to which it emulates the output of a baseload plant

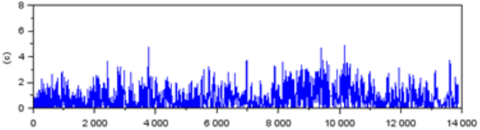
This is probably the most straightforward case to evaluate

Research question

What happen if we transform the wind hourly generation into a smoother baseload plant with the daily average?

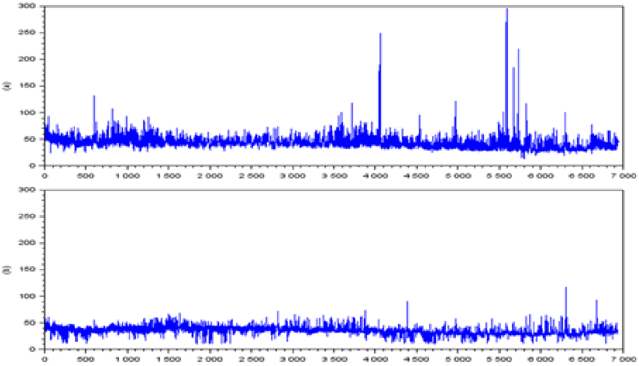


& absorb the forecast error with grid-scale storage?



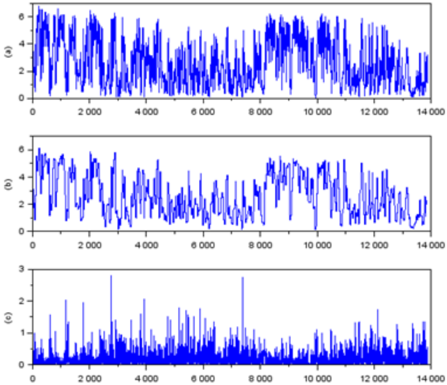
Data

- UK market hourly information Dec. 2014 - June 2016
- Split peak and off-peak to control for different system conditions



Data

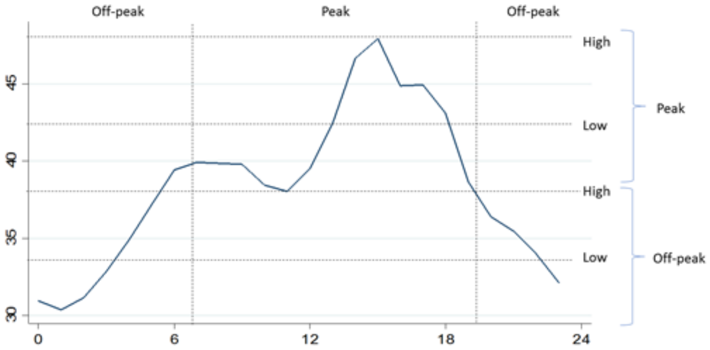
Relative deviation of hourly wind from daily average (c)



$$\theta_t = \frac{w_t}{\mu_w} - 1$$

Data

Average price (£/MWh)



Empirical approach

Analyse price effects of store capacity sufficient to absorb wind generation impact on prices

Two models:

- First - The impact of wind
- Second - Grid scale storage

Comparison

- Price level
- Price volatility

Markov regime switching model

Empirical approach - Markov regime switching model

- Diff approaches can be followed to capture price fluctuations, but:
  - Price spikes
  - The four price states -roughly- identified within the day
- Pricing model (Hamilton, 1989) - stock markets price spikes (Pagan and Schwert [1990]; Sola and Timmermann [1994])
- Electricity prices (Weron et al. [2004]; Mount et al. [2006]; Huisman and Kilic [2013]; Kilic and Trujillo-Baute [2016])
- Good fitting (Huisman [2009])

Empirical approach - Markov regime switching model

- Time series divided into regimes
- Independent underlying price processes
- Possible to identify different means, rates of mean reversion and volatilities depending on the state

Parameters of electricity price dynamics

- The electricity market in normal regime
- The electricity market in a non-normal regime
  - Positive spikes
  - Negative spikes

Markov regime switching model - Wind

The market price

$$s_t = d_t + x_t \tag{1}$$

Deterministic component

$$d_t = \mu_1 + \beta|\theta_t| \tag{2}$$

$$\theta_t = \frac{w_t}{\mu_w} - 1 \tag{3}$$

- μ_1, the constant of the mean price level in the normal regime
- β, effect (over-costs) of the relative deviation of wind at hour t from the day mean on the price level

Markov regime switching model - Wind

State 1 - Normal
Stochastic component

$$x_t^1 = (1 - \alpha)x_{t-1} + \sigma_1 \epsilon_{1,t} \tag{4}$$

State 2 - Non-normal
Stochastic component

$$x_t^2 = \mu_2 + \sigma_2 \epsilon_{2,t} \tag{5}$$

- α, the speed of mean reversion under normal market condition
- μ_2, the price increase or decrease in the non-normal regime
- σ_1 and σ_2, volatility of prices in the normal and non-normal regime

Markov regime switching model - Wind

Transition probability

$P_{i,t}$ conditional probability that the process is in regime i at time t given that the process was in regime i at time $t-1$

$$P_{i,t} = Pr\left\{S_t = i | S_{t-1} = i\right\}; (S_t = 1, 2) \tag{6}$$

Transition probability $=$ 1 - $P_{i,t}$

$$P_{i,t} = \lambda_i + \gamma_i |\theta_t| + \phi_i |\kappa_t| \tag{7}$$

- λ_1 and λ_2, transition probability constant of each state
- γ_1 and γ_2, effect on the state trans prob of the relative deviation of wind at hour t from the day mean
- ϕ_1 and ϕ_2, effect on the state trans prob of the wind forecast error

Markov regime switching model - Storage

The market price

$$s_t = d_t + x_t \tag{8}$$

Deterministic component

$$d_t = \mu_1 + \beta\tau_t \tag{9}$$

State 1 - Normal **Stochastic component**

$$x_t^1 = (1-\alpha)x_{t-1} + \sigma_1\epsilon_{1,t} \tag{10}$$

State 2 - Non-normal **Stochastic component**

$$x_t^2 = \mu_2 + \sigma_2\epsilon_{2,t} \tag{11}$$

Transition probability

$$P_{i,t} = \lambda_i + \gamma_i\tau_t \tag{12}$$

- τ, store with 70% efficiency
- β, effect of the store on price level
- γ_1 and γ_2, effect of the store on the state transition probability

Results - Wind

Estimates for the parameters μ_1, μ_2, α and β

	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)

- μ_1, is the constant of mean price level in the normal regime. Peak has the highest consum. and indeed shows a higher constant of mean price level compared to the hours with lower consum.
- μ_2 is positive for both peak and off-peak hours. This means that in the non-normal state the mean price tends to be higher than during the normal state
- β, effect of the relative deviation of wind at hour t from the day mean, is positive. Confirms that the cost of wind intermittency increase the price
- The speed of mean reversion under normal market conditions, α, indicates how long it will take to return to the mean price level. Is higher for peak than for off-peak hours

Results - Wind

Estimates for the parameters σ_1 and σ_2

	Peak		Off-peak	
σ_1	**0.082**	(0.0017)	**0.074**	(0.0014)
σ_2	**0.773**	(0.0516)	**0.989**	(0.0931)

- σ_1, which is the volatility in the normal regime, is lower than σ_2 the volatility in the non-normal regime. True for peak and off-peak
- The normal regime is characterized by lower price and volatility than in the non-normal regime ($\mu_2 > 0$ and $\sigma_1 < \sigma_2$)

Results - Wind

Estimates for the parameters λ_i, γ_i and ϕ_i

	Peak		Off-peak	
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)
ϕ_1	-0.011	(0.0879)	**-0.335**	(0.0721)
ϕ_2	**0.204**	(0.0137)	-0.048	(0.1151)

- γ_1 is negative, this indicates that **wind deviation from the average** decrease the probability of remaining in the normal regime i.e. wind deviation increase the probability of transition from the normal to the non-normal regime
- ϕ_1 is negative, implying that **wind forecast error** decrease the probability of remaining in the normal regime i.e. forecast error increase the probability of transition from the normal to the non-normal regime
- ϕ_2 is positive, this indicates that **wind forecast error** increase the probability of remaining in the non-normal regime i.e. forecast error decrease the probability of returning to the normal regime

Results - Storage

All parameters

	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)
σ_1	**0.080**	(0.002)	**0.073**	(0.001)
σ_2	**0.267**	(0.007)	**0.375**	(0.009)
λ_1	**1.858**	(0.115)	**2.963**	(0.147)
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)

- β, effect of storage on price levels when smoothing the wind, in line with the expected effect from baseload generation
- σ_2 higher than σ_1, similar to wind model, but with smaller values of σ_2
- γ_1, effect of storage on transition probability, positive in off-peak, implying that storage increase the probability of remaining in the normal regime
- γ_2, negative in peak, implying that storage decrease the probability of remaining in the non-normal regime

Implications

Price Level

	Wind	Storage	Diff (S-W)
Peak			
Normal	40.556	37.057	**-3.498 (-8.6%)**
Non-normal	46.291	44.212	-2.079 (-4.5%)
Off-peak			
Normal	28.097	29.021	0.924 (3.3%)
Non-normal	33.865	34.910	1.045 (3.1%)

Price Volatility

	Wind	Storage	Diff (S-W)
Peak			
Normal	00.082	0.080	-0.003 (-3.7%)
Non-normal	0.773	0.267	**-0.506 (-65.5%)**
Off-peak			
Normal	0.074	0.073	-0.001 (-1.4%)
Non-normal	0.989	0.375	**-0.614 (-62.1%)**

Implications

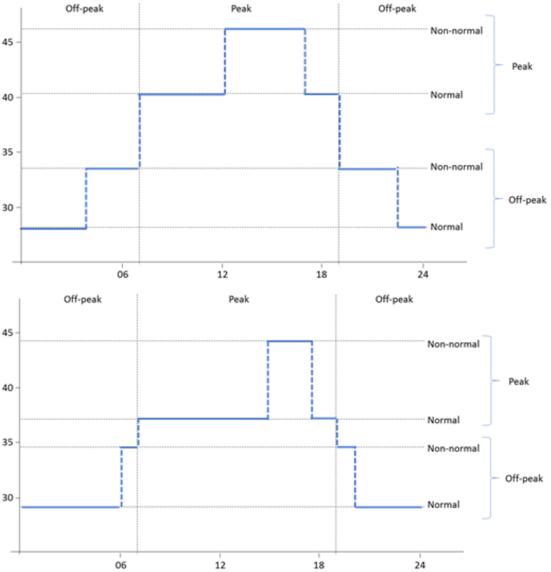
Transition Probability

	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

Probability of states

	Wind	**Storage**
Peak		
$\pi(1)$	0.56	**0.75**
$\pi(2)$	0.44	0.25
Off-peak		
$\pi(1)$	0.45	**0.95**
$\pi(2)$	0.55	0.05

Wind vs. Storage



Implications

Combining:

- Simulated prices
- Probability of states

Simulated weighted average prices (£/MWh)

	Wind	**Storage**
Peak	43.06	38.82
Off-peak	31.27	28.94

$\nabla Peak = 4.24£/MWh$
$\nabla Off\text{-}peak = 2.33£/MWh$

$\Rightarrow$ mitigating intermittency effects through storage captures the value of flexibility

Conclusions

Introducing grid-scale storage to flatten wind into a baseload generation will:

Prices and Volatility

- $\downarrow$ Price **level** of normal and non-normal reg. $\rightarrow$ saving for consumers
- $\downarrow$ Price **volatility** of non-normal reg. $\rightarrow$ spikes are softer and predictable

The lover volatility of non-normal reg. combined with the lower mean price implies that the market will become more stable

Probability

- $\downarrow$ spikes probability
- Once we have a spike the probability of returning to the normal price $\uparrow$

It will be more likely to face lower and more stable market prices

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Assuming that effects on market prices are pass-through final consumers $\Rightarrow$ social benefits from storage