Electrical Power and Energy Systems 74 (2016) 162–171

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Multifractal behavior of Electricity Bid Price in Indian Energy Market

Dipak Ghosh [a], Srimonti Dutta [b], Sayantan Chakraborty [c,*]

[a] UGC Emeritus Fellow, Department of Physics, Jadavpur University, Kolkata 700032, India
[b] Department of Physics, Behala College, Parnasree Pally, Kolkata 700060, India
[c] Department of Electrical Engineering, Dr. Sudhir Chandra Sur Degree Engineering College, Dum Dum, Kolkata 700074, India

A R T I C L E I N F O

Article history:
Received 14 September 2014
Received in revised form 3 July 2015
Accepted 21 July 2015
Available online 3 August 2015

Keywords:
Multifractals
Electricity consumption
Electricity biding prices
Time series analysis

A B S T R A C T

The bid price of power generation in a country is of extreme importance due to its obvious impact on the industry although it is difficult to explore correlation among cost of a product in any industry with fluctuations of biding price of power. This is due to the fact that the fluctuations are nonlinear and extremely complex. Recent years have witnessed the study of this type of complex systems with powerful tool involving fractal methodology. This paper reports for the first time in Indian scenario a study on the fluctuation pattern of biding price of power in five different bid areas of India with a robust and rigorous technique based on chaos and fractal behavior. The exhaustive study reveals very interesting patterns of the fluctuation process, namely in all domains, the fluctuations are multifractal in time and degree of multifractality is quite different in different zones. The data is completely new and has serious implications on product cost of industry and ultimately on stock price indices. The paper includes possible future applications including predictability of next day price.

Introduction

Electric power is a flow commodity having unique characteristics influencing the way it is traded and thus the behavior of spot and futures prices in the market [1]. It may be generated from natural gas, coal, oil, nuclear fuel, falling water, geothermal steam, alternative resources such as cogeneration, and from renewable resources such as wind power, solar energy and biomass. Electricity price is highly volatile as Electric power cannot be effectively stored excepting a few pumped-storage hydro power plants etc., the adjustment of demand and supply must be instantaneous [1]. Therefore, a delicate balance must be maintained between generation and consumption – 24 h a day, 7 days a week, and 8760 h a year [2]. There are no reserves that could be used in case of sudden increase in demand or weather change [3]. The prices are not only volatile; the volatility has also a tendency to cluster. Due to the properties described above, the electricity prices are often treated as non-stationary [1].

Seasonal fluctuations in price are mainly due to weather, in particular temperature and number of hours of daylight [4]. Demand for electricity is highly inelastic. In short run, it is absolutely inelastic so that the price is determined by the supply curve (merit order curve, marginal cost curve) completely [5]. The electricity prices are also influenced by factors that are unthinkable for other "typical" financial assets – technical constraints. Electricity can be easily and quickly transported but transmission lines have capacity constraints which must not be exceeded. That is the main reason why electricity prices differ in neighboring areas but it can also cause high levels of volatility due to potential instability of the whole system [6].

Electricity demand and also the prices depend on business-cycle, economic activity or growth. Electricity consumption and economic growth are bounded; different studies suggest different direction of the causality, from electricity consumption to GDP, vice versa or both [7–10]. Similar to the stock market [11], the electricity market exhibits non-linear behavior due to the highly apparent non-linear relationship between offers submitted by suppliers and the market clearing price [12]. The Hurst exponent is used for describing a stock market, but a filter process is necessary to reduce error as a result of various sources of error involved in the stock market [13]. Different from a stock market, electricity markets have highly ordered structure, and thus, no filter process is necessary for characterizing market based on the values of the parameters.

Due to sudden and unanticipated changes in electricity demand modeling electricity prices is particularly challenging and has inspired several researches to develop a variety of different methods to model electricity prices. Recently, the statistical properties of electricity prices have been investigated by some methods in chaos theory, multifractal analysis, long memory analysis and

* Corresponding author. Tel.: +91 9051246963.
E-mail address: sayantan.a2z@gmail.com (S. Chakraborty).

http://dx.doi.org/10.1016/j.ijepes.2015.07.026
0142-0615/© 2015 Elsevier Ltd. All rights reserved.

Table 1
List of bid areas of India.

Bid area	Region	States covered under bid area
A1	North East 1	Tripura, Meghalaya, Manipur, Mizoram, Nagaland
A2	North East 2	Assam, Arunachal Pradesh
N1	North 1	Jammu and Kashmir, Himachal Pradesh, Chandigarh, Haryana
N2	North 2	Uttar Pradesh, Uttaranchal, Rajasthan, Delhi
N3	North 3	Punjab
E1	East 1	West Bengal, Sikkim, Bihar, Jharkhand
E2	East 2	Orissa
S1	South 1	Andhra Pradesh, Telangana, Karnataka, Pondicherry (Yanam), South Goa
S2	South 2	Tamil Nadu, Kerala, Pondicherry (Puducherry, Karaikal & Mahe)
W1	West 1	Madhya Pradesh
W2	West 2	Maharashtra, Gujarat, Daman and Diu, Dadra and Nagar Haveli, North Goa
W3	West 3	Chhattisgarh

other stochastic methods for managing electricity price risk, valuing electricity derivatives and predicting future prices [14–19].

Numerous studies on electricity pricing have been conducted. Most studies of electricity pricing behavior have focused on industrial economic approach (market structure and market power), engineering approach (cost based pricing), or institutional aspects (impact of deregulation on price) [20–24]. Few studies have investigated the dynamic behavior of prices. Studies examining electricity price dynamics have usually indicated the following stylized facts concerning electricity prices: high volatility, seasonality, and frequent extreme jumps in prices [25]. In Ref. [26] more studies concerning modeling electricity prices are given. DeVany and Walls [27] using daily peak and off-peak data from 1994 to 1996 investigated electricity spot price behavior and tested for market integration for western U.S. markets. They found all electricity spot price series except for one off-peak price series are non-stationary. Further, all of off-peak price series and most of peak price series are pair-wise cointegrated. DeVany and Walls [28] used impulse response and variance decomposition analyses and found the electricity prices to show relatively rapid (four or five trading days) convergence with respect to external shocks. Jerko et al. [29] used directed graphs to examine the contemporaneous causal flows among spot markets and suggested that electricity flows north to south or south to north differ between seasons in the western U.S. Goto and Karolyi [30] showed the conditional autoregressive heteroscedasticity (ARCH) and time-dependent jumps are important features in modeling price volatility using four U.S. spot market prices, Nordic pool market prices, and Australia market price. Weron and Przybylowicz [2] conducted Hurst Rescaled Range analysis for distinguishing random time series from correlated time series to capture the price volatility using the electricity prices from California and Central Europe [31].

Alvarez-Ramirez et al. [32] analyzed Ontario and Alberta electricity markets using Detrended Fluctuation Analysis (DFA) and the Allan factor model to show that the long-term memory properties of both prices and demand strongly vary in time. Haugom et al. [33] modeled Nord Pool electricity prices using long-term memory mimicking Heterogeneous Autoregressive Model with Realized Variance (HAR-RV) and showed that incorporating the strongly persistent realized variance improves the predicting power of the model. Rypdal et al. [34] in modeled the Nord Pool data using the Multifractal Random Walk model adjusted for mean-reversion and volatility persistence to capture the most important characteristics of the electricity prices. Using the model, the authors showed that the electricity prices characteristics are very different from the ones of the stock market prices. Kristoufek et al. [35] applied DFA on hourly prices of the Czech Republic between 2009 and 2012. They found the electricity prices to be non-stationary but strongly mean-reverting which distinguishes them from other financial assets which are usually characterized as unit root series. They attributed this description to specific features of electricity prices, mainly to non-storability and also argued that the rapid mean-reversion is due to the principles of electricity spot prices [1]. Norouzzadeh et al. [19] applied Multifractal Detrended Fluctuation Analysis (MF-DFA) to numerically investigate correlation, persistence, multifractal properties and scaling behavior of the hourly spot prices for the Spain electricity exchange-Compania O Peradora del Mercado de Electricidad (OMEL).

In this paper we have applied MF-DFA to study the multifractal properties of monthly bid prices at 15 min interval of five different bid areas of India namely A1, N1, E1, S1 and W1 from 1st April 2012 to 31st March 2014. The details of the region associated with the bid areas are listed in Table 1. Multifractal Detrended Fluctuation Analysis (MF-DFA) was first conceived by Kantelhardt et al. [36] as a generalization of the standard DFA. MF-DFA has been applied successfully to study multifractal scaling behavior of various non-stationary time series [37–44]. The application of MF-DFA to the data will provide a method of determining if there is any evidence of self similarity or persistence in the series. The Hurst exponent is one of the measures that can provide this information and in turn will inform methods of forecasting [45].

Lipka and Los [46] measured the degrees of persistence of the daily returns of eight European stock market indices and found that the Hurst exponents measure the long-term dependence of the data series well. They found that the FTSE returns represent an ultra-efficient market with abnormally fast mean reversion, than that possible by a Geometric Brownian Motion. Corazza and Malliaris [47] analyzed returns of several foreign currency markets and found Hurst exponent value to be statistically different from 0.5 in most of the samples. They also noted that the Hurst exponent is not fixed but it varies overtime. Cajueiro and Tabak [48] tested long-range dependence and efficiency in stock indices for 11 emerging markets along with U.S. and Japan. They adopted a “rolling sample” approach and calculated median Hurst exponents to assess relative efficiency of these equity markets. They suggested that Asian equity markets show greater inefficiency than those of Latin America and developed markets rank first in terms of efficiency. Kyaw et al. [49] analyzed the degree of long-term dependence of Latin American financial markets, measuring mono-fractal Hurst exponents from wavelet multi-resolution analysis (MRA) of Latin American stock and currency markets. They found that the financial rates of return from are non-normal, non-stationary, non-ergodic and long-term dependent. Singh and Prabakaran [50] examined return spectrum of the Indian stock markets using various statistical tests for the normality of data.