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INDIAN ELECTRICITY MARKET VOLUME AND PRICE CROSS-CORRELATION ANALYSIS

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ABSTRACT

We apply the multifractal detrended cross-correlation analysis method to investigate the cross-correlation and fractal behavior between the price and volume of the electricity market. For this purpose, we have collected the data from the Indian electricity energy exchange from 1st April 2012 to 1st April 2015 with time interval of 1 hour. From the analysis, we observe a cross over near the scale (~ 32) in the fluctuation function, and thus we have calculated the Hurst scaling exponents for the scale <= 32 (short term) and > 32 (long term). The cross-correlation is observed persistent in short term and anti-persistent in long term. The multifractal nature is present in both short and long term and the strength of the multifractality was measured from the calculated singularity spectrum.

Keywords: electricity market, non-stationary time series, hurst exponent, multifractal detrended cross-correlation analysis, energy, power data.

INTRODUCTION

Generation of sufficient electricity to cater demand of the market is essential to the growth of any developing nation. Availability of different source of electricity power generation and grid efficiency plays an important part of demand and supply chain that fuels growth to the industry, employment, and infrastructure. Effective, efficient supply chain and utilization of various natural resources like hydro, thermal (coal, gas, diesel etc), nuclear, renewable (wind, solar etc) etc. plays an important part in electricity generation (Wang *et al.*, 2011), (Ramirez *et al.*, 2009), (Uritskaya *et al.*, 2008), (Uritskaya *et al.*, 2015).

For smooth supply chain and to provide competitive business environment, electricity power industry across the world is deregulated and liberalized. Due to deregulation in electricity markets diverse participants are involved like producers, intermediates, speculators, traders, consumers hence the electricity market price and traded volume is the result of many interacting factors combined within complex and nonlinear forms. Unlike any other traded commodities, electricity power cannot be stored hence any un-utilized demand is lost which is the unique feature in this market that drives extreme volatility and large stochastic dynamics into the future electricity price hence forecasting becomes very difficult (Ramirez *et al.*, 2010), (Malo et al., 2009), (Wang *et al.*, 2013), (Norouzzadeh *et al.*, 2007), (McArthur *et al.*, 2013). Also additionally peak demand and supply shortages drive extremely high price volatility due to the complex, non-linear wholesale electricity market dynamics. Hence with all these factor combination, the electricity volume and price market becomes complex. Thus analysis of electricity volume and price data becomes very crucial to understand and retrieve critical information from its underlying dynamics for its exhibited behavior.

Accurate forecast of demand in electricity volume and price would bring lot of stabilization in the electricity market with highly improved supply chain vs. the demand to cater the growing market. Hence any short-term volume demand and price forecasts would help the producers effectively plan the production, business efficiently (Fan *et al.*, 2015), (Wang *et al.*, 2012), (Erzgraeber et al., 2008). The forecast study and any future analysis are possible only if the market behavior is well analyzed.

Fractal and correlation study has been an efficient tool in analyzing the behavior of complex system. Study of such complex dynamical system through the time series data of the traded market using nonlinear dynamics models are essential to understand the market behavior (Peng *et al.*, 1994), (Kantelhardt *et al.*, 2002). Many studies had undertaken in understanding the electricity power market to study the correlation behavior and multifractal nature of the real world recordings which are in the form of time series so their multifractal properties are extensively investigated (Manimaran et.al., 2005 and refences there in). Similarly, the cross correlation behavior of two non-stationary time series signals were investigated using multifractal detrended cross correlation analysis (MF-X-DFA) approach (Podobnik et.al., 2008), (Zhou, 2008), (Jiang *et al.*, 2011), (Feng *et al.*, 2013), (Pal *et al.*, 2014).

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In this paper, we investigate the multifractal cross correlation behavior of Indian electricity market cleared volume and price before transmission congestion using the recently developed multifractal detrended cross-correlation analysis (MF-X-DFA) method. For this purpose, we have analyzed the time series collected over a period of 3 years i.e. from 1st April 2012 to 1st April 2015. In section 2 we describe the data and MF-X-DFA procedure while the section 3 describes the result and discussion and section 4 gives our conclusions to the study.

DATA AND METHODOLOGY

For this work, the data was obtained from the Indian Energy Exchange (http://www.iexindia.com). We chose market snapshot data of 1 hour time block interval from month 1st April 2012 to 1st April 2015, 3 years India electricity market data. Our data consists of market clearing volume and market clearing price before transmission congestion. Obtained each dataset consists of 26280 data points.

To perform the MF-X-DFA analysis, we calculated the scaled return of clearing price or volume as defined by, $r_t = [\ln(P_{t+1}) - \ln(P_t)]/\sigma$ where P_t being the clearing price or volume index at time t and σ is the standard deviation of P_t. The logarithmic return of a sample time series is given in Figure-1.

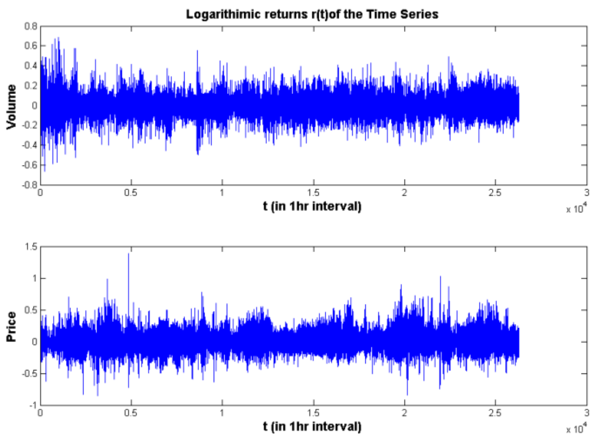

Figure-1. The logarithmic return of volume and price data of India electricity market.

The MF-X-DFA procedure is applied to two cross-correlated return time series as prescribed below:

Let x(i) and y(i) be the two time series to be analysed where i = 1, 2, . . . , N and N is the length of the time series. Then construct the profile of the time series

$$X(i) = \sum_{t=1}^{i} (x(t) - \bar{x}) \quad (1)$$

$$Y(i) = \sum_{t=1}^{i} (y(t) - \bar{y}) \quad (2)$$

Where $\bar{x}$ and $\bar{y}$ are the average of the two time series x(i) and y(i).

We then divide the profile of time series X(i) and Y(i) into $N_s = [N/s]$ non-overlapping windows of equal length s. The length N not always being the multiple of the scale s hence same procedure is repeated starting from the reverse end of each profile to avoid discard of any section of series. To the obtained $2N_s$ non-overlapping windows; the local polynomial trends X^v (i) and Y^v (i) for each segment ν (where, ν = 1, 2, 3, . . . , 2Ns) are removed by least square polynomial fitting of order m in each segment v to fit the data. Now the obtained detrended covariance is

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{t} \left|X((v-1)s+i) - X^v(i)\right| \left|Y((v-1)s+i) - Y^v(i)\right| \quad (3)$$

for each segment where v = 1,2,…Ns.

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{t} |X(N-(v-N_s)s+i) - X^v(i)||Y(N-(v-N_s)s+i) - Y^v(i)| \quad (4)$$

for each segment where v = Ns+1, Ns+2,…, 2Ns.

Now by squaring and averaging the detrended covariances of all segments, we obtain the qth order fluctuation function as,

$$F_q(s) = \left[\frac{1}{2N_s}\sum_{v=1}^{2N_s} [F^2(s,v)]^{q/2}\right]^{1/q} \quad (5)$$

For q = 0, the logarithmic averaging has to be employed to find the fluctuation function;

$$F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s} \ln[F^2(s,v)]\right\} \quad (6)$$

By analyzing the fluctuation functions we obtain the scaling behavior as

$$F_q(s) \sim s^{h_{xy}(q)} \quad (7)$$

Based on the range of scale s chosen for analysis of $F_q(s)$ we classify to short-term or long-term fluctuation hence its corresponding H(q) Hurst exponents.

If the $h_{xy}(q)$ values are independent of q then the cross correlated time series is monofractal while for $h_{xy}(q)$ values dependent q it is multifractal behavior. For H_{xy} i.e.

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$h_{xy}(q=2)$ greater than 0.5 the behavior is persistent while for H_{xy} equal to 0.5 uncorrelated and H_{xy} less than 0.5 for anti-persistent behavior between the two time series.

The scaling behavior of the cross-correlated data sets can also be studied by evaluating the $f_{xy}(\alpha)$ spectrum. $f_{xy}(\alpha)$ values are obtained from the Legendre transform of $\tau_{xy}(q)$:

$$f_{xy}(\alpha) \equiv q\alpha_{xy} - \tau_{xy}(q) \quad (8)$$

where $\tau_{xy}(q) = qh_{xy}(q)$ and $\alpha_{xy} = \frac{d\tau_{xy}(q)}{dq}$. If the two cross-correlated series has monofractal nature, then the values of $\alpha_{xy} = \text{const.}$ and for multifractal nature there occurs a distribution of α_{xy} values. The width of the spectrum describes the strength of multifractality and can be determined by $\Delta\alpha_{xy} = \max(\alpha_{xy}) - \min(\alpha_{xy})$. The broader spectrum is evident for strong multifractality nature and narrow spectrum is evident for weak multifractality nature of the cross-correlated time series.

RESULTS AND DISCUSSIONS

From our analysis from MF-X-DFA, we observe from Figure-2 that the fluctuation function, $F_q(s)$ for both short-term and long-term from year 2012 to 2015 increases linearly as the size of scale s increases hence there exists power law behavior in the cross-correlated time series of volume with price (V-P). In Figure-2 we could find that the log-log plots of fluctuation function $F_q(s)$ and scale s went a fundamental change in the linear trend with the cross-over found at about ln(s)=3.46 (i.e. 32 data point hence 32nd hour of the data which is ~1.3 days out of a monthly data length). Here fluctuations below the crossover are short-term while the fluctuations above are called long-term. The calculated Hurst exponents h(q) values for the cross-correlated time series for both long and short term depends on q values, which is evident of multifractality nature (See Table-1). In Figure-3 we had shown the short-term and long term h(q) plots based on the cross over observed from the fluctuation function plot.

From the Table-1 the Hurst scaling exponent H=h(q=2) for the cross-correlation analysis, we observe long range persistent behavior i.e. H = 0.53 for short-term whereas H = 0.07 for long-term (i.e. anti-persistent behavior). For short-term (s*<32) from the Hurst exponent H (h(q=2)) we could see the cross-correlated series of volume-price possess long term persistent behavior. From Figure-4, the broad spectrum width (1.2) for short term implies strong multifractality while narrower spectrum width (0.2) for long term indicates the weak multifractal behavior.

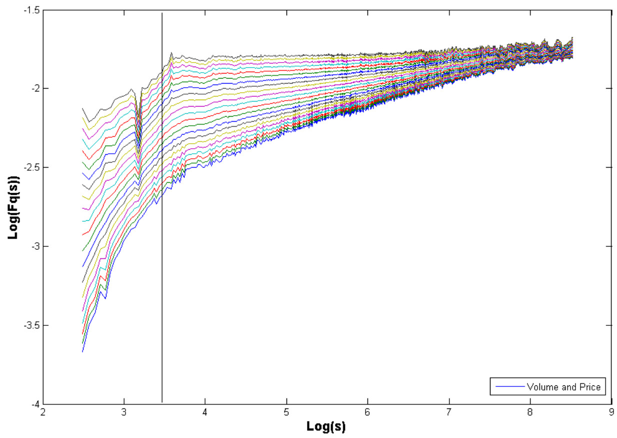

Figure-2. The log-log plots of fluctuation function $F_q(s)$ versus *s* for cross-correlated volume and price showing cross-over.

Table-1. The value of Hurst exponent h(q) for different q values of volume and price cross-correlation in both short-term and long-term.

q	h(q) Short-term	h(q) Long-term
-10	0.966	0.140
-9	0.945	0.136
-8	0.918	0.131
-7	0.887	0.126
-6	0.850	0.121
-5	0.807	0.116
-4	0.761	0.110
-3	0.714	0.104
-2	0.668	0.098
-1	0.626	0.092
0	0.589	0.086
1	0.556	0.080
2	**0.527**	**0.074**
3	0.499	0.068
4	0.471	0.062
5	0.441	0.055
6	0.409	0.049
7	0.375	0.044
8	0.339	0.038
9	0.304	0.033
10	0.272	0.028

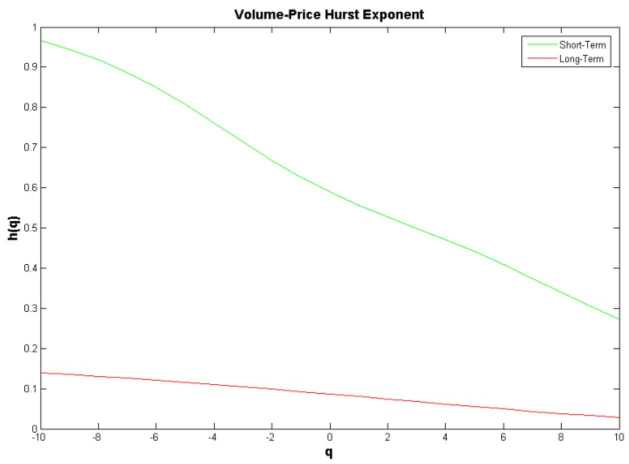

Figure-3. The Hurst exponent values $h_{xy}(q)$ for different q values of short-term and long-term of volume and price.

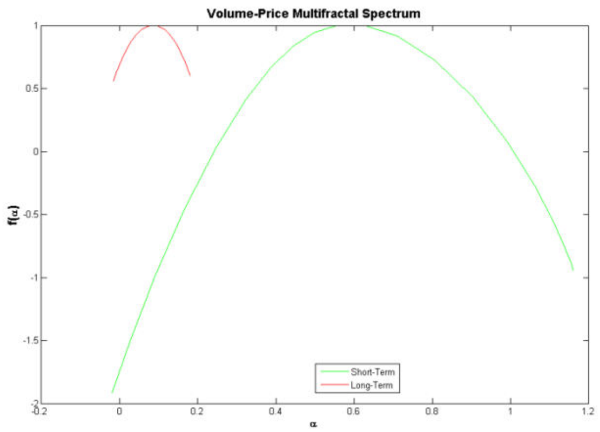

Figure-4. The multifractal behavior of short-term and long-term for the cross-correlated time series is shown through f(α) spectrum.

CONCLUSIONS

In this work, we investigate the multifractal detrended cross correlation analysis between the electricity market cleared volume and price of Indian market. From our analysis using the MF-X-DFA method, we observe there exists a cross-over in the fluctuation function (short-term i.e. < 32 hours and long-term i.e. > 32 hours). Also we have calculated the scaling exponents there exhibits anti-persistent behavior for long-term and persistent behavior in short-term. The multifractal nature is present in both the long-term and short-term analysis. The presence of multifractality indicates that non-linearities are involved in the dynamics of electricity market. The demand versus supply chain is very non-linear and would need many new power generation plants to stabilize for a long term predictable behavior of the market. Also it is evident from the volume-price long range anti-persistent behavior in long-term that electricity generation; supply versus demand in India to be balanced which calls for more power generation along with efficient operation and distribution through modernization and digitization of power grids and electrical distribution systems.

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