COMPUTING VALUE AT RISK ON ELECTRICITY MARKETS THROUGH MODELING INTER-EXCEEDANCES TIMES

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ABSTRACT

Since deregulation on electricity markets has expanded, one of the main concerns for traders has been the measure of risk on operations and optimal trading limits, due to the unique features electricity exhibits. Stylized facts on price's series, such as strong mean-reversing, heavy-tails and common spikes have been subject to revision on many studies.

Using Extreme Value Theory, researchers have acquired new tools for computing these measures, such as Value at risk, toward the characterization of maxima, although the series' features still fail on assumptions based on its use.

This paper presents a different approach, consisting on modeling the inter-exceedance times when extreme events occur, supported by high frequency models, while the distribution of extremes is still modeled by means of a generalized Pareto distribution.

The modeling technique is applied to four main electricity markets in Australia and results are compared with classical modeling.

KEYWORDS. Extreme value theory. Autoregressive conditional duration. Value at Risk.

Main areas, GF - Financial Management, EN - OR in Energy, MP - Probabilistic Models

1. Introduction

One of the main characteristics of electricity is its impractical storage, requiring not only large containers, but also possessing a short life span. For that, suppliers may likely sell it regardless its current price. In the same manner, as supply needs to respond to shifts in demand, power generation may need to be under regular adjustments.

Due to the non-stability of this commodity, the price series present spikes; this differs from standard jumps on classical financial returns, as in this case, the series returns immediately to regular values after an extreme event occurs.

For a trader's point of view, it is important to prevent such extreme price fluctuations from affecting their firm's profitability. As evidence in this concern, risk management measures need to be at hand in order to prepare for extreme events, whether defining trading limits of operation or estimating saving's requirements on a given period.

One of the most common of these measures is the Value at Risk (VaR), which is frequently used to establish trading limits, estimating the amount that a firm may lose in a certain horizon given a statistical probability. A more extended discussion on the application of VaR in electricity markets can be consulted on Clewlow and Strickland (2000) and Eydeland and Wolyniec (2003).

Some of the conventional approaches for the electricity spot prices take notice on predicting the trajectory of the series, modeling the entire data. We propose to employ a technique based on the modeling of inter-exceedances times between only extreme events through an Autoregressive Conditional Duration (ACD) model introduced by Engle and Russell (1998), due to the conditional nature of when the extremes occur; while the marks follow a classical Peaks-Over-Threshold (POT) model (see Smith, 1989). This allows us to concentrate only in these rare events rather than the whole data.

The main contribution of this paper is the ability to capture the short-term behavior of extreme events on electricity spot price's returns without involving additional parameters to model volatility in the series, such as ARMA models, which may lead to estimation error and modeling bias.

The rest of the paper is organized as follows. Section 2 presents a review on current articles dealing with electricity spot prices, Section 3 and 4 describe the approach taken, presenting the approach of the ACD-POT model and its parameterizations, Section 5 reviews an application and its performance against a classical EVT model, and Section 6 concludes the obtained results.

2. Literature review

The daily prices in the electricity markets are characterized for presenting stylized facts; features such as mean-reversing, high volatility, spikes (by shocks in price) and seasonality.

Most of the development on this matter has address modeling the data using ARMA models in order to study it, aimed to the trajectory of the series, in order to make a forecast, rather than the impact of extreme events and its undertaken risk.

Spikes present one of the common problems when dealing with this series, and for that, different approaches has been proposed in the literature to overcome its influence in modeling. For electricity spot prices, Weron and Misiorek (2005) present a brief review on ARMA and ARMAX models. Other works that deal with spikes come from Janczura and Weron (2009) and Higgs and Worthington (2008) proposing a Markov regime-switching model and a diffusion model were jumps on the series are introduced by modeling different components on a function.

An EVT approach has been referred by Chan and Gray (2006) who compute VaR through classical models, adjusting volatility in the series with a GARCH model as well as Byström (2005).

Christensen et al. (2011) present an ACH model focused on capture intensity dependence of the prices in the series, while focusing on extreme values.

Consequently, the application presented on this paper focus on the work presented by Herrera and Schipp (2011), who use an ACD model for dependence between the time of extreme events, and utilize a Point Process to estimate a measure for VaR in financial markets.

3. Methodology

This section intends to summarize the approach taken by the proposed methodology. It has the intention to familiarize the reader with the components of the formulation and its assumptions. Brief concepts regarding Extreme value theory, Point Process and ACD models are addressed.

3.1 Extreme value theory (EVT)

Following Embrechts et al. (1997) and McNeil and Frey (2000), we adopt a Peaks Over Threshold (POT) EVT method to identify extreme events that exceed a threshold u. Here, the exceedances' distribution, F_u, that is, the magnitude of all observation over this threshold, can be approximated by a Generalized Pareto Distribution (GPD).

Suppose a series of observations $Y_1, \ldots, Y_n$, are random variables with distribution function F_u, if it satisfies a series of variation properties, the non-degenerate limiting distribution function belong to the maximum domain of attraction, $H_{\xi,\mu,\sigma}$, must be the generalized extreme value distribution $H_{\xi,\mu,\sigma}$ given by

$$H(y)_{\xi,\mu,\sigma} = \begin{cases} exp\left\{-\left(1+\xi\dfrac{y-\mu}{\sigma}\right)^{\frac{-1}{\xi}}\right\}, \xi \neq 0 \\ exp\left\{-exp\left(-\dfrac{y-\mu}{\sigma}\right)\right\}, \xi = 0 \end{cases}$$

Where the Fisher-Tippett theorem allows to obtain, according to the value of ξ, the Gumbel ($\xi = 0$, thin-tailed), Fréchet ($\xi > 0$, heavy-tailed) or Weibull ($\xi < 0$) distributions.

3.2 Marked Point Process (MPP)

Consider a random distribution of points in the space. We define a point process N as a sequence that carries information of both the occurrence times and marks (the size of an exceedance, defined as $y_i - u$; $\{t_i, y_i\}$). A marked point process (MPP) presents also an influence on its previous marks, denoted by its history $\mathcal{H}_t = (\{t_i, y_i\}, \ldots, \{t_{i-1}, y_{i-1}\})$. We describe a point process N_g, the ground process, which denotes the stochastic process of the inter-exceedance times of these extreme events. A conditional intensity (hazard) function is given by

$$\lambda_g(t|\mathcal{H}_t) = \frac{p(t|\mathcal{H}_t)}{S(t|\mathcal{H}_t)}$$

Where $p(t|\mathcal{H}_t)$ and $S(t|\mathcal{H}_t)$ are the conditional duration and survival function respectively, while the conditional intensity function for N is defined for

$$\lambda(t, y|\mathcal{H}_t) = \lambda_g(t|\mathcal{H}_t) f(y|\mathcal{H}_t, t)$$

With $f(y|\mathcal{H}_t, t)$, the density function of the marks conditional on time and history, and λ_g the ground process, which can be composed by a baseline, λ_0, for inter-exceedances times and a positive function (see Hautsch, 2011 for a brief review and Smith, 1989 for a more in deep analysis).

3.3 The Autoregressive Conditional Duration Peaks Over Threshold (ACD-POT) model

First proposed with the intention to model intraday, high-frequency transactional data, the ACD model can be expanded in this matter.

As durations between extreme events (transactions on the original case) are not equally spaced, it seems natural to describe its process through an Autoregressive Conditional Duration (ACD) model.

Following Engle and Russell (1998) we define a conditional intensity function λ_g, for the ground process for fitting autocorrelated data from the inter-exceedance times, $x_i = t_i - t_{i-1}$. In this case, in order to standardize the data we utilize the most recent history, with ψ_i as the expectation of the current inter-exceedance time (a similar approach is presented in Christensen et al., 2011).

$$E(x|x_{i-1},\dots,x_1) = \psi_i(x_{i-1},\dots,x_1;\ \theta) \equiv \psi_i$$

And we define the ground process composed by this new data, where $\varepsilon_i = \frac{x_i}{\psi_i}$. The complete ground process is defined as follows

$$\lambda_g(t|\mathcal{H}_t;\theta) = \lambda_0\left(\frac{t - t_{N(T)}}{\varphi(\psi_{N(T)})}\right)\frac{1}{\varphi(\psi_{N(T)})}$$

Where θ is a parameter vector; φ, a positive function to standardize durations. With transformations at hand, we present the conditional intensity function, defined for an ACD model in durations.

$$\lambda(t|\mathcal{H}_t;\theta) = \lambda_0\left(\frac{t - t_{N(T)}}{\varphi(\psi_{N(T)})}\right)\frac{1}{\varphi(\psi_{N(T)})\beta(t,y|\mathcal{H}_t)}\left(1 + \xi\frac{y-u}{\beta(t,y|\mathcal{H}_t)}\right)_+^{-1/\xi-1}$$

Note that the function $f(y|\mathcal{H}_t,t)$ presented earlier is modeled as a GPD, though now is dependent on time through the value of β.

Keeping in mind the estimation of risk measures for electricity spot prices in the proposed model for the intensity function, the VaR, for the α-th quantile, can be extracted straightforward in this case as

$$VaR_\alpha^t = u + \frac{\beta(t,y|\mathcal{H}_t)}{\xi}\left(\left(\frac{1-a}{1-exp(-\lambda(t,s|\mathcal{H}_t;\theta))}\right)^{-\xi} - 1\right)$$

4. Parameters for the conditional intensity function

With the presented model, this section introduce different alternatives in order to parameterize the three components; the expected conditional duration function (ψ_i) and the distribution of probability of the standardized durations (ε_i) for the hazard function, and the scale parameter (β) of the GPD function

4.1 ACD models for the expected conditional duration

We define four alternatives for modeling the conditional duration function.

- *Lineal ACD model* (Engle and Russell, 1998), based on a lineal parameterization of the mean function. $\psi_i = w + \sum_{j=1}^{p} a_j x_{i-j} + \sum_{j=1}^{q} b_j \psi_{i-j}$
- *Logarithmic ACD (Log-ACD) model* (Bauwens and Giot, 2000), which presents a multiplicative relation on durations. $\psi_i = exp\left\{w + \sum_{j=1}^{p} a_j log x_{i-j} + \sum_{j=1}^{q} b_j log\psi_{i-j}\right\}$
- *Box-Cox ACD (BCACD) model* (Dufour and Engle, 2000) $\psi_i = w + \sum_{j=1}^{p}\frac{a_j}{\delta}\left(\varepsilon_{i-j}^{\delta} - 1\right) + \sum_{j=1}^{q} b_j\psi_{i-j}$

- *Exponential ACD (EXACD) model* (Dufour and Engle, 2000) $\psi_i = w + \sum_{j=1}^{p}\{a_j\varepsilon_{i-j} + \delta_j|\varepsilon_{i-j} - 1|\} + \sum_{j=1}^{q} b_j\psi_{i-j}$

4.2 Distributional assumptions for the standardized durations

Two different distributions are considered for this matter. Note that the Generalized Gamma distribution includes the Weibull, Half-Normal and ordinary Gamma distribution under different values for γ and *k*.

- *Generalized Gamma distribution*, $(x|\gamma,k) = \frac{\gamma x^{k\gamma-1}}{\lambda^{k\gamma}\Gamma(k)} exp\left\{-\left(\frac{x}{\lambda}\right)^{\gamma}\right\}, x > 0$, non-monotonic distribution used mostly under survival analysis, as a three parameter generalization of the regular Gamma ($\gamma = 1$) or Weibull ($\gamma = k$) for $\gamma, \lambda, k > 0$.
- *Burr distribution* (Grammig and Maurer, 2000) $f(x|\lambda,k,\gamma) = \frac{\lambda k t^{k-1}}{(1+\gamma^2\lambda t^k)^{\gamma^{-2}+1}}$

4.3 Models for the time varying scale parameter

For the scale parameter, β, there have been selected five approaches for its modeling in this paper

- *Constant scale* $\beta(t,y|\mathcal{H}_t) = \beta_1$
- *Lineal scale* $\beta(t,y|\mathcal{H}_t) = \omega + \beta_1 y_* + \beta_2\psi_*$
- *Polynomial scale* $\beta(t,y|\mathcal{H}_t) = \omega + \beta_1 y_* + \beta_2{\psi_*}^{\beta_3}$
- *The Hawke's scale* $\beta(t,y|\mathcal{H}_t) = \omega + \beta_1\sum_{i:t_i<t}(1+\beta_2 y_i)exp\big(\beta_3(t-t_i)\big)$
- *The autoregressive realized duration* (ARD) $\beta(t,y|\mathcal{H}_t) = \omega + \beta_1\beta(t_*,y_*|\mathcal{H}_{t*}) + \frac{\beta_2}{(t-t_*)^{\beta_3}}$

Note that the first three alternatives for β are aimed to model the intensity (y) of the parameter, depending only of the last mark and its times, while the other two take into account the durations between excesses (t-t_*) as part of the modeling.

5. Empirical results

The following presents the application results for the electricity market of Australia.

5.1 Data

This section presents the results obtained after using the proposed ACD-POT methodology to calculate a VaR measure. The considered data for this paper correspond to the Daily Regional Reference Price (RPP, in $/MWh) from the four mayor electricity markets of Australia; New South Wales (NSW), Queensland (QSL), South Australia (SA) and Victoria (VIC). The sample covers 1,493 observations, from January 1st, 2007 to December 31st, 2010. As we concentrate on the left tail for risk management, the negative log-returns are used for the analysis. Table 1 presents some descriptive statistics for these series.

	New South Wales	Queensland	South Australia	Victoria
Mean	-0.038	-0.033	-0.154	-0.183
Std. dev.	44.131	52.268	57.717	38.854
Min	-406.436	-426.687	-439.620	-361.756
Max	359.714	415.271	395.455	399.303
Skewness	0.292	0.062	-0.590	0.251
Kurtosis	22.725	21.727	20.851	29.920
Box test	0.000	0.000	0.000	0.000
Shapiro test	0.000	0.000	0.000	0.000

Table 1: Descriptive statistics of the time series

As it was exposed, stylized facts are present in these series, evidence by large values on both cases, minimum and maximum, which follow the form of a spike. Skewness most likely to be located on the positive side (of the negative log-returns), and heavy-tails, denoted by the excess of kurtosis.

Some of these properties can be observed at Figure 1, presented as a motivation to this study given the autocorrelation on inter-exceedances times, also supporting the idea of clustering between extreme events. Density functions are obtained in order to examine the probability of inter-events time.

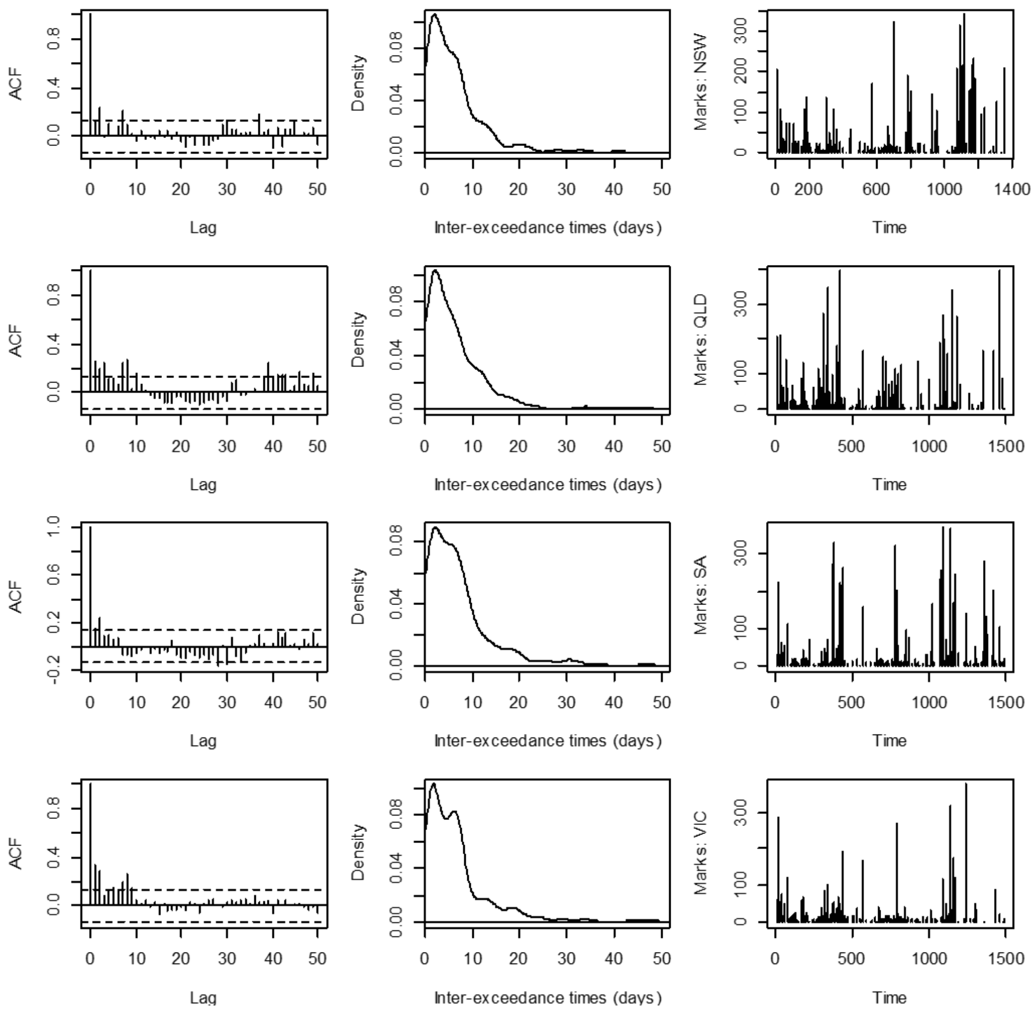

Figure 1: Stylized facts. Autocorrelogram and density graphs for inter-exceedances times and marks for the studied series.

One of the requirements for the methodology is the choice of a sufficiently high enough threshold (u) for applying EVT, without compromising variance of the sample. The instrument selected for this is the Hill plot, a common estimator for finding an optimal threshold (see Reiss and Thomas, 1997). For this application, we consider a 14% of maxima in the sample.

5.2 Model fit

The model names follow the classification scheme proposed by Herrera and Schipp (2011), were the first lower-case letter represents the distribution (b, burr; g, generalized gamma), the next capital letters denote the type of ACD model (ACD, Log-ACD, BCACD, EXACD) and the following number implies the scale of β (1, constant; 2, lineal; 3, polynomial; 4, Hawke; 5, ARD).

With regard to the log likelihood and AIC statistic, there are not significant changes between models, thought most of the selected ones follow a similar architecture. The most significant parameter belongs to the expected conditional duration over the intensity. This is also true for the ACD model's weights. The hazard rate for most of the models exhibit a general shape .

Results for selected models are presented on Table 2.

Model	Parameters											Loglike	AIC
	ACD model					POT model							
	W	α_1	b_1	δ	γ	k	ξ	ω	β_1	β_2	β_3		
New South Wales													
bACD2	0.74 (0.56)	0.10 (0.05)	0.79 (0.12)		0.64 (0.11)	1.47 (0.12)	0.72 (5.19)	1.42 (0.13)	0.06 (0.04)	66.4 (34.83)		-1508.15	3034.30
bLog-ACD1	0.03 (0.12)	0.00 (0.00)	0.98 (0.01)		0.62 (0.14)	1.41 (0.14)	0.81 (1.85)	13.44 (0.13)				-1509.45	3032.90
gLog-ACD1	0.04 (0.01)	0.00 (0.00)	0.98 (0.01)		0.37 (0.13)	8.00 (5.31)	0.79 (1.88)	13.64 (0.13)				-1505.98	3025.97
gEXACD1	0.09 (NA)	0.00 (0.01)	0.90 (NA)	0.15 (0.03)	0.19 (0.10)	31.05 (31.08)	0.79 (1.91)	13.83 (0.13)				-1504.58	3025.15
Queensland													
bACD2	1.15 (0.54)	0.23 (0.07)	0.62 (0.12)		0.65 (0.12)	1.45 (0.13)	0.60 (5.64)	6.87 (0.12)	0.07 (0.04)	75.51 (33.35)		-1578.30	3174.59
bBCACD2	0.35 (0.18)	0.17 (0.08)	0.81 (0.09)	1.31 (0.33)	0.66 (0.12)	1.46 (0.13)	0.60 (5.47)	6.50 (0.12)	0.08 (0.05)	75.42 (31.17)		-1578.85	3177.71
gACD2	1.06 (0.50)	0.21 (0.07)	0.65 (0.11)		0.17 (0.19)	36.98 (79.34)	0.60 (6.36)	8.59 (0.12)	0.06 (0.04)	63.75 (35.66)		-1575.35	3168.70
gLog-ACD2	0.27 (0.12)	0.15 (0.05)	0.75 (0.08)		0.19 (0.14)	30.25 (43.52)	0.60 (6.99)	7.70 (0.12)	0.06 (0.04)	71.41 (41.26)		-1576.55	3171.09
South Australia													
bACD2	1.66 (0.81)	0.15 (0.06)	0.62 (0.14)		0.59 (0.13)	1.35 (0.12)	0.73 (5.77)	3.05 (0.12)	0.00 (0.03)	92.82 (43.23)		-1564.42	3146.84
bBCACD2	0.63 (0.25)	0.16 (0.06)	0.70 (0.12)	0.40 (0.52)	0.57 (0.13)	1.33 (0.12)	0.73 (6.79)	0.72 (0.12)	0.00 (0.03)	108.40 (52.14)		-1564.58	3149.15
gACD2	1.65 (0.80)	0.13 (0.06)	0.64 (0.14)		0.21 (0.70)	23.14 (149.65)	0.73 (6.86)	2.03 (0.12)	0.00 (0.02)	98.12 (48.51)		-1561.03	3140.05
gLog-ACD3	0.50 (0.24)	0.12 (0.05)	0.65 (0.14)		0.28 (0.31)	13.95 (30.20)	0.74 (NA)	0.43 (0.11)	0.00 (0.03)	67.81 (29.76)	0.78 (NA)	-1559.74	3139.47
Victoria													
bACD2	0.47 (0.24)	0.11 (0.04)	0.83 (0.05)		0.52 (0.13)	1.33 (0.11)	0.47 (3.58)	2.64 (0.09)	0.05 (0.04)	65.80 (25.41)		-1465.41	2948.81
bLog-ACD3	0.14 (0.07)	0.11 (0.03)	0.85 (0.05)		0.44 (0.15)	1.28 (0.11)	0.46 (10.03)	0.00 (0.09)	0.05 (0.04)	76.24 (61.09)	0.94 (0.79)	-1463.79	2947.59
gACD3	0.53 (0.32)	0.11 (0.04)	0.82 (0.06)		0.31 (0.50)	11.73 (36.85)	0.48 (20.34)	0.17 (0.09)	0.05 (0.04)	46.41 (30.68)	0.69 (1.11)	-1462.77	2945.54
gLog-ACD3	0.18 (0.11)	0.10 (0.04)	0.84 (0.07)		0.30 (0.19)	11.76 (15.03)	0.48 (1.86)	12.60 (0.10)	0.08 (0.06)	4.19 (120.78)	6.09 (0.67)	-1466.14	2952.28

Table 2: Results of the ACD-POT model estimation

It should be noted that, for some values, there is a *NA* indicator and exhibit numerical problems at the time of calculations. On the other hand, some variations presented values less than the observed number, as the case of *(0.00)* being actually *(< 0.00)*.

To complement to the presented results, we expose a set of graphs for the New South Wales return's index, along with the measure of VaR obtained for some of our empirical application of the ACD-POT model on Figure 2, corresponding to $\alpha = 0.005$ for a (from the upper left corner) bACD1, bACD2, gACD1, gACD2, bEXACD1 and bEXACD2. The x marks above the estimation indicate violations at this confidence.

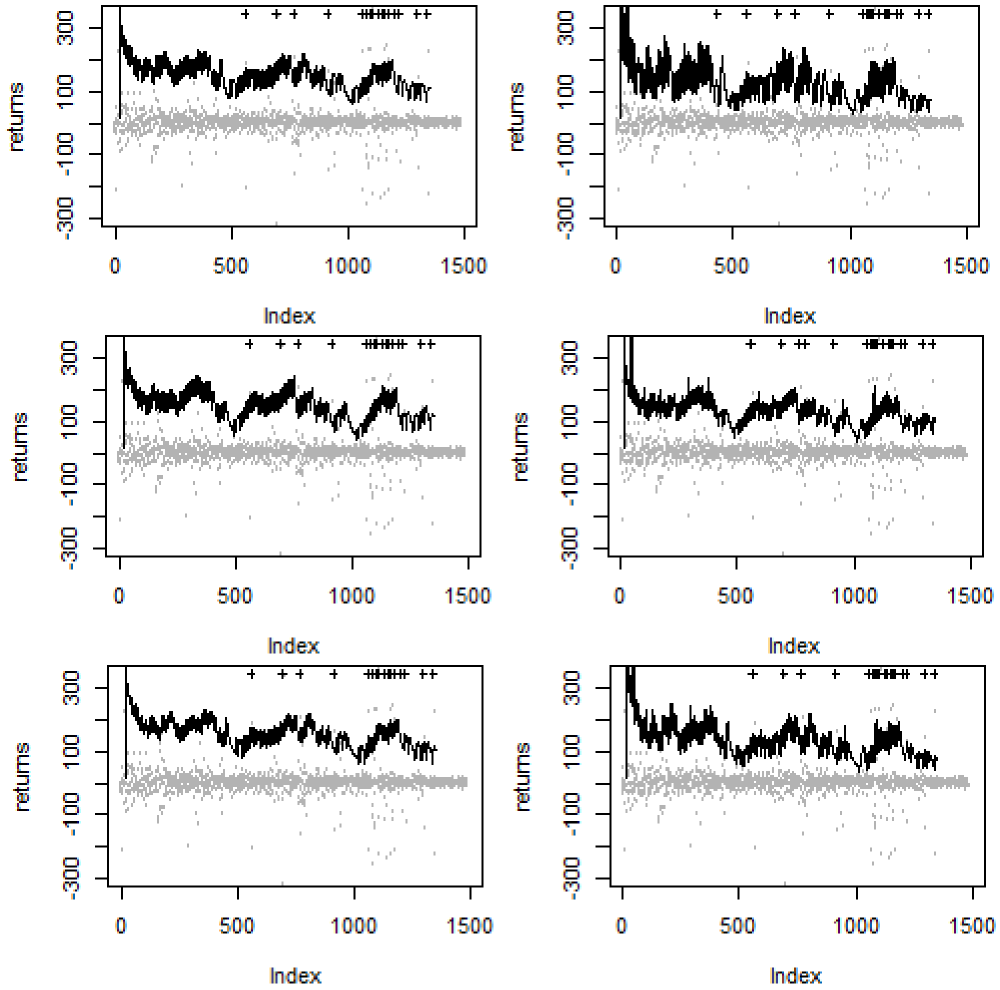

Figure 2: Estimation examples for the VaR

5.3 Comparison

In order to measure the performance of the proposed methodology, we proceed to compare the obtained results with a classic ARMA-GARCH-EVT model approach for computing VaR on electricity price returns.

For these models, volatility in the series is captured by an ARMA(1,1) and GARCH(1,1) with a Normal (*CondN*), t-Student (*CondT*) and Skewed t-Student (*CondST*) conditional distribution assumption.

For the matter, we present a variety of both fitting and accuracy tests for the estimated models in Table 3 for the New South Wales power market. Similar results can be obtained from the rest of the given series.

In short, the battery of tests selected covers *Kolmogorov-Smirnov test* (KS_{ACD}, KS_{POT}); to quantify the distance between the sample's residuals and the empirical distribution for both the ACD model and the POT methodology; *Anderson-Darling test* (*AD*) and *Density forecasting* (χ^2), as a second and third test for fitting the series based on different properties; *Ljung-Box test* (LB_{ACD}, LB_{VaR}), at lag 5, for testing the structure of the remaining data; as well as a *W-statistics* (*W*), for checking the residuals of the GPD.

As for VaR calculations, we consider a *Test of unconditional coverage* (LR_{uc}), to test correlation between failures; *Test of independence* (LR_{ind}), for independence of the failures; *Conditional Coverage* (LR_{cc}), for independence and correct coverage, a combination of the last two tests and a *Dynamic quantile test* (DQ_{hit} and DQ_{VaR}), to analyze VaR violations, testing independence.

Model	GoF ACD			GoF POT			Accuracy VaR							
	KS_{ACD}	*AD*	χ^2	LB_{POT}	*W*	KS_{POT}	α	*failures*	LR_{uc}	LR_{ind}	LR_{cc}	LB_{VaR}	DQ_{hit}	DQ_{VaR}
bACD2	0	0	0	0.02	0.98	0.81	0.050	69	0.78	0.08	0.21	0.05	0.09	0.22
							0.010	19	0.14	0.47	0.27	0.62	0.47	0.27
							0.005	7	0.90	0.80	0.96	0.87	0.80	0.16
bLog-ACD1	0	0	0	0.05	0.07	0.80	0.050	57	0.21	0.04	0.05	0.02	0.04	0.12
							0.010	18	0.23	0.50	0.38	0.64	0.50	0.01
							0.005	3	0.11	0.91	0.28	0.93	0.91	0.56
bEXACD1	0	0	0	0.03	0.07	0.82	0.050	58	0.26	0.14	0.17	0.10	0.15	0.29
							0.010	17	0.34	0.52	0.51	0.66	0.52	0.29
							0.005	5	0.50	0.86	0.78	0.91	0.86	0.45
gLog-ACD1	0.57	0.29	0.10	0.10	0.07	0.80	0.050	52	0.05	0.06	0.03	0.03	0.07	0.18
							0.010	19	0.14	0.47	0.27	0.62	0.47	0.02
							0.005	3	0.11	0.91	0.28	0.93	0.91	0.60
gLog-ACD2	0.63	0.32	0.18	0.10	0.92	0.90	0.050	57	0.21	0.04	0.05	0.02	0.04	0.13
							0.010	20	0.09	0.29	0.13	0.18	0.29	0.01
							0.005	8	0.62	0.77	0.85	0.85	0.77	0.24
gEXACD1	0.16	0.15	0	0.04	0.07	0.82	0.050	56	0.16	0.10	0.10	0.07	0.11	0.28
							0.010	16	0.48	0.55	0.65	0.68	0.55	0.31
							0.005	4	0.26	0.89	0.53	0.93	0.89	0.42
CondN	--	--	--	0	0	--	0.050	96	0.01	0.94	0.05	0.94	0.94	0
							0.010	51	0	NA	NA	0.06	0.06	0
							0.005	35	0	0.19	0	0.16	0.19	0
CondT	--	--	--	0	0	--	0.050	100	0	0.46	0.01	0.48	0.47	0
							0.010	47	0	NA	NA	0.21	0.08	0
							0.005	27	0	0.32	0	0.48	0.32	0
CondST	--	--	--	0	0	--	0.050	63	0.16	0.66	0.34	0.67	0.67	0.36
							0.010	28	0	0.11	0	0.04	0.11	0.20
							0.005	22	0	0.42	0	0.56	0.42	0.54

Table 3: Results for Goodness of fit (GoF) and Accuracy tests

The results show selected ACD-POT models, on which both the Goodness-of-fit (GoF) and Accuracy tests are approved, like fitting the distribution as well as the quantity and independence of both the times and failures occurrences, Computing a precise (at a p-value of 0.05) measure for VaR at all quantiles (95th, 99th, 99.5th).

The last three models of Table 3 present the competing models, on which the performance is not adequate for estimating a VaR on neither case, as evidenced by the excessive amount of failures for any given quantile as well as the result of the tests, while the best of the three models presented being the *CondST*.

It should be noted that, for the scale parameter β, the better performed models suggest a constant or a linear function over a more complex one (model names' that end with 1 or 2). Also, the generalized gamma distribution presented the best results overall, while the most efficient ACD model were both the lineal and logarithmic approach.

6. Conclusion

Electricity spot prices present a more difficult analysis than traditional financial markets, mostly because of its distinctive features, with a special attention for spikes on price.

This paper presented a new methodology exposed for financial series, focused on the inter-exceedance times of extreme events rather than the series itself in order for estimating a measure for VaR, applied on electricity markets. The model itself, and its components, show flexibility that allows more complex structures to be studied in the future. One of the advantages for this approach is that we concentrate on the distribution limit of maxima, rather than on the entire sample as is common on the studied literature.

With regard of the empirical application presented in this paper, computing VaR on the studied electricity markets performs well under both fitting models and accuracy statistics.

For the selected models, an interesting result is given by the performance of the constant scale parameter, which implies the minimum dependence the series exhibit, thought it's there on most of the series modeling. This particular outcome is not present on financial markets.

For a trader's point of view, the advantage of a more accurate method for estimating VaR can be translated on better policies for risk management (minimizing risk and adjusting provisions, giving more margins to invest).

Future work may need to be focused on dealing with modeling spikes on the series and regime switching methodology to be able to respond to these shifts.

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