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Consumption management in the Nord Pool region: A stability analysis

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HIGHLIGHTS

- We extend the Independent Spike Model used to model the electricity price.
- We find that consumption can be used predict extreme events on the Nord Pool market.
- The model is used then to evaluate the effects of consumption management strategies.
- The probability for extreme events can be substantially influences by our strategies.
- Our results indicate that spikes and drops are virtually independent of each other.

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ABSTRACT

Integration of fluctuating renewables like wind and solar power is nowadays a hot topic, but this comes at a cost of decreased stability of the power system. The deterioration often translates into so-called spikes and drops in the electricity spot price, very large (even extreme) deviations from the regular spot price, followed by a reversion to roughly the original level a few days later. We use the spikes and drops as an strong indication that there is an imbalance in the physical power system in this paper.

Independent Spike Models (ISM) is a popular class of models for the electricity spot price that uses regime switching, typically having three regimes (base regime, spikes and drops). We fit a such model to Nord Pool spot data to characterize the size and intensity of these deviations, and proceed by augmenting the standard second generation, three factor Independent Spike Model by relating the spike and drop intensity to several factors and find strong statistical support for relating the consumption to the spike and drop intensity.

The model is then used to quantitatively evaluate the effects when modifying the consumption in order to mimic how additional renewables are integrated into the power system or conversely the effects when smoothing consumption using strategies that can be implemented in smart grids. We use this tool to obtain a direct measure of how much the spike and drop intensity can be reduced by smoothing the consumption and see that even a small increase in the variability of the consumption translates into decreased stability (more spikes and/or drops) of the power system.

1. Introduction

Large scale integration of renewable energy, such as wind or solar energy, is increasing the complexity of the power system. Efficient production planning is difficult as the actual amount of power being generated is uncertain. This is reflected in the electricity spot price that is known to be very volatile and sometimes spike (extreme upward movement) or drop (extreme downward movement), see Escribano et al. [1] for an overview of stylized facts. There have even been instance with negative prices in the German (EEX), see Nicolosi [2], and Danish (Nord Pool) markets, see Nielsen et al. [3]. This trend can be expected to continue as the amount of renewable energy keeps increasing throughout Europe. The extreme spot electricity prices such sudden and very large jumps to extreme levels, are usually attributed to unexpected increases in demand, unexpected shortfalls in production, failures of transmission infrastructure, cf. Geman and Roncoroni [4], and/or the inelastic market structure, see Corradi et al. [5]. We utilize the information carried by the spikes and drops to characterize the stability of the power system, cf. Lindström and Regland [6], the intuition being that the number of spikes and drops experienced would decrease if additional capacity was available.

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Our paper contributes to the current literature in two dimensions. We extend the class of Independent Spike Models (ISMs) by combining external information, see Mount et al. [7], Huisman [8] with the class of second generation ISM models, cf. Janczura and Weron [9], Lindström and Regland [10]. The model in this paper is shown to provide a better fit to data than any of the models in those papers, as all parameters in the augmented model is statistically significant.

We then proceed by using the model to evaluate the effect of managing the electricity consumption in four different scenarios. The scenarios are constructed by (artificially) modifying the historical consumption, either by shaving peaks and/or troughs or by adding variability. The unconditional probability of experiencing spikes or drops are then computed using Monte Carlo simulations. Technical solutions for implementing smoothing strategies in our first three scenarios for the consumption are discussed in a Danish context in Meibom et al. [11], see Siano [12] for a more general overview. The simulations are primarily intended as a demonstration – more advanced strategies can easily be implemented and evaluated. This means that the tool provided in this paper can be used to test and design smart grid strategies without having to solve some complicated stochastic optimization problem.

The remainder of the paper is organized as follows. Section 2 reviews Independent Spike Models, including extensions introduced in this paper. Section 3 fits the models to Nord Pool data while Section 4 explores the unconditional probability of experiencing spikes and/or drops. Finally, Section 5 concludes the paper.

2. Modeling the electricity spot price

The electricity spot price is ultimately determined by equilibrium between supply and demand. The electricity spot market is currently characterized by being inelastic demand (but varies on a yearly, weekly and daily scale) while the supply curve that resembles a hockey stick, see Fig. 1. Consequently, a small change in demand can lead to a small or potentially very large change in the spot price, depending on the available capacity.

The yearly seasonality can be tricky to model, as it is related to factors like temperature, wind speed, the magnitude and arrival of the spring flood etc. – the problem being that the spring flood occurs every year but the actual time of the year is uncertain. This makes models that accounts for seasonality using sums of trigonometric functions or wavelets, see Weron et al. [13], prone to overfitting the data when forecasting. However, trigonometric techniques are still useful for modeling the weekly and daily seasonal patterns, as they are constant over time and they do also work well when removing the seasonal component for a fixed set of data. Another approach, which we follow in this paper is to use futures as these are cointegrated with the spot price, see De Jong and Schneider [14], as their price implicitly depends all the relevant factors listed above. The electricity price is also known to be mean reverting, see Escribano et al. [1], i.e. the price returns to some equilibrium price shortly after some external disturbance caused the price to spike or drop dramatically.

Another statistical problem is the extreme volatility and spikes/drops, see Escribano et al. [1] for an overview. It is well known in the statistical literature that time-varying volatility (heteroscedasticity), if not corrected for, degrade the efficiency of the estimators, see Engle [15]. Spikes can affect several markets simultaneously as markets are connected, see Lindström Regland [6] for a study on inter market extreme dependence. It is well known from robust statistics that removal of removed from the data often leads to better (in the sense that the stochastic variability of predictions generated by the model is decreased), but that general recommendation is not relevant in our context as we are interested in the frequency and magnitude of the extreme events in this paper.

Standard time series tools, see e.g. Madsen [16], does not work very well on heteroscedastic and volatile data. It is well known that the market changes over time, cf. the supply and demand curves presented in Fig. 1. Many non-linear model identification methods, see e.g. Lindström, [17], will also struggle with this type of dependence as many tests for non-linear dependence suffers implicitly from the curse of dimensionality in the parameter space of the non-linear specification.

We are instead focusing on so-called Independent Spike Models (ISM), which are Markov Regime Switching (MRS) models for the electricity spot price, that are being able to capture most stylized facts, see Janczura and Weron [9]. A latent Markov chain governs the dynamics, allowing the model dynamics to adapt to changing market conditions. It has been argued that MRS models are more capable than e.g. jump-diffusion models to describe spikes that lasts several days, see De Jong [18], as the reversion to the pre spike/drop level is part of the MRS model dynamics. An early study that used regime switching models for the electricity price is Davison et al. [19]. Their work was later extended by Mount et al. [7], Huisman [8] and Kanamura and Ōhashi [20] who introduced a simple time in-homogeneous transition probabilities in the latent Markov chain.

Our model in this paper is a second generation Independent Spike Model, essentially based on a combination of De Jong and

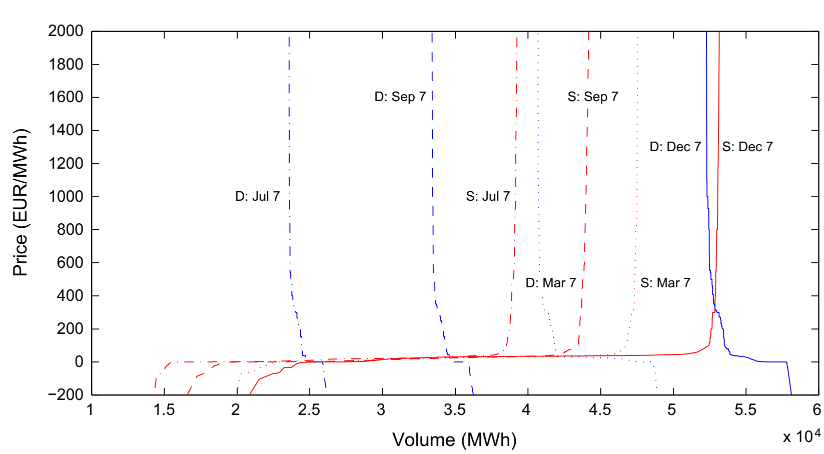

Fig. 1. Supply and demand curves Nord Pool at four different times of the year, March 7th (dotted line), July 7th (dash-dotted line), September 7th (dashed line) and December 7th (solid line).

Schneider [14], Janczura and Weron [9] and Regland and Lindström [10]. De Jong and Schneider [14] showed that the (logarithm of the) electricity spot price and the corresponding one month ahead forward contract at the APX market was cointegrated, meaning that the prices are strongly linked over time. The spot price and the spread between $\log(Spot) - \log(Forward)$ on the Nord Pool market is presented in Fig. 2 where it can be seen that the forward contract accounts for most of the seasonal variations.

The forward contract at time t_n, $F(t_n) = F_n$ (which is in fact a swap contract, see Haug [21]) is priced by the market as a risk-neutral expectation taken over the averaged future spot prices, formally defined as

$$F_n = p(t_n, t_n + T)\mathbf{E}^{\mathbb{Q}}\left[\frac{1}{T}\int_{t_n}^{t_n+T} s(u)\,\mathrm{d}u|\mathscr{F}(t_n)\right]. \tag{1}$$

Here $s(\cdot)$ is the electricity spot price and $p(t_n, t_n + T)$ is a zero coupon bond with maturity T. Short term disturbances in the power system is likely to influence the current spot price, but these variations are averaged out in the forward price as the price will revert to the normal level a few days later. This suggests that any forward with time to maturity that is long enough to smooth the short term variations in the spot, yet having a time to maturity that is short enough to have similar seasonal dynamics as the spot can be used to account for most of the seasonality. Weron and Zator [22] plots the electricity spot price, the 1 week future and the 6 week future and finds that it is difficult to visually distinguish between the 1 week future and the spot, while the 6 week future is noticeably smoother than the other two. We use the Nordic Electricity Base Month Forward contract as it is a nice compromise between the 1 week future and 6 week future and also in line with the results in De Jong and Schneider [14].

Our model is a three state MRS (several studies have indicated that three states are needed) where the logarithm of the electricity spot price $y_n = \log(s(t_n))$ is modeled as an autoregressive model with heteroscedastic noise in the base regime (reverting to the logarithm of the one-month ahead forward price adjusted for the risk premium), while the spikes and drops are modeled as *iid* random variables.

The mathematical formulation of our second generation Independent Spike Model is given by

$$y_{n+1} = \begin{cases} y_n + a(\mu_n - y_n) + \sigma y_n^{\gamma} z_n & \text{if } R_{n+1} = B \\ f_n + \xi^S & \text{if } R_{n+1} = S \\ f_n - \xi^D & \text{if } R_{n+1} = D \end{cases} \tag{2}$$

where the mean reversion level $\mu_n = \eta\log(F_n)$ is a factor compensating for the risk premium η times the logarithm of the month ahead forward, a and σ are positive constants while ξ^S and ξ^D are *iid* random variables having some distribution (typically Gaussian, log-normal or Gamma), see Regland and Lindström [10] for details. We take the risk premium as constant, even though Weron and Zator [22] indicates that it may be related to the levels in the water reservoirs (a substantial part of the power traded at Nord Pool is generated in hydro power plants). However, we believe that this approximation is justified as the effect from misspecifying the mean is small compared to misspecifying the variance when it comes the regime classification which is the primary purpose of the model.

The switching between regimes is governed by a Markov chain $\{R\}$ having a transition matrix

$$P = \begin{pmatrix} 1 - p_{BS} - p_{BD} & p_{BS} & p_{BD} \\ p_{SB} & 1 - p_{SB} & 0 \\ 1 - p_{DB} & 0 & p_{DB} \end{pmatrix} \tag{3}$$

The model does not allow for transitions directly from spikes S to drops B, as these transitions are very unlikely in the real world; including them in the model would add complexity without any real gains.

We extend the standard model by taking explanatory variables into account, cf. Mount et al. [7], Huisman [8], Kanamura and Ōhashi [20]. The transition matrix is then given by

$$P(Z_t) = \begin{pmatrix} 1 - p_{BS}(Z_t) - p_{BD}(Z_t) & p_{BS}(Z_t) & p_{BD}(Z_t) \\ p_{SB}(Z_t) & 1 - p_{SB}(Z_t) & 0 \\ 1 - p_{DB}(Z_t) & 0 & p_{DB}(Z_t) \end{pmatrix} \tag{4}$$

We parametrize the transition probabilities using a multinomial logistic mapping, i.e. $p_{BS}(Z_t)$ being parametrized as

$$p_{BS}(Z_t) = \frac{\exp(\beta_{BS,0} + \beta_{BS,1}Z_t)}{1 + \exp(\beta_{BS,0} + \beta_{BS,1}Z_t) + \exp(\beta_{BD,0} + \beta_{BD,1}Z_t)} \tag{5}$$

Multinomial logistic mappings are common in neutral networks, see Hastie et al. [23], and certain regression problems, see Madsen and Thyregod [24]. We also tried quadratic forms, $\beta_{\cdot,0} + \beta_{\cdot,1}Z_t + \beta_{\cdot,2}Z_t^2$ or combinations of different explanatory variable, but found little statistical support for these non-linearities, see Noren [25]. They are therefore excluded from the remainder of the paper.

Mount et al. [7] used the reserve margin as explanatory variable, since they observed a clear dependence between the reserve margin and the spike intensity on the PJM market. However, they also note that the reserve margin may be inaccurately reported or may not be available in the real time market. Another problem is that the quality of the reserve margin is not accounted for; it is easier to use hydro power than e.g. wind power when controlling the power system. This could lead to a situation where the nominal reserve margin is increased, while the controllable reserve margin is decreased. Cartea et al. [26] also use the reserve margin when studying the UK market and finds that it influences the probability for spikes, but not in a monotonically increasing fashion, as would

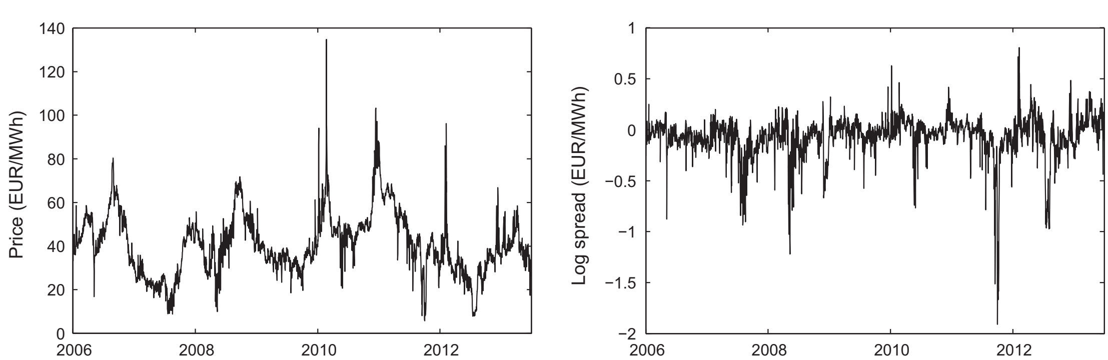

Fig. 2. The spot price (left) and spread between the logarithm of the spot price and the logarithm of the one-month ahead forward price on Nord Pool (right).

be expected. The lack of monotonicity indicates that other variables may be better predictors. Huisman [8] proposed that temperature could act as a proxy for the reserve margin while Jónsson et al. [27] studied the impact of wind energy forecast errors on the reserve margin. Escribano et al. [1] found that the explanatory variables needed (e.g. load, hydro reservoir level, ratio between load and generation capacity), depends on the market structure.

3. Empirical study

Our study used daily electricity spot data from Nord Pool, from January 1st 2006 to 30th June, 2013. All data was downloaded from http://www.nordpoolspot.com/. The model is defined by Eqs. (2), (4) and (5).

3.1. Fitting the model

The parameters in the model were fitted using the Expectation Maximization (EM)-algorithm, cf. Dempster et al. [28], Regland and Lindström [10], Janczura and Weron [29], Noren [25], testing several two and three factor specification with Gaussian, log-normal or Gamma distributed spike distributions. The EM-algorithm was introduced in Dempster et al. [28] and computes the (often intractable) Maximum Likelihood estimate by iterating between the E-step and the M-step. The E-step consists of computing the *intermediate quantity*

$$Q(\theta, \theta') = \mathbf{E}[\log p_\theta(X, Y)|Y, \theta'] \quad (6)$$

which can be done when the smoothing distribution of the latent regimes has been computed. The M-step maximizes the intermediate quantity

$$\hat{\theta}_m = \arg\max Q(\theta, \hat{\theta}_{m-1}). \quad (7)$$

The M-step can often be derived in closed form when the latent regime process is a time homogeneous Markov Chain. However, it is somewhat more complicated to compute the parameter estimates for a time in-homogeneous process, see Zucchini and MacDonald [30] for a discussion.

The preferred time homogeneous model (measured using AIC or BIC) for the Nord Pool market, cf. Janczura and Weron [9], Regland and Lindstroöm [10] is a three regime model, with Gamma distributed spikes and drops. The extreme events (spikes, drops) on the Nord Pool market are not as severe as they are on e.g. the EEX market where the preferred spike distribution is found to be log-normal (the large share of hydro seems to stabilize the system). We also find, similar to Janczura and Weron [9], that there is not support for assuming that the CEV parameter γ is different from zero (i.e. using a Vasicek model) when a sufficiently flexible regime switching model is used.

We found that the reserve margin does not work very well on the Nord Pool market, and proceeded with estimated the model using several other explanatory variables, generically denoted $\{Z_t\}_{t=1:T}$ (consumptions, production, the reserve margin and wind power), see Noren [25] for details. The all explanatory variables was scaled according to

$$\widetilde{Z}_t = \frac{Z_t}{\max_{u\in 1:T} Z_u} \quad (8)$$

as this makes it easier to interpret the estimates.

The log-likelihood (and hence AIC/BIC etc.) when using consumption or production data is nearly identical (this is not surprising as the consumption and production are similar, the main difference being imports/exports), both are clearly better than the reserve margin, which in turn is slightly better than wind power.

The estimates of the parameters in the transition matrix are reported in Table 1 (these are the only relevant parameters for the remainder of the paper). It can be seen that the most reliable variable for predicting spikes or drops in the Nord Pool market was the consumption, hereafter denoted $\{C_t\}_{t=1:T}$, closely followed by the production (these variables are very similar, the main difference is that the consumption includes information about imports and exports). All $\beta_{\cdot,1}$ parameters are statistically different from zero for the consumption model, meaning that the model is clearly an improvement upon the time-homogeneous independent spikes models. The estimates for using production data is similar, but the $\beta_{DB,1}$ is not statistically significant, even though the sign coincides with that of the consumption based model. We will therefore focus on the consumption based model.

There are no statistically significant $\beta_{\cdot,1}$ parameters when the reserve margin is used as explanatory variable (meaning that it is questionable whether it is any better than a time homogeneous model), and wind power is only marginal better, the only significant variable being $\beta_{SB,1}$, which indicates that additional wind power increases the probability of leaving the spike regime. This is plausible as more power being produced would reduce the risk for a power shortage.

It can be seen in Table 1 that the probability of going from the base regime to the spike regime is small when the consumption is low, while the probability is clearly different from zero (as $\beta_{BS,1} > \beta_{BS,0}$) when the consumption is large. Similarly, going from the spike regime to the base regime is unlikely when consumption is high, while relatively likely when the consumption is low.

The fit of the model is presented in Fig. 3, presenting the spread defined as $\log(Spot) - \log(Forward)$ (top panel), classification of the regimes (the classification is computed as $(\mathbf{E}[X_t|Y_T] = 1 \cdot p_{t|T}(Spike)$

Table 1
Exogenous data coefficients of three-state MRS models when applied to the Nord Pool market using Vasicek dynamics together with gamma spikes for daily day-ahead prices for consumption (C), production (P), the reserve margin (RM) and wind power (W). Significant coefficients are emphasized in bold with corresponding *p*-values for a standard Wald test printed beneath in parentheses. The time series is evaluated from January 1st, 2006 until June 30th, 2013, except for the wind power where only a subset of the data was available (October 1st, 2009–June 30th, 2013).

Var.	$\beta_{BS,0}$	$\beta_{BS,1}$	$\beta_{BD,0}$	$\beta_{BD,1}$	$\beta_{SB,0}$	$\beta_{SB,1}$	$\beta_{DB,0}$	$\beta_{DB,1}$
C	−**27.84**	**28.14**	**6.53**	−**17.54**	**13.27**	−**16.34**	−**6.02**	**7.71**
06-Q1	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.013)	(0.002)	(0.013)
P	−**30.96**	**31.23**	**5.87**	−**16.75**	**29.80**	−**33.61**	−**4.31**	4.42
06-Q1	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.018)	(0.036)	(0.177)
RM	−**4.45**	1.11	−**4.30**	0.08	−**1.79**	0.45	−**1.63**	−1.48
06-Q1	(0.000)	(0.059)	(0.000)	(0.853)	(0.000)	(0.474)	(0.000)	(0.089)
W	−**4.58**	1.66	−**4.52**	1.20	−**3.96**	**5.37**	−0.48	−4.43
09-Q4	(0.000)	(0.101)	(0.000)	(0.335)	(0.000)	(0.003)	(0.298)	(0.079)

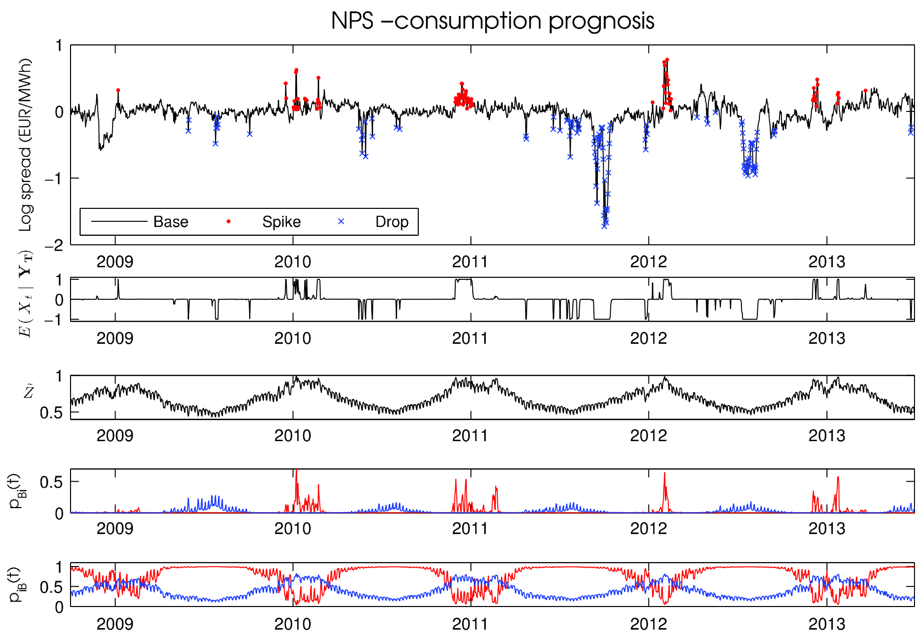

Fig. 3. Log spread with identified spikes (red dots) and drops (blue dots) in the top panel, corresponding classification of the regimes (second panel), the scaled consumption process (middle panel) and the estimated regime transition probabilities for going from the base regime to any of the spike regimes (second last panel) and the probability of going from any of the spikes to the base regime (last panel). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$+0 \cdot p_{t|T}(Base) + (-1) \cdot p_{t|T}(Drop))$, the consumption process and the estimated transition probabilities. The difference between the classification by this model, and a homogeneous model where the spikes are expected to arrive uniformly in time is striking!.

4. Simulation study

In this section we shall illustrate how the proposed modeling framework can be used to study the effect of the power consumption on the unconditional probabilities for price spikes and drops. We will studied four very simple scenarios; eliminating low consumption, eliminating high consumption, eliminating both or simulating additional renewables by adding variability. The four different scenarios are selected such that they illustrate important main characteristics of a future electric energy system. The scenarios are inspired by the various realizations of a future energy system with a large share of wind power described in Meibom et al. [11].

The assumed consumption strategies may be overly simplistic. However, a description of an energy system which in a proper way describes future interactions between eg. power and district heating systems and markets will readily become complicated and questionable. The risk by using this approach is that the focus will be on the assumptions behind these scenarios and the mathematical formulation of more realistic future consumption profiles. Consequently the simplicity is justified by the fact that the scenarios in this paper are used mainly for illustrating the proposed statistical modeling framework. More advanced strategies can easily be evaluated within the same modeling framework.

Even given the overly simplistic assumptions, we believe that the setup and the scenarios give an indication of how the price spike and drop probabilities are influenced when managing the consumption by adding storage solutions. In a similar simplistic setting we aim at studying the consequences of adding more fluctuating renewables, like wind and solar power, on the unconditional price spike and drop probabilities.

A review of physical energy storage technologies for wind power integration support is given in Zhao et al. [31]. The physical energy storage solutions considered are pumped hydro, compressed air, flywheel, superconducting magnetic systems, and a list of battery systems. The paper provides also a review of related operational and control strategies for wind power integration. In Ibrahim et al. [32] the main characteristics of the different electricity storage techniques and their field of application (long- or short-term storage, permanent or portable, maximum power required, etc.) are described.

However, it is clear that intelligent and IT-based methods for demand side management in combination with energy systems integration (power, gas, thermal, biomass) provide very efficient virtual storage solutions, see e.g. Meibom et al. [11] and Corradi et al. [5]. The later also describes methods for price based demand side management or control of the power consumption using the thermal mass of buildings. The simple concepts of a superb battery used in this paper can be considered as a simplistic approach for describing physical or virtual storage solutions in an ideal setting.

Methods for implementing consumption control and optimization strategies for demand side management are discussed in Meibom et al. [11] and Morales Gonzále [33]. A comprehensive overview in a general setting is presented in Siano [12].

In the simplistic approach taken in the following we shall, however, use the concept of a superb battery which without any cost and any restrictions on the amount and rate can store large amounts of energy.

The parameter estimation routine using in Section 3 provides an estimate of the states for each day in our sample, $\{p_t\}_{t=1:T}$. The unconditional probability for being in a specific state is therefore computed as the sample mean over time

$$\hat{p} = \frac{1}{T}\sum_{t=1}^{T} p_t, \tag{9}$$

where the vector p_t is computed as

$$p_t = p_{t-1} P(Z_t). \tag{10}$$

The same technique is used for our four scenarios, replacing the historical consumption with the corresponding modified consumption process. The sample mean is a consistent estimate of the unconditional probability vector as the any of the consumption processes and hence the regime probabilities are stationary and ergodic. The impact of the initial condition on the computation of the unconditional probabilities is negligible, as the Markov chain is mixing well.

4.1. Scenario: Increasing the minimum consumption

It is possible to increase the minimum electricity consumption by installing additional district heating, by converting electricity into e.g. gas through electrolysis, by charging electrical cars or by running additional cooling (such as smart refrigerators). We model this mathematically by imagining a superb battery that can charge large amounts of energy instantaneously without any cost. The modified consumption is then defined as

$$\widetilde{C}_t^{Floor} = \max\left(\min_{u\in 1:T}(\widetilde{C}_u) + Battery, \widetilde{C}_t\right). \tag{11}$$

The resulting consumption process, with a battery with capacity that corresponds the 10% of the total system consumption, is presented in Fig. 4.

The unconditional probabilities for some different size of the batteries are analyzed in Table 2, where it can be seen that this strategy reduces the unconditional drop probability (from 9% down to 2% when the battery is 20%) while leaving the spike probability unchanged for all practical purposes.

4.2. Scenario: Reducing the top consumption

Another scenario that we study is the effect limiting top demand. This can e.g. be achieved by adding reserve gas power plants to the grid, by modernizing (e.g. smart grids) the control and market design of the power system and combinations thereof, see Siano [12]. We have modeled this by shaving the electricity consumption using a perfect battery that will discharge instantaneously whenever the consumption is above some threshold. Hence, the modified consumption process is then be given by

$$\widetilde{C}_t^{Cap} = \min\left(\max_{u\in 1:T}(\widetilde{C}_u) - Battery, \widetilde{C}_t\right). \tag{12}$$

The modified consumption process is graphically presented in Fig. 5.

The implications on spike and drop probabilities are analyzed in Table 3. It can be seen capping the consumption reduces spike probabilities (from 3% down to a 1/4% when the battery is 20%), but does hardly influence the drop probabilities.

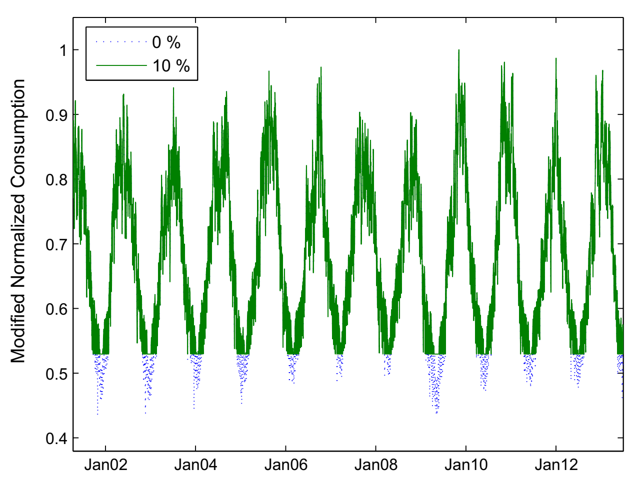

Fig. 4. Modified consumption when a lower boundary (here 10%) is introduced.

Table 2
Unconditional regime probabilities when increasing the lowest consumption by 0%, 5%, 10%, 15% and 20 % of the total system capacity.

Battery capacity (%)	0	5	10	15	20
Base prob.	0.8794	0.8815	0.8958	0.9239	0.9485
Spike prob.	0.0304	0.0304	0.0304	0.0304	0.0304
Drop prob.	0.0902	0.0881	0.0738	0.0458	0.0211

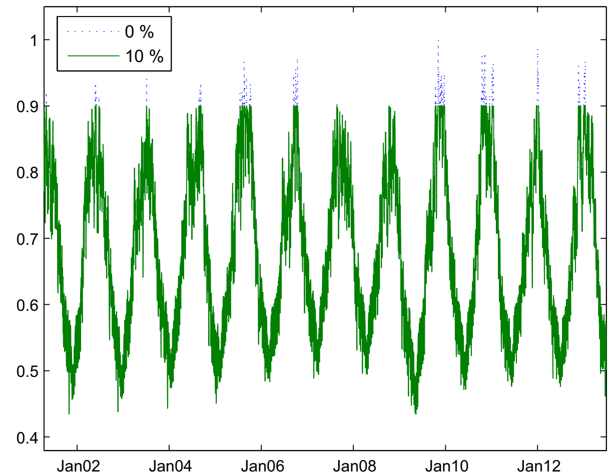

Fig. 5. Modified consumption when an upper boundary (here 10%) is introduced.

Table 3
Unconditional regime probabilities when shaving the largest consumption, with 0%, 5%, 10%, 15% and 20 % of the total system capacity.

Battery capacity (%)	0	5	10	15	20
Base prob.	0.8794	0.8806	0.8902	0.9016	0.9072
Spike prob.	0.0304	0.0292	0.0196	0.0081	0.0025
Drop prob.	0.0902	0.0902	0.0902	0.0902	0.0904

4.3. Scenario: Perfect battery

A perfect battery would be able to absorb or deliver energy instantaneously. Here we disregard any technical and economical limitations that current batteries suffers from in order to analyze what can be achieved in an idealized world. Our simplified model replaces the historical consumption with the modified consumption $\widetilde{C}_t$ defined as

$$\widetilde{C}_t^{Bat} = \max\left(\min_{u\in 1:T}(\widetilde{C}_u) + Battery, \min\left(\max_{u\in 1:T}(\widetilde{C}_u) - Battery, \widetilde{C}_t\right)\right). \tag{13}$$

This is graphically presented in Fig. 6, where a battery of at most 10% of the total market capacity is used. All peaks and troughs are eliminated.

The resulting unconditional regime probabilities are presented in Table 4. It can be seen that adding a perfect battery reduces both spikes and drops, but there are few other gains compared to what was achieved in the other scenarios presented in Sections 4.1 and 4.2. However, we acknowledge that real world batteries often are

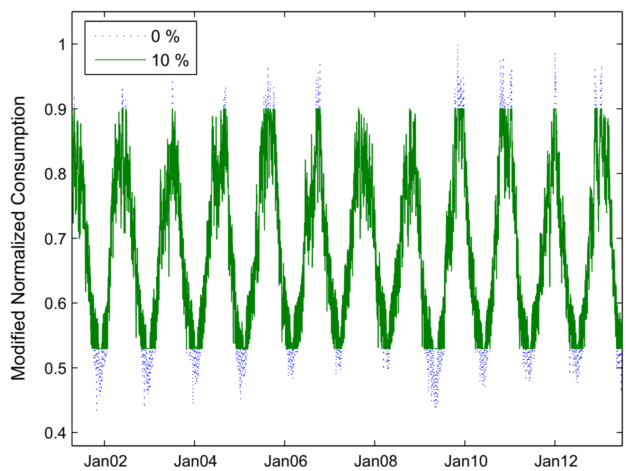

Fig. 6. Original and modified consumption with the perfect battery 10% capacity.

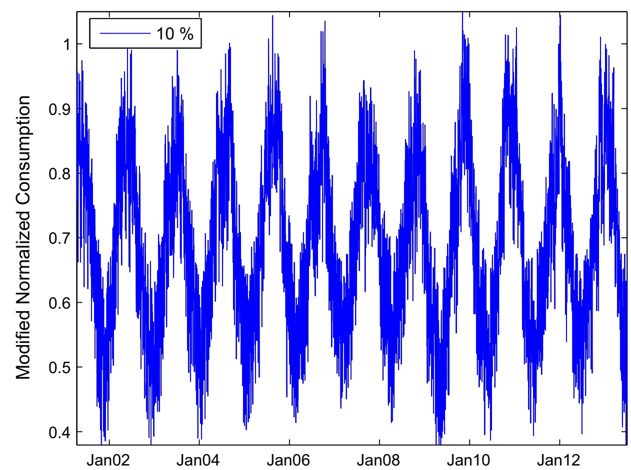

Fig. 7. Modified consumption when adding $U(-10\%, 10\%)$ *iid* noise.

Table 4
Unconditional regime probabilities when having a perfect battery with 0%, 5%, 10%, 15% and 20 % of the total system capacity.

Battery capacity (%)	0	5	10	15	20
Base prob.	0.8794	0.8827	0.9066	0.9461	0.9763
Spike prob.	0.0304	0.0292	0.0196	0.0081	0.0025
Drop prob.	0.0902	0.0881	0.0738	0.0458	0.0213

used for smoothing steep ramps in consumption, something we are not modeling in this paper.

4.4. Scenario: Additional renewables

Production of renewables is less predicable than more traditional sources of energy. We will model additional renewables being integrated into the power system (replacing the more dependable, traditional sources) as negative consumption, here as random noise. We simplify this scenario as much as possible for two reasons: transparency, and due to the fact the variations in weather typically operates on an daily scale. Hence, or modified consumption is given by

$$\widetilde{C}_t^{Renew} = C_t + \epsilon_t, \epsilon_t \in U(-a, a) \tag{14}$$

Generalizing this to dependent noise would be straightforward, but it would not be clear whether it is the noise per se, or the dependence that is the main driver behind the findings. A realization of the noisy consumption process is given in Fig. 7. The process is similar to the original consumption process, but it can be seen that the new modified consumption sometimes exceeds 1, meaning that we are likely to see more extreme events.

The estimate of unconditional probabilities varies between different simulations, as the sequence of noise $\{\epsilon_t(\omega)\}_{t=1:T}$ results in slightly different estimates, cf. Eqs. (9) and (10) for different simulations. We report the means and standard deviations across 1000 independent estimates for different levels of noise parametrized by the parameter a in Table 5.

It can be seen that the electricity spot price is expected to become much more volatile (the unconditional probability for base regime decreases from 88% down to 75% when the noise is 20%), due to an increase in both spikes and drops. The can equivalently be expressed as the probability of experiencing spikes or drops increased from 12% (roughly one day out of eight) to 25% (which roughly means one day out of four days). Even more concerning

Table 5
Unconditional regime probabilities when adding *iid* uniform random noise $U(-a, a)$ to the historical consumption process with $a = 0\%$, 5%, 10%, 15% and 20% of the total system capacity. The second row (numbers in parentages) are estimated standard deviations computed over 1000 replications.

a (%)	0	5	10	15	20
Base prob.	0.8794	0.8696	0.8421	0.8013	0.7524
	(0.0000)	(0.0014)	(0.0027)	(0.0039)	(0.0049)
Spike prob.	0.0304	0.0349	0.0460	0.0624	0.0829
	(0.0000)	(0.0009)	(0.0016)	(0.0023)	(0.0030)
Drop prob.	0.0902	0.0958	0.1121	0.1360	0.1636
	(0.0000)	(0.0011)	(0.0021)	(0.0031)	(0.0039)

is that the increase is primarily (at least in relative terms) in the probability for spikes, indicating that there will be shortage of power more often.

5. Conclusion

We fit an extended Independent Spike Model to Nord Pool spot price data, testing several explanatory variables to improve the forecast of spike and drop intensity. Spikes are often due to lack of capacity in the power system while drops are due to surplus capacity, both events indicating that the power system is not operating optimally. We found, after considering several variables, that the consumption can improve forecasts in all directions (going to and from spikes or drops), resulting in a model that is significantly better (in a statistical sense) than the corresponding time-homogeneous model in describing the extreme dynamics in the Nord Pool electricity spot market.

The estimated model is used to analyse the effects when modifying the consumption. It is shown that the spike and/or drop intensity can be reduced substantially if additional production capacity or storage is added. Furthermore, we find that it is possible reduce the probability for spikes without influencing the probability for drops and vice versa. This means that a strategy that caps consumption has very little effect on drops and vice versa which is reasonable as it would be unlikely to face too much and too little power at the same time. We also observe that there are no noticeable gains from using a perfect battery, compared to separate strategies related to energy system integration for dealing with very high or very low electricity consumption. We interpret this results as an indication that modern energy system integration techniques may be an attractive solution for solving future power system problems.

The statistical results also indicate, when extrapolating from the model, that the electricity spot price is going to become much more volatile (power shortage will be more frequent) as more and more renewable energy is being integrated into the power system, meaning that modern energy system integration is necessary as the scenario of not integrating additional renewables is unacceptable for many reasons.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2015.01.113.

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