Measuring volatility in the Nordic spot electricity market using Recurrence Quantification Analysis

F. Strozzi [a,*], E. Gutiérrez [b], C. Noè [a], T. Rossi [a], M. Serati [a], J.M. Zaldívar Comenges [b]

[a] *Università Carlo Cattaneo, Castellanza, Italy*

[b] *Joint Research Centre, European Commission, Ispra, 21020, Italy*

Abstract

In this work, we have applied Recurrence Quantification Analysis (RQA) to the Nordic spot electricity market data. Our main interest was on trying to classify these series and analysing if their dynamical behaviour were in some way correlated with known events, e.g. the evolution of the Nord Pool and the climatic factors. Furthermore, we were interested in developing alternative measures to correlate the high volatility of these series with historical and meteorological events. The analysis suggests that two RQA measures: DET and LAM are able to produce a better resolution for distinguishing between several periods than by measuring the time series standard deviation.

Key words: Econophysics; Non-linear dynamics; Recurrence Quantification Analysis; Volatility; Electricity markets

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1. INTRODUCTION

The complex behaviour of financial time series, which linear stochastic models are not able to account for [1], has been attributed to the fact that financial markets are non-linear stochastic, chaotic or a combination of both. Even though there is no conclusive evidence of low dimension deterministic structure, in the last few years, nonlinear time series analysis has expanded rapidly in the fields of Economics and Finance [2]. This is also due to the fact that economic and financial time series seem to provide a promising area for the development, testing and application of non-linear techniques and the fact that high frequency financial time series are readily available [3]. Among these time series, energy spot prices have also been analysed with several nonlinear techniques.

In [4],[5] the authors established, using Hurst R/S analysis, that the electricity prices are anti-persistent with a Hurst exponent lower that 0.5, i.e. $H \simeq 0.41$. Also the Lyapunov exponents has been estimated in a recent study [6]. Even though volatility (the standard deviation of the value change at a specific time horizon) is a fundamental characteristic of financial markets, power markets have levels well above other financial time series [7]. Simonsen [7] has demonstrated that power market volatility has some features in common with other financial markets, such as clustering and log-normal distribution, but also presents some differences such as higher level and price-level dependence.

In this work we have applied non-linear time series techniques to the Nordic spot electricity market data. Our main interest was on trying to classify these series and analysing if their dynamical behaviour was in some way correlated with known events, e.g. the evolution of the Nord Pool and the climatic factors. This work is a first step in the direction of finding if there exists a correlation between some features of the time series with the volatility, frequency and intensity of blackouts. First, we have analysed the stationarity of these series using space time separation plot [8] and we have found that energy spot prices are more stationary than other financial time series [9],[10]. Furthermore, as volatility is normally used to estimate the risk associated with a financial instrument, we were interested in finding related non-linear measures. Assuming that during high volatility periods there is an increase in the stochasticity of the system, we have applied two measures obtained from the application of Recurrence Quantification Analysis (RQA) [11], which allows the quantification of the Recurrence Plots (RP) [12]. The results suggest that these two RQA measures: DET and LAM are able to give a better resolution for distinguishing between several periods than

* corresponding author

Email address: fstrozzi@liuc.it (F. Strozzi).

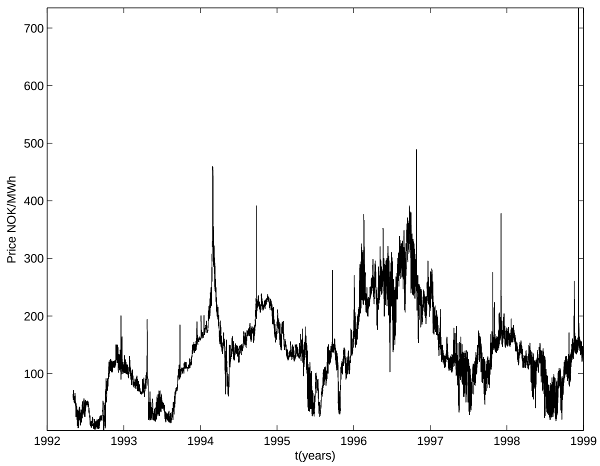

Fig. 1. Spot prices in the Nordic electricity market (Nord Pool) in NOK/MWh from May 1992 until December 1998.

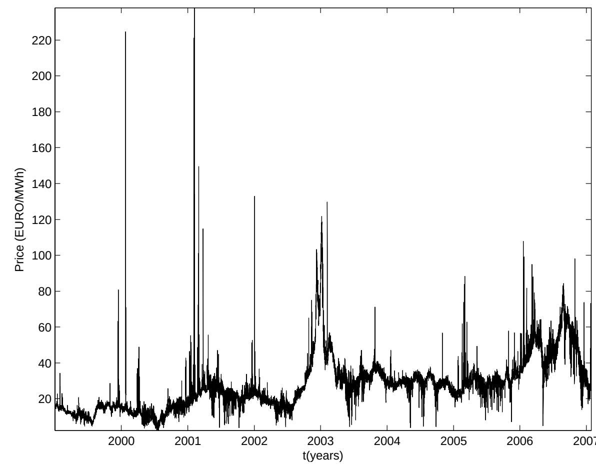

Fig. 2. Spot prices in the Nordic electricity market (Nord Pool) in EUR/MWh from January 1997 until January 2007.

by measuring the time series standard deviation. In this sense, they open the possibility to use them as a surrogate for the measure of the financial time series volatility.

2. DATA PROVISION AND HISTORICAL BACKGROUND

We have analyzed hourly data from the Nord Pool system spot prices. The series is divided into two parts. In the first part (which lasts from 4^{th} May 1992 until 31st December 1998 and comprises 58,392 data points, see Fig.1), the prices are indicated in Norwegian Krone (NOK)/MWh, whereas in the second time series (which lasts from 1^{st} January 1999 until 26^{th} January 2007 and comprises 70,752 data points, see Fig.2), the prices are expressed in EUR/MWh. The Nordic electricity market, known as Nord Pool was created in 1993 and it is owned by the two national grid companies, Statnett SF in Norway (50%) and Affrverket Svensa Kraftnt in Sweden (50%), which was established as a consequence of the decision in 1991 by the Norwegian Parliament to deregulate the market for power trading.

Between 1992 and 1995 only Norway contributed to the market, in 1996 a joint Norwegian-Swedish power exchange was started-up and the power exchange was renamed Nod Pool ASA. Finland started a power exchange market of its own, EL-EX, in 1996, and joined Nord Pool in 1997. Beginning of 15^{th} June 1998, Finland became an independent price area on the Nord Pool Exchange. The western part of Denmark (Jutland and Funen) has been part of the Nordic electric power market since 1^{st} July 1999, whereas the eastern part of Denmark entered after 1st October 2000. On 5^{th} October 2005 also the German area KONTEK was added in the Nord Pool exchange market. Table 1 summarises the historical evolution of the Nord Pool.

The spot market operated by Nord Pool is an exchange market where participants' trade power contracts for physical delivery the next day and is thus referred to as a day-

Table 1
Nord Pool participating countries and dates of entry.

Countries	Date of entry
Norway	1/1/93
Norway and Sweden	1/1/96
Norway, Sweden and Finland	29/12/97
Norway, Sweden, Finland and W. Denmark	1/7/99
Norway, Sweden, Finland, W. & E. Denmark	1/10/00
KONTEK zone (Germany)	5/10/05

ahead market. When no grid congestion exists there will be a single identical price across the area with no congestions. However, when there is insufficient transmission capacity in a sector of the grid, grid congestion will arise and the market system will establish different "price areas". Sometimes the prices are of the entire Nordic region. Sometimes more than one price area exists [13],[14].

In this work we will only consider the "system price". The variation of the prices in the Nord pool system is well correlated with the variations in precipitation in Norway and Sweden because of its strong dependence of the hydropower generation. Table 2 summarises the climatic conditions during the last years. Very special hydrological conditions appeared during the autumn and winter season of 2002-2003 with a sharp decline of precipitation. This was a rare event [15] which resulted in the spot prices increasing in 2003. By looking into Figs. 1 and 2 and comparing with Table 2, we can observe these correlations in the electricity price. However, weather conditions are not able to explain all the features in the time series. Moreover spot prices can increase tenfold during a single hour. These spikes, which are normally quite short lived, tend to be more severe during high price periods [8].

Table 2
Summary of meteorological conditions: Dry and wet years.

Year	State	Period considered
1996	dry	complete year
1997-2000	wet	complete years
2000	not very wet	all year
2001	dry	first eight months
2001	very wet	last four months
2002-2003	very dry (rare event)	complete years

3. DATA ANALYSIS AND RESULTS

The theory of embedding is a way to move from a temporal time series of measurements to a state space "similar" -in a topological sense- to that of the underlying dynamical system we are interested in analysing. State space reconstruction techniques were introduced in [16],[17]. In nonlinear time series analysis usually delay coordinates are used to reconstruct a representation of the original state space that generated the dynamics. The state at a time t of a measured variable $s(t)$ is given by $S(t) = s(t), s(t-\Delta t), s(t-2\Delta t), , s(t-(d_E-1)\Delta t)$, whereas Δt is the time delay between data when reconstructing the state space, and d_E is the embedding dimension or the dimension of the space required to unfold the dynamics. However, state space reconstruction techniques assume stationarity in the time series which does not always hold (for a detailed discussion see [18] and references therein).

3.1. *Finding the time delay and embedding dimension*

Determining the time delay and the embedding dimension is the first step in nonlinear time series modelling and prediction. The time delay, for the Nord Pool time series, has been obtained using the first minimum of the AMI (Average Mutual Information function, [19]) with values of 15 and 13 hours, respectively. The embedding dimension has been computed using the E1&E2 method [20]. Both series give the same value, $d_E = 10$. These high values are in agreement with similar analysis carried out by Strozzi et al [9] for high frequency foreign exchange time series.

3.2. *Detecting non-stationarity*

As a preliminary step, we have analysed the stationarity of the Nord Pool time series using the space time separation plot (stp), introduced in [8] and implemented in the TISEAN software package (http://www.mpipks-dresden.mpg.de/ tisean) [21]. The idea below this test is that in the presence of temporal correlations the probability that a given pair of state points in the reconstructed state space -Si, Sj - have a distance $d_{ij} = \|S_i - S_j\|$ smaller than r, does not depend only on the position of the state points but also on the time that has elapsed between them. This dependence can be detected by plotting the number of neighbouring points as a function of two variables: time and distance. Provenzale [8] showed that in the case of a random walk the contour curves does not saturate, whereas in the case of a random series there was saturation in the state space separation plot. Fig. 3 shows the results of the test on the Nord Pool time series.In those graphics the separation time is represented in the horizontal axis whereas the separation in space is represented in the vertical axis. We have represented the lines of constant probability density, with 5% increments, with a given temporal separation Δt.

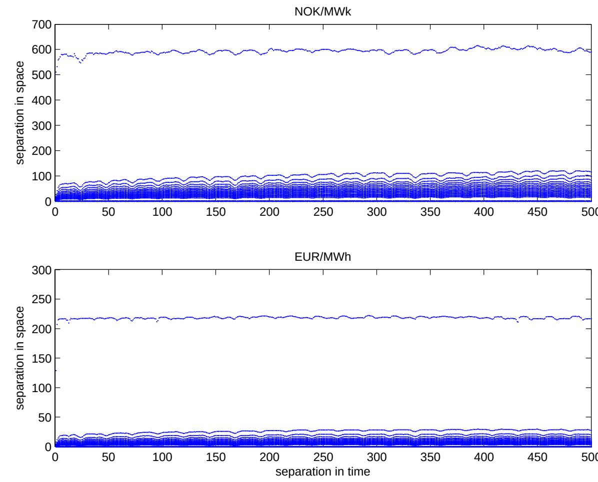

Fig. 3. Space-time separation plot (stp) of the Nord Pool spot prices (NOK/MWh); Space-time separation plot of the Nord Pool spot prices (EUR/MWh).

It can be seen in Fig. 3 that the Nord Pool time series saturate and this gives the indication that the Nord Pool time series are more stationary than other financial high frequency time series such as exchange rates for which the stp does not saturate [9],[10]. This is probably related with the way the spot market is operated as a day-ahead market and the iterations carried out before defining the prices, which does not exist in other financial markets.

3.3. *Quantification of the Recurrence Plots*

Eckmann et al. [14] introduced a new graphical tool, which they called a recurrence plot (RP). The recurrence plot is based on the computation of the distance matrix between the reconstructed points in the phase space:

$$d_{ij} = \|S_i - S_j\| . \quad (1)$$

This produces an array of distances in a nxn square matrix, $\mathbf{D}$, n being the number of points under study. If this distance is lower that a predetermined cutoff, r, the pixel located at specific (i, j) coordinates is darkened. These points highlight the recurrences of the dynamical systems and the recurrent plot provides insight into periodic structures and clustering properties that are not apparent in the original time series. In order

Table 3
RQA measures for NOK/MWk original time series ant its surrogates.

Data set	RR	DET	L_{max}	ENTR	Trend	LAM	TT
NOK	16.10	67.13	3545	8.59	-8.69	69.99	308
$Surr_{01}$	8.15	6.13	4808	6.74	2.31	1.80	124
$Surr_{02}$	1.93	4.52	1355	4.91	-0.14	0.0	-
$Surr_{03}$	2.81	8.03	4808	6.03	-1.62	0.0	-
$Surr_{04}$	30.22	36.31	4808	7.99	-3.36	35.52	215
$Surr_{05}$	1.74	13.22	1844	6.12	-0.98	0.06	110
$Surr_{06}$	1.01	32.02	1178	6.29	-0.75	16.98	166
$Surr_{07}$	4.79	13.28	2674	6.90	-0.80	7.53	154
$Surr_{08}$	14.12	17.88	4350	7.36	-4.48	9.29	155
$Surr_{09}$	5.93	13.53	3130	7.20	-2.46	6.30	159
$Surr_{10}$	1.19	5.90	1064	4.70	-0.68	0.35	120
$Surr_{11}$	4.86	51.64	4808	7.92	-1.54	52.44	266
$Surr_{12}$	31.90	52.68	4808	8.42	12.41	54.52	218
$Surr_{13}$	4.80	9.42	4808	6.88	0.52	0.72	144
$Surr_{14}$	5.73	9.17	4154	6.78	-2.98	1.77	145
$Surr_{15}$	4.97	6.34	2370	6.61	-2.34	1.72	115
$Surr_{16}$	18.05	23.40	4808	7.68	-4.18	12.85	161
$Surr_{17}$	10.85	43.19	4614	8.80	-7.22	38.30	339
$Surr_{18}$	4.96	8.52	4808	6.60	-2.65	3.48	142
$Surr_{19}$	6.32	4.46	4808	6.18	-1.99	0.38	114

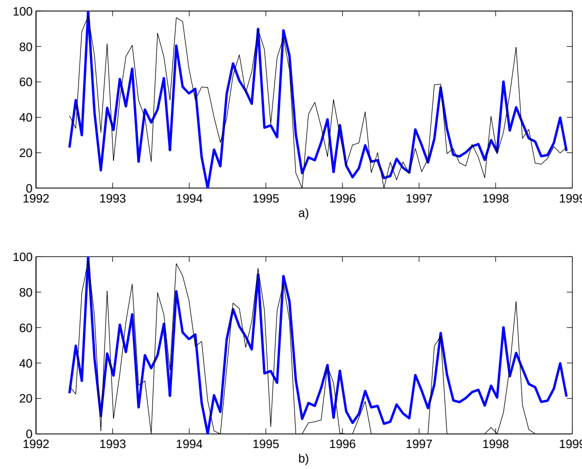

Fig. 4. Inverse of standard deviation and DET (top) and LAM (bottom) for NOK/MWh

Table 4
RQA measures for EUR/MWk original time series ant its surrogates.

Data set	RR	DET	L_{max}	ENTR	Trend	LAM	TT
EUR	7.12	35.33	2094	7.66	-4.59	33.94	264
$Surr_{01}$	12.52	3.67	3340	6.36	-6.26	2.54	149
$Surr_{02}$	1.64	5.89	2238	5.27	-1.10	1.87	119
$Surr_{03}$	3.84	1.40	2150	4.53	-1.00	0.0	-
$Surr_{04}$	4.38	1.11	1324	3.97	-0.29	0.0	-
$Surr_{05}$	10.68	1.83	4187	5.73	-5.48	1.53	127
$Surr_{06}$	8.66	18.81	4826	7.54	-5.64	9.85	146
$Surr_{07}$	0.49	3.89	690	2.81	-0.35	0.0	-
$Surr_{08}$	23.79	11.11	4826	7.51	-7.64	9.25	162
$Surr_{09}$	30.27	10.83	4826	7.39	-1.83	7.11	151
$Surr_{10}$	20.54	4.70	4826	6.85	-7.47	6.42	151
$Surr_{11}$	2.34	3.78	1888	5.09	-1.16	1.53	134
$Surr_{12}$	3.72	1.48	3517	4.06	-1.63	0.11	117
$Surr_{13}$	4.99	3.74	3721	6.88	0.52	0.72	144
$Surr_{14}$	21.65	9.02	4826	7.16	-2.90	9.66	155
$Surr_{15}$	20.05	8.14	2669	7.25	-4.24	4.17	146
$Surr_{16}$	6.81	5.38	3998	6.57	-4.10	0.76	125
$Surr_{17}$	3.16	4.11	1964	5.64	-2.08	0.72	132
$Surr_{18}$	7.81	3.37	2429	6.20	-0.47	2.77	132
$Surr_{19}$	12.19	1.33	4826	5.43	1.50	0.09	126

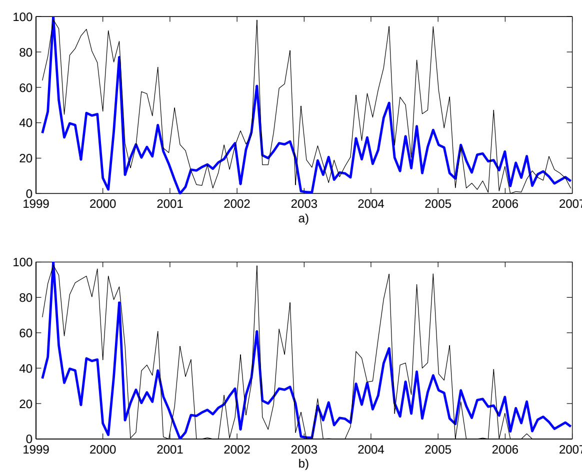

Fig. 5. Inverse of standard deviation and DET (top) and LAM (bottom) for EUR/MWh

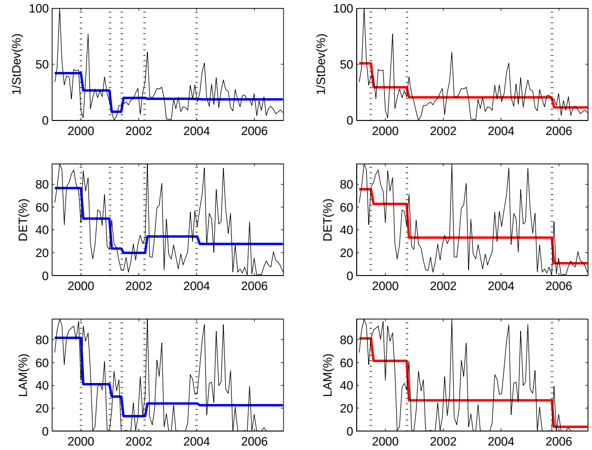

Fig. 6. RQA measures of EUR/MWh: Values are computed from a 720 point window (one month), shifted by 720 points. RQA parameters: $\Delta t = 13$, $d_E = 10$, distance cutoff: line definition: 100 points (≈ 4 days). Vertical lines correspond to the following dates: 1^{st} October 2000, 5^{th} October 2005 (see historical background).

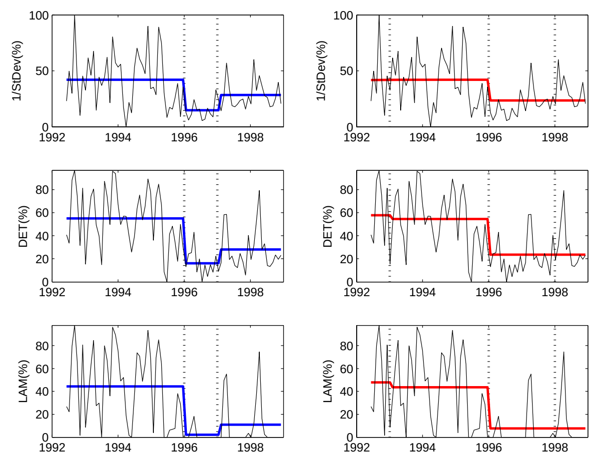

Fig. 7. Nonlinear metrics of the Nord Pool spot prices time series in NOK/MWh: Values are computed from a 720 point window (one month), data are shifted by 720 points. RQA parameters: $\Delta t = 15$, $d_E = 10$, distance cutoff: , line definition: 100 points (≈ 4 days days). Vertical lines correspond to the following dates: 1^{st} January 1993, 1^{st} January 1996, 29^{th} December 1997 and 1^{st} July 1999 (see historical background).

to extend the original concept and make it more quantitative, Zbilut and Webber [22] developed a methodology called Recurrence Quantification Analysis (RQA). As a result, several variables to quantify RPs have been defined [23], (http://homepages.luc.edu/ cwebber, http://tocsy.agnld.uni-postdam.de).

We have observed that RR (%recurrence, the percentage of darkened pixels in recurrence plot), L_{max} (the longest diagonal line found in the RP), ENTR (refers to the Shannon entropy), Trend (It is a measure of the paling recurrence points away from the central diagonal) and TT (trapping time which estimates the mean time that the system will stay at a specific state) parameters could not distinguish (with a 95% of confidence) between a linear Gaussian dynamics and the dynamics behind the Nord pool time series. Of course, this does not imply that those parameters are not useful for their quantification, but only that the values of the parameters in the surrogate time series were indistinguishable from those of the original time series. On the contrary, DET (points forming diagonal line structures) and LAM (%laminarity, quantifies the presence of laminar states in intermittent regimes) produced always values which were higher in the original data set when compared with surrogate data.

It is possible to assume that during high volatility periods there is an increase in the stochasticity of the Nord Pool market and therefore measures related with the determinism of our time series will tend to decrease. In addition, one can also consider that the changes in the historical evolution of the Nord Pool will have a direct effect on the Nord Pool electricity prices. For these reasons, we were interested in finding RQA variables that could be able to discriminate between these effects.

To check if RQA measures were appropriate to analyse the spot prices time series, we have created surrogate time series generated by a Gaussian linear random process with the same FFT of the real data set[20],then we have computed the RQA parameters for all the time series. The results are summarized in Table 3 and Table 4 for NOK/MWh and EUR/MWh time series, respectively.

The fact that these two parameters were able to distinguish between the original and the surrogate time series can be explained by assuming that there is more structure in the original series, and therefore the state space remained closer or for longer times when compared with their surrogate linear Gaussian process.

By way of assessing if these two measures were able to detect some events that were not clear from a direct inspection of the time series, we have computed these RQA measures in a moving window. For this analysis, we used a one month shifting moving window (720 points) for NOK/MWh and EUR/MWh, respectively. For example; we were interested in observing if some changes in the RQA parameters occur in correspondence of the entry of a new country in the Nord Pool 1 or in correspondence with dry and wet years 2. It is well-known that high volatility periods are those in which it is more difficult to make the forecast. Higher DET and LAM mean that the states of the system stay closer in time for longer periods forming diagonal or vertical segments in the RPs. Then, we may assume that higher values imply smaller volatility.

To study the relationship with volatility, we have compared the profiles of these quantities with the inverse of standard deviation normalized between 0 and 100 and, as it can be seen in Figs. 4 and 5, we have found a qualitative agreement.

Even though there is a high linear relationship between

DET and LAM, with r^2 values of 0.88 and 0.89 for NOK and EUR, respectively, there is no a clear linear relationship between these values and the inverse of the standard deviation (r^2 values 0.47 -DET-, 0.58 -LAM- for NOK and 0.47 -DET-, 0.45 -LAM- for EUR). In fact the relationship in this case is sigmoidal. This means that they will tend to highlight or smooth certain features as we will see below. In order to extract more information from RQA measures, we have compared the mean values of DET and LAM with the mean values of the inverse of the standard deviation (StDev) during the periods between changes in weather conditions (for EUR Fig. 6, left, and Fig. 7 left for NOK) and the periods between the entrance of new states in Nord Pool (Fig. 6 right for EUR, Fig. 7 right for NOK). In both cases, it is possible to observe that using RQA, the changes in the means are more evident (the steps are higher) than using the inverse of the standard deviation. Then, using the RQA measures it is possible to improve the detection of changes in the time series analyzed.

4. CONCLUSIONS

Nonlinear time series analysis has been carried out for the Nord Pool time series. The saturation in the space time separation plot shows that the time series may be considered close to stationary. This is in contrast to other high frequency time series, such as exchange rates, in which there is no saturation, which is typical of non-stationary time series. We have shown that the inverse of DET and LAM are correlated with the volatility of the time series. Therefore, we may conclude that they provide another method to measure volatility in financial time series.

We have compared the information given by these RQA parameters and the standard deviation, and have calculated the mean values of these three quantities between the periods in which there were important changes in weather conditions or in correspondence of which there was the incorporation of new states into the Nord Pool.

We have shown that DET and LAM detect these changes more clearly than the standard deviation. The future developments of this work will be to find a correlation between market prices (or some related variable such as volatility, DET, LAM) and the likelihood of blackouts.

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